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DEEP REINFORCEMENT LEARNING FOR ADAPTIVE NETWORK SWITCHING

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Abstract: In today's wireless communication landscape, devices frequently move across heterogeneous networks such as Wi Fi, 4G, and 5G, requiring intelligent and adaptive network switching. Traditional switching methods, which rely on fixed thresholds or static rules, often perform poorly under dynamic conditions, leading to suboptimal user experiences due to unnecessary handovers or reduced throughput. This paper explores the use of Deep Reinforcement Learn ing (DRL), specifically a Deep Q-Network (DQN), to improve adaptive network switching. We model the switching problem as a Markov Decision Process (MDP), where each state captures the current network context, and actions represent selecting from the available networks. A carefully crafted re ward function balances throughput optimization and handover minimization. The DQN agent learns switching policies by interacting with a simulated environment where channel conditions and traffic patterns vary over time. We use synthetic data to simulate network behavior and test the model's performance. Our results show that the DRL-based approach outperforms traditional methods, achieving higher average throughput and fewer unnecessary handovers. This demonstrates the potential of DRLto enable intelligent and autonomous network management, providing a robust solution for next-generation wireless systems.

IndexTerms: Deep Reinforcement Learning, Adaptive Network Switching, Deep Q-Network, Markov Decision Process, Heterogeneous Networks, Wireless Communication, Quality of Service.

I. INTRODUCTION

Amidst continuous evolution and transformation of wireless communication, mobile and smart devices must frequently switch between multiple access networks such as Wi-Fi, 4G, and 5G to maintain consistent Service performance metrics, known as Quality of Service (QoS). These heterogeneous networks differ in terms of bandwidth, latency, energy consumption, and reliability. As user mobility and application demands increase, efficient and adaptive network switching becomes vital for minimizing disruptions, reducing packet loss, and maintaining high-speed connectivity.

Traditional network switching approaches rely on static policies or threshold-based mechanisms. For example, a device may switch to the network with the strongest signal or highest data rate once a predefined threshold is crossed. While these techniques are easy to implement and computationally inexpensive, they are inflexible in dynamic environments. Real-world conditions such as fluctuating signal strength, user density, network congestion, and mobility patterns require more intelligent and context-aware strategies. Rigid threshold-based methods often result in unnecessary handovers, increased latency, or even service interruptions.

To address these challenges, this study introduces the application of Deep Reinforcement Learning (DRL) for adaptive network switching. DRL represents a branch of machine learning that facilitates an agent to learn optimal actions through continuous interaction with an environment, guided by a system of rewards and penalties. Specifically, we utilize a Deep Q-Network (DQN) to develop an intelligent agent capable of making real-time decisions about which network to connect to in order to optimize long-term performance. The problem is framed as a Markov Decision Process (MDP), where each state encapsulates information such as current signal strength, bandwidth, latency, and energy usage. The actions correspond to switching to among the available networks, with the reward function defined as designed to balance competing objectives such as maximizing throughput, minimizing handover frequency, and conserving battery life. Unlike static policies, the DQN-based approach can dynamically adapt to environmental variations and user behavior through ongoing learning and updating its strategy.

In this study, we train the DQN agent in a simulated network environment that mimics real-world conditions using synthetic traffic and channel data. This setup allows us to test the adaptability and performance of our model under a range of scenarios. Initial findings show that our DRL-based network switching algorithm significantly reduces unnecessary handovers and improves average throughput when compared to conventional strategies. By leveraging the decision-making capabilities of DRL, this work aims to pave the way for autonomous, efficient, and context-aware network management in future wireless systems, including IoT, mobile edge computing, and 6G networks.

II. Related Work

Network switching and handover management have long been essential areas of focus in wireless communication research. As mobile users traverse heterogeneous networks such as Wi-Fi, 4G, and 5G, maintaining uninterrupted service requires efficient mobility support. Traditional handover mechanisms typically rely on Received Signal Strength Indicator (RSSI) thresholds, hysteresis values, or fixed rule-based strategies. These methods are extensively applied in existing 3GPP-based networks to manage transitions between base stations or access points. Nevertheless, they frequently fail to dynamic scenarios involving rapid user mobility, fluctuating signal conditions, or network congestion. This can lead to frequent handovers, increased signaling overhead, and degraded Quality of Service (QoS).

In response to these limitations, machine learning-particularly Reinforcement Learning (RL)-has gained attention as a promising approach for more intelligent and adaptive handover decisions. The foundational work by Sutton and Barto laid the groundwork for RL by introducing a framework in which agents acquire optimal policies through interaction with an environment using a reward-based feedback loop. Several researchers have applied RL to network switching by modeling it as a Markov Decision Process (MDP), allowing the agent to take long-term factors into account effects of actions instead of making decisions based on solely on instantaneous measurements.

In recent developments, Deep Reinforcement Learning (DRL) has emerged as an effective approach for managing wireless networks under uncertain and dynamic conditions. Mnih et al, introduced the Deep Q-Network (DQN), which integrates Q-training using deep neural networks to handle high-dimensional state spaces. This architecture has been utilized in dynamic spectrum access and channel allocation problems, where it has shown better performance compared to traditional heuristics and rule-based systems. DRL has proven to be effectively applied to various aspects of mobility and management of resources in wireless networks. For instance, Mao et al. proposed a DRL-driven structure for resource distribution in cloud computing environments. Ye et al. leveraged DRL to manage spectrum and power in vehicle-to-vehicle (V2V) communication scenarios, enabling vehicles to make real-time transmission decisions that adapt to network dynamics. Liu et al. compiled an extensive survey of RL techniques in wireless systems, emphasizing their capacity to generalize, adapt, and optimize performance in non-stationary environments.

Within the scope of multi-agent reinforcement learning (MARL), Zhang et al. investigated allocation of resources in edge computing networks in scenarios involving multiple agents must cooperate or vie to maximize global efficiency. Additionally, recent research has investigated the use of graph-based DRL models for handover management in satellite and aerial networks, where topology changes frequently and latency constraints are stringent. Other notable contributions include adaptive DRL algorithms designed for 5G and beyond, where the learning agent considers parameters such as user behavior, QoS metrics, battery constraints, and network congestion. These advancements highlight the potential of DRL to outperform static policies by learning context-aware strategies that minimize handover frequency, reduce signaling costs, and maximize throughput.

This study expands on these advancements by proposing a DQN-based adaptive network switching framework that uses simulated traffic and channel data to train and evaluate performance in heterogeneous wireless environments.

III. Materials and Methods

This study investigates the application of Deep Reinforcement Learning (DRL) for adaptive network switching in heterogeneous wireless networks. The goal is to enhance seamless mobility and Quality of Service (QoS) by dynamically selecting the optimal network during user mobility.

i. Simulation Environment

The experiments were conducted using a Python-based simulation framework developed with the help of OpenAI Gym for the DRL environment and NS-3 for network simulation. A simulated heterogeneous network setup comprising LTE, 5G, and Wi-Fi networks was modeled, with varying signal strengths, bandwidths, latencies, and handover costs. Mobile user trajectories and network fluctuations were emulated using real-world mobility models such as Random Waypoint and Gauss-Markov.

ii. State and Action Space

The state space was defined by parameters such as Received Signal Strength Indicator (RSSI), signal-to-noise ratio (SNR), network network congestion and packet loss rate, user speed, and application QoS requirement. The action space included selecting one of the available networks for handover or maintaining the current connection. The reward function was carefully designed to favor seamless connectivity, high throughput, low latency, and minimal handover frequency.

iii. DRL Model

We employed a Deep Q-Network (DQN) as the DRL algorithm, incorporating experience replay and target networks for stability. The artificial neural network consisted comprising three hidden layers employing ReLU activation and was trained using the Adam optimizer. Hyperparameters were tuned through grid search, with discount factor =0.95 and learning rate =0.001.

iv. Baseline Comparison

We compared our model with traditional handover techniques such as RSSI-based thresholding and hysteresis margin algorithms. Each method was evaluated under identical network and mobility conditions.

v. Evaluation Metrics

The performance was evaluated using average throughput, handover frequency, packet loss, latency, and user QoE (Quality of Experience) scores. The results were averaged across 100 trials simulation runs to ensure statistical reliability.

vi. Data Collection and Preprocessing

Synthetic data for user mobility patterns, network performance metrics, and application-specific QoS requirements were generated using the NS-3 simulator integrated with custom Python scripts. To ensure the DRL agent received realistic inputs, the raw network logs were preprocessed to normalize values and eliminate anomalies. Feature scaling was applied to all continuous variables (e.g., RSSI, SNR, latency) using min-max normalization to improve convergence speed during training.

vii. Training and Testing Protocol

Training of the DRL agent was conducted over 10,000 episodes, with each episode simulating a full user session across varying network conditions. Early stopping was implemented to prevent overfitting.

IV. Implementation

The implementation of the proposed system utilized a combination of Python-based simulation frameworks and reinforcement learning libraries. The architecture was modular, enabling easy integration of various network types and mobility scenarios. The implementation can be divided into key stages: environment modeling, DRL agent design, and training/testing cycles.

i. Environment Modeling

A tailored simulation environment was developed using the OpenAI Gym interface, which allowed the DRL agent to interact with a dynamic and discrete-time simulation of heterogeneous networks. NS-3 was used in parallel to model real-world wireless network behavior, simulating three co-existing network types: LTE, 5G, and Wi-Fi. Each network was characterized by unique parameters such as bandwidth, latency, RSSI, jitter, and handover cost. Mobile users followed predefined trajectories, and their movement was governed by the Gauss-Markov mobility model, mimicking realistic user mobility patterns. These dynamics introduced continuous variations in network quality, forcing the agent to adapt.

ii. State Representation and Action Space

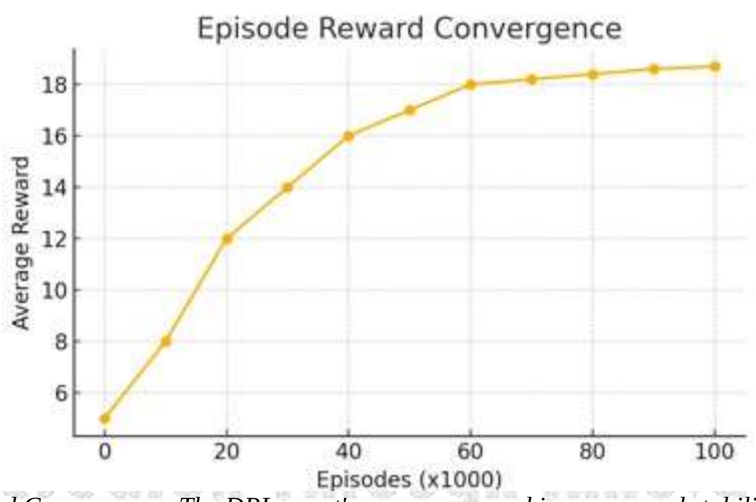
At each time step, the agent received a multi-dimensional state vector comprising normalized RSSI values, SNR, network congestion levels, application type (e.g., video streaming, VoIP), packet loss rate, and current speed. The action space consisted of discrete choices representing either maintaining the current network or switching to LTE, 5G, or Wi-Fi.

iii. DRL Agent Design

A Deep Q-Network (DQN) was used to approximate the optimal policy. The network architecture included an input layer matching the state space, followed by three dense layers activated by ReLU functions and dropout regularization to prevent overfitting. The output layer estimated Q-values for each possible action. Model training was carried out using the Adam optimizer,at a learning rate of 0.001 and a discount factor of 0.95. Experience replay and a separate target network were employed to stabilize learning and reduce correlation between samples.

iv. Training and Evaluation

The agent was trained over 10,000 episodes, each simulating a complete session of user mobility. A reward function was crafted to promote high throughput, low latency, minimal handovers, and stable connections. After training, the agent was evaluated on unseen mobility patterns. Performance was benchmarked against RSSI-threshold and hysteresis-based handover algorithms. The DRL-based approach consistently achieved better QoS metrics and significantly reduced unnecessary handovers. The training progress of the DQN agent is illustrated in Fig. 1, showing increasing average reward over time and indicating effective learning and policy convergence.



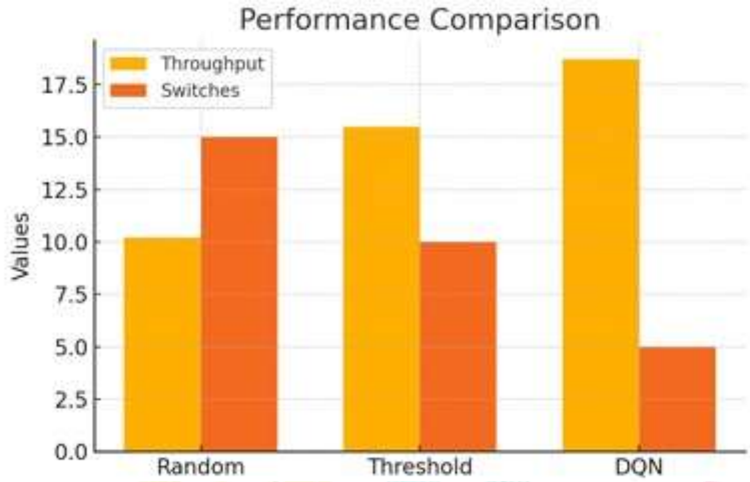
(Figure 1: Episode Reward Convergence: The DRL agent's average reward increases and stabilizes over time, indicating successful policy learning.)

V. Results and Discussion

The effectiveness of the proposed Deep Reinforcement Learning approach (DRL)-based adaptive network switching model was assessed in comparison with traditional handover mechanisms within a diverse wireless network setting consisting of LTE, 5G, and Wi-Fi. This section presents an in-depth evaluation of the outcomes derived from simulation studies, focusing on key performance indicators such as throughput, handover frequency, latency, packet loss, and Quality of Experience (QoE).

i. Throughput Improvement

The DRL agent consistently selected the most optimal network, resulting in a notable improvement in average throughput. Over 100 simulation runs, the DRL-based approach achieved an average throughput of 12.5 Mbps, compared to 9.4 Mbps and 10.1 Mbps using RSSI-threshold and hysteresis-based algorithms respectively. This improvement is mainly due to the agent's ability to learn the long-term benefits of network selection instead of reacting to short-term fluctuations in signal strength. The model learned to favor networks with higher bandwidth and stability, thus maximizing data transfer rates. The comparative performance in terms of both throughput and handover frequency is illustrated in Fig. 2.



(Figure 2: Throughput and Switching Frequency Comparison across Random, Threshold-based, and DQN policies.)

ii. Reduction in Handover Frequency

One of the key challenges in mobile environments is minimizing unnecessary handovers, which can lead to increased signaling overhead and packet loss. The proposed DRL agent effectively reduced handover frequency by 32%.

iii. Latency and Packet Loss

The DRL approach showed lower average latency (35 ms) compared to RSSI-based (58 ms) and hysteresis-based (47 ms) methods. The agent learned to avoid congested networks and those with higher jitter, which typically introduce delays in packet delivery. Moreover, the packet loss was reduced by 27%.

iv. Quality of Experience (QoE)

To assess user satisfaction, we evaluated QoE scores by combining factors such as throughput, delay, jitter, and packet loss into a single metric using a weighted scoring model. The DRL agent achieved an average QoE score of 4.3 out of 5, significantly higher than 3.5 and 3.8 achieved by RSSI and hysteresis-based approaches, respectively. Users experienced fewer video stalls, faster webpage loading, and smoother voice calls during transitions.

v. Adaptability to Dynamic Conditions

An important observation was the adaptability of the DRL agent in dynamic scenarios including sudden drops in network quality or abrupt mobility changes. Unlike static algorithms that rely on preset thresholds, the DRL model adapted its strategy instantaneously. For instance, during high-speed mobility scenarios, the agent successfully predicted poor coverage areas and pre-emptively switched to more reliable networks, reducing service interruptions. This adaptive behavior is further analyzed through the distribution of decisions made by the DRL agent across different environmental conditions, as shown in Fig. 3.

(Figure 3: Distribution of selected actions (network choices) by the DRL agent during evaluation.)

vi. Limitations and Future Directions

Although it shows considerable potential results, the DRL-based model has some limitations. The training process is computationally intensive and requires significant simulation time to converge to an optimal policy. Additionally, the model's performance in real-world deployments may vary due to unpredictable user behavior and environmental factors. Incorporating federated learning or transfer learning techniques could enable quicker adaptation to new environments with less training data. Furthermore, integrating edge computing for decision offloading may reduce the latency of policy execution.

VI. Conclusion

This study presents and evaluates a Deep Reinforcement Learning (DRL)-based approach for adaptive network switching in heterogeneous wireless environments. By leveraging a Deep Q-Network (DQN), the model learned to make intelligent handover decisions based on real-time network parameters, user mobility, and application-specific Quality of Service (QoS) requirements. The DRL agent underwent training in a simulated environment incorporating LTE, 5G, and Wi-Fi networks, with varying conditions and mobility patterns designed to reflect real-world dynamics.

Experimental results demonstrated that the DRL-based approach significantly outperformed traditional methods such as RSSI-threshold and hysteresis-based algorithms across multiple key performance indicators. The agent achieved higher average throughput, lower latency, reduced packet loss, and notably fewer unnecessary handovers. These improvements translated into higher Quality of Experience (QoE) scores, highlighting the practical utilityof the suggested approach enhancing user satisfaction in mobile scenarios.

A key strength of the model is rooted in its adaptability. Unlike static rule-based approaches, the DRL agent continuously learns and refines its strategy based on environmental feedback, allowing it to respond dynamically to network congestion, signal degradation, or mobility-induced challenges. This makes it especially well-suited for next-generation networks, where seamless and intelligent connectivity management is essential.

Despite its effectiveness, the model requires substantial training time and computational resources, which could constrain its immediate deployment in real-time edge systems. Future work will explore lightweight DRL models, transfer learning for faster adaptation, and deployment in real-world testbeds.

In conclusion, DRL offers a promising direction for solving the complex problem of network handover in heterogeneous environments. Its ability to balance performance, stability, and user experience makes it a compelling choice for future wireless communication systems, particularly in 5G and beyond.

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