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A Reinforcement Learning-Based Approach to Optimize Network Performance in Wireless LANs

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Abstract: The IEEE 802.11 wireless networks commonly employ the distributed coordination function (DCF) for distributed channel access among competing stations. However, the conventional contention-based backoff mechanism suffers from increased collisions, packet loss, latency, and reduced throughput under varying network loads and asymmetric traffic conditions. In this project, we present a lightweight reinforcement learning (RL)-based adaptive contention-window mechanism specifically designed to enhance the IEEE 802.11 DCF protocol. Utilizing tabular Q-learning, the proposed method maintains a Q-table to learn optimal contention-window adjustment strategies based on real-time network states. The RL agent dynamically decides to increase, decrease, or maintain the contention window, guided by a reward function that considers successful transmission rate, end-to-end latency, MAC failures, and queue pressure. Implementation and evaluation were conducted using the NS-3 network simulator across diverse traffic scenarios with varying traffic rates and transmission start times, simulating different contention levels and asymmetric traffic patterns. Comparative performance analysis against the standard IEEE 802.11 DCF and Enhanced Distributed Channel Access (EDCA) protocols demonstrates that the RL-based approach effectively improves wireless network performance under dynamic contention conditions. This project investigates a lightweight and interpretable reinforcement learning framework for adaptive medium access control in IEEE 802.11 networks.

Keywords: IEEE 802.11, DCF, EDCA, Reinforcement Learning, Tabular Q-Learning, Adaptive Contention Window, Wireless Networks

I. INTRODUCTION

Wireless communication has become an essential component of modern networking, with IEEE 802.11 wireless local area networks (WLANs) widely deployed to support an increasing number of devices and diverse traffic demands. As network density and traffic load increase, efficient management of the shared wireless medium becomes important for maintaining throughput, latency, and reliability. In particular, dynamic and asymmetric traffic conditions can significantly affect the performance of contention-based medium access mechanisms.

At the MAC layer, IEEE 802.11 employs the Distributed Coordination Function (DCF), which uses Carrier Sense Multiple Access with Collision Avoidance (CSMA/CA) and random backoff to reduce transmission collisions. Each station selects a backoff interval within a contention window (CW) before accessing the channel. However, under varying traffic loads and high contention, the predefined CW adjustment behaviour of DCF may result in either increased collisions or excessive channel-access delay. Therefore, selecting an appropriate CW according to the prevailing network conditions remains an important challenge.

Reinforcement learning (RL) provides a potential approach for adaptive contention-window control by allowing an agent to learn suitable actions through interaction with the network. Previous studies have explored both tabular Q-learning and deep reinforcement learning (DRL) for contention-window optimization. While DRL-based approaches can learn complex policies, they generally introduce greater computational and model complexity. A lightweight tabular approach can provide a simpler and more interpretable alternative for adaptive medium access control.

Enhanced Distributed Channel Access (EDCA) provides differentiated channel access through multiple access categories with distinct contention parameters. Although EDCA improves traffic prioritization, its contention parameters are

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primarily determined by predefined configurations. This provides a useful reference for evaluating learning-based mechanisms that dynamically adapt contention-window behaviour according to network conditions.
This paper proposes a lightweight RL-based adaptive contention-window mechanism for IEEE 802.11 DCF using tabular Q-learning. The proposed agent maintains a Q-table and selects one of three actions: increase the CW, decrease the CW, or maintain the current CW. The selected action is determined from the observed network state, while a reward provides feedback based on the resulting network behaviour. The objective is to balance multiple aspects of network performance rather than optimize a single metric.

The proposed mechanism is implemented and evaluated using the NS-3 network simulator under multiple traffic scenarios with varying traffic rates and transmission start times. Its performance is compared with conventional IEEE 802.11 DCF and EDCA using throughput, latency, packet-loss rate, and collision rate. The project investigates whether a lightweight tabular Q-learning mechanism can provide effective adaptive contention-window control under changing traffic and contention conditions.

II. RELATED WORK

Research on IEEE 802.11 medium-access performance has explored contention-window (CW) adaptation, traffic differentiation, and learning-based channel access. Conventional Distributed Coordination Function (DCF) uses binary exponential backoff (BEB) to adjust the contention window according to transmission outcomes. However, its predefined adaptation mechanism may be less effective under varying traffic loads, motivating the investigation of adaptive CW-control approaches to improve throughput and reduce collision-related performance degradation.

Reinforcement learning (RL) has been investigated for contention-window optimization in wireless networks. Wydmański and Szott [2] explored contention-window optimization using deep reinforcement learning in IEEE 802.11ax networks. Cruz et al. [3] investigated reinforcement learning-based Wi-Fi contention-window optimization. These works illustrate the potential of learning-based approaches to adaptive channel access. However, deep reinforcement learning approaches may introduce additional computational and model complexity compared with tabular Q-learning.

Further research has explored more advanced learning-based contention-control mechanisms. Tu et al. [4] proposed Enhanced-SETL, a multi-variable deep reinforcement learning approach for contention-window optimization in dense Wi-Fi networks. Zuo et al. [5] presented PDCF-DRL, which applies deep reinforcement learning to contention-window backoff while differentiating access categories. These studies provide relevant approaches for investigating adaptive channel access under different network conditions.

IEEE 802.11 Enhanced Distributed Channel Access (EDCA) provides traffic differentiation through multiple access categories with predefined contention parameters. Unlike a learning-based approach, conventional EDCA does not inherently use a reinforcement-learning agent to adapt contention-window values according to observed network conditions. Therefore, EDCA serves as an important baseline for evaluating the proposed mechanism.

Motivated by these works, this project investigates a lightweight, tabular Q-learning-based Adaptive DCF mechanism with three actions: increase, decrease, or maintain the contention window. The proposed approach is evaluated against conventional DCF and EDCA using NS-3 under multiple traffic scenarios. Throughput, latency, packet-loss rate, and MAC-failure-related measurements are considered to examine the performance trade-offs of adaptive CW control.

III. SYSTEM MODEL AND PROBLEM FORMULATION

A) *System Model*

The proposed system considers an IEEE 802.11 wireless network consisting of multiple contending stations sharing a common wireless channel. Each station generates traffic according to the configured scenario and accesses the channel using the Distributed Coordination Function (DCF). The network is modelled and evaluated using the NS-3 network simulator. Multiple traffic scenarios with varying traffic-generation rates and transmission start times are considered to represent different contention conditions**.**

In conventional DCF, each station selects a random backoff value within its current contention window (CW) before attempting transmission. The CW is adjusted according to the conventional backoff procedure following successful transmissions and collisions. Under high contention, simultaneous transmission attempts can result in collisions,

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retransmissions, and increased access delay. This motivates the use of adaptive contention-window control.
Enhanced Distributed Channel Access (EDCA) is considered as a reference mechanism. EDCA provides differentiated channel access through multiple access categories with different contention parameters. It is evaluated under the same traffic scenarios and simulation conditions as the other approaches to ensure a consistent comparison.
The proposed reinforcement-learning-based adaptive DCF incorporates a tabular Q-learning agent into the CW control process. The agent observes the current network state and selects one of three actions: increase the CW, decrease the CW, or maintain the current CW. The resulting network behaviour is used to calculate a reward, which is then used to update the Q-table. The interaction between the agent and the network can be represented as:

Network State → Q-Learning Agent → CW Adjustment → Network Response → Reward

Through repeated interaction with the network, the Q-table learns the relationship between observed network conditions and contention-window adjustment actions.

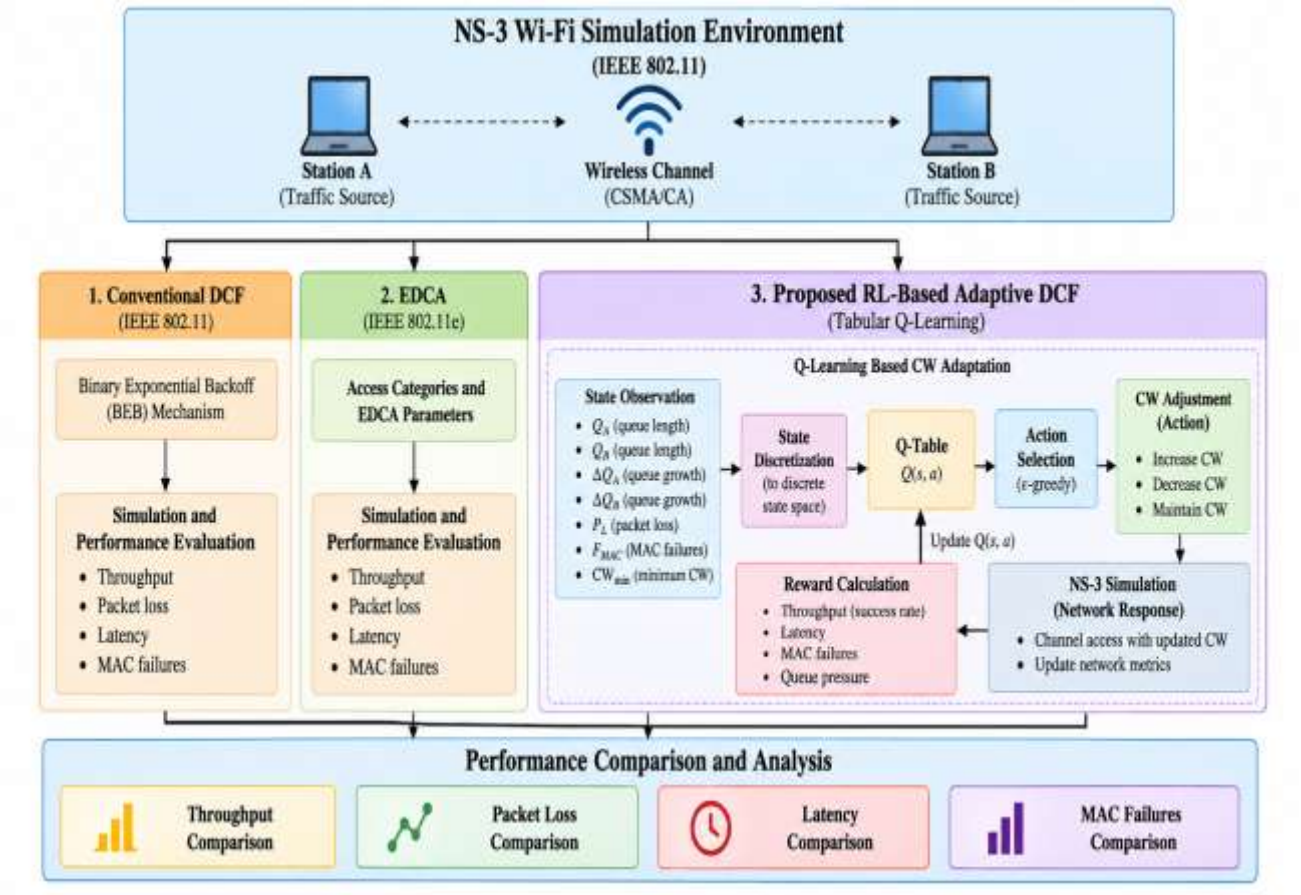


Fig. 1. Overall system architecture of the proposed Q-learning-based Adaptive DCF mechanism and its performance evaluation against conventional DCF and EDCA.

B) ***Problem Formulation***

The primary objective of this work is to dynamically select an appropriate contention-window (CW) size under varying network conditions. A small CW can reduce channel-access delay but may increase the likelihood of simultaneous transmission attempts and collisions. Conversely, a large CW can reduce contention by distributing transmission attempts over a wider backoff range, but may introduce additional waiting time and latency. Therefore, an adaptive CW-control mechanism is required to balance channel contention and access delay according to the observed network conditions.

Let the network state at decision step (t) be represented by (s_t). Based on this state, the Q-learning agent selects an

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action (a_t)from the action set:

$$A = \{Increase\ CW, Decrease\ CW, Maintain\ CW\}$$

The selected action adjusts the CW, after which the network proceeds with channel access and packet transmission. The resulting network conditions define the next state (s_{t+1}), and a reward (r_t) is calculated from the observed network behaviour. The Q-table is updated using the standard Q-learning rule:

$$Q(s_t, a_t) \leftarrow Q(s_t, a_t) + \alpha\,[r_t + \gamma \max_{a'} Q(s_{t+1}, a') - Q(s_t, a_t)]$$

where **α** denotes the learning rate and **γ** denotes the discount factor.

The objective is to balance throughput, packet-loss rate, latency, and collision-related behaviour rather than optimize a single performance metric independently. Under high contention, increasing the CW may help reduce simultaneous transmission attempts, whereas decreasing or maintaining it may be preferable when additional backoff delay outweighs the potential benefit. The appropriate action therefore depends on the observed network state and the reward associated with the resulting performance.

The proposed Q-learning-based Adaptive DCF mechanism is evaluated against conventional IEEE 802.11 DCF and Enhanced Distributed Channel Access (EDCA) under comparable simulation conditions. Throughput, latency, packet-loss rate, and MAC-failure-related measurements are used to assess the performance of the proposed mechanism across varying traffic loads and contention conditions.

IV. PROPOSED RL-BASED ADAPTIVE DCF

A) *Reinforcement Learning Framework*

The proposed mechanism integrates a tabular Q-learning agent with IEEE 802.11 DCF for adaptive contention-window (CW) control. The NS-3 wireless network acts as the RL environment, while the agent observes network conditions, selects a CW adjustment action, receives a reward, and updates the Q-table.

The learning interaction is represented as

$$s_t \rightarrow a_t \rightarrow CW_{t+1} \rightarrow r_t \rightarrow s_{t+1}$$

where (s_t) is the current state, (a_t)is the selected action, (CW_{t+1}) is the resulting CW configuration, (r_t) is the reward, and (s_{t+1}) is the next state. The same learned CW policy is applied to both communicating stations, enabling coordinated CW adjustment according to the observed network conditions.

B) *State Representation*

The state representation captures network conditions relevant to CW adaptation. The agent observes seven parameters:

- Queue lengths of Stations A and B, (Q_A) and (Q_B).
- Queue-growth values of Stations A and B, (ΔQ_A) and (ΔQ_B).
- Packet-loss condition, (P_L).
- MAC-failure condition, (F_{MAC}).
- Current minimum contention window, (CW_{min}).

The state is represented as

$$s_t = (Q_A, Q_B, \Delta Q_A, \Delta Q_B, P_L, F_{MAC}, CW_{min})$$

To support tabular learning, the observed values are discretized into a finite state space. Queue lengths are classified into five categories: zero, 1–100, 101–300, 301–499, and 500 or more packets. Queue growth is represented by three categories: decreasing, unchanged, and increasing. Packet-loss and MAC-failure conditions are represented as binary indicators, while the current CW is mapped to predefined discrete levels. The resulting state is used to index the corresponding action values in the Q-table.

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C) ***Action Space***

The agent selects one of three discrete actions:

$$A = \{Increase\ CW, Decrease\ CW, Maintain\ CW\}$$

Increasing the CW provides a wider backoff range under contention, whereas decreasing it reduces the backoff range when additional waiting may not be necessary. The maintain action preserves the current CW. The selected adjustment is applied to both stations, providing a simple and interpretable approach to adaptive CW control without requiring a neural-network-based policy.

D) ***Reward Function***

The reward function evaluates network performance following each CW adjustment. In the implemented system, it combines successful transmission rate, measured end-to-end latency, MAC failures, and combined queue pressure. The reward is expressed generally as

$$R_t = f(SR_t, L_t, F_t, QP_t)$$

where (SR_t) denotes the successful transmission rate, (L_t) represents measured end-to-end latency, (F_t) denotes the MAC-failure measurement, and (QP_t)represents the combined queue pressure of both stations.

Successful transmission performance contributes positively to the reward, whereas latency, MAC failures, and queue pressure contribute negatively. Although packet-loss information is included in the observed state, a separate packet-loss penalty is not active in the current reward implementation. This reward design encourages successful transmission while penalizing delays, failures, and excessive queue occupancy.

E) ***Q-Learning Algorithm***

The Q-table stores the estimated value of each action for every discrete network state. The Q-values are updated using the standard Q-learning rule:

$$Q(s_t, a_t) \leftarrow Q(s_t, a_t) + \alpha\,[r_t + \gamma \max_{a'} Q(s_{t+1}, a') - Q(s_t, a_t)]$$

where α is the learning rate and γ is the discount factor. During training, the agent follows an ε-greedy policy to balance exploration and exploitation. The exploration probability decreases after each complete training episode, consisting of five scenarios, while maintaining a minimum value of 0.05. This allows the agent to explore alternative actions before increasingly relying on learned Q-values.

F) ***Adaptive Contention-Window Control***

The adaptive control process follows these steps:

1. Observe the current network conditions.
2. Construct the discretized network state.
3. Select a CW adjustment action using the training or evaluation policy.
4. Apply the selected action to adjust the CW of both stations.
5. Allow channel access and packet transmission, then observe the resulting network behaviour.
6. Calculate the reward and, during training, update the Q-table.

These steps are repeated at successive decision intervals. Through this interaction, the agent learns action values for

different network conditions. The resulting mechanism provides adaptive CW control while retaining the relatively low computational complexity and interpretability of tabular Q-learning.

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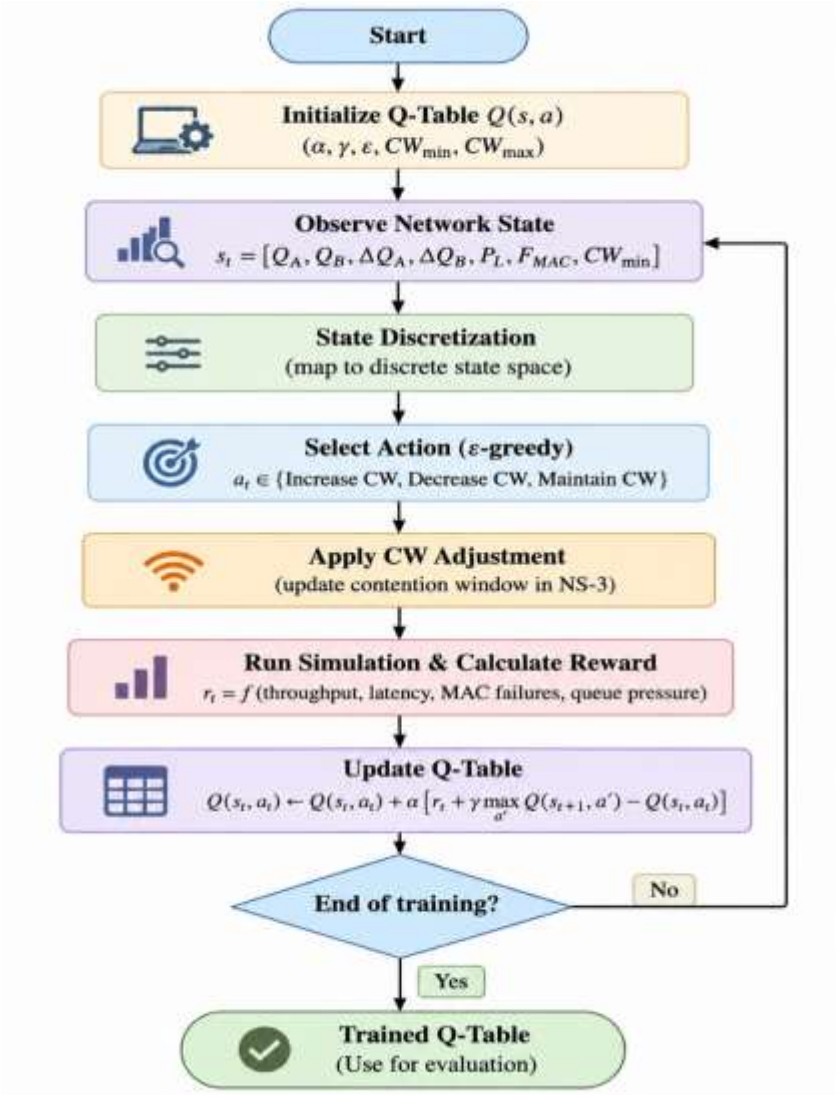


Fig. 2. Flowchart of the proposed Q-learning-based adaptive contention-window control mechanism.

V. EXPERIMENTAL SETUP

A) *Simulation Environment*

The proposed Q-learning-based Adaptive DCF mechanism is implemented and evaluated using NS-3.46.1. Three channel-access mechanisms are compared: conventional IEEE 802.11 DCF, EDCA, and the proposed adaptive approach. All approaches use equivalent traffic configurations to enable a consistent comparison.

The RL agent employs tabular Q-learning and observes network conditions at 0.1-second decision intervals. Training is performed over five traffic scenarios for ten episodes, after which the learned Q-table is used for evaluation.

B) *Traffic Scenarios*

Five scenarios are configured by varying the traffic-generation rates and transmission start times of two communicating stations. These scenarios represent different traffic loads and contention conditions, ranging from low offered traffic to heavy congestion. The same traffic configurations are used for all three approaches to facilitate comparative evaluation. To evaluate the proposed mechanism under different network conditions, three representative traffic scenarios are selected from the configured simulation scenarios: low traffic, asymmetric traffic, and heavy congestion. These scenarios

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are used to demonstrate the performance of conventional DCF, EDCA, and the proposed RL-based Adaptive DCF under different traffic-generation patterns.

Scenario	Traffic condition	Station A	Station B
1	Low traffic	2 Mbps, start at 1 s	2 Mbps, start at 5 s
2	Asymmetric traffic	2 Mbps, start at 1 s	20 Mbps, start at 3 s
3	Heavy congestion	40 Mbps, start at 1 s	40 Mbps, start at 1 s

Table I. Traffic Scenario Configuration

C) *Evaluation Metrics*

The performance of the three approaches is evaluated using the following metrics:

- **Throughput:** Rate of successfully delivered data.
- **End-to-end latency:** Average delay experienced by successfully received packets.
- **Packet-loss rate:** Percentage of transmitted packets that are not successfully received.
- **MAC failures:** Number of MAC transmission failures, used to assess transmission-related contention.

These metrics provide complementary information about channel utilization, delay, packet delivery, and transmission reliability.

VI. RESULTS AND DISCUSSION

A) *Overall Performance Comparison*

Scenario	Metric	DCF	EDCA	RL Adaptive DCF
1: Low traffic	Throughput (Mbps/flow)	2.04784	2.04784	**2.04783**
	Packet loss (%)	0	0	**0**
	Average latency (ms)	0.222658	0.222469	**0.22105**
	MAC data failures	2	2	**0**
2: Asymmetric traffic	Throughput (Flow 2, Mbps)	20.4351	20.4351	**20.4493**
	Packet loss (%)	0.119994	0.119994	**0.067497**
	Average latency (ms)	0.273598	0.270092	**0.264963**
	MAC data failures	58	14	**0**
3: Heavy congestion	Throughput (Mbps, total)	55.8945	55.8946	**58.2371**
	Packet loss (%)	10.4987	10.4987	**7.6384**
	Average latency (ms)	1798.82	1798.82	**1456.73**
	MAC data failures	20,998	20,998	**17,284**

Table II: Performance Comparison of DCF, EDCA, and RL-Based Adaptive DCF

The performance of conventional IEEE 802.11 DCF, EDCA, and the proposed RL-based Adaptive DCF is evaluated under different traffic conditions. Scenarios 1, 2, and 3 represent low traffic, asymmetric traffic, and heavy congestion, respectively. Throughput, packet-loss rate, average latency, and MAC data failures are considered to examine the

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performance trade-offs of the three approaches.

Note: The results correspond to the selected simulation scenarios and configuration parameters. Performance may vary with traffic load, network conditions, simulation settings, and random variations across runs. The reported values should therefore be interpreted within the scope of the evaluated scenarios.

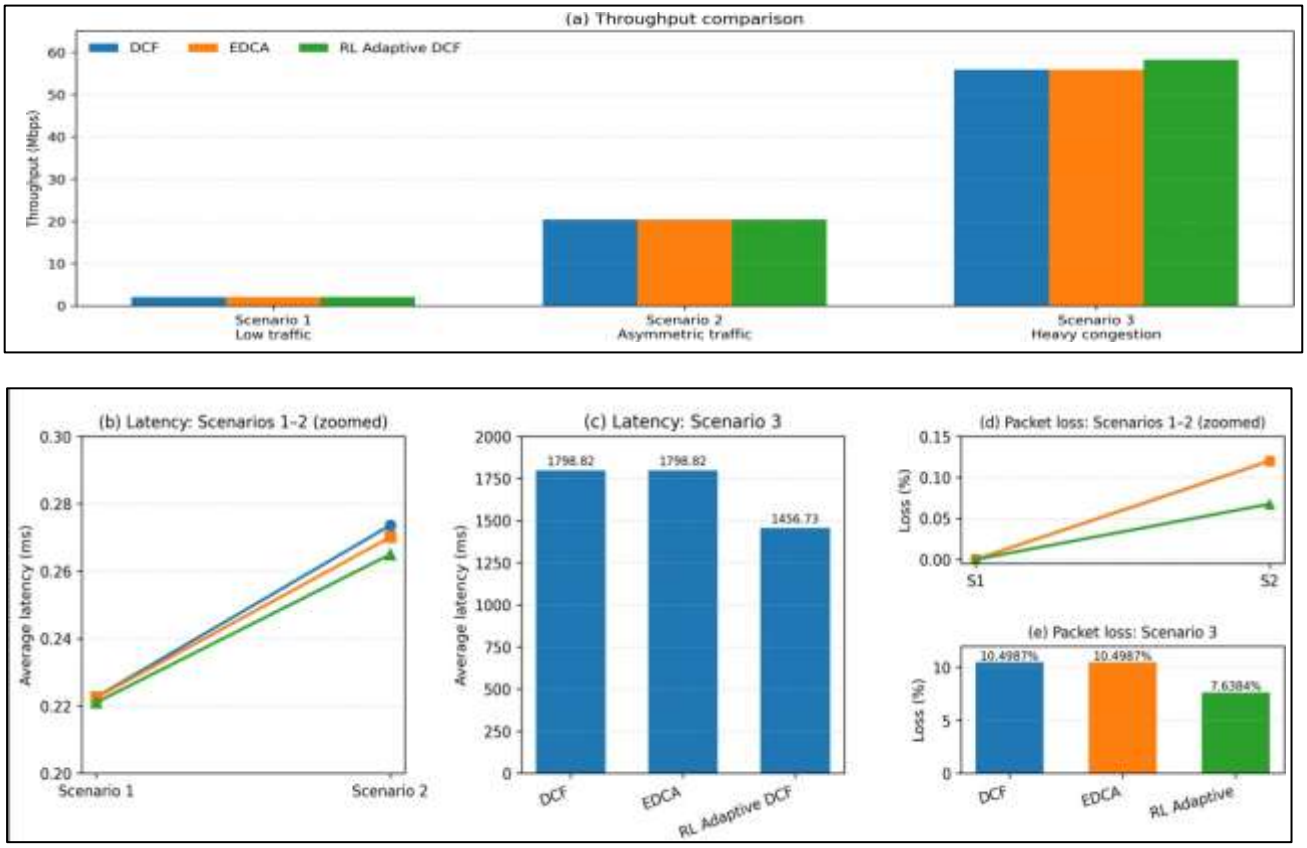


Fig. 3. Performance comparison of DCF, EDCA, and RL-Based Adaptive DCF under low-traffic, asymmetric-traffic, and heavy-congestion scenarios.

B) ***Throughput and Latency***

In Scenario 1, all three approaches achieve nearly identical throughput and zero packet loss. RL-Based Adaptive DCF records the lowest average latency of 0.22105 ms, compared with 0.222658 ms for DCF and 0.222469 ms for EDCA. In Scenario 2, RL-Based Adaptive DCF achieves a slightly higher throughput for Flow 2 (20.4493 Mbps) than DCF and EDCA (20.4351 Mbps each). It also records lower average latency of 0.264963 ms, compared with 0.273598 ms for DCF and 0.270092 ms for EDCA.

Under heavy congestion in Scenario 3, RL-Based Adaptive DCF achieves a total throughput of 58.2371 Mbps, compared with 55.8945 Mbps for DCF and 55.8946 Mbps for EDCA. Its average latency is also lower at 1456.73 ms, compared with 1798.82 ms for both reference approaches. These results indicate that the proposed mechanism performs differently across traffic conditions and shows improved values for the reported throughput and latency metrics under heavy congestion.

C) ***Packet Loss and MAC Failures***

In Scenario 1, all three approaches achieve zero packet loss. RL-Based Adaptive DCF records zero MAC data failures, compared with two failures each for DCF and EDCA. In Scenario 2, the proposed mechanism achieves a packet-loss rate

of 0.067497%, compared with 0.119994% for both DCF and EDCA. It also records zero MAC data failures, whereas DCF records 58 and EDCA records 14.

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In Scenario 3, RL-Based Adaptive DCF records a packet-loss rate of 7.6384%, compared with 10.4987% for both DCF and EDCA. It also records 17,284 MAC data failures, compared with 20,998 for each reference approach. These results indicate lower packet loss and fewer MAC data failures for the proposed mechanism in the reported heavy-congestion scenario.

D) *Comparative Discussion*

The results show that RL-Based Adaptive DCF achieves competitive performance across the three evaluated traffic scenarios. Under low traffic, all approaches exhibit nearly identical throughput and zero packet loss, while the proposed mechanism records the lowest latency and no MAC data failures. Under asymmetric traffic, it achieves slightly higher Flow 2 throughput, lower latency, lower packet loss, and fewer MAC data failures. Under heavy congestion, it records higher total throughput and lower packet loss, latency, and MAC data failures than DCF and EDCA in the reported results.

These findings suggest that the proposed tabular Q-learning mechanism has potential for adaptive contention-window control under the evaluated conditions. Further experiments across repeated runs, different network sizes, and varying traffic loads are needed to establish the consistency and generalizability of these results.

VII. CONCLUSION

This project presented a tabular Q-learning-based Adaptive DCF mechanism for dynamic contention-window control in IEEE 802.11 networks. The proposed approach employs three actions—increase, decrease, and maintain—to adjust the contention window according to observed network conditions. Implemented in NS-3.46.1, the mechanism was evaluated under multiple traffic scenarios and compared with conventional DCF and EDCA using throughput, end-to-end latency, packet-loss rate, and MAC-failure measurements. This project provides a framework for investigating the effectiveness of lightweight reinforcement learning in adaptive wireless channel access while examining the trade-offs among network performance metrics.

VIII. FUTURE WORK

Future work will investigate the proposed mechanism under larger network topologies, varying numbers of stations, and more diverse traffic patterns. Improvements to state representation and reward design may help the agent respond more effectively to changing contention conditions. Further research can also explore comparisons with advanced reinforcement-learning algorithms and validate the approach using a real wireless testbed to assess its practical applicability beyond simulation.

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