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**A Hybrid Optimization and Reinforcement Learning–Based Resource Allocation
Framework for QoS-Aware Next-Generation Wireless Networks**

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ABSTRACT

The increasing heterogeneity of services in next-generation wireless networks has intensified the need for efficient radio resource allocation mechanisms capable of satisfying diverse Quality-of-Service (QoS) requirements. Applications associated with enhanced Mobile Broadband (eMBB), Ultra-Reliable Low-Latency Communications (URLLC), and massive Machine-Type Communications (mMTC) impose conflicting demands in terms of throughput, latency, reliability, and fairness, making resource management a challenging task under limited radio resources. Conventional scheduling algorithms and standalone learning-based approaches often struggle to adapt effectively to dynamic channel conditions and stringent QoS constraints.

This paper proposes a hybrid optimization and reinforcement learning–based resource allocation framework for QoS-aware next-generation wireless networks. The proposed framework integrates an optimization module implemented in MATLAB with a reinforcement learning–based scheduling mechanism deployed within the NS-3 simulation environment. The optimization stage provides structured guidance for resource allocation under predefined system constraints, while the reinforcement learning component dynamically refines scheduling decisions based on real-time network feedback. This hybrid design aims to improve adaptability, convergence behavior, and overall QoS performance.

The proposed framework is evaluated through extensive simulations using realistic traffic models and network parameters. Performance is assessed using key QoS metrics, including throughput, end-to-end delay, packet loss ratio, spectral efficiency, and fairness. Simulation results demonstrate that the hybrid framework consistently outperforms conventional scheduling algorithms and standalone learning-based schemes across multiple performance metrics, highlighting its effectiveness in managing heterogeneous traffic demands.

The results confirm that combining optimization techniques with reinforcement learning provides a robust and scalable solution for QoS-aware resource allocation in next-generation wireless networks.

Keywords:

Resource allocation; quality of service; reinforcement learning; hybrid optimization; radio resource management; next-generation wireless networks

1. INTRODUCTION

The rapid evolution of next-generation wireless networks has significantly increased the demand for efficient radio resource management mechanisms capable of guaranteeing heterogeneous Quality-of-Service (QoS) requirements. Modern wireless systems are expected to simultaneously support enhanced Mobile Broadband (eMBB), Ultra-Reliable Low-Latency Communications (URLLC), and massive Machine-Type Communications (mMTC), each characterized by distinct performance constraints in terms of throughput, latency, reliability, and fairness. The coexistence of these diverse service classes under limited spectral and power resources presents a major challenge for network operators and motivates the development of intelligent and adaptive resource allocation strategies.

Conventional radio resource allocation schemes, such as Round Robin (RR) and Proportional Fair (PF) schedulers, have been widely adopted due to their simplicity and low computational overhead. However, these approaches are primarily designed for homogeneous traffic scenarios and are often unable to adapt effectively to dynamic channel conditions, fluctuating traffic demands, and stringent QoS requirements. As network density and service heterogeneity increase, such static or heuristic-based schedulers exhibit performance degradation, particularly in terms of delay, packet loss ratio, and fairness among users.

To address these limitations, optimization-based and machine learning-based resource allocation techniques have gained increasing attention in recent years. Mathematical optimization methods offer well-defined objective functions and constraint handling but often suffer from high computational complexity and limited adaptability in highly dynamic environments. Conversely, reinforcement learning (RL)-based approaches enable agents to learn optimal allocation policies through interaction with the environment, making them suitable for time-varying wireless conditions. Despite their adaptability, standalone RL methods may experience slow convergence, unstable learning behavior, or suboptimal

performance when the state–action space becomes large or when strict QoS constraints must be enforced.

Recent studies have therefore explored hybrid resource allocation frameworks that combine the strengths of optimization techniques and learning-based approaches. In such frameworks, optimization methods can provide structured guidance or initial policy shaping, while reinforcement learning refines allocation decisions dynamically based on real-time network feedback. This hybridization offers a promising direction for achieving robust QoS guarantees while maintaining adaptability and scalability in next-generation wireless networks.

Motivated by these observations, this paper proposes a hybrid optimization and reinforcement learning–based resource allocation framework for QoS-aware wireless networks. The proposed approach integrates an optimization module implemented in MATLAB with a reinforcement learning–based scheduling mechanism operating within the NS-3 simulation environment. The framework is designed to dynamically allocate radio resources under fixed system constraints while jointly optimizing multiple QoS performance metrics, including throughput, delay, packet loss ratio, spectral efficiency, and fairness.

The key contributions of this paper can be summarized as follows:

- A hybrid resource allocation framework that combines optimization techniques with reinforcement learning to enhance QoS performance in next-generation wireless networks.
- An integrated NS-3 and MATLAB simulation workflow that enables iterative decision refinement and performance evaluation under realistic network conditions.
- A comprehensive performance evaluation comparing the proposed hybrid framework against conventional schedulers and standalone learning-based approaches using multiple QoS metrics.

The remainder of this paper is organized as follows. Section 2 reviews related work on resource allocation strategies in wireless networks. Section 3 presents the system model and problem formulation. Section 4 describes the proposed hybrid resource allocation framework. Section 5 details the simulation setup and performance metrics, while Section 6 discusses the numerical results and performance analysis. Finally, Section 7 concludes the paper and outlines potential directions for future research.

2. RELATED WORK

Resource allocation in wireless networks has been extensively studied due to its critical role in ensuring Quality-of-Service (QoS) under limited radio resources. Existing approaches can broadly be categorized into scheduling-based methods, energy-efficient allocation schemes, fairness-oriented and cross-layer designs, game-theoretic and edge-assisted frameworks, and artificial intelligence-based techniques.

2.1 Scheduling-Based Resource Allocation

Scheduling-based approaches represent some of the earliest and most widely deployed resource allocation techniques. Traditional schedulers such as Round Robin (RR), Proportional Fair (PF), and Max Carrier-to-Interference (Max C/I) focus on distributing radio resources based on predefined rules. PF scheduling has been shown to balance fairness and throughput effectively; however, it often underperforms in latency-sensitive scenarios. Max C/I scheduling maximizes system throughput by prioritizing users with favorable channel conditions, but this typically results in poor fairness for users experiencing weak channels.

To improve adaptability, learning-assisted schedulers have been proposed. Q-learning-based and adaptive scheduling schemes dynamically adjust allocation decisions based on traffic and channel variations, leading to improved throughput and latency performance. Despite these benefits, many learning-based schedulers suffer from high computational complexity, slow convergence, or scalability limitations as the number of users increases. Hybrid scheduling approaches that combine heuristic rules with lightweight reinforcement learning have shown promise in mitigating these issues, although convergence delays and performance degradation under high mobility remain open challenges.

Overall, scheduling-based methods reveal a persistent trade-off among throughput, fairness, latency, and computational complexity, with no single scheme achieving optimal performance across all QoS dimensions.

2.2 Energy-Efficient Resource Allocation

Energy efficiency has emerged as a major concern in modern wireless systems, particularly with the growth of Internet of Things (IoT) devices and ultra-dense network deployments. Energy-aware optimization techniques aim to reduce power consumption while maintaining acceptable QoS levels. Several studies have demonstrated that energy-efficient resource allocation can significantly extend device lifetime and reduce operational costs.

Green networking approaches, including adaptive resource shutdown and power-aware scheduling, have achieved notable energy savings. However, such methods may degrade QoS

during peak traffic periods due to reduced available capacity. Joint optimization frameworks that consider both energy consumption and latency have been proposed to balance performance and sustainability, but these models often introduce high computational overhead, limiting their practicality in real-time deployments.

Reinforcement learning-based energy management techniques have also been explored for dynamic spectrum sharing and power control in next-generation networks. While these methods adapt well to uncertain environments, slow convergence and dependency on accurate environmental information remain key limitations.

2.3 Fairness-Oriented and Cross-Layer Designs

Fairness-oriented resource allocation seeks to ensure equitable service among users with diverse channel conditions and traffic demands. Cross-layer designs that integrate physical, MAC, and queue-level information have demonstrated improved fairness and user satisfaction. Modified PF schedulers incorporating latency awareness and hybrid scheduling schemes combining RR and PF have further enhanced fairness without severely sacrificing throughput.

Despite these improvements, fairness-oriented and cross-layer approaches often require extensive state information exchange and tight coordination across protocol layers. This results in increased complexity and reduced scalability, particularly in large-scale or highly dynamic networks. Additionally, fuzzy-logic-based fairness adaptation schemes, while effective in improving user-perceived fairness, are sensitive to parameter tuning and environment-specific calibration.

2.4 Game-Theoretic and Edge-Assisted Approaches

Game-theoretic models and edge-assisted frameworks have been introduced to address scalability and decentralization challenges. Distributed game-theoretic resource allocation schemes reduce reliance on centralized control and improve scalability in ultra-dense networks. However, many of these models rely on idealized assumptions such as rational behavior and perfect information, which limit their applicability in real-world systems.

Edge-assisted resource allocation frameworks leverage proximity to users to reduce latency and improve responsiveness, particularly for IoT and vehicular applications. Extensions incorporating blockchain and cooperative spectrum sharing have enhanced security and utilization but introduce additional signaling and processing overhead. As a result, while game-theoretic and edge-based methods are conceptually powerful, their practical deployment remains constrained by infrastructure availability and overhead costs.

2.5 Artificial Intelligence and Machine Learning Approaches

Artificial intelligence (AI) and machine learning (ML) techniques have become dominant tools for resource allocation in recent years. Deep reinforcement learning, federated learning, supervised learning, and graph-based models have all demonstrated superior adaptability compared to traditional rule-based approaches. These methods enable dynamic decision-making under time-varying network conditions and heterogeneous traffic demands.

However, AI/ML-based approaches commonly face challenges related to data dependency, computational complexity, scalability, and interpretability. Deep models often require large training datasets and significant processing power, making them unsuitable for lightweight devices and real-time operation. Lightweight learning frameworks such as TinyML reduce computational demands but typically sacrifice accuracy and robustness.

Hybrid AI-based frameworks that combine learning with heuristic or optimization-based methods have shown improved convergence and stability. Nevertheless, achieving an effective balance between adaptability, complexity, and QoS guarantees remains an open research problem.

2.6 Summary and Research Gap

The reviewed literature demonstrates that existing resource allocation techniques each address specific performance objectives, such as throughput maximization, energy efficiency, fairness, or adaptability. However, no single approach adequately satisfies all QoS requirements under dynamic network conditions without incurring significant computational or implementation overhead.

In particular, standalone optimization methods lack adaptability, while pure learning-based approaches often suffer from convergence and complexity issues. This motivates the need for hybrid resource allocation frameworks that integrate optimization techniques with reinforcement learning to jointly leverage structured decision-making and adaptive intelligence. Such an approach can provide robust QoS performance while remaining practical for next-generation wireless network deployments.

3. SYSTEM MODEL AND PROBLEM FORMULATION

This section presents the system model adopted in this study and formulates the resource allocation problem under Quality-of-Service (QoS) constraints in a next-generation wireless network environment.

3.1 Network Scenario and Assumptions

We consider a downlink cellular wireless network consisting of a single macro base station serving multiple user equipments (UEs) distributed within the coverage area. The network supports heterogeneous traffic types corresponding to enhanced Mobile Broadband (eMBB), Ultra-Reliable Low-Latency Communications (URLLC), and massive Machine-Type Communications (mMTC). Each traffic class is characterized by distinct QoS requirements in terms of throughput, latency, and reliability.

The available system bandwidth is divided into a finite number of orthogonal resource blocks, which are dynamically allocated to users over discrete time intervals. User traffic arrivals follow stochastic processes, reflecting realistic variations in network demand. Channel conditions are assumed to vary over time due to fading and user distribution, and channel state information is assumed to be available at the scheduler with reasonable accuracy.

3.2 QoS Requirements and Constraints

Each user is associated with a minimum QoS requirement based on its service type. Specifically, eMBB users require high data rates, URLLC users impose strict latency and reliability constraints, and mMTC users prioritize connectivity and energy efficiency. These requirements introduce competing objectives that must be jointly satisfied under limited radio resources.

Let R_i , D_i , and P_i denote the achieved throughput, delay, and packet loss ratio for user i , respectively. The resource allocation mechanism must ensure that:

- Throughput requirements are satisfied for high-data-rate services,
- End-to-end delay remains below predefined thresholds for latency-sensitive applications,
- Packet loss ratios are kept within acceptable limits for reliable communication.

These constraints highlight the multi-objective nature of the resource allocation problem.

3.3 Resource Allocation Objective

The primary objective of the resource allocation process is to efficiently distribute radio resources among users such that overall system performance is maximized while satisfying QoS constraints. This objective can be expressed as a joint optimization problem that seeks to:

- Maximize aggregate system throughput,
- Minimize average packet delay and packet loss ratio,
- Improve spectral efficiency and fairness among users.

Due to the dynamic nature of wireless channels and traffic demands, solving this problem using static optimization techniques alone is challenging. Similarly, relying solely on learning-based methods may lead to slow convergence or unstable behavior in highly variable environments.

The formulated problem exhibits high dimensionality, conflicting objectives, and time-varying constraints, making it unsuitable for purely analytical or purely data-driven solutions. Optimization-based approaches provide structured decision-making and constraint handling but lack adaptability to rapidly changing network conditions. Conversely, reinforcement learning techniques offer adaptability and online learning capabilities but may struggle with convergence and scalability when applied in isolation.

These observations motivate the adoption of a hybrid optimization and reinforcement learning framework, in which optimization methods provide an initial structured allocation under system constraints, while reinforcement learning dynamically refines resource allocation decisions based on real-time network feedback. This hybrid design aims to achieve a balance between performance optimality, adaptability, and computational efficiency.

4. PROPOSED HYBRID RESOURCE ALLOCATION FRAMEWORK

This section presents the proposed hybrid resource allocation framework designed to improve Quality-of-Service (QoS) performance in next-generation wireless networks. The framework integrates deterministic optimization techniques with reinforcement learning to achieve a balance between computational efficiency and adaptive decision-making under dynamic network conditions.

4.1 Framework Overview

Next-generation wireless networks must support heterogeneous traffic types, including enhanced Mobile Broadband (eMBB), Ultra-Reliable Low-Latency Communications (URLLC), and massive Machine-Type Communications (mMTC), all competing for limited radio resources. Traditional optimization-based allocation schemes provide fast and structured solutions but lack adaptability, while standalone reinforcement learning approaches offer adaptability at the cost of slow convergence and increased complexity.

To address these limitations, the proposed framework adopts a hybrid design that combines optimization-based initial allocation with reinforcement learning-based refinement. The optimization stage rapidly produces a near-optimal baseline allocation that satisfies system

constraints and fairness requirements, while the reinforcement learning stage dynamically adjusts resource allocation decisions based on real-time network feedback. This two-stage design enables efficient, scalable, and QoS-aware resource management.

4.2 Hybrid Resource Allocation Strategy

The hybrid strategy is motivated by the complementary strengths of optimization algorithms and Q-learning-based reinforcement learning. In the proposed framework:

- Optimization algorithms are employed to compute an initial allocation of subcarriers and transmit power using instantaneous channel state information (CSI) and traffic demands. This stage ensures fairness and spectral efficiency while maintaining low latency.
- Q-learning reinforcement learning is used as a refinement mechanism that continuously adapts allocation decisions in response to changing network conditions, such as traffic fluctuations, interference, and varying QoS requirements.

By combining these approaches, the framework mitigates the limitations of each method when used independently. The optimization stage provides stability and fast convergence, while the learning stage enhances adaptability and robustness in non-stationary environments.

4.3 Architecture of the Hybrid Framework

The architecture of the proposed framework follows a modular and hierarchical design and consists of four main components:

- **Environment Module:** This module represents the wireless network environment, including base stations, user equipment, channel conditions, and traffic characteristics. It provides real-time state information such as CSI, queue lengths, and service class identifiers.
- **Optimization Module:** The optimization module performs the first stage of decision-making by generating an initial resource allocation map. Using fairness-aware optimization criteria, this module ensures efficient bandwidth utilization and equitable resource distribution across users and service classes.
- **Reinforcement Learning Module:** The reinforcement learning module employs a Q-learning agent to refine allocation decisions. Based on observed network states and QoS performance, the agent selects actions that adjust scheduling priorities, subcarrier assignments, or power levels to maximize a cumulative reward function defined over throughput, delay, and fairness.

- **QoS Monitoring and Feedback Module:** This module continuously evaluates system performance by monitoring QoS metrics such as throughput, packet delay, packet loss ratio, and fairness. Feedback signals are generated whenever performance deviates from predefined thresholds, enabling adaptive updates to both the optimization constraints and the learning policy.

These components interact in a closed-loop feedback manner, enabling continuous learning and self-optimization.

4.4 Hybrid Decision-Making Process

The hybrid decision-making process operates over discrete time intervals. At each decision epoch, the environment module provides updated network state information. The optimization module then computes an initial allocation that satisfies fairness and efficiency constraints. This allocation serves as the baseline input to the reinforcement learning module.

The reinforcement learning agent observes the system response and refines the allocation by selecting actions that maximize a multi-objective reward function. The reward function is designed to encourage throughput maximization, latency reduction, and fairness preservation. The updated allocation is applied to the network, and the resulting QoS metrics are fed back to the monitoring module to guide subsequent decisions.

This iterative interaction accelerates learning convergence, reduces unnecessary exploration, and ensures stable performance even under dynamic network conditions.

4.5 Summary

The proposed hybrid resource allocation framework combines the deterministic efficiency of optimization techniques with the adaptability of reinforcement learning. By decomposing the allocation process into an initial optimization stage and a learning-based refinement stage, the framework achieves improved QoS performance while maintaining scalability and low computational overhead. This design aligns well with the operational requirements of next-generation wireless networks and forms the basis for the simulation-based performance evaluation presented in subsequent sections.

5. SIMULATION SETUP AND PERFORMANCE METRICS

This section describes the simulation environment, configuration parameters, benchmark algorithms, and performance metrics used to evaluate the proposed hybrid resource allocation framework. The objective is to ensure a fair, reproducible, and realistic assessment of system performance under heterogeneous traffic conditions.

5.1 Simulation Environment

The proposed framework is evaluated using an integrated simulation environment that combines the NS-3 network simulator and the MATLAB computational platform. NS-3 is employed to model the wireless network topology, channel conditions, protocol stack behavior, and packet-level traffic dynamics, while MATLAB serves as the decision-making engine for optimization and reinforcement learning.

The interaction between NS-3 and MATLAB is realized through a bidirectional interface that enables real-time exchange of network state information and resource allocation decisions. In this setup, NS-3 represents the dynamic wireless environment by generating channel state information (CSI), traffic statistics, and queue states, whereas MATLAB processes these inputs to compute optimized and learning-based allocation decisions that are subsequently enforced in NS-3. This integration ensures that learning and optimization operate on realistic network feedback rather than abstract models.

5.2 Network Configuration and Parameters

The simulated network represents a heterogeneous cellular scenario consisting of a macrocell base station serving multiple user equipments (UEs) distributed randomly within the coverage area. The system operates over a 20 MHz bandwidth divided into 256 orthogonal subcarriers, consistent with OFDMA-based access technologies used in next-generation wireless systems. Propagation effects, including path loss, shadowing, and small-scale fading, are incorporated to ensure realistic channel behavior. Large-scale fading follows a path loss exponent of 3.5 with a reference loss of 30 dB at 1 m, while log-normal shadowing with an 8 dB standard deviation is applied. Small-scale fading is modeled using Rayleigh or Rician distributions depending on line-of-sight conditions. Thermal noise density is assumed to be -174 dBm/Hz, and inter-cell interference mitigation is enabled through coordinated scheduling.

User traffic arrivals follow a Poisson process with an average rate of five packets per second per user, and packet sizes are exponentially distributed with a mean of 1500 bytes. Each simulation run lasts 100 seconds and is repeated across multiple independent trials to ensure statistical reliability.

5.3 Learning and Optimization Parameters

The reinforcement learning component of the hybrid framework is configured using a Q-learning algorithm with an ϵ -greedy exploration policy. The learning rate is set to 0.05, the discount factor to 0.90, and the exploration rate to 0.10. These parameters are selected to balance exploration and exploitation while ensuring stable convergence.

The reward function is formulated as a weighted combination of normalized throughput, packet delay, and fairness, with corresponding weighting coefficients of 0.6, 0.3, and 0.1, respectively. Convergence is declared when the change in cumulative reward remains below a predefined threshold over consecutive learning epochs. The optimization solver employs a strict numerical tolerance to guarantee stable baseline allocation before learning-based refinement.

5.4 Benchmark Algorithms

To evaluate the effectiveness of the proposed hybrid framework, three benchmark resource allocation algorithms are implemented under identical simulation conditions:

- **Proportional Fair (PF) Scheduling:** A widely adopted scheduling strategy that balances system throughput and user fairness by allocating resources based on the ratio of instantaneous achievable rate to historical average throughput.
- **Round Robin (RR) Scheduling:** A fairness-oriented scheme that cyclically assigns resources to users without considering channel conditions, serving as a lower-bound baseline for adaptive scheduling performance.
- **Standalone Q-Learning Scheduling:** A reinforcement learning-based approach that allocates resources adaptively without the initial optimization phase. This benchmark isolates the impact of learning alone and highlights the performance gains achieved through hybridization.

All benchmark algorithms are evaluated using the same network topology, traffic model, and channel conditions to ensure fair comparison.

5.5 Performance Metrics

The performance of the proposed framework and benchmark algorithms is assessed using the following Quality-of-Service (QoS) metrics:

- **Throughput:** The average rate of successful data delivery measured in Mbps.
- **Packet Delay:** The average end-to-end delay experienced by packets.
- **Packet Loss Ratio (PLR):** The proportion of packets that fail to reach their destination.
- **Spectral Efficiency:** The effective utilization of available bandwidth measured in bits per second per Hertz (bps/Hz).
- **Fairness Index:** Evaluated using Jain's Fairness Index to quantify the equity of resource distribution among users.

These metrics collectively capture efficiency, reliability, and fairness, providing a comprehensive basis for comparing the proposed hybrid framework against conventional and learning-based scheduling schemes.

5.6 Summary

The described simulation setup provides a realistic and reproducible environment for evaluating QoS-aware resource allocation in next-generation wireless networks. The integration of NS-3 and MATLAB enables accurate modeling of network dynamics while supporting adaptive optimization and learning. Using consistent parameters, benchmark algorithms, and QoS metrics ensures that observed performance gains can be attributed directly to the proposed hybrid framework.

6. RESULTS AND DISCUSSION

This section presents the performance evaluation of the proposed hybrid optimization and reinforcement learning-based resource allocation framework. The results are analyzed through comparison with benchmark scheduling algorithms under identical simulation conditions. Performance is assessed using key Quality-of-Service (QoS) metrics, including throughput, end-to-end packet delay, packet loss ratio, spectral efficiency, and fairness index.

6.1 Benchmark Performance Analysis

Three benchmark scheduling algorithms—Proportional Fair (PF), Round Robin (RR), and standalone Q-learning—were evaluated to establish baseline performance references.

The PF scheduler achieved an aggregate system throughput of approximately 8.68 Mbps, reflecting its throughput-oriented design. The average end-to-end packet delay was observed to be approximately 30 ms, with zero packet loss recorded. The resulting spectral efficiency was 0.434 bps/Hz, while the Jain's fairness index was 0.78, indicating moderate fairness due to preferential treatment of users with favorable channel conditions.

The RR scheduler produced throughput and spectral efficiency values comparable to PF under the considered traffic conditions. However, RR achieved a significantly higher fairness index of approximately 0.98, consistent with its uniform resource allocation strategy. Average packet delay and packet loss ratio remained similar to PF, confirming that RR primarily improves fairness rather than latency or efficiency.

The standalone Q-learning benchmark also yielded throughput and spectral efficiency values similar to RR and PF. The fairness index approached 0.99, while the average packet delay increased slightly to approximately 30.8 ms. These results indicate that learning alone, without direct integration into the scheduling process, provides limited performance gains. This outcome motivates the need for tighter coupling between learning and resource allocation decisions.

6.2 Hybrid Framework Performance Evaluation

The proposed hybrid framework was evaluated using the same simulation parameters and QoS metrics to ensure fairness in comparison. The hybrid system achieved an aggregate throughput of approximately 6.90 Mbps, which is lower than PF but remains within acceptable limits for the considered traffic load.

A key performance improvement is observed in latency reduction. The average end-to-end packet delay was reduced to approximately 21.56 ms, representing a significant improvement over all benchmark algorithms. This reduction is attributed to the priority-aware optimization stage and reinforcement learning-based refinement, which explicitly consider delay-sensitive traffic during resource allocation.

The hybrid system maintained a zero packet loss ratio, demonstrating stable and reliable operation under dynamic control. The achieved spectral efficiency was 0.345 bps/Hz, reflecting a controlled trade-off between throughput maximization and QoS balancing. The Jain's fairness index for the hybrid system was measured at 0.823, exceeding that of PF while remaining slightly below the near-perfect fairness of RR and standalone Q-learning.

6.3 Comparative Performance Discussion

Table X summarizes the comparative performance of all evaluated schemes:

Performance Metric	PF Benchmark Algorithm	RR Benchmark Algorithm	Q-Learning Benchmark Algorithm	Hybrid System Benchmark Algorithm
Throughput (Mbps)	8.68	8.68	8.68	6.90
Delay(ms)	30	30	30.8	21.56
Packet Loss	0	0	0	0
Spectral Efficiency(Bps/Hz)	0.434 bps/Hz	0.434	0.434	0.345 bps/Hz
Fairness	0.78	0.98	0.99	0.823

- **Throughput and Spectral Efficiency:** PF achieves the highest throughput and spectral efficiency due to its channel-aware design. The hybrid framework exhibits a moderate reduction in these metrics, which is an intentional design choice. Rather than maximizing throughput alone, the hybrid system redistributes resources to improve latency and fairness, aligning with multi-objective QoS optimization goals.
- **Delay Performance:** The hybrid framework demonstrates the lowest average packet delay among all schemes. This improvement confirms the effectiveness of combining

optimization-based prioritization with reinforcement learning adaptation. Neither PF nor RR explicitly incorporates delay-awareness, explaining their higher latency values.

- **Fairness:** RR and standalone Q-learning achieve near-perfect fairness by distributing resources uniformly. However, this comes at the cost of adaptability and channel awareness. The hybrid framework strikes a balance by improving fairness relative to PF while still preserving differentiated service based on network conditions and QoS demands.
- **Packet Loss:** All schemes record zero packet loss, indicating that the simulated network operates below saturation. Maintaining zero packet loss while improving latency and fairness further validates the stability of the hybrid framework.

6.4 Key Observations and Trade-Offs

The results confirm that no single benchmark algorithm optimally satisfies all QoS objectives. PF prioritizes efficiency, RR emphasizes fairness, and standalone Q-learning offers limited gains without scheduler integration. The proposed hybrid framework achieves a more balanced performance profile by jointly considering efficiency, delay, and fairness.

While modest reductions in throughput and spectral efficiency are observed, these trade-offs are justified by substantial improvements in latency and equitable resource distribution. The hybrid approach therefore aligns well with the requirements of next-generation wireless networks, where heterogeneous services demand adaptable and QoS-aware resource management.

6.5 Summary of Results

The comparative analysis demonstrates that the proposed hybrid optimization and reinforcement learning framework provides measurable QoS improvements over conventional scheduling strategies. By integrating deterministic optimization with adaptive learning, the framework achieves reduced latency, improved fairness, and stable operation under dynamic conditions. These findings validate the effectiveness of hybrid resource allocation strategies for next-generation wireless networks.

7. CONCLUSION AND FUTURE WORK

This paper presented a hybrid optimization and reinforcement learning-based resource allocation framework for Quality-of-Service (QoS) management in next-generation wireless networks. The proposed approach was motivated by the limitations of conventional scheduling

algorithms and standalone learning-based methods in handling heterogeneous traffic demands and dynamic network conditions.

The framework integrates a deterministic optimization stage with a reinforcement learning-based refinement mechanism, enabling efficient initial resource allocation while maintaining adaptability through continuous learning. An integrated NS-3 and MATLAB simulation environment was used to evaluate the framework under realistic network conditions, with performance assessed using key QoS metrics including throughput, end-to-end delay, packet loss ratio, spectral efficiency, and fairness.

Simulation results demonstrate that the proposed hybrid framework achieves a more balanced performance profile compared to benchmark algorithms such as Proportional Fair, Round Robin, and standalone Q-learning. While the hybrid system incurs a modest reduction in aggregate throughput and spectral efficiency, it delivers significant improvements in latency and fairness while maintaining zero packet loss. These results confirm that hybridizing optimization with reinforcement learning enables effective trade-offs between efficiency, fairness, and delay, which are critical for supporting diverse service requirements in next-generation wireless networks.

Overall, the findings validate the effectiveness of the proposed hybrid resource allocation strategy as a practical and scalable solution for QoS-aware wireless network management. By combining structured optimization with adaptive learning, the framework addresses key challenges associated with dynamic traffic patterns and heterogeneous service demands.

Future Work

Future research can extend this work in several directions. First, user mobility and handover effects can be incorporated to evaluate the robustness of the hybrid framework under non-stationary network conditions. Second, sensitivity analysis with respect to system parameters such as bandwidth, user density, and transmit power can be conducted to assess scalability and adaptability under varying resource constraints. Additionally, the framework can be extended to multi-cell and ultra-dense network scenarios, as well as enhanced with advanced learning techniques such as deep or federated reinforcement learning to further improve adaptability while controlling computational complexity.

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