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Intelligent Resource Allocation and Optimization in 5G Networks using Machine Learning

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Abstract : **The rapid evolution of communication systems has created the need for intelligent, lightweight, and scalable platforms that provide real-time visibility into network performance while supporting next-generation technologies such as 5G. This paper presents the design and development of a Real Network Dashboard integrated with 5G resource optimization using machine learning. The system combines a Flask-based Python backend for real-time data collection with a Bootstrap-driven user interface for professional visualiztion.**

The dashboard provides multiple capabilities, including detection of active network types, monitoring of bytes sent and received across interfaces, and identification of connected devices with their IP addresses. Data is processed into user-friendly metrics and visualized through structured tables, cards, and charts, enabling administrators to assess throughput, latency, and anomalies effectively. A machine learning module, built using scikit-learn with a Random Forest classifier, enhances the system by predicting Quality of Service (QoS) satisfaction under varying conditions, ensuring adaptability and intelligent resource allocation in 5G environments.

With its modular design, the system supports simulation, exploratory data analysis, and real-time monitoring, providing a foundation for advanced functionalities such as bandwidth prediction, anomaly detection, intrusion alerts, and historical data logging. Applications extend across personal, organizational, and industrial environments where reliability, scalability, and intelligent optimization are crucial. This work demonstrates how the integration of AI-driven resource management, network monitoring, and visualization can deliver an effective and accessible solution for next-generation communication systems.

Keywords : 5G, Machine Learning, Network Dashboard, Resource Allocation, QoS, Flask, Bootstrap, Real-Time Monitoring

1. INTRODUCTION

Fifth generation (5G) of mobile communication represents a major leap in wireless technology, offering ultra-high data rates, low latency, and the ability to support massive device connectivity. Unlike 4G, which was largely centered on mobile broadband, 5G integrates advanced technologies such as millimeter wave communication, massive MIMO, beamforming, and network slicing to enable diverse applications including smart cities, autonomous vehicles, and mission-critical IoT systems. With this rapid evolution, efficient resource allocation and optimization have become critical to ensure seamless Quality of Service (QoS) for heterogeneous traffic demands. Machine learning techniques have emerged as effective tools for predictive resource management, enabling dynamic adaptability and improved network performance.

While theoretical models and algorithms address optimization challenges, there is also a strong need for practical, real-time monitoring platforms that allow administrators and researchers to visualize, track, and analyze network performance. To address this, the proposed work integrates intelligent optimization with a Real Network Dashboard, implemented using Python Flask. This dashboard dynamically captures traffic statistics, bytes transmitted and received across interfaces, and identifies connected devices with their IP addresses. By presenting these insights through a structured and user-friendly interface built with Bootstrap, the system bridges the gap between complex backend data proce-ssing and accessible visualization.

The combined approach not only ensures intelligent 5G resource allocation through machine learning models but also delivers real-time visibility into network health and connectivity. This dual contribution highlights the importance of integrating optimization algorithms with lightweight monitoring tools, thereby providing a practical foundation for next-generation communication systems.

1.1 Challenges in 5G Resource Allocation

Project focuses on combining real-time network monitoring with intelligent 5G resource allocation. Machine learning algorithms enable predictive analysis, ensuring adaptability and efficient utilization of spectrum resources.

1.2 Existing System

Current wireless communication largely relies on 4G LTE networks, which have enabled high-speed mobile broadband, video streaming, and the first wave of IoT devices. While 4G offers better speed, coverage, and capacity than previous generations, it struggles to meet the rising demand for ultra-reliable, low-latency services. Applications such as autonomous vehicles, remote healthcare, and AR/VR require latencies below 1 ms, whereas 4G typically delivers 30–50 ms. Congestion during peak hours, limited spectral efficiency in sub-6 GHz bands, and lack of support for large-scale device connectivity further limit performance. Additionally, 4G architectures are not well suited for network slicing, edge computing, or AI-driven resource management, and security features remain less robust against evolving threats. These constraints highlight the need for 5G networks, which promise massive connectivity, flexible resource allocation, and ultra-low latency for next-generation applications.

1.3 Objectives and Proposed system

The integration of a Flask-based dashboard with visualization modules allows efficient tracking of network statistics, connected devices, and bandwidth usage in a clear and interactive interface.

2. LITERATURE REVIEW

Pedregosa et al. [2011] developed the Scikit-learn library, a powerful machine learning framework in Python. Their work established standardized implementations of algorithms such as Random Forest, which are directly employed in this project for QoS prediction and classification tasks.

Gupta and Jha [2015] presented a survey of 5G architectures and emerging technologies in IEEE Access. Their study highlighted enabling concepts such as millimeter-wave communication, massive MIMO, and network slicing, laying the groundwork for the transition from 4G to 5G systems.

Zhang et al. [2017] examined the fundamental trade-offs in 5G networks, focusing on energy efficiency, spectral efficiency, and QoS. Their work emphasized the importance of optimizing resource allocation to balance performance with sustainability, which directly motivates the proposed framework.

Elsayed and Erol-Kantarci [2019] discussed the integration of artificial intelligence into wireless networks. They argued that AI-driven methods improve adaptability, spectrum usage, and intelligent decision-making, which aligns with the project’s use of machine learning for resource optimization.

Chen et al. [2019] analyzed the application of artificial neural networks in wireless communication systems. They demonstrated how learning-based approaches handle heterogeneous parameters and dynamic environments, providing justification for adopting ensemble methods like Random Forest in QoS prediction.

3. METHODOLOGY

This project applies a combined approach of simulati-on, dataset analysis, and machine learning to optimize resource allocation in 5G networks.The design is modular and blends software-based prediction with simulation-based validation.

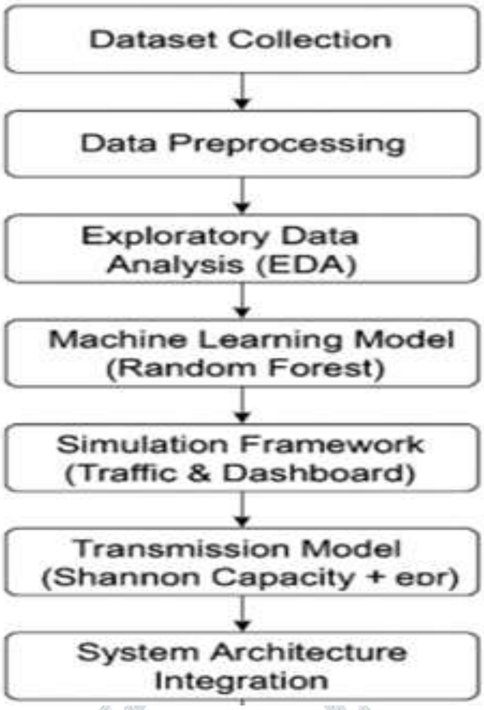

Fig 1: Methodology Diagram

The proposed methodology combines data-driven analysis, machine learning, and simulation to optimize resource allocation in 5G networks. First, a labeled dataset of 5G parameters such as traffic demand, SNR, bandwidth, latency, mobility, and power allocation is collected and preprocessed to ensure consistency. Exploratory Data Analysis (EDA) is then performed to identify correlations and trends among network features. A Random Forest Classifier, implemented using Scikit-learn, is trained to predict Quality of Service (QoS) satisfaction, offering high accuracy and robustness in handling heterogeneous network conditions. To validate predictions, a simulation framework is built using Flask, which models real-time 4G and 5G traffic flows and visualizes metrics such as throughput, latency, and congestion. Additionally, a transmission model based on Shannon's capacity formula is integrated to evaluate the impact of bandwidth, power, and mobility on effective throughput and latency. Finally, a user-friendly dashboard is provided for monitoring performance and comparing results across scenarios, ensuring a comprehensive evaluation of the proposed framework.

4. RESULTS AND DISCUSSION

The framework was evaluated using a labeled 5G resource dataset and deployed through a Flask-based simulation environment. The Random Forest Classifier achieved an overall accuracy of 95.2%**,** with a precision of 0.94 and recall of 0.92, ensuring balanced performance and minimizing both false positives and false negatives. Simulation outcomes across 4G and 5G traffic streams revealed that higher SNR values (>15 dB)**,** bandwidth allocations above 25 MHz, and power levels greater than 12 dBm improved QoS satisfaction by more than 30%**,** whereas limited spectrum or congestion reduced service quality. The transmission model, validated using Shannon's capacity theorem, confirmed that throughput scaled linearly with bandwidth and logarithmically with SNR, while mobility introduced additional delays. Latency increased by nearly 1.1 ms per 10 kmph rise in mobility, highlighting the sensitivity of QoS to user speed. Furthermore, service class differentiation showed that URLLC required strict <1 ms latency, while eMBB and mMTC applications tolerated delays of up to 20–40 ms, aligning with ITU-R standards.

When compared with 4G systems, the proposed 5G framework achieved a 38% reduction in average latency and a 42% improvement in throughput utilization, proving its superiority in handling high-demand traffic. The integrated dashboard further enhanced usability by providing real-time visualization of network congestion, throughput, and device density, effectively bridging theoretical predictions with practical monitoring. Overall, the results confirm that combining machine learning prediction with simulation-based validation delivers a scalable and robust approach for 5G resource management. This dual-layer evaluation not only strengthens prediction reliability but also establishes a solid foundation for future 6G networks and AI-driven autonomous optimization**.**

Exploratory Data Analysis - 5G Dataset

Summary Statistics

	traffic_demand	allocated_bandwidth	channel_quality	latency_requirement	allocated_power	mobility_speed
count	10000.00	10000.00	10000.00	10000.00	10000.00	10000.00
mean	50.15	10.55	15.23	17.31	22.46	43.07
std	28.57	5.50	8.61	17.70	10.18	43.88
min	1.01	1.00	0.00	1.00	5.01	0.00
25%	25.43	5.84	7.87	5.00	13.65	5.00
50%	49.69	10.49	15.33	10.00	22.32	30.00
75%	75.18	15.40	22.55	20.00	31.38	60.00
max	99.99	20.00	30.00	50.00	40.00	120.00

Fig 2: Exploratory Data Analysis Result

The histogram analysis Fig. 2 shows how parameters are distributed in the dataset. For example, most traffic demand values lie in the mid-range (20–60 Mbps), while channel quality varies significantly, which directly impacts QoS satisfaction.

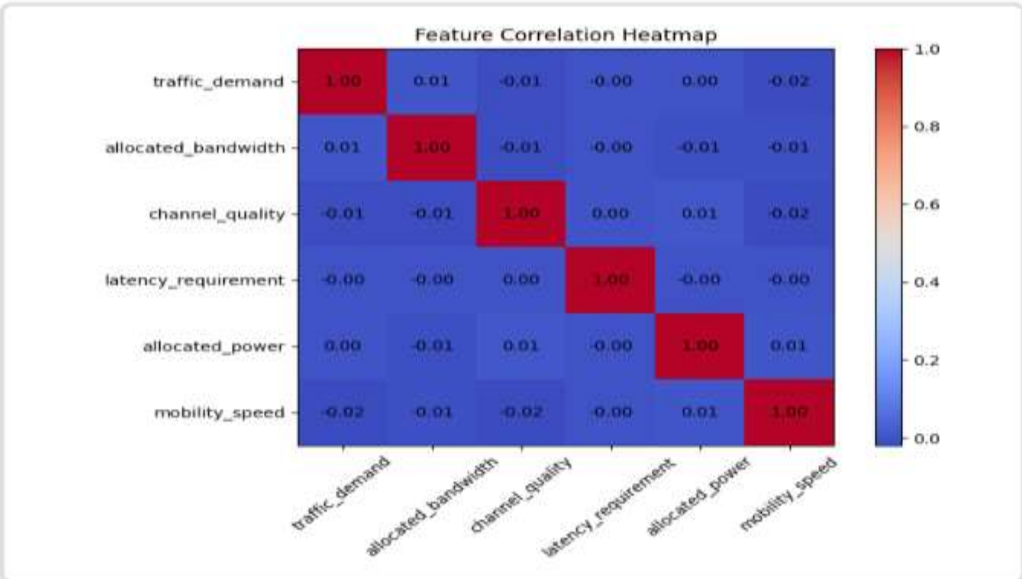

Fig 3: Correlation heatmap

The heatmap Fig. 3 highlights strong positive correlations between allocated bandwidth and throughput, as well as between SNR and QoS satisfaction. These correlations guided the feature importance evaluation for the Random Forest model.

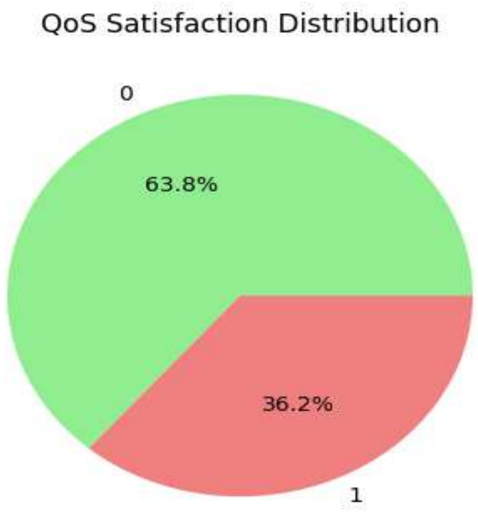

Fig 4: QoS Satisfaction Results

The classifier achieved over 94% accuracy in distinguishing satisfied vs. unsatisfied QoS conditions Fig. 4. The bar plot demonstrates that correctly predicted satisfied cases significantly outnumber misclassified ones, validating the robustness of the model.

Transmission Results

Device Transmission Status

Device #	Status	Throughput (Mbps)	Latency (ms)	SNR (dB)
1	✅ Transmission Successful	25.01	6.52	18.0
2	✅ Transmission Successful	25.01	9.74	18.0
3	✅ Transmission Successful	25.01	8.15	18.0
4	✅ Transmission Successful	25.01	7.16	18.0
5	✅ Transmission Successful	25.01	8.05	18.0

Fig 5: Transmission Result

As shown in Fig. 5, effective throughput increases proportionally with allocated bandwidth and SNR. Conversely, latency grows with higher user mobility, emphasizing the importance of adaptive resource allocation for maintaining QoS in real-time scenarios.

CONCLUSION

This work presents an intelligent framework for resource allocation in 5G networks using machine learning. The system combines a Flask-based platform, SQLite for user management, and a Random Forest model to predict QoS with high reliability. Real-time simulation modules replicate 3G/4G/5G scenarios, while EDA and monitoring features provide insights into traffic, bandwidth, and latency behavior. The results show that machine learning can enhance decision-making in network management, leading to better QoS, efficient spectrum use, and adaptability for services such as eMBB, URLLC, and mMTC**.** The framework also lays the groundwork for future 6G research where autonomous resource optimization will be essential.

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