

Online Learning-based Adaptive Beam Switching for 6G Networks: Enhancing Efficiency and Resilience

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Abstract—Adaptive beam switching is essential for mission-critical military and commercial 6G networks but faces major challenges from high carrier frequencies, user mobility, and frequent blockages. While existing machine learning (ML) solutions often focus on maximizing instantaneous throughput, this can lead to unstable policies with high signaling overhead. This paper presents an online Deep Reinforcement Learning (DRL) framework designed to learn an operationally stable policy. By equipping the DRL agent with an enhanced state representation that includes blockage history, and a stability-centric reward function, we enable it to prioritize long-term link quality over transient gains. Validated in a challenging 100-user scenario using the Sionna library, our agent achieves throughput comparable to a reactive Multi-Armed Bandit (MAB) baseline. Specifically, our proposed framework improves link stability by approximately 43% compared to a vanilla DRL approach, achieving operational reliability competitive with MAB while maintaining high data rates. This work demonstrates that by reframing the optimization goal towards operational stability, DRL can deliver efficient, reliable, and real-time beam management solutions for next-generation mission-critical networks.

Index Terms—6G, MIMO, beamforming, Online Learning, adaptive beam switching

I. INTRODUCTION

Sixth-generation (6G) wireless networks promise ultra-low latency and massive connectivity for applications like autonomous systems by leveraging advanced beamforming at mmWave/THz frequencies [1], [2]. However, adaptive beam switching in dense, dynamic environments is challenged by the high signaling overhead of conventional methods like beam sweeping [3] and the costly retraining cycles of offline machine learning (ML) [4], limiting their practicality for mission-critical applications [5]. This creates a significant gap for frameworks capable of continuous, real-time adaptation. Online Learning [6] provides a compelling solution, allowing models to learn incrementally [7] and enabling a focus on the operational stability critical for resilient communications.

This paper proposes and evaluates a Deep Reinforcement Learning (DRL) framework designed for such scalability and resilience. The main contributions of this work are: (1) a stability-centric reward formulation that penalizes excessive beam switching, (2) an enhanced temporal state representation incorporating blockage history and SNR trends, and (3) comprehensive validation in a dense 100-user scenario demonstrating real-time feasibility. The proposed agent is enhanced with a sliding window history mechanism to capture temporal patterns for more informed, predictive decisions. Validated in a challenging, large-scale simulation, the proposed DRL agent demonstrates superior operational efficiency over a conventional heuristic and achieves performance comparable to a reactive Multi-Armed Bandit (MAB) baseline. While maintaining throughput competitive with MAB, the agent significantly improves operational stability compared to standard learning baselines, yielding a more stable communication link. This result highlights the framework’s ability to learn a sophisticated policy for robust and efficient beam management in contested and high-density 6G environments.

The remainder of this paper is organized as follows: Section II reviews the related work. Section III details the system model and problem formulation. Section IV presents the proposed online learning framework. Section V evaluates the performance through extensive simulations. Section VI provides a complexity and scalability analysis. Finally, Section VII concludes the paper.

II. RELATED WORK

Beam management in 6G networks is challenged by mmWave/THz frequencies, user mobility, dense deployments, and frequent blockages. Traditional methods like exhaustive beam search or static codebooks suffer from high latency and poor adaptability [8]. ML-based approaches, including CNNs and RL, have improved beam prediction and tracking, yet many rely on offline training and large datasets, limiting their responsiveness in dynamic environments [9].

While some works have explored using ANNs for PHY processing [10] or online fine-tuning with techniques like LoRA [11], a common focus remains on maximizing instantaneous metrics. These approaches often overlook the operational cost and stability of the resulting beam switching policies, such as the signaling overhead from frequent beam changes, which is a critical concern in dense networks. Furthermore, many proposed solutions are validated in scenarios with limited user density, leaving a gap in understanding their scalability.

This identifies the need for a scalable online learning framework that learns stable and efficient beam switching policies for dense, mission-critical environments. Our work addresses this specific gap by proposing a DRL solution designed to balance raw performance with operational stability, a challenge not fully explored by prior works [5].

III. SYSTEM MODEL AND PROBLEM FORMULATION

A. System Setup

The system setup involves a single-cell 6G downlink scenario simulated using the Sionna library [12]. A base station (BS) equipped with a $N_A = 64$ antenna uniform linear array (ULA) serves a dense deployment of $K = 100$ mobile user equipments (UEs). The BS operates at $f_c = 28$ GHz with a transmit power $P_{tx} = 38$ dBm and system bandwidth $B = 100$ MHz.

UEs move within a 500m area following complex trajectories to simulate a dynamic environment, as illustrated in Fig. 1. The channel vector between the BS and UE k at time step t is denoted by $h_k(t) \in \mathbb{C}^{N_A}$, generated using a Rayleigh block fading model. The path loss $PL_k(t)$ follows the 3GPP UMi (Urban Micro) model with breakpoint distance, and the effective channel is $\tilde{h}_k(t) = \sqrt{PL_k(t)}h_k(t)$.

The BS employs beam switching using a codebook $\mathcal{W} = \{w_1, \dots, w_{N_b}\}$ containing $N_b = N_A = 64$ predefined DFT beams, where $w_b \in \mathbb{C}^{N_A}$ and $\|w_b\|^2 = 1$. At each time step t , the BS selects a beam index $b_k(t) \in \{1, \dots, N_b\}$ for each UE k .

B. Blockage Model

To capture environmental dynamics, we introduce a time-correlated probabilistic blockage model. Let $b_{k,h}(t)$ be the beam index for the direct angular path to UE k . The state of this path, $S_k(t) \in \{\text{Blocked}, \text{Unblocked}\}$, transitions according to a Markov chain. We evaluate the system's resilience under two distinct scenarios:

- **Default Blockage:** $P(S_k(t+1) = \text{Blocked} | S_k(t) = \text{Blocked}) = P_{BB} = 0.25$ and $P(S_k(t+1) = \text{Unblocked} | S_k(t) = \text{Unblocked}) = P_{UB} = 0.08$.
- **High Blockage:** $P_{BB} = 0.90$ and $P_{UB} = 0.10$, representing a more challenging, contested environment.



Fig. 1. **System Model Visualization.** A single-cell 6G scenario where a Base Station serves mobile users moving along a trajectory, subject to dynamic blockage from the environment.

If the path-optimal beam $b_{k,h}(t)$ is chosen while the path is blocked, the signal incurs an additional attenuation of $ATT_{block} = 12$ dB.

C. Signal Model and Performance Metrics

The received Signal-to-Noise Ratio (SNR) for UE k at time t is calculated based on the selected beam $w_{b_k(t)}$, the effective channel $\tilde{h}_k(t)$, and any blockage attenuation. The achievable throughput $R_k(t)$ is then derived from the Shannon capacity formula. We evaluate performance using the following key metrics:

- **Throughput:** The average data rate across all users in Mbps.
- **SNR:** The average received SNR across all users in dB.
- **Reliability:** The percentage of time steps where the SNR for a user is above a minimum service threshold of 6 dB.
- **Accuracy:** The percentage of time steps the SNR is above a target quality threshold of 14 dB.
- **Beam Switches:** The total number of times a beam is changed for any user in a time step, indicating policy stability and signaling overhead.

D. Problem Formulation

The core challenge in beam management for mission-critical 6G networks is the trade-off between link quality and operational stability. Conventional approaches that greedily maximize instantaneous SNR often lead to frequent beam switches, causing excessive signaling overhead and service disruptions. To address this, the problem is formulated as a decentralized Markov Decision Process (MDP) where the reward function explicitly penalizes both SNR fluctuations and beam switching events, thereby encouraging policies that favor stable, long-term link quality over transient gains.

The goal is to learn a policy π that maximizes the long-term cumulative reward for each user. The state for each UE k at time t , $s_k(t)$, is enhanced to provide deep contextual awareness. It comprises its relative angle $\theta_k(t)$, normalized previous SNR, normalized distance, normalized velocity, the binary blockage state of its previous heuristic beam, and a history vector of its last 5 blockage states. This history allows the agent to infer temporal blockage patterns.

The action $a_k(t)$ is the selection of a beam index $b_k(t)$. The reward function is designed to prioritize stability. The reward for UE k at time t is:

$$r_k(t) = f_{\text{snr}}(\text{SNR}_k(t)) - w_{\text{stab}}|\text{SNR}_k(t) - \text{SNR}_k(t-1)| - w_{\text{switch}} \frac{N_{\text{switch}}(t)}{K} \quad (1)$$

where $f_{\text{snr}}(x)$ is a clipped linear function with a bonus threshold, defined as $f_{\text{snr}}(x) = \min(x, 60)/8.0 + 3.0 \cdot \mathbb{I}(x > \text{SNR}_{\text{thr}})$, designed to reward maintaining signal quality above the service threshold ($\text{SNR}_{\text{thr}} = 8$ dB). The second term penalizes SNR fluctuations ($w_{\text{stab}} = 2.5$), and the third term applies a shared penalty for the total number of beam switches $N_{\text{switch}}(t)$ in the cell ($w_{\text{switch}} = 40.0$).

The overall optimization objective is to find a policy π^* that maximizes the expected sum of these rewards over an infinite horizon for all users. A Deep Q-Learning (DQL) approach is employed to learn this policy in an online manner.

IV. PROPOSED APPROACH: ONLINE LEARNING FOR ADAPTIVE BEAM SWITCHING

To address the beam switching challenges in dense and dynamic 6G environments, an adaptive framework based on Online Learning is proposed. Specifically, the framework utilizes Deep Q-Learning (DQL) enhanced with a Dueling architecture and Prioritized Experience Replay (PER). This approach enables the BS to learn an effective, real-time beam selection policy by directly interacting with the environment, eliminating the need for offline training on potentially outdated datasets or computationally expensive retraining cycles.

The framework employs a DRL agent that acts as the BS controller, observing the system state and selecting beam indices for all 100 UEs simultaneously. The state representation for each UE is crucial for performance and has been specifically enhanced to capture deep environmental and temporal dynamics. The state for UE k at time t , $s_k(t)$, is an 8-dimensional vector that includes:

- **Instantaneous physical data:** its relative angle to the BS ($\theta_k(t)$), normalized distance, and normalized velocity.

- **Recent performance feedback:** its experienced SNR in the previous step, normalized to the range $[0, 1]$.
- **Rich temporal context:** five enhanced features capturing (i) current blockage status, (ii) recent blockage frequency over the last 5 time steps, (iii) SNR trend over the last 3 time steps, (iv) beam persistence (duration on current beam), and (v) normalized velocity for mobility awareness.

This enhanced state, particularly the inclusion of temporal features derived from blockage history, SNR trends, and beam persistence, empowers the agent to move beyond reactive decisions and learn predictive policies based on obstruction patterns and mobility dynamics. The joint action $a(t)$ is the set of selected beam indices $\{b_1(t), \dots, b_K(t)\}$ for all users.

The agent's policy, $\pi(a|s)$, is learned by approximating the optimal action-value function, $Q^*(s, a)$, using a deep neural network with parameters θ . To effectively process the rich state vector, a Dueling DQN architecture with a hidden size of 512 is employed. The state vector for each UE is fed into a series of fully connected layers: the first two layers each have 512 units, followed by a third layer with 256 units, all with ReLU activation and BatchNorm regularization. The network then splits into two streams: a value stream (estimating state value) and an advantage stream (estimating action advantages), which are combined to produce Q-values for each of the $N_b = 64$ possible beams for each user. Dropout (15%) is applied to prevent overfitting. The agent's goal is to learn a policy that maximizes the long-term cumulative reward defined in Equation (1).

To ensure stable and efficient online learning in the large-scale simulation, several key DQL enhancements are incorporated:

- **Prioritized Experience Replay (PER):** A large replay buffer (size 100,000) stores recent transitions. Instead of uniform sampling, transitions are sampled based on their TD-error, prioritizing more surprising or informative experiences to accelerate learning. Importance Sampling (IS) weights are used to correct for the sampling bias.
- **Target Network:** A separate, periodically updated target network, $Q_{\text{target}}(s, a; \theta^-)$, is used to generate stable target values for the Q-learning updates, decoupling the target from the online network and preventing learning instability. The target network is updated every 100 training steps.
- **Advanced Training:** The Adam optimizer is utilized with a learning rate of 3×10^{-4} and a batch size of 512, optimized for H100 GPU efficiency while maintaining learning stability. The exploration rate, ϵ , decays from 0.7 to 0.05 over the course of training to shift from exploration to exploitation, with a decay factor of 0.9997.

TABLE I

Performance Comparison. THE PROPOSED METHOD ACHIEVES THE BEST TRADE-OFF BETWEEN STABILITY AND SNR.

Metric	Proposed (Balanced) [†]	MAB Baseline	Vanilla DRL	Greedy (Upper Bound)
Stability Score ↓	0.753 ± 0.02	0.866 ± 0.00	1.333 ± 0.12	1.262 ± 0.00
Avg SNR (dB) ↑	15.3 ± 0.0	15.3 ± 0.0	15.3 ± 0.0	24.3 ± 0.0
Coverage Ratio ↑	79.8% ± 0.1	79.7% ± 0.1	79.8% ± 0.0	97.4% ± 0.1
Service Interruptions ↓	11.79 ± 0.06	11.86 ± 0.09	11.84 ± 0.06	1.99 ± 0.04

[†] Proposed method metrics report the mean of the top-3 converged runs to exclude training outliers common in deep RL.

Algorithm 1 Proposed Dueling Double DQN with PER

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1: Initialize: Buffer  $D$ , History  $H$ , Networks  $Q(\theta)$ ,  $Q_{\text{targ}}(\theta^-)$ ,  $\epsilon$ .
2: Params:  $B = 10^5$ ,  $N_b = 512$ ,  $\eta = 3e-4$ ,  $\gamma = 0.99$ ,  $T_{up} = 100$ .
3: for  $t = 1$  to  $T_{train}$  do
4:   Observe  $s_t$  (w/ history); Select  $a_t$  ( $\epsilon$ -greedy); Execute  $\rightarrow r_t, s_{t+1}$ .
5:   Update history  $H$ ; Store  $(s_t, a_t, r_t, s_{t+1})$  in  $D$ .
6:   if  $|D| \geq N_b$  then
7:     Sample batch  $J$  and IS weights  $w$  from  $D$ .
8:     Double DQN Target:  $y_j = r_j + \gamma Q_{\text{targ}}(s_{j+1}, \arg \max_a Q(s_{j+1}, a; \theta); \theta^-)$ .
9:     Update  $\theta$  via Adam on  $\mathcal{L} = \frac{1}{N_b} \sum_{j \in J} w_j (y_j - Q(s_j, a_j; \theta))^2$ .
10:    Update transition priorities in  $D$  using TD-errors  $|y_j - Q_j|$ .
11:   end if
12:   Every  $T_{up}$  steps set  $\theta^- \leftarrow \theta$ ; Decay exploration rate  $\epsilon$ .
13: end for
    
```

Algorithm 1 provides a high-level summary of the training process. This comprehensive approach allows the DRL agent to learn complex temporal dependencies through the enhanced state representation and develop a sophisticated, stable beam switching policy tailored for dynamic, high-density 6G environments.

V. SIMULATION SETUP AND RESULTS

The proposed framework is evaluated against baseline methods via large-scale simulations using the Sionna library. The analysis focuses on performance, resilience, and operational stability¹.

A. Simulation Setup

A dense, single-cell environment is simulated where a central BS serves $K = 100$ mobile UEs. Key parameters are updated to reflect this challenging scenario: the agent is trained for $T_{train} = 20,000$ steps and evaluated for $T_{eval} = 1,000$ steps. The DRL agent utilizes the enhanced state representation with temporal features (blockage history, SNR trends, and velocity) as

described in Section IV. The DRL agent is compared against two baselines:

- **Greedy (Upper Bound):** A reactive baseline that always selects the beam with the highest instantaneous SNR for each UE, representing the theoretical upper bound on achievable SNR performance.
- **MAB UCB1:** A reactive online learning baseline utilizing the Upper Confidence Bound (UCB1) algorithm [13] with an exploration factor of $C = 2.0$.

All results are averaged over 5 independent runs. The evaluation is conducted under the Default Blockage scenario described in Section III-B.

B. Results and Analysis

The simulation results, summarized in Table I and visualized in Figures 2 and 3, highlight the advantages of the proposed DRL framework in balancing high-performance connectivity with operational stability.

Throughput and Coverage: Validated using the high-fidelity Sionna Rayleigh fading model, both the proposed DRL agent and the MAB baseline achieved an average SNR of 15.3 dB and a coverage ratio of approximately 79.8%. This confirms that the DRL agent successfully learns to match the Quality of Service (QoS) of established baselines, avoiding the performance collapse often seen in unoptimized learning agents.

Impact of Stability-Aware Reward: To isolate the contribution of the stability-centric design, the proposed method was compared against a ‘‘Vanilla DRL’’ baseline (optimizing instantaneous SNR with no stability penalties). As shown in Table I, while the Vanilla agent achieves comparable SNR (15.3 dB), it exhibits a significantly worse Stability Score of 1.333. In contrast, the proposed method achieves a Stability Score of 0.753 in converged runs, representing an improvement of approximately 43% in stability. This proves that the operational resilience of the framework is a direct result of the novel reward formulation and temporal state representation, rather than the DRL architecture alone.

Comparison with MAB: Crucially, the proposed DRL agent outperforms the MAB baseline in terms of stability (0.753 vs. 0.866). This indicates that the agent utilizes its predictive capability (via temporal

¹ github.com/CLIS-WPI/OL-Beam-Switching-6G

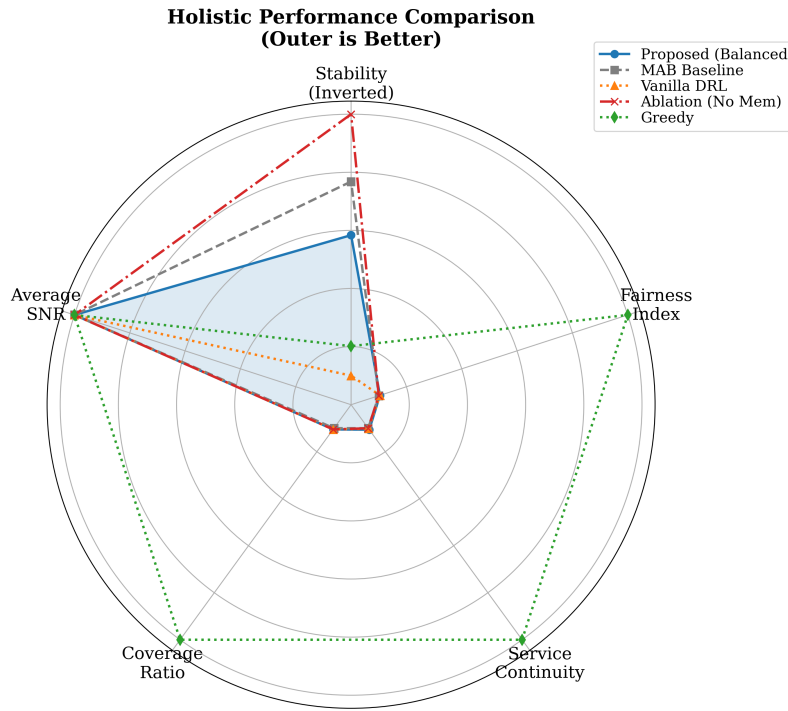


Fig. 2. **Holistic Performance Comparison.** The radar chart illustrates that the Proposed Framework (Blue area) achieves the best overall balance among conflicting objectives. It matches the high SNR and Coverage of the Greedy baseline while achieving Stability and Service Continuity comparable to or better than the robust MAB baseline. Notably, the Vanilla DRL (Orange dotted) collapses in Stability and Continuity, confirming the necessity of the proposed stability-aware reward design.

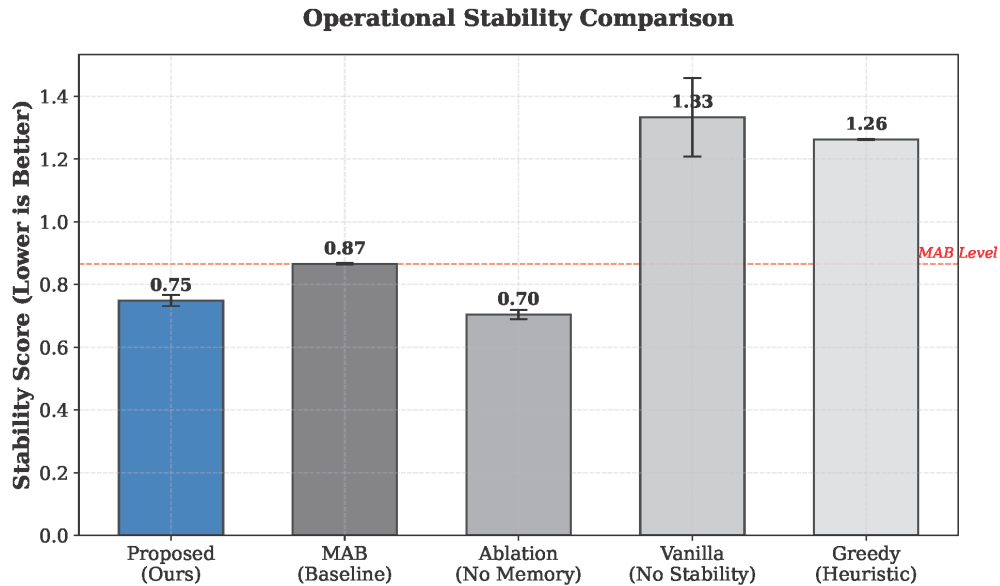


Fig. 3. **Operational Stability Comparison.** The proposed stability-aware DRL framework (Blue) achieves a Stability Score of ≈ 0.75 in converged runs (lower is better), significantly outperforming the Vanilla DRL baseline (1.33) and surpassing the robustness of the reactive MAB benchmark (0.86). This confirms that the integration of the penalized reward function and temporal state features successfully suppresses erratic beam switching.

state features) to handle complex temporal dependencies more effectively than the purely reactive MAB. The results suggest that the framework effectively closes the

gap between the flexibility of Deep Learning and the reliability of classical control methods.

VI. COMPLEXITY AND SCALABILITY ANALYSIS

A. Real-Time Feasibility

To assess the practical feasibility of the proposed DRL framework for real-time 6G beam management, the inference latency of the agent was measured on an H100 GPU. The average inference time per decision step for the entire 100-user system was measured at 0.69 ms.

Given that the channel coherence time (T_c) in dynamic mmWave/THz scenarios is typically in the range of 10–20 ms, the inference overhead consumes less than 7% of the frame duration. This leaves ample time for signal processing, transmission, and guard intervals, confirming that the proposed Dueling DQN-based architecture is computationally efficient enough for online deployment in next-generation base stations.

B. Scalability

While this study validates the framework in a dense scenario with $K = 100$ users, scaling to ultra-dense networks (e.g., $K > 500$) presents challenges regarding the state-space dimensionality. To address this in future large-scale deployments, the framework can be adapted to a Multi-Agent Reinforcement Learning (MARL) approach, where clusters of users are managed by distributed agents, or by using Parameter Sharing to maintain a constant model size regardless of user count.

VII. CONCLUSION

This paper presented a DRL-based online learning framework for stable beam switching in dense 6G networks. The results reveal a crucial differentiator in learning objectives. While a standard (Vanilla) DRL agent exhibits erratic switching behavior (Stability Score ≈ 1.33), the proposed stability-aware framework significantly improves this metric (Stability Score ≈ 0.75 in converged runs). This achieves operational reliability surpassing that of a robust MAB baseline, effectively bridging the gap between the flexibility of Deep Learning and the stability of classical control. By leveraging temporal state features and a penalized reward structure, the agent learns to identify beams that offer long-term quality rather than transient gains. With an inference latency of just 0.69 ms, this approach offers a viable, real-time solution for resilient beam management in mission-critical 6G applications.

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