Deep Reinforcement Learning for Adaptive Non-Primary Channel Access in IEEE 802.11bn

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***Abstract*—Efficient spectrum utilization is critical in modern Wi-Fi networks as traditional systems require primary channel occupancy for transmission, limiting efficiency in overlapping BSS (OBSS) environments. IEEE 802.11bn introduces non-primary channel access (NPCA) capability, yet optimal decision strategies remain challenging. This paper presents a deep reinforcement learning approach for adaptive NPCA decision-making using Semi-Markov Decision Process formulation with Deep Q-Network. Simulations across varying network scenarios demonstrate significant throughput improvements over baseline strategies, with contention window index as the most critical decision factor. The learning algorithm exhibits conservative strategies favoring long-term stability, providing insights for next-generation Wi-Fi channel access mechanisms.**

***Index Terms*—Deep Reinforcement Learning, Non-Primary Channel Access, Wi-Fi Networks, Semi-MDP, OBSS, Channel Access, DQN**

I. Introduction

Modern wireless networks face increasing challenges in spectrum efficiency as Wi-Fi deployments become denser and user demands grow. Traditional channel access mechanisms, while effective in simple scenarios, struggle to adapt to dynamic interference patterns and varying network conditions.

IEEE 802.11 systems traditionally require the primary channel to be idle before wide-band transmissions can occur [1]. This constraint leads to significant spectrum waste when secondary channels remain unused despite primary channel occupancy by overlapping BSS (OBSS) traffic. While IEEE 802.11bn introduces non-primary channel access (NPCA) capability [2], existing approaches rely on static heuristics that cannot adapt to dynamic network conditions, leaving a critical gap in intelligent decision-making strategies.

Consider a scenario where a station detects OBSS activity on its primary channel while secondary channels are available. The station must decide whether to wait for primary channel access or switch to NPCA, balancing factors such as transmission duration, channel switching overhead, and future network conditions. Such decisions require adaptive intelligence beyond static rules.

In this paper, we describe an intelligent NPCA decision-making framework that enables stations to learn optimal channel access policies through interaction with dynamic network environments. We formulate this as an online learning problem where stations adapt their behavior based on observed network states and reward feedback.

Our approach employs deep reinforcement learning, specifically a Semi-Markov Decision Process (Semi-MDP) formulation with Deep Q-Network (DQN) [3], [4], to capture temporal dependencies in NPCA decisions. The framework enables stations to learn from experience and adapt to varying OBSS patterns and network densities.

The main contributions of this work are:

- A Semi-MDP framework for NPCA decision-making that captures temporal dynamics and network state transitions
- A DQN-based learning algorithm that enables adaptive channel access policies in dynamic environments
- Comprehensive performance evaluation demonstrating throughput improvements over baseline strategies
- Analysis of key decision factors revealing the critical role of contention window index in NPCA decisions

The remainder of this paper is organized as follows. Section II reviews related work in NPCA and reinforcement learning applications. Section III presents our system model and problem formulation. Section IV describes the proposed DRL framework. Section V presents simulation results and analysis. Finally, Section VI concludes the paper and discusses future work.

II. Related Work

NPCA mechanisms have been extensively studied in the context of spectrum efficiency improvement. Traditional approaches rely on heuristic rules and static thresholds for channel switching decisions [5]. However, these methods fail to adapt to dynamic network conditions and varying traffic patterns.

Reinforcement learning has shown promising results in wireless network optimization [3]. Recent works have applied DRL to various wireless problems, including resource allocation and interference management. Semi-MDP formulations have been particularly effective in capturing temporal dependencies in wireless environments [6].

Existing NPCA studies focus primarily on theoretical analysis and static optimization. This work addresses the gap by proposing an adaptive learning approach that can respond to real-time network dynamics.

III. System Model and Problem Formulation

This section presents the formal mathematical framework for the NPCA decision-making problem, establishing the Semi-MDP [7] formulation that enables intelligent channel access learning.

A. Network Architecture and System Model

We consider a wireless local area network (WLAN) consisting of two basic service sets (BSSs) operating in the IEEE 802.11bn framework in which Channel 0 with no OBSS interference and Channel 1 with OBSS activity. The stations (STAs) in Channel 1 can opportunistically access the NPCA channel when OBSS activity is detected on the channel.

Each STA in Channel 1 operates according to the enhanced distributed channel access (EDCA) mechanism while maintaining NPCA capability. When OBSS activity is detected on its associated channel during the backoff procedure, the STA will make a strategic decision regarding channel access.

B. State Space Design

The state space $\mathcal{S}$ captures the essential environmental information required for intelligent NPCA decision-making. At decision epoch t, the system state $s_t \in \mathcal{S}$ is represented as a 4-dimensional vector:

$$s_t = \begin{bmatrix} s_t^{(1)} \\ s_t^{(2)} \\ s_t^{(3)} \\ s_t^{(4)} \end{bmatrix} = \begin{bmatrix} T_{obss}(t) \\ T_{radio} \\ T_{tx}(t) \\ CW_{idx}(t) \end{bmatrix} \tag{1}$$

where $s_t^{(1)} = T_{obss}(t)$ represents the remaining OBSS occupation time on the primary channel in slots, $s_t^{(2)} = T_{radio}$ denotes the radio transition time required for channel switching in slots, $T_{tx}(t)$ indicates the planned transmission duration for the current PPDU in slots, and $s_t^{(4)} = CW_{idx}(t)$ specifies the current contention window stage index $\in \{0, 1, \dots, 6\}$.

To ensure numerical stability and bounded input ranges for the neural network, each state component is normalized as

$$\tilde{s}_t^{(i)} = \frac{\min(s_t^{(i)}, C_i)}{C_i}, \quad i \in \{1, 2, 3, 4\} \tag{2}$$

where $C_1 = C_2 = C_3 = 1024$ slots and $C_4 = 8$ represent the normalization caps for each dimension.

State observations occur at specific decision epochs when the STA is in the `PRIMARY_BACKOFF` state and detects OBSS activity, regardless of the backoff counter value. This Semi-MDP structure allows decisions at irregular time intervals, capturing the temporal dynamics of wireless channel access.

C. Action Space Formulation

The action space $\mathcal{A}$ is discrete and binary, representing the fundamental NPCA decision:

$$\mathcal{A} = \{a_0, a_1\} \tag{3}$$

where a_0 represents `StayPrimary` and a_1 represents `GoNPCA`.

The semantic meaning of each action is:

- a_0 (`StayPrimary`): The STA maintains its position on the primary channel, transitioning to `PRIMARY_FROZEN` state and preserving its current contention window parameters
- a_1 (`GoNPCA`): The STA switches to the NPCA channel, resetting its contention window index to 0 and generating a new backoff value

Once selected, an action defines an "option" in the Semi-MDP framework that persists until completion of the transmission attempt. This temporal extension allows the learning algorithm to evaluate long-term consequences of channel access decisions.

D. Reward Function Design

The reward function implements a delayed reward mechanism that evaluates both throughput efficiency and temporal cost over complete option cycles. Unlike traditional MDP formulations with immediate rewards, our Semi-MDP approach calculates rewards upon option termination.

The option reward is defined as:

$$R_{opt} = w_t \cdot L_{tx} \cdot \mathbb{I}_{success} - w_l \cdot \tau_{opt} \tag{4}$$

where w_t is the throughput weight, L_{tx} represents the attempted transmission duration in slots, $\mathbb{I}_{success}$ is an indicator function equal to 1 if the transmission is successful, w_l is the latency penalty weight, and τ_{opt} is the total option duration in slots.

The success criteria are defined as the canonical conditions for IEEE 802.11 EDCA. This reward structure balances throughput maximization with latency minimization, encouraging the agent to make efficient channel access decisions while considering temporal overhead in dense WLAN environments.

IV. Proposed DRL Framework

This section describes the deep reinforcement learning framework for solving the Semi-MDP formulated NPCA decision problem. We adopt a DQN-based approach with experience replay to handle the temporal dependencies and irregular decision intervals inherent in the Semi-MDP structure.

A. Semi-MDP Learner Architecture

Our `SemiMDPLearner` class implements a DQN-based learning algorithm with experience replay and target network stabilization with Semi-MDP consideration. The neural network architecture consists of three fully connected layers (128, 128, 64 neurons) with ReLU activations and dropout regularization, mapping normalized state observations to Q-values for each action.

The key components include policy network $Q(s, a; \theta)$ for action-value estimation, target network $\hat{Q}(s, a; \hat{\theta})$ for stable learning targets, experience replay memory $\mathcal{D}$ with capacity

10,000 transitions, and Semi-MDP specific transition structure $(s, a, s', R, \tau, done)$, where τ represents the option duration in slots.

B. Semi-MDP Training Algorithm

The algorithm initializes the DQN components and iteratively runs episodes of interaction with the environment. At each decision point, it observes the current state, selects an action using an ϵ-greedy policy, and begins a new option. The option continues until termination conditions are met, at which point the accumulated reward and transition are stored in replay memory. Algorithm 1 presents the complete training procedure for the Semi-MDP based NPCA learning system.

Algorithm 1 Semi-MDP Training for NPCA Decision Making

Initialize $Q(s, a; \theta)$, target network $\hat{Q}(s, a; \hat{\theta})$, and replay memory $\mathcal{D}$
for $epi = 1$ to N_{epi} **do**
  Reset environment and initialize option variables
  for $slot = 0$ to $T_{epi} - 1$ **do**
    Advance simulation to next decision point
    if decision point reached **then**
      Observe and normalize state $\tilde{s}_t$
      if pending option exists **then**
        Store transition in $\mathcal{D}$
      end if
      Select action a_t using ϵ-greedy with $Q(\tilde{s}_t, a; \theta)$
      Begin new option: $(s_{opt}, a_{opt}) \leftarrow (\tilde{s}_t, a_t)$
    end if
    Execute step and accumulate option duration τ_{opt}
    if option terminates **then**
      Calculate option reward R_{opt}
      Set pending transition
    end if
    if $|\mathcal{D}| \geq batch\_size$ **then**
      Sample mini-batch from $\mathcal{D}$
      Compute TD targets:
      if not done **then**
        $y_i = R_i + \gamma^{\tau_{opt}} \max_{a'} \hat{Q}(s'_i, a'; \hat{\theta})$
      else
        $y_i = R_i$
      end if
      Update θ by minimizing $L = \frac{1}{N} \sum_i (y_i - Q(s_i, a_i; \theta))^2$
      Soft update target network: $\hat{\theta} \leftarrow \tau\theta + (1 - \tau)\hat{\theta}$
    end if
  end for
  Finalize episode with delayed reward based on channel occupancy ratio
end for
return $Q(s, a; \theta)$

TABLE I
SIMULATION AND DQN CONFIGURATION PARAMETERS

Parameter	**Value**
Simulation Environment	
Slot duration	9 μs
Episode duration	100 ms (Typical beacon interval)
Number of channels	2 $\times$ 20 MHz
STAs per channel	2, 10, or 20
PPDU duration	10 – 200 slots
OBSS generation rate	0.01 per slot if the channel is idle
OBSS duration	100 slots
NPCA switching delay	1 slot
DQN Network Architecture	
Hidden layers	[128, 128, 64] neurons
Activation function	ReLU
Dropout rate	0.1
Training Parameters	
Learning rate, α	1×10^{-4}
Discount factor, γ	0.99
Batch size, $batch\_size$	128
Replay memory capacity, $\lvert\mathcal{D}\rvert$	10,000
Target network update, τ	0.005
Number of episodes, N_{epi}	1,000

V. Simulation Results

A. Experimental Setup

We evaluate our DRL-based NPCA approach using a discrete-time simulation framework with 9 μs slot duration following IEEE 802.11ax/bn specifications. The network consists of two 20 MHz channels: Channel 0 (secondary/NPCA) without OBSS interference and Channel 1 (primary) with controlled OBSS activity generated by Poisson process ($\lambda = 0.01$ per slot). Each channel hosts 2, 10, and 20 stations with varying network densities. STAs on Channel 1 have NPCA capability and can switch to Channel 0 during OBSS detection. PPDU durations are randomized between 10–200 slots per transmission, while OBSS duration is fixed at 100 slots. Radio switching delay is set to 1 slot.

Our evaluation compares the DRL approach against three baseline policies: **Primary-Only** (always stay on primary channel), **NPCA-Only** (always switch during OBSS), and **Random** (uniformly random decisions). Each policy is evaluated over 50 independent runs of 1,000 episodes with 11,111 slots per episode.

The DQN implementation uses a three-layer neural network (128, 128, 64 neurons) with ReLU activation and 0.1 dropout rate. Key training parameters include: learning rate $\alpha = 1 \times 10^{-4}$, discount factor $\gamma = 0.99$, batch size 128, replay memory capacity 10,000, and target network soft update $\tau = 0.005$. Epsilon-greedy exploration decays from 0.9 to 0.05 over 1,000 steps. Performance metrics include throughput (successful transmission ratio), channel utilization, and learning convergence over episodes.

Table I summarizes the key simulation and DQN configuration parameters used in our experiments. Other settings not explicitly mentioned follow standard IEEE 802.11ax/bn specifications.

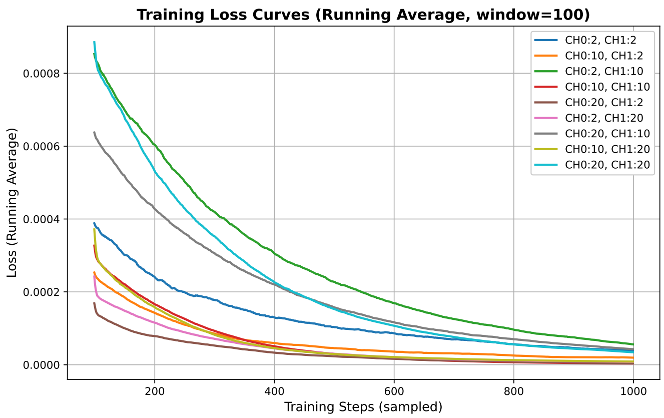

Fig. 1. Training convergence showing episode rewards over time for DRL-based NPCA learning in different network densities.

B. Training Convergence

Fig. 1 demonstrates that our DRL algorithm achieves stable convergence across different network density scenarios. The training curves show consistent improvement in episode rewards, with the algorithm reaching stable performance within 400–600 episodes. The learning process exhibits smooth convergence without significant oscillations, indicating robust policy optimization under varying PPDU durations and network conditions.

C. Performance Analysis

Fig. 2 compares the throughput performance of our DRL-based NPCA approach against baseline strategies across various frame durations with 10 STAs per channel. Results demonstrate that the DRL-based approach achieves superior performance compared to static strategies. Across different network scenarios, our method shows significant throughput improvement over baseline approaches including primary-only, NPCA-only, and random strategies. The learning algorithm effectively adapts to varying OBSS patterns and channel conditions, demonstrating the effectiveness of the Semi-MDP formulation for temporal decision-making in wireless networks.

Analysis reveals that contention window index serves as the most critical decision factor, followed by OBSS occupation time. The learned policy exhibits conservative behavior, favoring long-term stability over aggressive short-term gains.

D. Channel Density Impact Analysis

To understand the influence of channel density on NPCA decision-making, we analyze Q-values across different network density configurations. Table II presents the Q-values for `StayPrimary` and `GoNPCA` actions under representative network conditions with varying STA densities.

The analysis reveals that channel density configuration significantly influences NPCA decision-making patterns. Models consistently choose to switch to NPCA when Channel 0 (NPCA) has low STA density (2 STAs), regardless of Channel 1 density, indicating that low competition environments

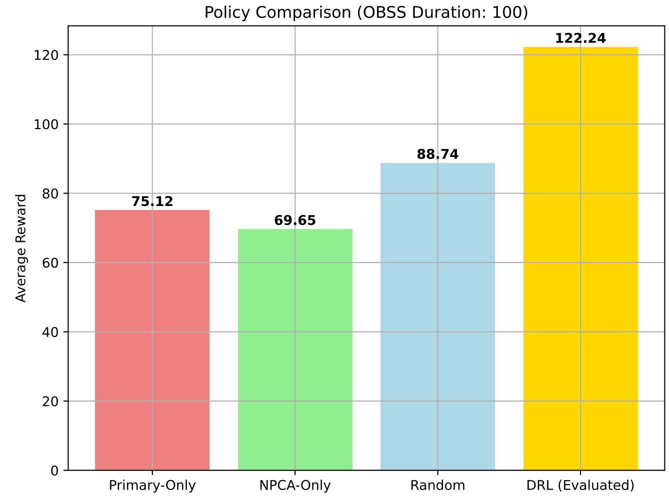

Fig. 2. Policy comparison under different OBSS durations for DRL-based NPCA learning with 10 STAs each channel.

TABLE II
Q-VALUES BY CHANNEL DENSITY CONFIGURATION

CH0 STAs	CH1 STAs	Decision	Q_Stay	Q_Switch	Q_Diff
Test Scenario: OBSS=30, Radio=1, PPDU=33, CW=1					
2	2	Switch	-1.127	1.924	-3.051
2	10	Switch	0.275	1.729	-1.454
2	20	Switch	2.332	2.730	-0.398
10	2	Stay	2.712	-2.033	4.745
10	10	Switch	-3.777	-2.474	-1.303
10	20	Stay	0.630	-1.363	1.993
20	2	Switch	0.104	2.841	-2.737
20	10	Stay	0.158	-0.801	0.959
20	20	Switch	-0.690	0.902	-1.592

strongly favor channel switching. Conversely, when Channel 0 density is moderate to high (10-20 STAs), the decision becomes more nuanced, with the algorithm weighing the relative density difference between channels.

Notably, the Q-value differences show clear decision boundaries: negative Q_Diff values (Q_Stay ¡ Q_Switch) consistently lead to NPCA switching, while positive values result in staying on the primary channel. The magnitude of Q_Diff reflects decision confidence, with larger absolute values indicating stronger preference for the selected action.

VI. CONCLUSION AND FUTURE WORK

This paper presented a DRL-based approach for adaptive NPCA decision-making in IEEE 802.11bn networks. The Semi-MDP formulation with DQN learning enables stations to intelligently choose between primary and secondary channel access based on dynamic network conditions.

Key findings include the importance of contention window index as a decision factor and the effectiveness of conservative learning strategies. Future work will explore multi-agent learning scenarios and adaptive frame duration optimization based on real-time network conditions.

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