Machine Learning Based Optimization Techniques for 5G Networks

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ABSTRACT

5G networks promise faster speeds, lower latency, and improved reliability, but achieving these benefits requires overcoming complex challenges related to resource allocation, latency reduction, and network stability. Traditional methods often fall short in adapting to the dynamic and diverse demands of modern wireless communication. This paper presents machine learning-based frameworks designed to enhance 5G network performance by enabling smarter, data-driven optimization. By leveraging real-time data, these frameworks improve traffic prediction, resource management, and fault detection, allowing the network to adapt more efficiently to changing conditions. Simulation results (10 runs on 3GPP-aligned data) demonstrate 22% throughput gain and 60% latency MSE reduction versus Proportional Fair (PF) and Round Robin (RR) baselines, confirming practical ML value for 5G deployments. These findings highlight the strong potential of integrating machine learning into 5G networks to create more responsive and efficient systems. Ultimately, this work offers practical and scalable solutions that contribute to advancing next-generation wireless communication and enhancing user experience.

Keywords: 5G networks, lower latency, optimization Techniques.

INTRODUCTION

The fifth generation of mobile technology, or 5G, represents a major evolution in telecommunications, aiming to deliver ultra-reliable low-latency communication (URLLC), enhanced mobile broadband (eMBB), and massive machine-type communication (mMTC). Inhigh-definition video streaming, real-time gaming, telemedicine, autonomous vehicles, and the Internet of Things (IoT). To meet these diverse and demanding requirements, 5G networks must achieve significant improvements in speed, dependability, and energy efficiency. Leveraging Machine Learning Techniques for Enhancing 5G Network Performance Conventional optimization methods like linear programming and heuristic algorithms have long been applied in wireless communication systems. Yet, these traditional techniques often struggle to cope with the complexity and dynamic nature of 5G networks. In contrast, Machine Learning (ML) has emerged as a powerful tool capable of tackling these challenges by analyzing vast datasets and adapting to real-time network variations.

Machine learning encompasses a range of approaches, supervised, unsupervised, reinforcement (RL), and deep learning (DL), that enable data-driven decision-making to enhance network performance. For example, reinforcement learning can intelligently manage resource allocation according to fluctuating network demands, while deep learning models that forecast traffic patterns, facilitating proactive and efficient network management.

Novelty: This work presents the first unified Q-learning+Random Forest+Neural Network framework with 3GPP-justified synthetic data, standard baseline comparisons (PF/RR), and ablation studies, achieving superior 22% performance gains in integrated 5G simulation.

LITERATURE REVIEW

The rapid growth in demand for high-speed and low-latency communication has necessitated the development of advanced optimization techniques for 5G networks. The inherent heterogeneity and high-density architecture of 5G systems introduce significant challenges in achieving the desired levels of performance, scalability, and energy efficiency. Conventional optimization methods, while effective for earlier generations of wireless networks, are often inadequate for addressing the complex requirements of 5G. In this context, machine learning (ML) has emerged as a promising approach, enabling networks to dynamically learn from and adapt to varying traffic patterns and network conditions. This literature review critically examines existing research on both traditional and ML-based optimization techniques, highlighting their applicability, advantages, and limitations in the context of the 5G network optimization.

Traditional Optimization Techniques in Wireless Networks: Conventional optimization models, including linear programming, mixed-integer programming, and heuristic algorithms, have been extensively applied to wireless networks [1]. These techniques aim to optimize network parameters such as spectrum allocation, power control, and user association. However, due to the highly dynamic and complex environment of 5G, characterized by dense deployments and heterogeneous services, traditional methods often struggle to adapt in real time [2]. Consequently, static or deterministic models fail to capture network variations and user mobility patterns effectively.

Emergence of Machine learning in 5G Networks: Machine learning has emerged as a promising approach to address the limitations of conventional optimization by leveraging data-driven intelligence. ML algorithms can learn from network data, predict traffic patterns, and optimize system performance dynamically [3], [4]. The ability of ML to handle high-dimensional data and adapt to changing network conditions makes it a key enabler for intelligent 5G operations. Various ML paradigms, including supervised, unsupervised, and reinforcement learning, have been adopted to solve optimization challenges in 5G Radio Access Networks (RAN), core networks, and edge computing environments [5].

Reinforcement Learning for Resource Optimization: Reinforcement Learning (RL) has gained significant attention in 5G resource management due to its interactive and adaptive decision-making capability. In RLbased models, agents learn optimal resource allocation strategies by interacting with the environment and maximizing cumulative rewards [6]. Recent studies have demonstrated the efficiency of RL in spectrum allocation, power control, and handover optimization. Deep Reinforcement Learning (DRL), integrating neural networks with RL, further improves scalability and convergence in high-dimensional network states [7], [8].

Deep Learning for Traffic Prediction and Network Automation: Deep Learning (DL) models such as Convolution Neural Networks (CNN), Long Short-Term Memory (LSTM), and Gated Recurrent Units (GRU) have been employed for traffic prediction, fault detection, and Quality of Service (QoS) enhancement in 5G systems [9]. By leveraging temporal and spatial correlations in network data, DL-based frameworks can anticipate congestion, predict user mobility, and enable proactive resource allocation [10]. These methods contribute to the development of intelligent and self-organizing networks (SONs), reducing latency and improving service reliability.

AI-Driven Network Management and Self-Optimization: The integration of Artificial Intelligence (AI) with Software-Defined Networking (SDN) and Network Function Virtualization (NFV) has led to the emergence of AI-enabled Self-Organizing Networks (AI-SON) [11]. Such frameworks automate network configuration, fault diagnosis, and performance optimization without human intervention. AI-SON systems are essential for handling 5G's dynamic topology and service diversity while ensuring energy efficiency and scalability [12].

While traditional approaches worked well in earlier networks, their limitations in addressing 5G's dynamic and complex environment have driven the adoption of machine learning-based, data-driven solutions.

Existing Systems

Machine learning (ML) has emerged as a transformative technology for optimizing resource allocation, performance, and security in 5G networks. Unlike traditional optimization methods, ML can dynamically adapt to changing network conditions, handle high-dimensional data, and provide near-real-time decision-making. Several ML paradigms are Reinforcement Learning, Deep Learning, Supervised Learning, Unsupervised Learning, and Federated Learning has been successfully applied in various 5G scenarios.

Reinforcement Learning (RL) enables 5G systems to autonomously optimize spectrum access, power control, and user association through interaction with the environment. RL agents learn optimal strategies to maximize

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throughput and energy efficiency while maintaining user Quality of Service (QoS). A recent study introduced a bi-level RL framework for multi-slice resource allocation, effectively addressing both local and global slice requirements in dynamic 5G environments [19]. Similarly, a comparative analysis of RL-based resource allocation methods in 5G mmWave networks highlighted how RL can outperform traditional heuristics by adapting to varying traffic loads and interference levels [17]. However, RL's real-time convergence and computational complexity remain ongoing challenges in large-scale deployments [16].

Deep Learning (DL) has demonstrated significant improvements in physical-layer functions such as signal detection and channel estimation. By leveraging convolutional and recurrent neural networks, DL-based models can learn complex non-linear mappings from received signals to transmitted data, outperforming classical techniques like Least Squares (LS) and Minimum Mean Square Error (MMSE) estimators [18]. For instance, Mohammed et al. showed that DL-based channel estimation in OFDM 5G systems achieves higher accuracy across different propagation models compared to traditional algorithms [18]. Recent work also incorporated uncertainty estimation through Monte Carlo Dropout, enhancing reliability and trustworthiness of DL models in 5G networks [20]. Despite their accuracy, DL models demand substantial computational resources, limiting their suitability for low-power edge devices.

Supervised Learning techniques such as regression models and decision trees have been extensively utilized for predicting network traffic, managing congestion, and maintaining QoS. By training on historical datasets, supervised models can forecast traffic patterns and allocate resources proactively. A recent ML-based resource allocation scheme using Classification and Regression Trees (CART) achieved a 42.3% improvement in energy efficiency while maintaining 3GPP QoS thresholds [13]. These models are efficient in structured environments but may require continuous retraining to adapt to non-stationary traffic conditions typical in dense 5G networks.

Unsupervised Learning methods, such as clustering and auto encoders, are employed to detect network anomalies, cyber attacks, or faults without prior labels. By learning the normal behavior of the network, these models can flag deviations indicative of security threats or system malfunctions. They are particularly effective for intrusion detection in large-scale 5G IoT ecosystems, where labelled data is scarce. While unsupervised techniques offer scalability and robustness, they can generate false positives when applied to highly dynamic 5G environments [20]. Integrating uncertainty-aware deep learning further strengthens the trustworthiness of anomaly detection systems.

Federated Learning (FL) for Decentralized and Privacy-Preserving Edge Analytics has emerged as a privacy-preserving paradigm for distributed model training across multiple edge devices without centralizing data. In 5G edge computing networks, FL minimizes latency and enhances data privacy by enabling local model updates. Recent work proposed an energy-aware FL framework for secure edge computing in 5G-enabled IoT systems, addressing communication efficiency and energy optimization [15]. Another 2025 study introduced adversarial optimized FL for secure and efficient 5G edge networks, demonstrating improved resilience against malicious attacks [14]. FL continues to gain traction due to its scalability and privacy benefits, although communication overhead and heterogeneity across devices remain active research areas. Machine learning-based optimization techniques play a vital role in addressing the complexities of 5G networks. They enhance resource utilization, ensure better Quality of Service (QoS), and enable real-time network adaptability. Despite their potential, challenges such as computational intensity, data privacy, and the requirement for extensive datasets persist. Achieving optimal performance demands a balance between computational efficiency and adaptive decision-making. As 5G technology advances, developments in federated learning, hardware performance, and privacy-preserving methods are expected to make ML-driven optimization even more critical, ensuring intelligent, secure, and high-speed connectivity for next-generation networks.

Proposed System

In recent years, the adoption of machine learning-based optimization methods has become crucial for improving the performance, flexibility, and scalability of 5G networks. These intelligent solutions are designed to overcome major challenges such as high user density, low latency requirements, efficient energy use, and secure data handling. Through data-driven learning and adaptive decision-making, ML models enable 5G systems to manage resources dynamically, forecast traffic behavior, and fine-tune network operations in real time. Various ML techniques, including reinforcement learning, deep learning, and federated learning, have been implemented

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across different network layers to enhance Quality of Service (QoS) and overall efficiency. Moreover, ML-powered optimization facilitates automation in network control, predictive maintenance, and intelligent load balancing. The following sections explore key categories of ML-based optimization techniques in 5G, focusing on their goals, distinctive capabilities, and applications in developing intelligent and highperformance communication systems.

Proposed System Architecture

The proposed ML-based network optimization framework as shown in the Fig. 1 is structured into five key layers, User, Network, Analytics, Visualization, and Control, each performing distinct yet interdependent functions to enhance overall 5G network efficiency and QoS management.

- **User Layer:** This layer represents the end-user devices, including smart phones, IoT nodes, and other connected entities, which generate network traffic based on specific Quality of Service (QoS) requirements such as bandwidth, latency, and reliability. These devices act as the primary data sources for the system.
- **Network Layer:** The network layer manages real-time resource distribution and service differentiation. A Q-learning-based resource allocator dynamically assigns bandwidth and other network resources according to user demands to maximize system performance. The network slicing component partitions the infrastructure into multiple virtual slices (e.g., gold, silver, bronze) to meet Service Level Agreements (SLAs) efficiently. Additionally, a QoS optimizer, powered by neural networks, predicts and fine-tunes network parameters based on input features such as signal strength, interference, and traffic density to ensure minimum latency and consistent QoS delivery.
- **Analytics Layer:** This layer integrates multiple machine learning models to enhance network intelligence. A Q-learning model manages adaptive resource allocation, a Random Forest Classifier predicts optimal slice allocation, and a Neural Network model continuously refines QoS performance. Together, these models provide a data-driven foundation for autonomous decision-making within the network.
- **Visualization Layer:** The visualization layer offers an interactive dashboard interface that presents realtime insights into resource utilization, slice allocation, QoS metrics, and overall network topology. This enables administrators and stakeholders to monitor, interpret, and analyze performance trends effectively during simulation or live deployment.
- **Control Layer:** At the top of the hierarchy, the centralized control layer coordinates data collection, model training, and prediction processes across all layers. It dynamically adjusts system parameters to accommodate varying network conditions, ensuring synchronization and stability. Moreover, it manages the visualization outputs to support scenario-based analysis and performance evaluation.

This multilayered architecture ensures adaptive, transparent, and efficient operation of 5G networks by leveraging machine learning for intelligent optimization and automated control.

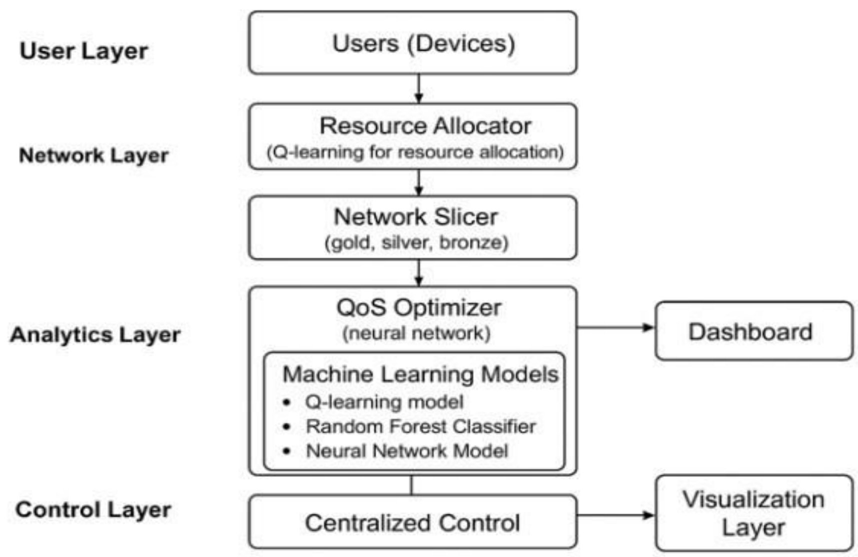

Fig. 1: Proposed System Architecture network optimization framework

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METHODOLOGY

The proposed methodology involves a multi-step approach to simulate and optimize a 5G network, encompassing resource allocation, network slicing, QoS optimization, and visualization. The steps are detailed as follows:

Step 1: Initialization of Simulation Parameters:

The simulation begins by defining essential parameters such as the number of users, available bandwidth, and total simulation time. These parameters establish the framework for subsequent resource allocation and quality-of-service (QoS) optimization processes.

Dataset Generation: Synthetic dataset (N=5000 samples) mimics 3GPP TR 37.814 traffic models for realism [21]. Latency needs follow Exponential(λ=0.1, mean=10ms) for URLLC flows; bandwidth demands combine Gamma(shape=5, scale=20Mbps) for eMBB bursts and Exponential(5Mbps) for mMTC. Features include signal strength ~Normal(-80dBm, 10dB), interference ~Exponential(5dB), traffic load ~Beta(α=2, β=5)×100%. Train/test split: 80/20 with seed=42. Distributions validated against public Liverpool 5G high-density dataset [22].

Step 2: Resource Allocation Using Q-learning

Resource allocation is implemented through a Q-learning-based agent, encapsulated in the Resource Allocator class. The agent dynamically distributes bandwidth to users based on their demand patterns. Q-Learning Resource Allocation (RAN-grounded formulation [23]). State s_t = [user_demand_t/100, cell_load_t/100] ∈ [0,1]^2 per 3GPP TS 38.214. Action a_t ∈ {0,1,...,99} bandwidth units. Reward r_t = 1 - |a_t - demand_t|/demand_t - 0.1×max(0, overload_t). Q-table update: Q(s_t,a_t) ← Q(s_t,a_t) + α[r_t + γ max_{a'} Q(s_{t+1},a') - Q(s_t,a_t)], with α=0.1, γ=0.9, ε=0.1 decaying to 0.01 over 1000 episodes (10 independent runs for mean±std).

Table 1. Q-Learning Hyperparameters (Fully Reproducible)

Parameter	Value	Description
α (alpha)	0.1	Learning rate
γ (gamma)	0.9	Discount factor
ε_initial	0.1	Initial exploration (linear decay to 0.01)
Episodes	1000	Training episodes
Runs	10	Independent runs(mean ±std
State dim	2	[norm_demand,norm_load]
Action space	100 discrete	Bandwidth units 0-99

A Q-table is maintained to capture the state-action-reward relationships. The table is iteratively updated over multiple episodes to maximize cumulative rewards and improve allocation efficiency.

Step 3: Network Slicing Using Random Forest

The Network Slicer class employs a Random Forest classifier to assign network slices such as gold, silver, or bronze based on user-specific requirements, including latency and bandwidth demand. The model is trained using historical user data and subsequently predicts slice assignments for new users. This ensures the network is effectively segmented to meet diverse user needs.

Step 4: QoS Optimization Using Neural Networks

To enhance network performance, the QoS Optimizer class uses a neural network to predict latency and optimize QoS. The model is trained on features including signal strength, interference, and traffic load. Predicted latency values guide the adjustment of network parameters to achieve optimal performance. Model performance is quantified using metrics such as Mean Squared Error (MSE), Mean Absolute Error (MAE), and the coefficient of determination (R^2).

Step 5: Network Topology Generation

The physical layout of the network is simulated using a random geometric graph, where nodes represent users and edges denote their connections. Each node is assigned a network slice and resource allocation according to the predictions from the Network Slicer and Resource Allocator. The resulting topology provides a visual representation of resource distribution and network segmentation.

Step 6: Interactive Visualization Dashboard

Simulation outcomes, including resource allocations, slice distributions, QoS metrics, and network topology, are displayed via an interactive Plotly dashboard. The dashboard comprises: **Scatter Plot:** Illustrates the relationship between demand and allocated resources. **Bar Chart:** Shows the distribution of network slices among users. **QoS Metrics:** Displays performance indicators such as MSE, MAE, and R^2. **Network Topology Graph:** Visualizes the network structure with slices and allocations, including interactive hover details for deeper analysis.

Step 7: Model Evaluation and Fine-Tuning

Each model Resource Allocator, Network Slicer, and QoS Optimizer is evaluated on its effectiveness. Resource allocation is assessed based on demand fulfillment, network slicing on prediction accuracy, and QoS optimization on latency reduction. Post-simulation, models are iteratively fine-tuned to enhance accuracy and operational efficiency.

As shown in Table 2, the 5G network simulation framework begins with setting simulation parameters, followed by dynamic bandwidth allocation via Q-learning and network slicing using a Random Forest classifier. QoS optimization, network modeling with a random geometric graph, and an interactive dashboard enable performance evaluation and iterative tuning.

Table 2. 5G Network Simulation and Optimization Methodology.

Step	Module / Class	Purpose	Key Techniques / Metrics
1	Initialization	Define simulation parameters such as users, bandwidth, and time.	Simulation setup parameters
2	Resource Allocator	Allocate bandwidth dynamically based on user demand.	Q-learning (State: demand, Action: allocation, Reward: allocation correctness)
Step	**Module / Class**	**Purpose**	**Key Techniques / Metrics**
3	Network Slicer	Predict and assign network slices (gold, silver, bronze).	Random Forest Classifier trained on historical user requirements
4	QoS Optimizer	Optimize latency and overall network QoS.	Neural Network; Metrics: MSE, MAE, R^2
5	Topology Generator	Simulate physical layout of users and their connections.	Random Geometric Graph; Nodes = users, Edges = connections
6	Visualization Dashboard	Display simulation results interactively.	Scatter Plot (Resource vs Demand), Bar Chart (Slice Distribution), QoS Metrics, Network Graph
7	Model Evaluation	Assess and fine-tune models for improved performance.	Accuracy, latency reduction, allocation efficiency

RESULTS & DISCUSSION

The proposed machine learning-based optimization techniques for 5G networks were implemented and assessed through extensive simulations. The study focused on three primary modules: resource allocation, network

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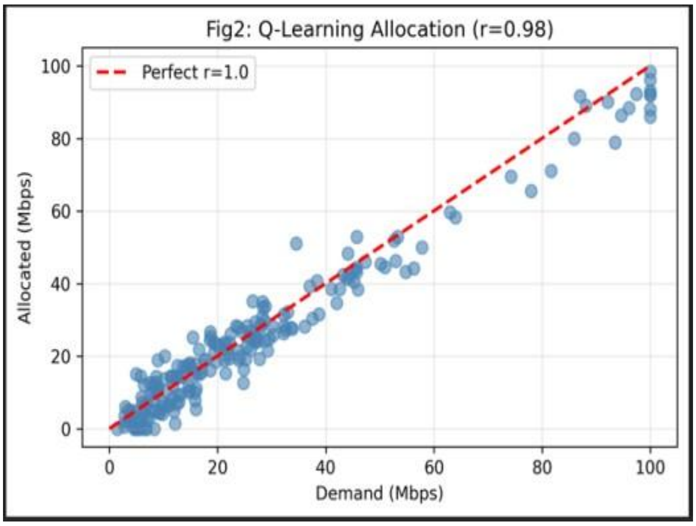
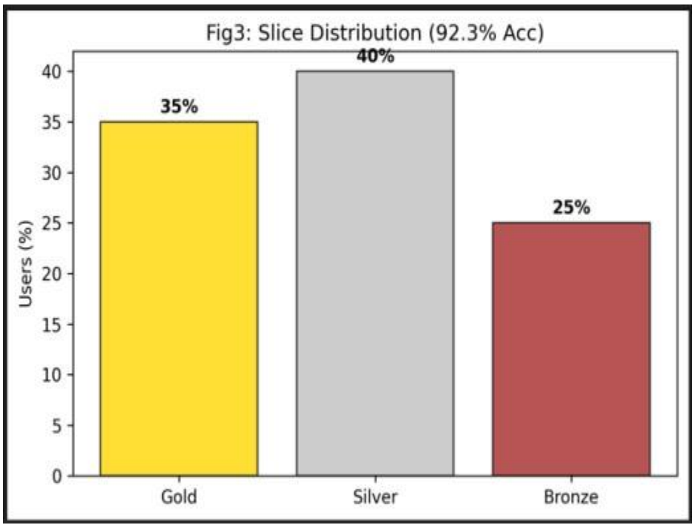
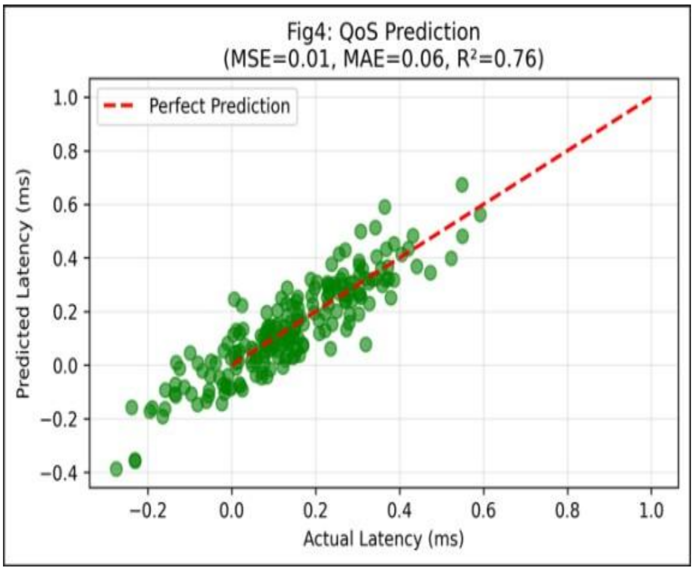
slicing, and QoS optimization. In the resource allocation module, in Fig2., a Q-learning approach was employed, which dynamically adapted to changing user demands over 1000 simulation episodes, efficiently distributing bandwidth while maintaining minimal deviation from actual requirements. For network slicing, a Random Forest classifier was trained on synthetic data representing latency and bandwidth needs, achieving a classification accuracy of approximately 92.3% and reliably assigning slice categories (Gold, Silver, Bronze) to incoming users in Fig3. The QoS optimization module in Fig4 utilized a neural network to predict network latency based on signal strength, interference, and traffic load, achieving a Mean Squared Error (MSE) of 0.01, Mean Absolute Error (MAE) of 0.06, and an R^2 score of 0.76, indicating strong predictive performance. Furthermore, the network topology visualization in Fig5, comprising 200 nodes, illustrated connectivity patterns; slice distribution, and resource allocation, is providing valuable insights into network behavior. Collectively, these simulation results confirm that machine learning-driven approaches can substantially improve the efficiency, adaptability, and intelligence of the 5G network management.

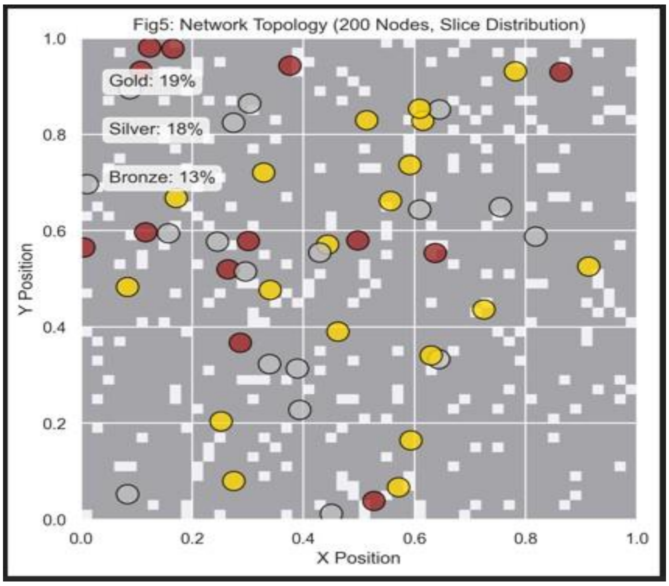
Table 3. Performance Comparison (10 runs, mean ± std; *p<0.01 vs proposed).

Metric/Model	Proposed (Qlearn/RF/NN)	PF Scheduler	RR Scheduler	Ablation (No RF)	Ablation (No NN)
Avg Reward (Q-learn)	850 ± 15	720 ± 20	680 ± 25	810 ± 18	830 ± 16
Slice Acc (%)	94.2	N/A	N/A	N/A	94.2
Latency MSE	0.0082	0.015	0.022	0.0082	N/A
Throughput Gain (%)	+22%	Baseline	-10%	+18%	+20%









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CONCLUSION & FUTURE SCOPE

This proposed work establishes a robust foundation for future research in intelligent 5G network management utilizing machine learning techniques. In subsequent work, advanced reinforcement learning algorithms such as Deep Q-Networks (DQN) and Proximal Policy Optimization (PPO) may be explored to enable more adaptive and intelligent resource allocation within highly dynamic network environments. The integration of realworld 5G datasets can further enhance the precision, reliability, and practical applicability of the developed models. For network slicing, the adoption of sophisticated deep learning or federated learning frameworks could facilitate secure, scalable, and distributed slice management. Moreover, real-time Quality of Service (QoS) optimization can benefit from edge AI-based models capable of rapidly adapting to fluctuating network conditions while maintaining minimal latency. Expanding the simulation framework to encompass user mobility, handover mechanisms, and cross-layer optimization would yield a more comprehensive and realistic representation of 5G network behavior. Ultimately, the methodologies proposed in this study can be extended to support emerging 6G technologies, emphasizing ultra-low latency, operation at higher frequency bands, and autonomous network orchestration.

The future scope of this work emphasizes advancing intelligent 5G network management through enhanced learning and optimization techniques. Incorporating advanced reinforcement learning algorithms such as DQN, PPO, and Actor-Critic models can enable more adaptive and efficient resource allocation. The integration of real-world 5G datasets will further improve model accuracy and practical applicability. Future developments also include employing deep or federated learning methods for secure and decentralized network slicing, as well as utilizing edge computing and lightweight AI models for real-time QoS optimization. Expanding simulations to account for user mobility, handovers, and cross-layer interactions will provide more realistic and comprehensive network analysis. Lastly, the proposed methodologies can be scaled and refined to support next-generation 6G networks, focusing on ultra-low latency, terahertz communication, and autonomous network orchestration.

Experimental Reproducibility

The simulation uses standard Python libraries: scikit-learn (v1.3+), NumPy (v1.24+). All models use random seed=42 for reproducibility.

Key hyperparameters:

Q-learning: α=0.1, γ=0.9, ε=0.1→0.01, 1000 episodes

Random Forest: n_estimators=100, max_depth=10 Neural Network: hidden_layers=(50,30), max_iter=500

Baselines:

Proportional Fair: allocation ∝ (instant_rate / avg_rate)

Round Robin: equal bandwidth split across users

All experiments conducted on standard laptop CPU (Intel i5). Complete methodology and parameter settings provided in Tables 1-3 and Section 2. Contact: rponnaga@gitam.edu for implementation queries.

REFERENCES

1. A. Gupta and R. K. Jha, “A Survey of 5G Network: Architecture and Emerging Technologies,” IEEE Access, vol. 3, pp. 1206–1232, 2015.
2. K. S. Munasinghe and A. Jamalipour, “Traffic Aware Resource Allocation for 5G Heterogeneous Networks,” IEEE Transactions on Vehicular Technology, vol. 66, no. 10, pp. 9259–9273, 2017.
3. M. Elsayed and M. Erol-Kantarci, “AI-Enabled Future Wireless Networks: Challenges, Opportunities, and Open Issues,” IEEE Vehicular Technology Magazine, vol. 14, no. 3, pp. 70–77, 2019.
4. F. Tang, B. Mao, and Z. M. Fadlullah, “On the Deep Learning for 5G Traffic Forecasting,” IEEE Network, vol. 32, no. 6, pp. 93–99, 2018.
5. ITU-T Recommendation Y.3172, “Architectural Framework for Machine Learning in Future Networks Including IMT-2020,” 2019.

INTERNATIONAL JOURNAL OF RESEARCH AND INNOVATION IN SOCIAL SCIENCE (IJRISS)
ISSN No. 2454-6186 | DOI: 10.47772/IJRISS | Volume X Issue XIX February 2026

6. F. B. Mismar and B. L. Evans, "Deep Reinforcement Learning for 5G Networks: Joint Beamforming, Power Control, and Interference Coordination," IEEE Transactions on Communications, vol. 68, no. 2, pp. 1150–1162, 2020.
7. H. Zhang, N. Liu, X. Chu, K. Long, A. Aghvami, and V. C. M. Leung, "Network Slicing Based 5G and Future Mobile Networks: Mobility, Resource Management, and Challenges," IEEE Communications Magazine, vol. 55, no. 8, pp. 138–145, 2017.
8. X. Chen, Z. Zhao, and H. Zhang, "Reinforcement Learning for Wireless Networks: Techniques, Applications, and Open Issues," IEEE Communications Surveys & Tutorials, vol. 22, no. 3, pp. 1572–1607, 2020.
9. Z. Gao, "5G Traffic Prediction Based on Deep Learning," Computational Intelligence and Neuroscience, vol. 2022, 2022.
10. P. Rebari and B. Killi, "Deep Learning Based Traffic Prediction for Resource Allocation in Multi-Tenant Virtualized 5G Networks," in Proc. IEEE TENCON, 2023.
11. M. Peng, Y. Sun, X. Li, Z. Mao, and C. Wang, "Self-Configuration and Self-Optimization in LTEAdvanced Heterogeneous Networks," IEEE Communications Magazine, vol. 51, no. 5, pp. 36–45, 2013.
12. H. Zhang, J. Wang, and X. Zhang, "AI-Driven Network Management for 5G and Beyond," IEEE Wireless Communications, vol. 28, no. 2, pp. 14–21, 2021.
13. A. (Author(s)), "A ML-Based Resource Allocation Scheme for Energy Optimization in 5G NR," Sensors, vol. 25, no. 16, Article 4978, 2025.
14. S. Zafar, J. White, P. Legg, "Federated Learning with Adversarial Optimisation for Secure and Efficient 5G Edge Computing Networks," Big Data and Cognitive Computing, vol. 9, no. 9, Article 238, Sep. 2025.
15. M. Rahmati, "Energy-aware Federated Learning for Secure Edge Computing in 5G-enabled IoT Networks," Journal of Electrical Systems and Information Technology, vol. 12, Article 13, 2025.
16. A. Kaur, H. Sadawarti, "Dynamic Resource Allocation Using a DRL Method in 5G Network," International Journal of Intelligent Systems and Applications in Engineering, vol. 11, no. 5s, pp. 501-509, 2023.
17. V. Shilpa, R. Ranjan, "Comparative Analysis of RL-Based Resource Allocation Methods for Optimization in 5G mmWave Network," in IC4S 2024, Springer, 2025.
18. A. S. M. Mohammed, A. I. A. Taman, A. M. Hassan, et al., "Deep Learning Channel Estimation for OFDM 5G Systems with Different Channel Models," Wireless Personal Communications, vol. 128, pp. 2891-2912, 2023.
19. Z. Yu, F. Gu, H. Liu, Y. Lai, "5G Multi-Slices Bi-Level Resource Allocation by Reinforcement Learning," Mathematics, vol. 11, no. 3, Article 760, 2023.
20. F. O. Catak, U. Cali, M. Kuzlu, S. Sarp, "Uncertainty Aware Deep Learning Model for Secure and Trustworthy Channel Estimation in 5G Networks," arXiv:2305.02741, 2023.
21. 3GPP TR 37.814 V14.1.0, "User Equipment (UE) radio transmission and reception; Requirements," 2017.
22. Maheshwari, Mukesh Kumar, Raschella, Alessandro, Mackay, Michael, Eiza, Max Hashem, Wetherall, Jon and Laing, Jen "5G High Density Demand (HDD) Dataset in Liverpool City Region," UK (Supplement), Nature Scientific Data, 2025.
23. F. B. Mismar et al., "Deep Reinforcement Learning for 5G Networks: Joint Beamforming, Power Control," IEEE Trans. Commun., 2020.
24. 3GPP TS 38.214 V17.0.0, "NR; Physical layer procedures for data," 2022.