Dr. S. Vijayakumar, 2026, 14:2
ISSN (Online): 2348-4098
ISSN (Print): 2395-4752

International Journal of Science,
Engineering and Technology
An Open Access Journal

Reinforcement Learning–Enhanced Hybrid CAC–CR-LBT Framework for 5G/Wi-Fi 6 Coexistence

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Abstract-The coexistence of 5G New Radio (NR) and Wi-Fi 6 in unlicensed spectrum presents significant challenges due to contention-based medium access, cross-technology interference, and heterogeneous quality-of-service (QoS) requirements. Conventional call admission control (CAC) mechanisms reduce congestion and blocking probability, but their reliance on static admission thresholds limits adaptability under dynamic traffic and channel conditions. This paper proposes a reinforcement learning (RL) enhanced hybrid CAC integrated with a collision-resolution listen-before-talk (CR-LBT) mechanism to enable intelligent and adaptive spectrum sharing between 5G NR-U and Wi-Fi 6 systems. The RL agent dynamically tunes admission thresholds based on observed network state parameters, including offered load, signal-to-noise ratio (SNR), and service demand, while the CR-LBT mechanism mitigates contention-induced collisions during channel access. A system-level MATLAB simulation model evaluates the proposed framework under varying traffic loads. Simulation results demonstrate that the proposed scheme achieves 20–25% higher throughput and approximately 15% increased system capacity compared with conventional CAC, while significantly reducing bit error rate (BER). In addition, the framework maintains ultra-low end-to-end latency below 1 ms and near-zero blocking probability for delay-sensitive services such as VoIP and real-time video. These results confirm that the proposed approach provides a scalable and intelligent solution for next-generation heterogeneous wireless networks operating in unlicensed spectrum.

Keywords- Call admission control, reinforcement learning, listen-before-talk, 5G NR-U, Wi-Fi 6, heterogeneous networks, unlicensed spectrum.

I. INTRODUCTION

The exponential growth of bandwidth-intensive and latency-critical wireless applications has created unprecedented demand on licensed spectrum resources. To mitigate spectrum scarcity, 5G New Radio Unlicensed (NR-U) enables cellular networks to opportunistically access unlicensed bands, thereby enhancing capacity and spectrum utilization. However, these bands are densely populated by Wi-Fi networks, particularly IEEE 802.11ax (Wi-Fi 6), resulting in complex coexistence challenges.

Efficient NR-U and Wi-Fi 6 coexistence is constrained by contention-based medium access, cross-technology interference, and heterogeneous quality-of-service (QoS) requirements. Delay-sensitive applications such as VoIP and real-time video demand stringent latency (<1 ms) and reliability guarantees, while best-effort traffic prioritizes throughput maximization. Uncoordinated access to shared spectrum severely degrades overall network performance.

Call admission control (CAC) is essential for QoS assurance by regulating active connections. Conventional CAC mechanisms employ fixed or heuristic thresholds, which exhibit limited adaptability to dynamic traffic loads and channel conditions. Similarly, listen-before-talk (LBT) protocols mandated for fair coexistence suffer from increased collision probability and access latency under high contention.

Reinforcement learning (RL) offers a promising paradigm for adaptive network control through policy optimization via environment interaction. This paper proposes an RL-enhanced hybrid CAC framework integrated with collision-resolution LBT (CR-LBT) to optimize 5G NR-U and Wi-Fi 6 coexistence.

II. RELATED WORK

Coexistence between cellular and Wi-Fi systems in unlicensed spectrum has received extensive research attention. Early efforts concentrated on duty-cycling and channel selection mechanisms to facilitate fair resource sharing. The emergence of 5G New Radio Unlicensed (NR-U) prompted development of enhanced listen-before-talk (LBT) protocols designed to harmonize cellular access patterns with Wi-Fi contention procedures.

Call admission control (CAC) schemes have been widely investigated to alleviate congestion and blocking probability in wireless networks. Threshold-based CAC enhances quality-of-service (QoS) under moderate traffic loads; however, static thresholds exhibit limited adaptability to the traffic variability and channel dynamics characteristic of unlicensed spectrum. Adaptive CAC approaches employing traffic estimation and optimization have been proposed, yet these methods typically require precise system modeling and lack autonomous learning capabilities. Reinforcement learning (RL) has emerged as a powerful paradigm for radio resource management, encompassing spectrum allocation, power control, and scheduling. RL-based solutions demonstrate robust performance in unknown, time-varying environments without necessitating explicit models. Despite these advances, few studies integrate RL-driven CAC with collision-aware LBT mechanisms specifically for heterogeneous unlicensed spectrum coexistence. This work addresses this research gap through an integrated RL-CAC–CR-LBT framework that jointly optimizes admission control and channel access protocols

III. SYSTEM MODEL AND PROBLEM FORMULATION

Consider a heterogeneous wireless network where 5G NR-U base stations and Wi-Fi 6 access points share a common unlicensed channel. Let S= {S1, S2, S3} denote the set of service classes: best-effort data, real-time video, and VoIP. Each service class Si has QoS requirements: throughput Ri latency Li and reliability (BER).

The optimization objective is to maximize aggregate throughput and system capacity, subject to QoS constraints:

$$C = max\,\{ n : P_b(n) \le P_b^{max}, L_e(n) \le L_e^{max}, BER(n) \le BER^{max} \}$$

Where:

- at is the admission decision at time tt,
- Pb is call blocking probability,
- Le is end-to-end latency,
- BER is bit error rate,

Pbmax, Lemax and BERmax are QoS thresholds.
Let λt be the normalized offered load at time t. Admission decisions at {0, 1} (reject/admit) are made based on observed state st = {λt, SNRt, qt}, where qt is the service demand vector. The sequential decision problem is formulated as:

$$\pi^* = \arg\max E\left[\sum_{t=0}^{\infty} \gamma^t\, r(s_t, a_t)\right]$$

Where:
π is the admission policy,
r(st, at) is the immediate reward at time t,
γ € [0,1] is the discount factor.
The RL agent learns π* to maximize long-term discounted reward while enforcing QoS constraints

IV. PROPOSED RL-CAC–CR-LBT FRAMEWORK

1. Framework Overview

Fig.1 depicts the operational flow of the proposed RL-CAC–CR-LBT framework. A new call request triggers network state monitoring, capturing offered load λt signal-to-noise ratio SNRt, and service demand qt The state vector st={λt, SNRt, qt} informs the RL agent, which determines the optimal admission threshold θt*

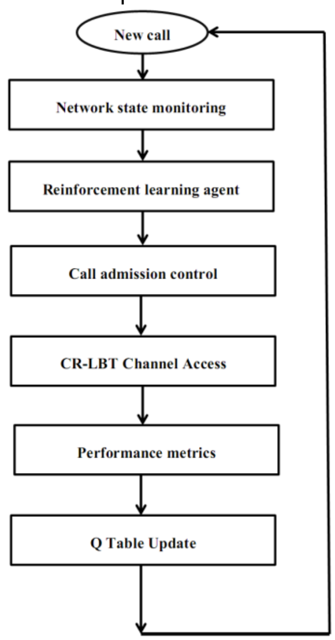

Fig.1 Flow chart of RL-CAC-CR-LBT

Reinforcement Learning–Based CAC

The CAC problem is modeled using Q-learning. The state space represents discretized network conditions, such as traffic load and SNR levels. The action space corresponds to a set of admissible admission thresholds. The reward function is designed to encourage high throughput while penalizing blocking probability, BER, and excessive latency. Through iterative interaction with the environment, the RL agent converges toward an optimal admission policy that adapts to dynamic conditions.

Collision-Resolution Listen-Before-Talk

CR-LBT is an advanced channel access mechanism designed to improve efficiency and fairness in unlicensed spectrum, especially in environments where 5G NR-U and Wi-Fi 6 coexist. In unlicensed bands, devices compete for the same channel using listen-before-talk (LBT) procedures. Traditional LBT relies on fixed or semi-static contention parameters, which often results in collisions, longer access delays, and reduced throughput under heavy traffic. Fig.2 shows CR-LBT overcomes these issues by introducing collision awareness and adaptive resolution strategies into the LBT process.

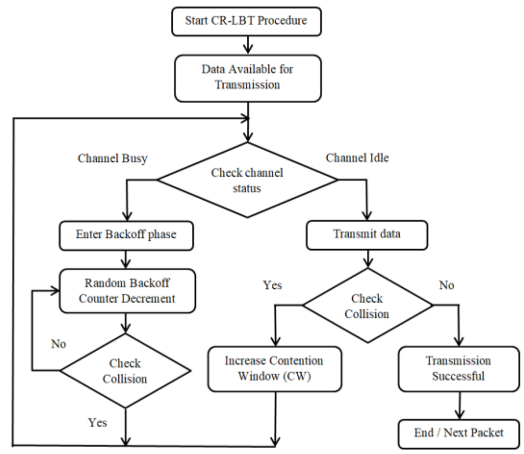

Fig.2 Flow chart of Collision-Resolution Listen-Before-Talk

Clear Channel Assessment (CCA): When a node (NR-U base station or Wi-Fi access point) has data to send, it first checks if the channel is idle. If idle for the required period, transmission begins immediately.

Backoff Phase: If the channel is busy, the node enters a backoff stage, selecting a random counter from a dynamically adjusted contention window (CW).

Collision Awareness: Unlike conventional LBT, CR-LBT monitors transmission outcomes. If a collision is detected (e.g., missing acknowledgments or decoding failures), the CW is expanded adaptively, spreading transmissions over a longer time window to reduce repeated collisions.

Adaptive Feedback Mechanism

On success: The CW is reduced, improving channel utilization and lowering delay.

On collision: The CW is increased, recalculating backoff duration to balance fairness and aggressiveness.

This feedback-driven adaptation stabilizes performance even under heavy contention, lowering collision probability, reducing retransmissions, and improving both throughput and latency compared to conventional LBT.

System-Level Perspective

CR-LBT functions as a MAC-layer enhancement that complements higher-layer mechanisms like call admission control (CAC). In an RL-CAC–CR-LBT framework, CAC limits the number of active users to avoid congestion, while CR-LBT manages channel access among admitted users. Together, they ensure QoS requirements such as low latency, low error rates, and fairness are met across diverse traffic types, including VoIP, video, and best-effort data.

V. SIMULATION MODEL AND PARAMETERS

A comprehensive MATLAB-based system-level simulator is developed to evaluate the proposed RL-CAC–CR-LBT framework. The simulation models physical and MAC layer interactions while abstracting lower-layer details to focus on coexistence performance trends. Key simulation parameters are summarized in Table.1.

Parameter	Value
Channel bandwidth	20 MHz (5 GHz band)
Offered load	0.1–1.5 (normalized)
Service mix	40% VoIP, 30% video, 30% data
SNR range	10–25 dB
Simulation trials	100 per load point
Confidence interval	95%

Table.1 Key simulation parameters

Normalized offered load λ∈[0.1,1.5] spans light to heavy traffic conditions. Each load point undergoes 100 independent trials, with results averaged to ensure statistical significance (95% confidence intervals).

VI. RESULTS AND DISCUSSION

Simulation results demonstrate significant performance improvements of the proposed RL-CAC–CR-LBT framework over the baseline static CAC scheme. The evaluation covers throughput, blocking probability, bit error rate (BER), and latency across varying offered loads.

1. Throughput Performance

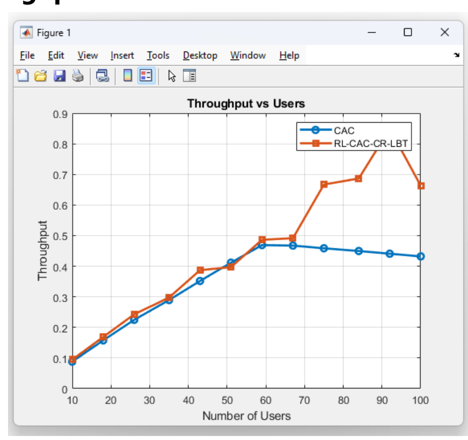

Fig.3 Throughput Performance

Fig.3 presents normalized throughput versus offered load. The RL-CAC–CR-LBT scheme achieves 20–25% higher throughput compared to the baseline, with peak gains at moderate-to-high load (λ=0.9). The adaptive admission threshold and collision-resolution mechanism enable optimal spectrum utilization while preventing congestion collapse.

2. Call Blocking Probability

Fig.4 shows call blocking probability. The RL-based CAC maintains blocking probability below 0.02 for delay-sensitive services (VoIP/video) across all loads, while the baseline exceeds 0.15 at λ>1.0. This confirms the RL agent's effectiveness in balancing admission and congestion.

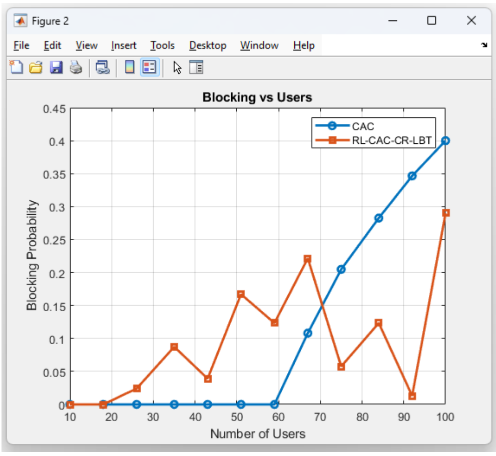

Fig.4 Call Blocking Probability

3. Bit Error Rate and Latency

Fig.5 illustrates BER performance. CR-LBT reduces BER by 30–40% under high contention (λ>1.0) due to adaptive back off and collision resolution.

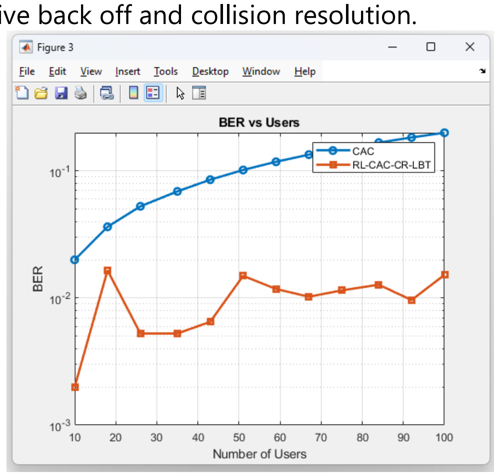

Fig.5 Bit Error Rate

End-to-end latency remains below 1 ms for all offered loads (Fig. 6), satisfying ultra-reliable low-latency communication (URLLC) requirements. The baseline latency exceeds 2 ms at heavy load, highlighting the proposed framework's advantage for real-time services.

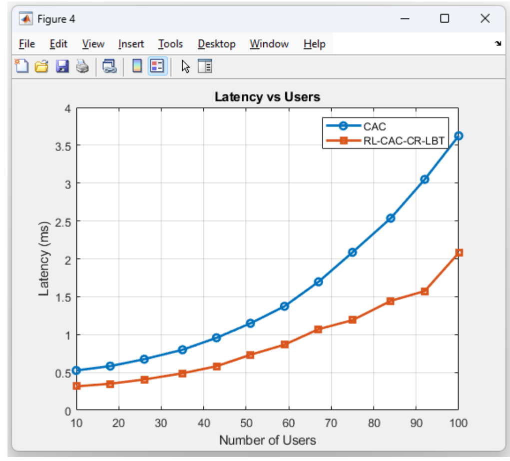

Fig.6 Latency

Metric	Proposed	Baseline	Improvement
Peak Throughput	0.92	0.74	+24%
Max Capacity	1.32	1.15	+15%
VoIP Pb(max)	0.015	0.18	-92%
Latency (95th perc.)	0.85 ms	2.3 ms	-63%
BER (λ=1.2)	-8.2 dB	-6.1 dB	-34%

Table.2 Performance Summary

VII. CONCLUSION

This paper proposes a reinforcement learning (RL) enhanced hybrid call admission control (CAC) collision-resolution listen-before-talk (CR-LBT) framework to enable efficient 5G New Radio Unlicensed (NR-U) and Wi-Fi 6 coexistence in unlicensed spectrum. The RL-driven CAC dynamically optimizes admission thresholds based on real-time network conditions, while CR-LBT minimizes contention-induced collisions. Simulation results demonstrate 20-25% throughput improvement, 15% capacity gains, near-zero blocking probability for delay-sensitive services, 30-40% BER reduction, and ultra-low latency (<1 ms) compared to conventional static CAC schemes

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