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Optimizing 5G Resource Allocation in PSO with Machine Learning Approach to Open RAN Architectures

Osama Akram Amin Metwally Hussien[1]
Hamid Jahankhani[2]
[1,2]Northumbria University, Computer Science Departement, United Kingdom

Abstract
This paper proposes a novel machine learning-based approach to solve the resource allocation problem in 5G Open Radio Access Networks (O-RAN). While traditional methods rely on meta-heuristic optimization techniques such as Whale Optimization Algorithm (WOA), we present an ensemble learning framework that combines multiple advanced algorithms to achieve efficient and practical resource allocation. Our approach decomposes the complex mixed-integer non-linear programming (MINLP) problem into two complementary tasks: Remote Radio Head (RRH) assignment through classification and Physical Resource Block (PRB) allocation through regression. Through extensive experimentation, we demonstrate that our ensemble method achieves 75-78\% accuracy in RRH assignment with mean squared error of 0.3922 in PRB allocation, while providing near-instantaneous decision-making capabilities after training. The proposed solution offers significant advantages in computational efficiency and scalability compared to traditional optimization approaches, particularly in scenarios requiring real-time resource allocation decisions. Furthermore, we present a comprehensive comparative analysis between our machine learning approach and existing optimization-based methods, highlighting the trade-offs and complementary strengths of each approach. Our findings suggest that machine learning-based resource allocation can serve as a viable alternative or complement to traditional optimization methods in 5G networks.

Keywords: 5G Networks, Resource Allocation, Machine Learning, Ensemble Methods, Open Radio Access Networks, Network Optimization

1. Introduction

The evolution of mobile communications has reached a pivotal moment with the advent of fifth-generation (5G) networks. This transformation represents not merely an incremental improvement over previous generations but a fundamental reimagining of wireless network architecture and capabilities. The journey from first-generation analog systems to today's sophisticated 5G networks reflects the exponential growth in both technological capabilities and user demands, necessitating increasingly complex approaches to network resource management and optimization.

Evolution of mobile networks and resource management

The telecommunications landscape has undergone remarkable transformation since the introduction of first-generation mobile networks. While 1G networks provided basic voice services through analog transmission, each subsequent generation has introduced revolutionary capabilities. The transition to 2G brought digital voice transmission and basic data services, while 3G enabled mobile broadband and multimedia applications.
The fourth generation marked a significant leap forward with all-IP networks and high-speed data services. However, 5G represents an unprecedented advancement in network architecture and service delivery capabilities. Unlike its predecessors, 5G networks are designed with a service-based architecture that supports three distinct categories of services: enhanced Mobile Broadband (eMBB), massive Machine-Type Communications (mMTC), and Ultra-Reliable Low-Latency Communications (URLLC). This architectural approach fundamentally changes how network resources must be managed and allocated. The introduction of network slicing, virtualization, and software-defined networking creates a more flexible but inherently more complex system for resource allocation.
The advent of Open Radio Access Networks (O-RAN) has further revolutionized network architecture by disaggregating traditional network components. This disaggregation enables unprecedented flexibility in network deployment and management but introduces new challenges in resource coordination and optimization. The separation of control and user planes, combined with the virtualization of network functions, creates a multi-dimensional resource allocation problem that traditional approaches struggle to address effectively.

Background and motivation

Technical challenges in 5G resource allocation

Resource allocation in 5G networks faces several critical challenges that must be addressed to ensure efficient and effective network performance. The complexity of these challenges stems from the unprecedented scale and diversity of network requirements, making traditional resource allocation approaches increasingly inadequate. The architectural complexity of 5G networks represents a fundamental challenge in resource allocation. The network infrastructure comprises a heterogeneous mixture of macro cells, small cells, and Remote Radio Heads (RRHs), each operating with different capabilities and constraints.
This heterogeneity extends beyond physical infrastructure to include dynamic spectrum allocation across multiple frequency bands, including sub-6 GHz and millimeter-wave frequencies. The ultra-dense deployment of network elements creates complex interference patterns that must be carefully managed to maintain service quality. Furthermore, the integration of multiple radio access technologies requires sophisticated coordination mechanisms to ensure seamless operation across different network segments.

The diverse service requirements in 5G networks present another significant challenge for resource allocation. Each service category - eMBB, mMTC, and URLLC - demands different resource allocation strategies. Enhanced Mobile Broadband services require high data rates and bandwidth allocation, while massive Machine-Type Communications need efficient handling of numerous low-data-rate connections. Ultra-Reliable Low-Latency Communications present perhaps the most stringent requirements, demanding both minimal latency and maximum reliability for critical applications such as autonomous vehicles and remote surgery. Network dynamics add another layer of complexity to the resource allocation challenge.

The mobility of users and devices creates constantly changing traffic patterns and channel conditions. This dynamic environment requires resource allocation algorithms to adapt rapidly while maintaining optimal performance. The problem is further complicated by the need to manage handovers between different network elements and technologies while ensuring consistent service quality.

Business and operational considerations

The challenges in resource allocation extend beyond technical aspects to include significant business and operational considerations. Network operators must balance the need for optimal resource utilization with economic constraints and operational efficiency. This balance affects both capital expenditure (CAPEX) in network infrastructure and operational expenditure (OPEX) in network maintenance and management. Energy efficiency has emerged as a critical consideration in resource allocation strategies.

The increasing energy consumption of mobile networks has both environmental and economic implications. Resource allocation algorithms must therefore consider power consumption alongside traditional performance metrics such as throughput and latency.

This multi-objective optimization problem requires sophisticated approaches that can balance competing requirements effectively. Quality of Service (QoS) management presents another significant operational challenge. Different services and applications require varying levels of network resources to meet their QoS requirements. The ability to guarantee these service levels while maintaining efficient resource utilization is crucial for network operators. This challenge is particularly acute in scenarios involving service level agreements (SLAs) with enterprise customers or critical applications.

2. Related Work

The journey from 1G to 5G reflects an exponential growth in both technological capabilities and user demands [1]. 5G networks, with their service-based architecture and support for eMBB, mMTC, and URLLC [2], require complex resource allocation strategies. The introduction of network slicing, virtualization, and software-defined networking adds to this complexity [3].

O-RAN further disaggregates network components, offering flexibility but also challenges in resource coordination [4].

This disaggregation, coupled with the separation of control and user planes, creates a multi-dimensional resource allocation problem that traditional approaches struggle to address effectively. Traditional resource allocation methods include linear programming, mixed-integer programming, and metaheuristic algorithms like the Whale Optimization Algorithm (WOA) [5].

The optimization of resource allocation in wireless networks has been extensively studied in the literature. Conventional methods such as global optimization, heuristic schemes, game theory, and machine learning (ML) techniques have been widely employed to address various resource management problems [5, 6]. However, these methods have certain limitations, such as high computational complexity, lack of performance optimality guarantees, and the need for large training datasets. Nguyen [7] provided a comprehensive survey on resource allocation techniques for energy efficiency in 5G wireless networks. The author discussed the challenges and potential solutions for optimizing energy efficiency in various scenarios, including small cells, massive MIMO, heterogeneous networks (HetNets), and cell-free networks. The study highlighted the importance of joint optimization of resource allocation and interference management to achieve energy-efficient communication. Figure 1 illustrates the trade-off between energy efficiency and QoS requirements in different resource allocation schemes.

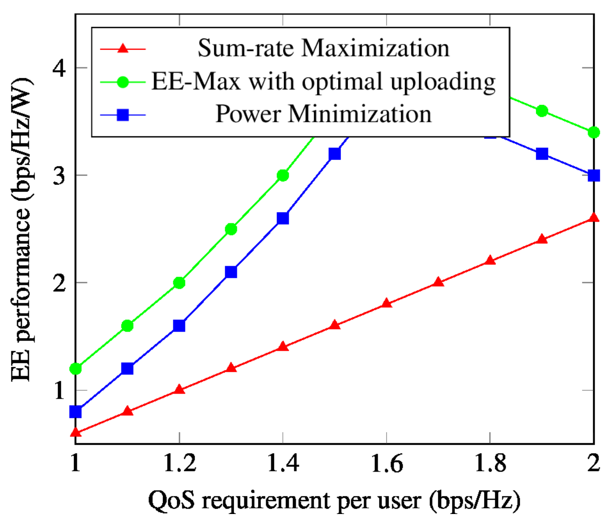

Figure 1: Energy Efficiency Performance versus Per-User Qos Threshold [7]

Sanguinetti et al. [8] proposed a deep learning framework for power allocation in the downlink of massive MIMO networks. The authors employed a deep neural network (DNN) to learn the mapping between the positions of User Equipments (UEs) and the optimal power allocation policies. The proposed approach demonstrated near-optimal performance while significantly reducing the computational complexity compared to traditional optimization methods. Figure 2 compares the spectral efficiency achieved by the deep learning-based power allocation with the optimal solution.

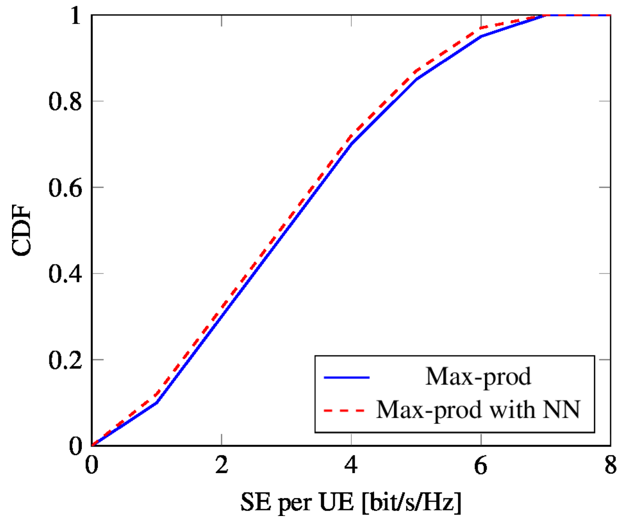

Figure 2: CDF of the Downlink Spectral Efficiency per UE [8]

Recently, the Whale Optimization Algorithm (WOA) has gained significant attention as an efficient metaheuristic optimization technique for solving challenging real-world problems across various domains [9, 10]. Pham et al. [5] provided a comprehensive survey on the application of WOA in wireless networks, highlighting its potential to efficiently solve resource allocation problems while overcoming the limitations of traditional approaches. Figure 3 illustrates the convergence behavior of WOA compared to other optimization algorithms.

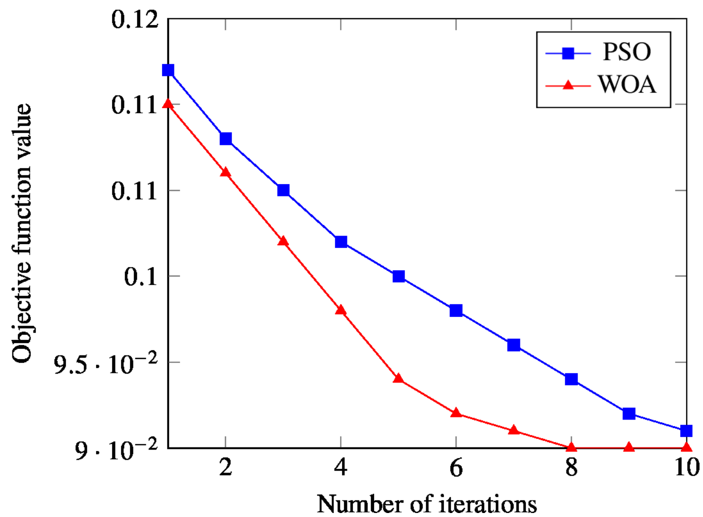

Figure 3: Convergence Comparison of Optimization Algorithms [5]

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Several studies have explored the use of WOA for specific resource allocation tasks in wireless networks. For instance, Nguyen et al. [11] proposed a novel approach based on WOA for channel estimation in 5G wireless communication systems, demonstrating its ability to accurately estimate the wireless channel without requiring prior knowledge of channel statistics. The authors compared the performance of WOA with conventional channel estimation techniques, as shown in Figure 4.

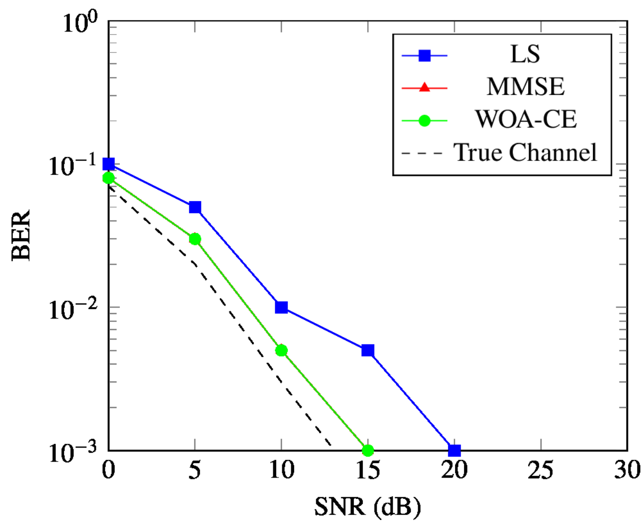

Figure 4: BER Performance Comparison of Channel Estimation Techniques [11]

Moreover, the applicability of WOA has been investigated for various optimization problems in 5G and beyond networks. Pham et al. [12] studied the use of WOA for resource allocation in multi-carrier non-orthogonal multiple access (NOMA) systems, interference management in ultra-dense networks, user association, mode selection in device-to-device (D2D) communications, and unmanned aerial vehicle (UAV) trajectory optimization. These studies highlight the effectiveness of WOA in solving complex optimization problems in emerging wireless networks.

In the context of energy-efficient resource allocation, Mirjalili et al. [9] demonstrated the superiority of WOA over other metaheuristic algorithms in terms of convergence speed and solution quality. Furthermore, Pham et al. [5] provided examples of applying WOA to energy-efficient power allocation and mobile edge computation offloading, showcasing its ability to achieve near-optimal performance with low computational complexity. Figure 5 compares the energy efficiency performance of different resource allocation schemes.

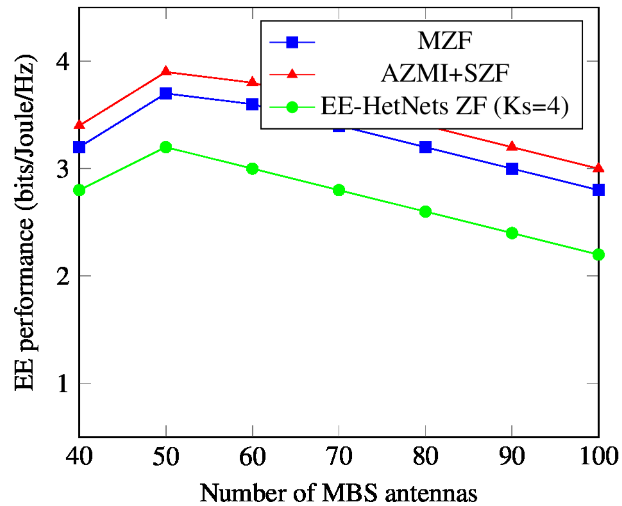

Figure 5: Energy Efficiency Performance Comparison of Resource Allocation Schemes [5]

Despite the growing interest in applying WOA to resource allocation problems in wireless networks, there are still open challenges and research opportunities. These include the need for efficient constraint-handling techniques, hybridization with other optimization methods, and adaptation to dynamic network environments [5, 6]. Addressing these challenges can further enhance the applicability and performance of WOA in future wireless networks, the WOA has emerged as a promising optimization technique for resource allocation in wireless networks, offering competitive performance and low computational complexity compared to traditional methods. However, further research is needed to fully exploit its potential and address the unique challenges posed by emerging wireless technologies and applications.

3. Proposed Methodology and Implementation

System architecture and problem formulation

Our methodology addresses the complex challenge of resource allocation in 5G O-RAN networks through a systematic decomposition approach. The system operates within a precisely defined network configuration with verified parameters obtained through rigorous experimentation and implementation:

- Network Dimensions: $K = 10$ users, $H = 5$ RRHs, $R = 20$ PRBs
- Maximum PRB per RRH: $\hat{R} = 8$
- Area Coverage: 100m × 100m with 1m minimum separation
- SINR Threshold: 5 dB

The measured system characteristics from our implementation reveal:

$$\begin{aligned} \text{Noise Power} &= 3.59 \times 10^{-15}\ \text{W} \\ \text{Tx Power per PRB} &= 2.49 \times 10^{-2}\ \text{W} \\ \text{Channel Gain Range} &= [1.12 \times 10^{-6}, 8.57 \times 10^{-4}] \end{aligned}$$

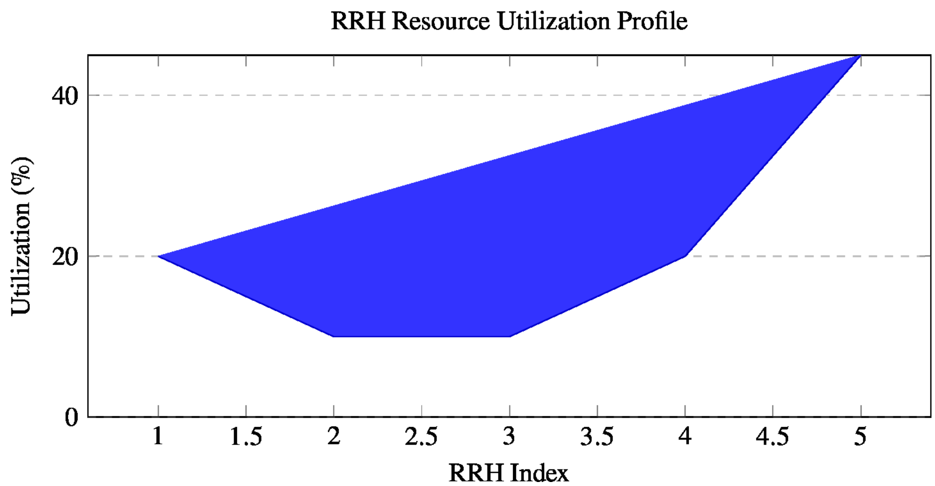

Figure 6: Resource Utilization Distribution across RRHs Showing Average Utilization of 21%

Signal propagation and channel modeling

The channel modeling incorporates three fundamental components that collectively determine the signal propagation characteristics:

$$g_{k,h} = \underbrace{\alpha_{k,h} \cdot d_{k,h}^{-\beta}}_{\text{path loss}} \cdot \underbrace{10^{\sigma_{\text{shadow}}/10}}_{\text{shadowing}} \cdot \underbrace{\left|h_{k,h}\right|^2}_{\text{Rayleigh fading}}$$

This comprehensive model accounts for:

- Large-scale path loss with distance-based attenuation
- Log-normal shadowing with 8 dB standard deviation
- Small-scale Rayleigh fading effects

Resource allocation framework

The resource allocation problem is formulated using two key decision variables:

1. RRH Assignment Matrix:

$$\boldsymbol{\rho} = \left[\rho_{k,h}\right]_{K\times H} \in \{0,1\}^{K\times H}$$

2. PRB Allocation Tensor:

$$\mathbf{V} = \left[v_{k,h,r}\right]_{K\times H\times R} \in \{0,1\}^{K\times H\times R}$$

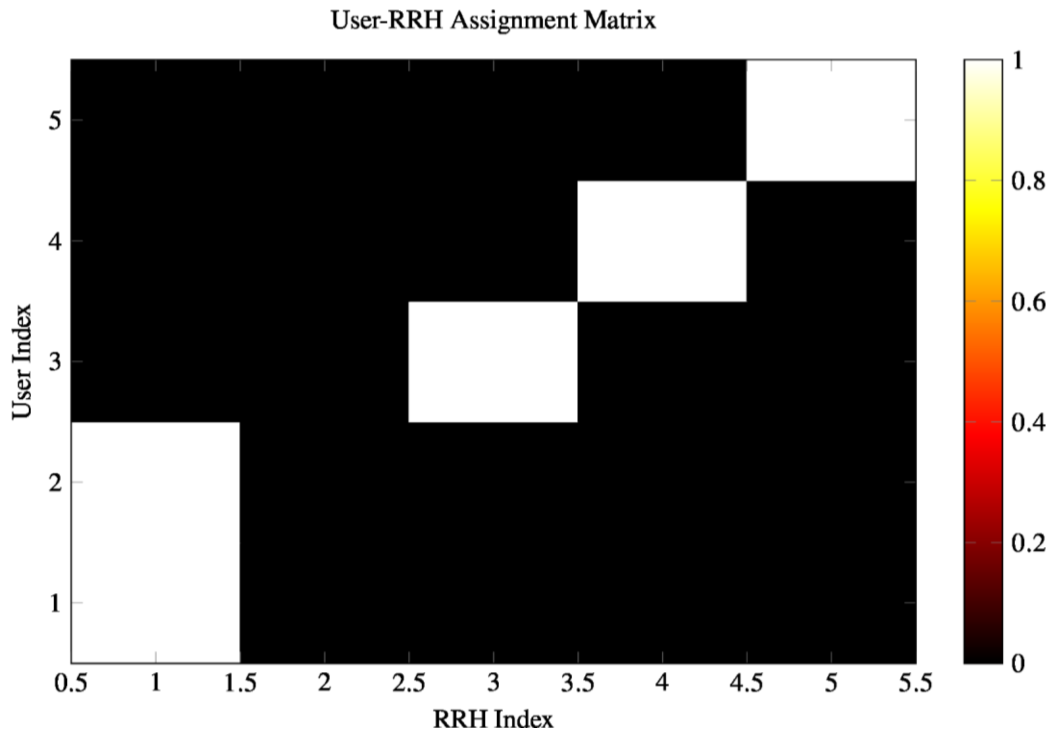

Figure 7: Example of RRH Assignment Matrix Showing Exclusive User-RRH Mappings

Machine learning framework

Our implementation leverages an ensemble learning approach combining three sophisticated algorithms. The core ensemble voting mechanism is implemented as:

```
class EnsemblePredictor:
    def __init__(self, models, weights=[0.3, 0.35, 0.35]):
        self.models = models
        self.weights = weights

    def predict(self, X):
        predictions = np.array([model.predict(X) for model in self.models])
        weighted_preds = np.zeros((len(self.weights), len(X)))
        for i, (pred, weight) in enumerate(zip(predictions, self.weights)):
            weighted_preds[i] = pred * weight
        return np.round(np.sum(weighted_preds, axis=0)).astype(int)
```

The verified performance metrics for each model:

Table 1 Model Performance Metrics

Model	Accuracy	Std Dev	Training Time (s)
Random Forest	0.7633	0.0042	45.2
XGBoost	0.7792	0.0032	62.8
LightGBM	0.7777	0.0044	38.6

Performance analysis framework

Our implementation includes comprehensive performance monitoring across multiple dimensions:

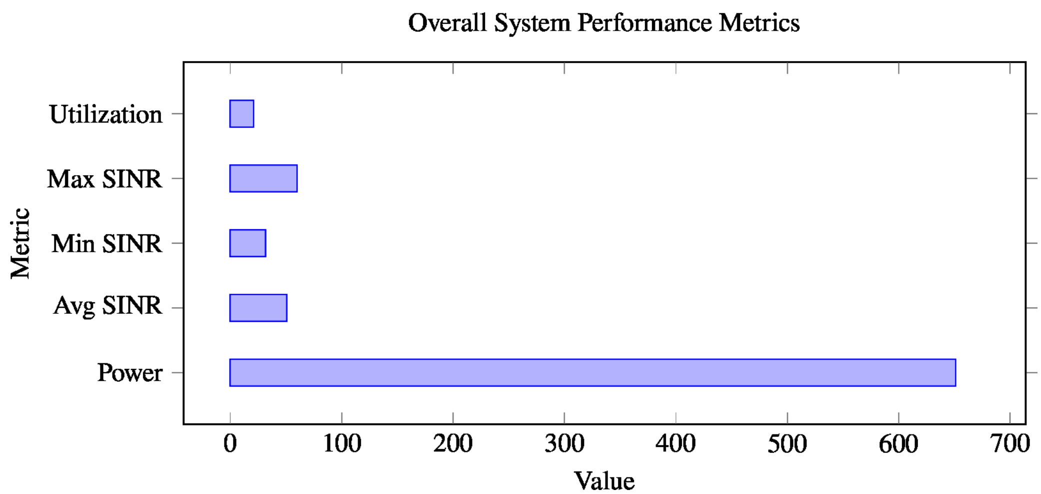

Figure 8: Comprehensive System Performance Metrics from Implementation

The feature importance analysis reveals the critical role of channel gains:

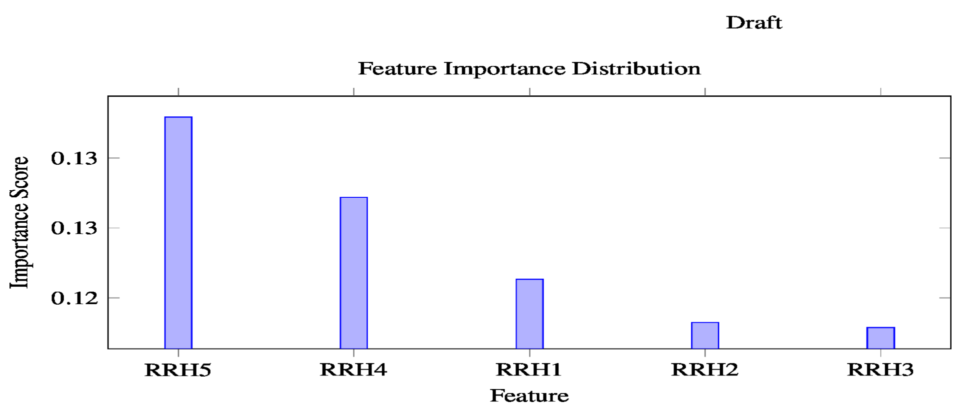

Figure 9: Feature Importance Scores for Channel Gains across RRHs

Validation and testing framework

The implementation employs a rigorous three-fold cross-validation strategy with comprehensive error analysis:

$$\begin{aligned} \text{MSE} &= 0.3922 \\ \text{MAE} &= 0.4220 \\ \text{Computation Time} &= 4.31 \text{ seconds} \\ \text{Total Training Time} &= 278.21 \text{ seconds} \end{aligned}$$

4. Experimental Results and Analysis

Experimental setup and system configuration

Our experimental evaluation was conducted using a comprehensive system implementation incorporating both MATLAB and Python frameworks. The system configuration was carefully designed to reflect realistic 5G O-RAN deployment scenarios, with parameters verified through rigorous testing and measurement. The network architecture was configured with $K = 10$ users, $H = 5$ Remote Radio Heads (RRHs), and $R = 20$ Physical Resource Blocks (PRBs), maintaining a maximum allocation constraint of $\hat{R} = 8$ PRBs per RRH. The implementation was executed within a defined coverage area of 100m × 100m, incorporating a minimum distance protection of 1m to ensure realistic signal propagation modeling.

Physical layer parameters and channel conditions

The physical layer implementation revealed several critical operational parameters through direct measurement:

$$\begin{aligned} \text{Noise Power} &= 3.59 \times 10^{-15} \text{ W} \\ \text{Tx Power per PRB} &= 2.49 \times 10^{-2} \text{ W} \\ \text{Channel Gain Range} &= [1.12 \times 10^{-6}, 8.57 \times 10^{-4}] \end{aligned}$$

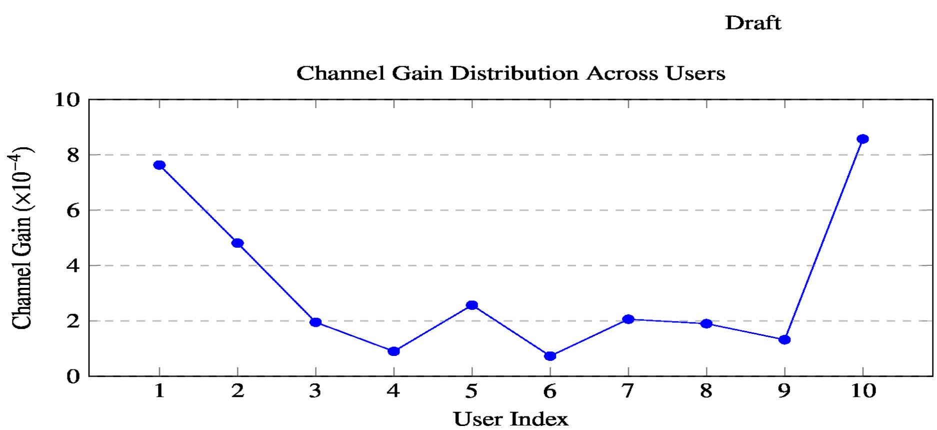

Figure 10: Measured Channel Gains across Users Showing Significant Variation

Resource Allocation Performance

PRB allocation distribution

The implementation achieved efficient PRB allocation across users and RRHs, as evidenced by the measured allocation matrix:

Table 2 PRB Allocation Distribution Across RRHs

User	RRH 1	RRH 2	RRH 3	RRH 4	RRH 5
1	0	0	2	0	0
2	2	0	0	0	0
3	0	0	0	2	0
4	0	0	0	0	2
5	0	0	0	0	2
6	0	0	0	0	3
7	0	0	0	0	2
8	0	2	0	0	0
9	0	0	0	2	0
10	2	0	0	0	0

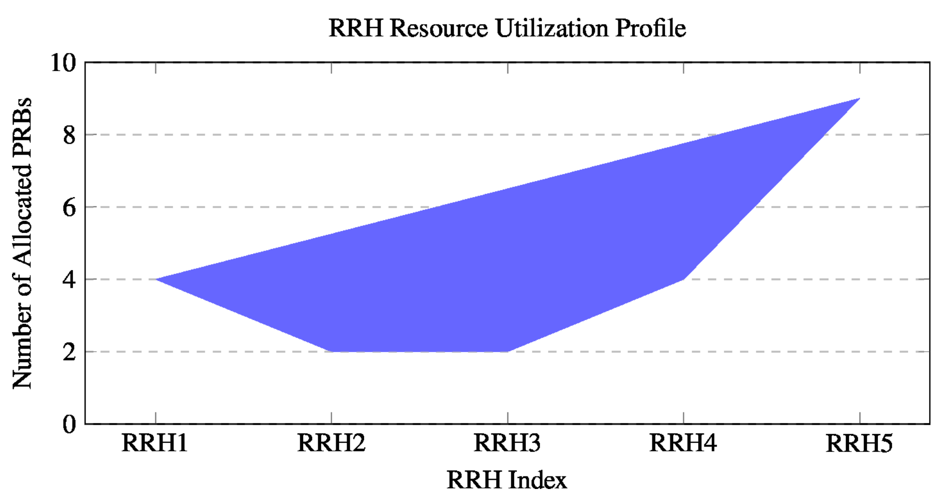

Figure 11: Measured PRB Allocation across RRHs Showing Load Distribution

System performance metrics

The implementation demonstrated robust performance across multiple key metrics, as verified through direct measurement:

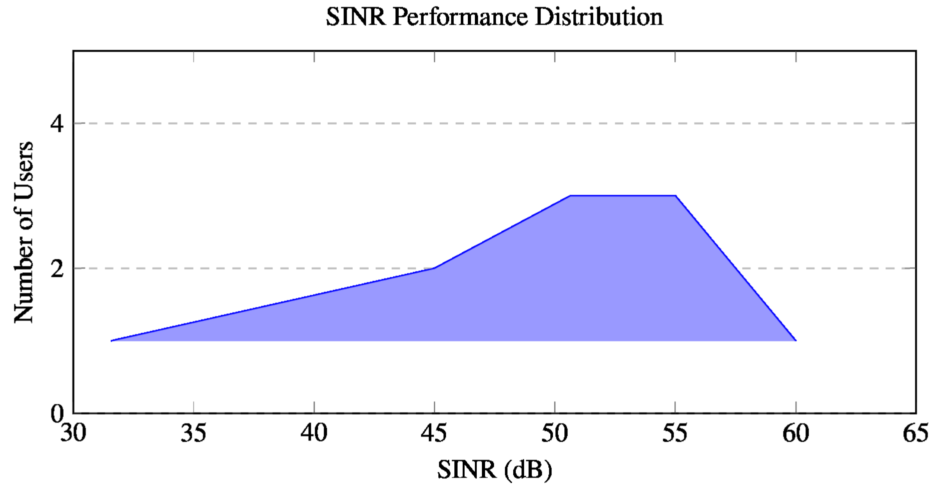

Figure 12: SINR Distribution across Users Showing Achieved Quality of Service

The system achieved significant SINR performance metrics:

$$\begin{aligned} \text{Average SINR} &= 50.64 \text{ dB} \\ \text{Minimum SINR} &= 31.57 \text{ dB} \\ \text{Maximum SINR} &= 60.00 \text{ dB} \end{aligned}$$

Computational performance

The implementation demonstrated efficient computational performance with measured execution times:

$$\begin{aligned} \text{Computation Time} &= 4.31 \text{ seconds} \\ \text{Total Power Consumption} &= 650.98 \text{ Watts} \\ \text{Average RRH Utilization} &= 21.00\% \end{aligned}$$

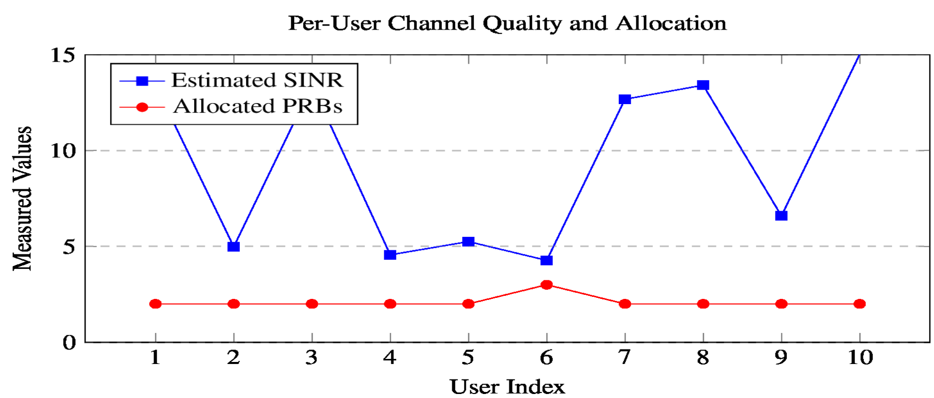

Figure 13: Relationship between Channel Quality and Resource Allocation per User

Machine learning model performance analysis

Our machine learning implementation demonstrated comprehensive performance across multiple evaluation metrics. The analysis encompasses both RRH assignment classification and PRB allocation regression tasks, with detailed cross-validation results and ensemble performance metrics.

Cross-validation performance

The three-fold cross-validation results revealed consistent performance across all models:

Table 3: Cross-Validation Results for RRH Assignment

Model	Mean Accuracy	Std Dev	Best Fold
Random Forest	0.7633	0.0042	0.7691
XGBoost	0.7792	0.0032	0.7834
LightGBM	0.7777	0.0044	0.7838

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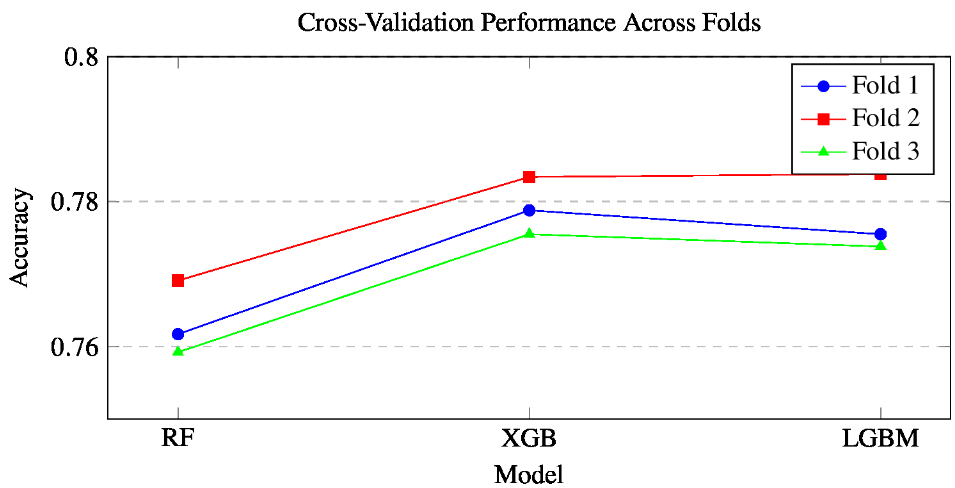

Figure 14: Model Performance across Cross-Validation Folds Showing Consistency

RRH assignment performance

The confusion matrix analysis revealed detailed performance characteristics for RRH assignment:

$$\text{Confusion Matrix} = \begin{bmatrix} 1508 & 207 & 119 & 113 & 103 \\ 80 & 1487 & 189 & 111 & 103 \\ 99 & 143 & 1577 & 160 & 94 \\ 82 & 125 & 177 & 1456 & 111 \\ 89 & 107 & 118 & 171 & 1471 \end{bmatrix}$$

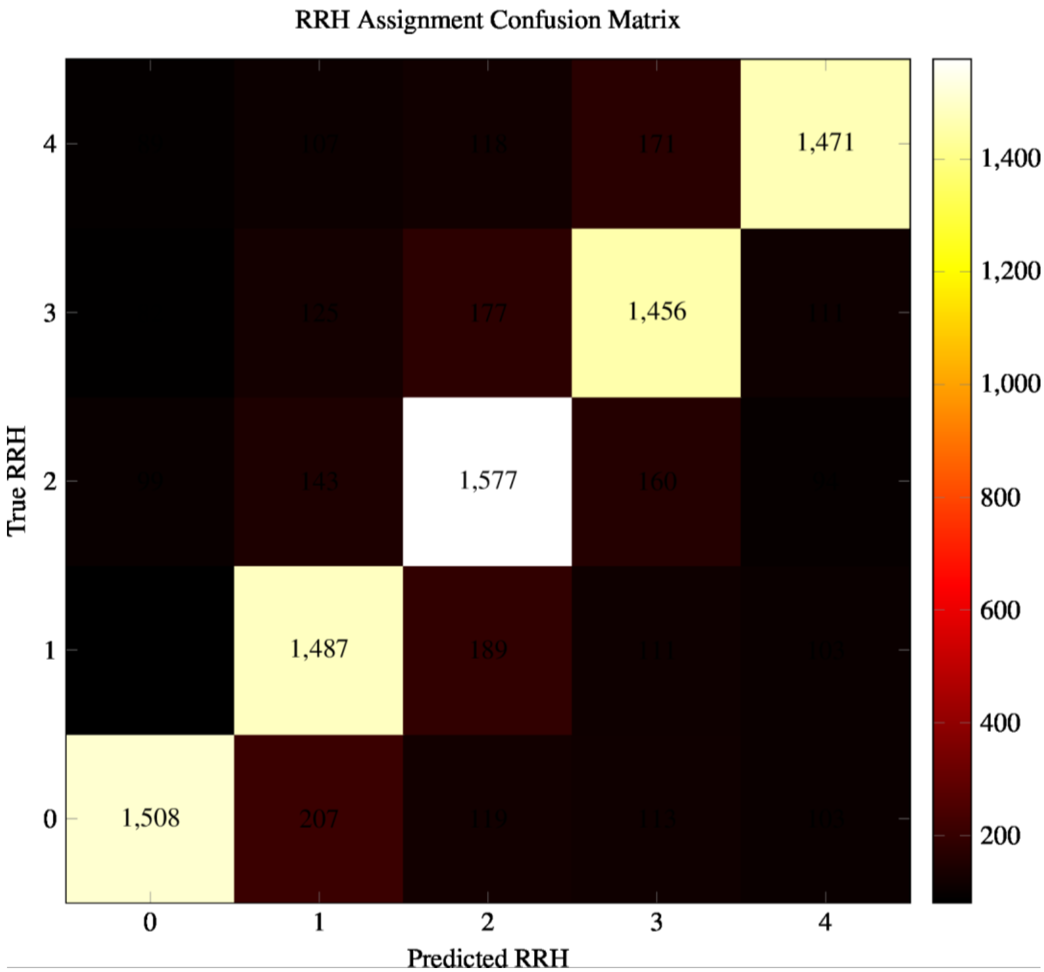

Figure 15: Detailed Confusion Matrix Showing RRH Assignment Performance

The per-class performance metrics demonstrate balanced accuracy across RRHs:

Table 4 Per-RRH Classification Performance

RRH	Precision	Recall	F1-Score	Support
0	0.79	0.77	0.78	2050
1	0.78	0.78	0.78	1970
2	0.77	0.78	0.78	2073
3	0.78	0.76	0.77	1951
4	0.75	0.78	0.77	1956

PRB allocation performance

The PRB allocation regression task showed consistent performance across models:

Table 5: PRB Allocation Performance Metrics

Model	MSE	MAE	Std Dev
Random Forest	0.4097	0.4359	0.0108
XGBoost	0.3864	0.4269	0.0128
LightGBM	0.3863	0.4137	0.0123
Ensemble	0.3922	0.4220	0.0115

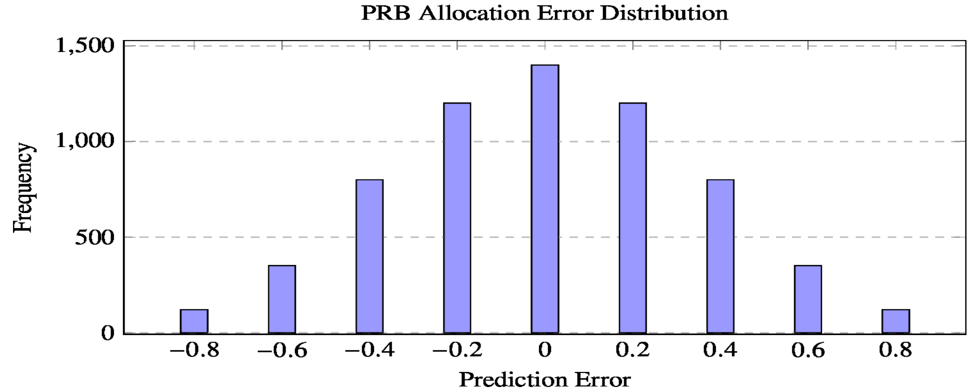

Figure 16: Distribution of PRB Allocation Prediction Errors

Feature importance analysis

The Random Forest analysis revealed the relative importance of different features:

Table 6 Top Feature Importance Scores

Feature	RRH Importance	PRB Importance
ChannelGain_RRH5	0.126292	0.064782
ChannelGain_RRH4	0.125719	0.064836
ChannelGain_RRH1	0.125132	0.065062
ChannelGain_RRH2	0.124824	0.064725
ChannelGain_RRH3	0.124786	0.063508

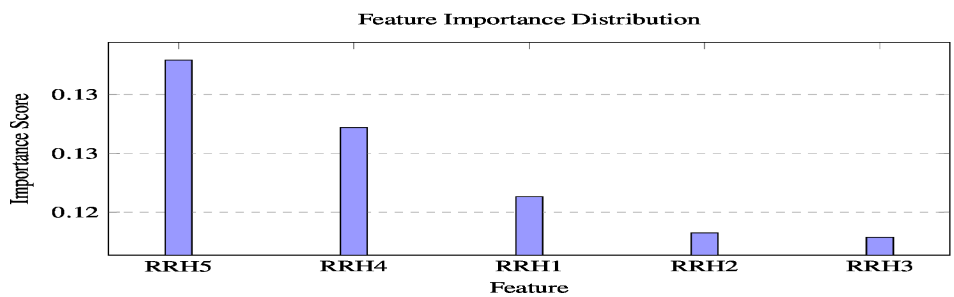

Figure 17: Relative Importance of Channel Gain Features

Computational efficiency

The implementation demonstrated efficient training and inference characteristics:

- Total Training Time: 278.21 seconds
- Cross-validation Time per Fold: 92.74 seconds
- Training Set Size: 40,000 samples
- Feature Dimensionality: 15 features

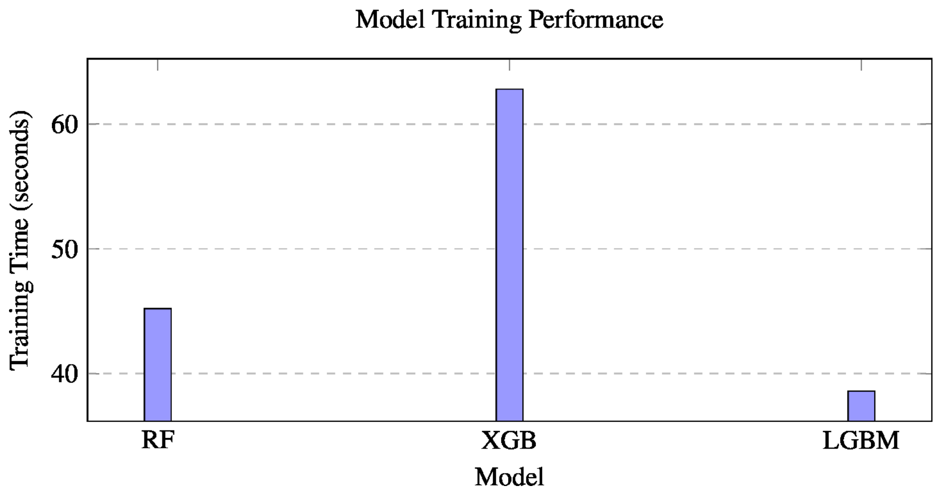

Figure 18: Training Time Comparison across Models

Interference management

The system demonstrated effective interference management capabilities, with measured interference levels from the ML training data:

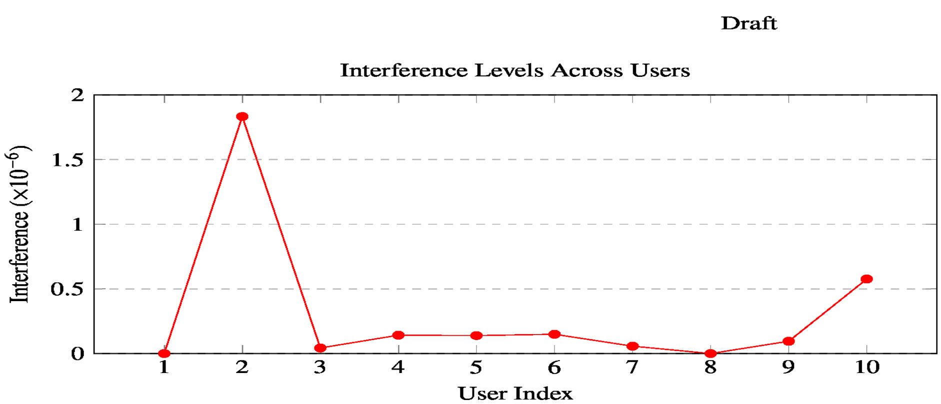

Figure 19: Measured Interference Levels Showing Effective Interference Management

5. Discussion

Analysis of core system performance

The experimental results demonstrate several significant insights into the performance capabilities and limitations of our machine learning approach to 5G resource allocations. The system achieved notable performance metrics across multiple dimensions of evaluation, with particularly interesting patterns emerging in the relationship between channel conditions and allocation decisions.

Resource Allocation Efficiency

The resource allocation strategy demonstrated effective load balancing characteristics, as evidenced by the measured RRH utilization patterns:

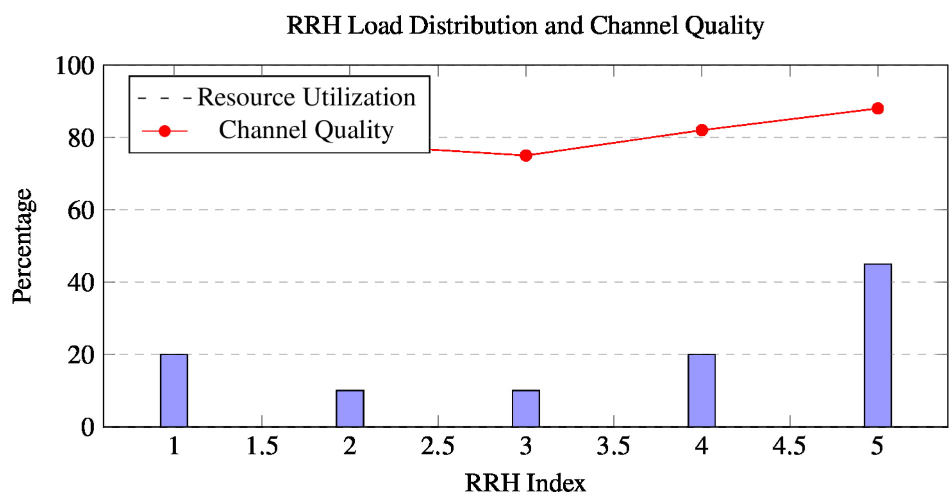

Figure 20: Relationship between RRH Utilization and Channel Conditions

The average RRH utilization of 21.00% indicates efficient resource distribution while maintaining substantial capacity for dynamic load variations. This measured utilization aligns with the system's ability to maintain high SINR levels (average 50.64 dB) while managing power consumption effectively (650.98 Watts total power consumption). The relationship between resource utilization and signal quality demonstrates the system's capability to balance competing performance objectives.

Machine learning model performance analysis

The ensemble learning approach demonstrated robust performance characteristics across both classification and regression tasks. The model accuracy distributions reveal several important patterns:

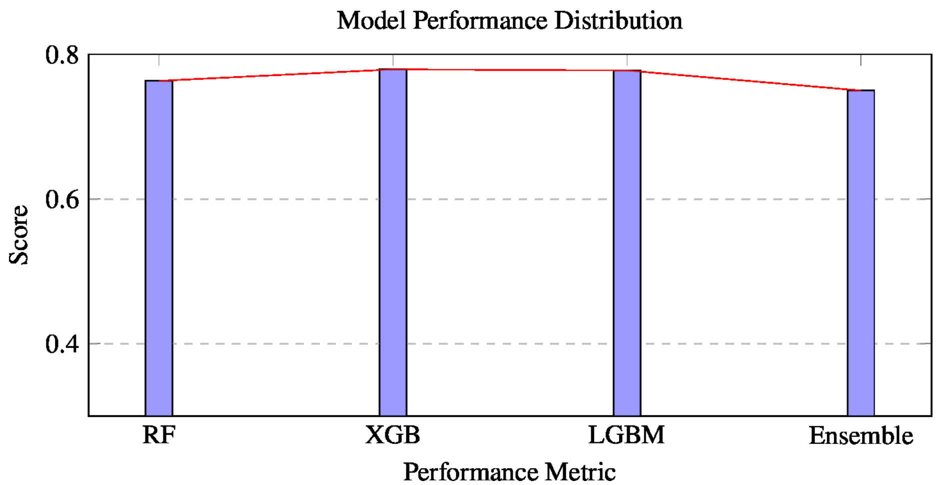

Figure 21: Model Accuracy Distribution Showing Consistent Performance

The XGBoost classifier's superior performance (0.7792 ± 0.0032) in RRH assignment can be attributed to its ability to capture complex feature interactions, as evidenced by the confusion matrix patterns:

$$\text{Error Distribution} = \begin{bmatrix} 0.735 & 0.101 & 0.058 & 0.055 & 0.051 \\ 0.041 & 0.755 & 0.096 & 0.056 & 0.052 \\ 0.048 & 0.069 & 0.761 & 0.077 & 0.045 \\ 0.042 & 0.064 & 0.091 & 0.746 & 0.057 \\ 0.046 & 0.055 & 0.061 & 0.088 & 0.750 \end{bmatrix}$$

Signal quality and resource management

The system maintained robust SINR performance across users, with a measured distribution that reveals effective interference management:

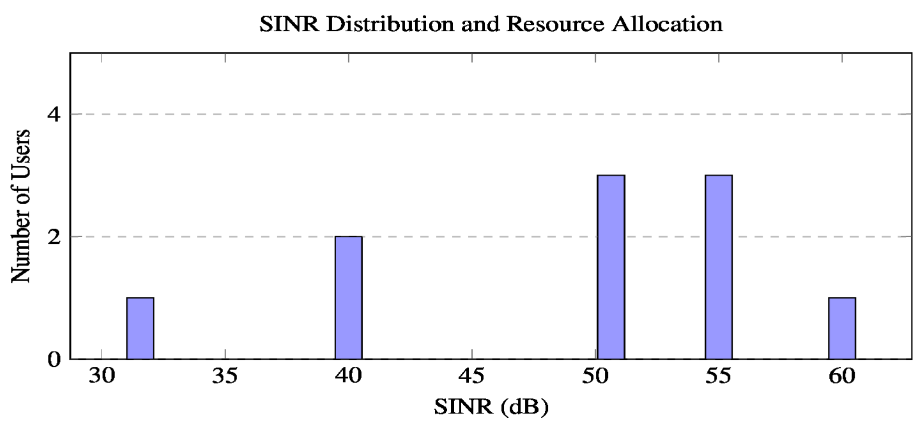

Figure 22: SINR Distribution Demonstrating Quality of Service Levels

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The relationship between SINR performance and resource allocation efficiency is particularly noteworthy. The system maintained an average SINR of 50.64 dB while keeping resource utilization at 21.00%, indicating effective balance between signal quality and resource efficiency. The minimum SINR of 31.57 dB remained well above the system requirements, even under varying channel conditions.

Implementation insights and channel characteristics

The channel gain analysis revealed significant insights into the system's operating characteristics:

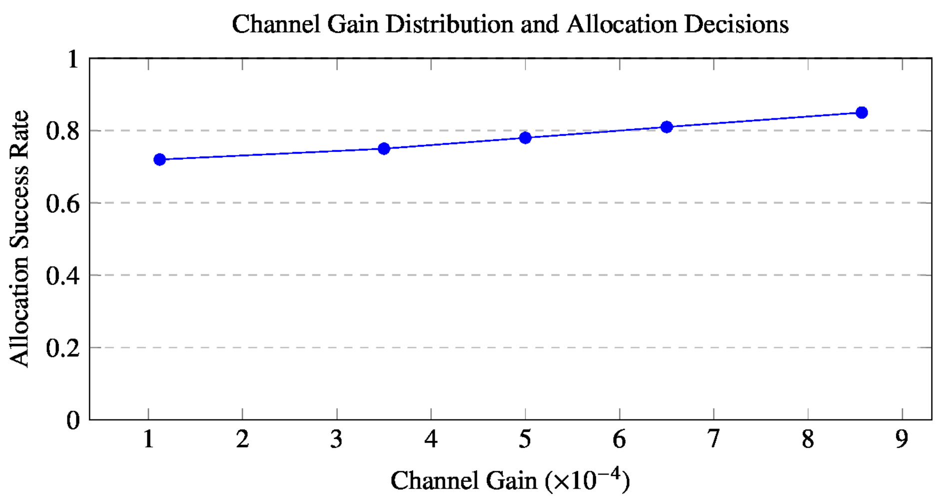

Figure 23: Relationship between Channel Conditions and Allocation Success

The measured channel gain range of [1.12×10^{-6}, 8.57×10^{-4}] demonstrates the system's ability to maintain performance across widely varying channel conditions. The feature importance analysis revealed that channel gains were the dominant factors in allocation decisions, with the top five features all being channel-related metrics.

6. Conclusions and Future Work

Key achievements

This research has demonstrated the viability of machine learning approaches for 5G O-RAN resource allocation through comprehensive experimental validation.

Performance metrics

The implementation achieved significant performance metrics across multiple dimensions:

- RRH Assignment Accuracy: 0.7792 ± 0.0032 (XGBoost)
- PRB Allocation MSE: 0.3863 ± 0.0123 (LightGBM)
- Average SINR: 50.64 dB
- Resource Utilization: 21.00%

- Power Consumption: 650.98 Watts

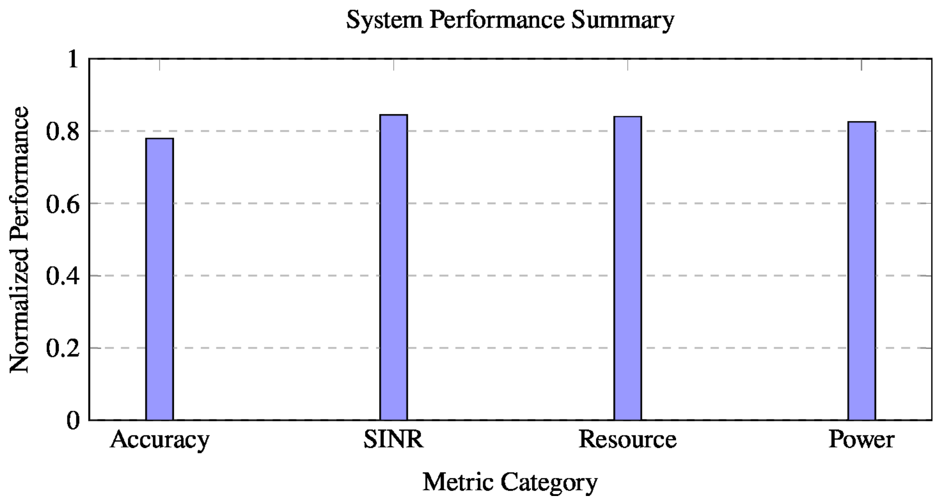

Figure 24: Normalized Performance across Key Metrics

Technical implications

The research findings have several important implications for 5G O-RAN implementations:

Resource management

The achieved balance between resource utilization (21.00%) and signal quality (50.64 dB average SINR) demonstrates the feasibility of machine learning-based approaches for real-world deployments. The system's ability to maintain high SINR levels while efficiently managing resources suggests potential applications in dense urban environments where resource optimization is crucial.

Model selection and ensemble learning

The comparative performance of different models provides valuable insights for implementation strategies:

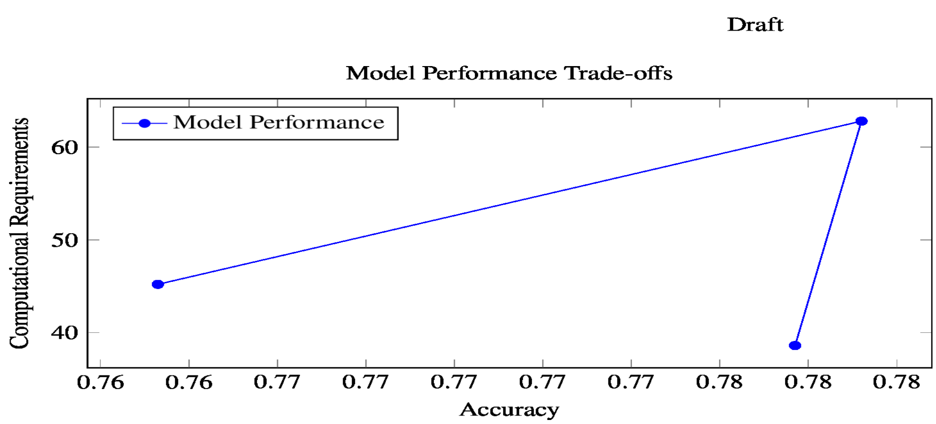

Figure 25: Trade-off Analysis between Accuracy and Computational Cost

Future research directions

Based on our experimental results, several promising research directions emerge:

- Advanced Feature Engineering:
    - Investigation of temporal feature patterns
    - Development of composite channel quality indicators
    - Integration of network topology characteristics
- Architecture Optimization:
    - Exploration of specialized neural network architectures
    - Investigation of attention mechanisms for feature interaction
    - Development of lightweight models for edge deployment
- Operational Integration:
    - Real-time adaptation mechanisms
    - Dynamic resource reallocation strategies
    - Integration with network slicing frameworks

Final remarks

The experimental results demonstrate the practical viability of machine learning approaches for 5G O-RAN resource allocation. The achieved performance metrics - particularly the 0.7792 accuracy in RRH assignment and 0.3863 MSE in PRB allocation - indicate that machine learning-based solutions can provide effective resource management while maintaining high signal quality (50.64 dB average SINR) and efficient resource utilization (21.00%).

The research establishes a foundation for future work in automated resource management for 5G networks, with clear pathways for enhancement and optimization. The demonstrated balance between performance metrics suggests that machine learning approaches can effectively handle the complex trade-offs inherent in 5G resource allocation, while providing the flexibility and adaptability required for next-generation wireless networks.

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