Coexistence of NR-U and Wi-Fi Networks Using Deep Q-Learning

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Abstract

This report explores the coexistence of NR-U (New Radio-Unlicensed) and Wi-Fi networks in unlicensed spectrum bands, characterized by conflicting access mechanisms. A deep Q-learning-based approach is proposed to address coexistence challenges, optimizing occupancy times and energy consumption for each of the three 120-degree sectored antennas in the NR-U base station. The method ensures fairness, throughput, and performance in dynamic network conditions.

Contents

1 Introduction

The unlicensed spectrum is traditionally dominated by Wi-Fi, which relies on a ”listen before talk” mechanism. With NR-U adopting a scheduled access mechanism, interference arises, necessitating intelligent coexistence strategies. This research develops a deep Q-learning-based solution to balance coexistence without degrading network performance. The approach focuses on optimizing the occupancy times and energy levels of three 120-degree sectored antennas deployed in the NR-U base station.

2 Literature Survey

The performance analysis and viability of LTE-WiFi deployment in the unlicensed spectrum have garnered significant attention in recent years. Various studies have explored coexistence mechanisms, regulatory considerations, and novel solutions to address challenges in LTE-U and Wi-Fi coexistence.

- **Vijeth J. K. et al. (2024):** Proposed an energy-efficient Q-Learning model to address the coexistence challenges of cellular networks in unlicensed spectrum. The study emphasizes optimizing fairness and energy consumption while maintaining throughput. It highlights the dynamic nature of spectrum sharing and the importance of reinforcement learning techniques in adaptive network environments.

- **Chen et al. (2018):** Discuss the coexistence issue between LTE-U and Wi-Fi, exploring various deployment scenarios and medium access control (MAC) protocols. They highlight challenges and solutions for fair coexistence in unlicensed bands.

- **Naik et al. (2020):** Provide insights into regulatory considerations for opening the 6 GHz bands for unlicensed access in the US and Europe, addressing opportunities for Wi-Fi and 5G NR-U technologies.

- **Hirzallah et al. (2020):** Analyze the efficiency of 5G NR-U in unlicensed bands, evaluating coexistence mechanisms with other technologies such as Wi-Fi.

- **Wszoaek et al. (2021):** Conduct an experimental assessment of LTE-License Assisted Access (LAA) on Wi-Fi, discussing coexistence challenges and their impact on latency-sensitive applications.

- **Kishimoto et al. (2020):** Propose a reinforcement learning-based channel selection scheme for LTE-U access points, optimizing coexistence with Wi-Fi networks by improving fairness and reducing packet loss rates.

- **Zhou et al. (2021):** Introduce Deterministic Channel Aggregation (DCA) for LTE-U, optimizing data rates through channel aggregation while analyzing collision probabilities and occupancy ratios.

- **Loginov et al. (2022):** Propose a Listen-Before-Talk With Collision Resolution (CR-LBT) method for NR-U, enhancing fairness and throughput in unlicensed spectrum coexistence scenarios.

- **Yusof et al. (2023):** Develop an energy detection method for LTE-LAA and Wi-Fi coexistence, dynamically adjusting detection thresholds to improve spectrum efficiency and reduce interference.
- **Kala et al. (2022):** Utilize machine learning to optimize LTE-Wi-Fi coexistence networks, proposing a Network Feature Relationship-based Optimization (NeFRO) framework for improved performance.
- **Frangulea et al. (2024):** Optimize coexistence between 5G NR-U and Wi-Fi in sub-7 GHz unlicensed spectrum, aligning with 3GPP TS 37.213 standards to enhance spectrum efficiency and fairness.

Many studies propose solutions to improve LTE-Wi-Fi coexistence, including frameworks for channel selection, enhancing Listen-Before-Talk (LBT), adjusting LTE-U duty cycles, and applying machine learning for optimal channel access. However, much of the focus has been on maximizing throughput and minimizing interference, with less emphasis on energy efficiency. To address these challenges, we propose Q-Learning-based models that enhance fairness and energy efficiency without compromising other performance metrics while accounting for the dynamic nature of the network.

3 Proposed Algorithm

The algorithm that was proposed is deep Q learning to find the optimal occupancy times and energy levels for each NR-U antenna, specifically targeting the three 120-degree sectored antennas in the NR-U base station.

3.1 Problem Definition

The task involves optimizing NR-U and Wi-Fi coexistence by:

- Analyzing NR-U's occupancy times and energy efficiency for three sectored antennas.
- Evaluating key metrics such as fairness, throughput, and user satisfaction.

3.2 State and Action Spaces

- State space: Represented by the 6-tuple (l, m, n, p, q, r), where:
  - l, m, n: Occupancy times (1-7ms) for the three sectored antennas.
  - p, q, r: Energy levels (100%, 95%, 90%) for the three antennas.
- Total states: $7 \times 7 \times 7 \times 3 \times 3 \times 3 = 9261$.
- Actions: Adjust occupancy times by 1ms or energy levels by 5%.

3.3 Deep Q-Learning Framework

- Neural network with two hidden layers (64 neurons each, ReLU activation).
- Output layer produces Q-values for all 13 possible actions.
- Experience replay and target networks enhance training stability.

3.4 Reward Function

The reward function in this model evaluates fairness in channel access between LTE-U and Wi-Fi. The agent determines a reward $r(s, a)$ based on Jain's Fairness Index J, which is calculated as:

$$J = \frac{(U_{\text{LTE}} + U_{\text{Wi-Fi}})^2}{2 \times (U_{\text{LTE}}^2 + U_{\text{Wi-Fi}}^2)}$$

Where:
- U_{LTE} is the utilization of the LTE (NR-U) network.
- $U_{\text{Wi-Fi}}$ is the utilization of the Wi-Fi network.

The reward is then given by:

$$r(s, a) = m(J)$$

Where $m(J)$ is defined as:

$$m(J) = \begin{cases} \frac{0.8-J}{\left(\frac{1}{k}-0.8\right)} & \text{if } J < 0.8 \\ \frac{J-0.8}{0.2} & \text{if } J \geq 0.8 \end{cases}$$

Here:
- k represents the total number of users or systems in the network (for scaling purposes).

As shown in Figure 5, the reward behaves as follows:
- If J is below 0.8, the reward is negative and decreases as J gets smaller.
- When J exceeds 0.8, the reward increases linearly, encouraging fairness improvement.

This reward mechanism discourages actions that lead to unfairness (low J) and incentivizes actions that improve fairness, driving the agent towards a more equitable distribution of resources between LTE-U and Wi-Fi.

4 Results and Analysis

Simulations were conducted to evaluate the algorithm's performance under varying network conditions. The study compared the proposed algorithm, DQN-E, with two baseline approaches: Deep Q-Learning (DQN) and Q-Learning with Energy Optimization (QL-E).

4.1 Overview of Algorithms

- **DQN (Deep Q-Learning):** DQN uses a neural network to approximate the Q-value function for state-action spaces. It focuses on optimizing occupancy times (l, m, n) for the three NR-U antennas but does not account for energy levels.

- **QL-E (Q-Learning with Energy Optimization):** QL-E incorporates energy levels (p, q, r) into the optimization but relies on a tabular Q-learning approach, making it less scalable for high-dimensional environments such as the coexistence of NR-U and Wi-Fi.

- **DQN-E (Deep Q-Learning with Energy Optimization):** The proposed algorithm extends DQN by incorporating energy levels into the state space, efficiently optimizing both occupancy times and energy levels. DQN-E leverages a neural network to handle the large 6-dimensional state space and significantly outperforms the other two algorithms.

4.2 Simulation Results

The following metrics were evaluated to compare DQN, QL-E, and DQN-E:

4.2.1 Fairness

Fairness was measured using Jain's Fairness Index. DQN-E consistently achieved higher fairness scores compared to DQN and QL-E, ensuring more equitable resource allocation among users.

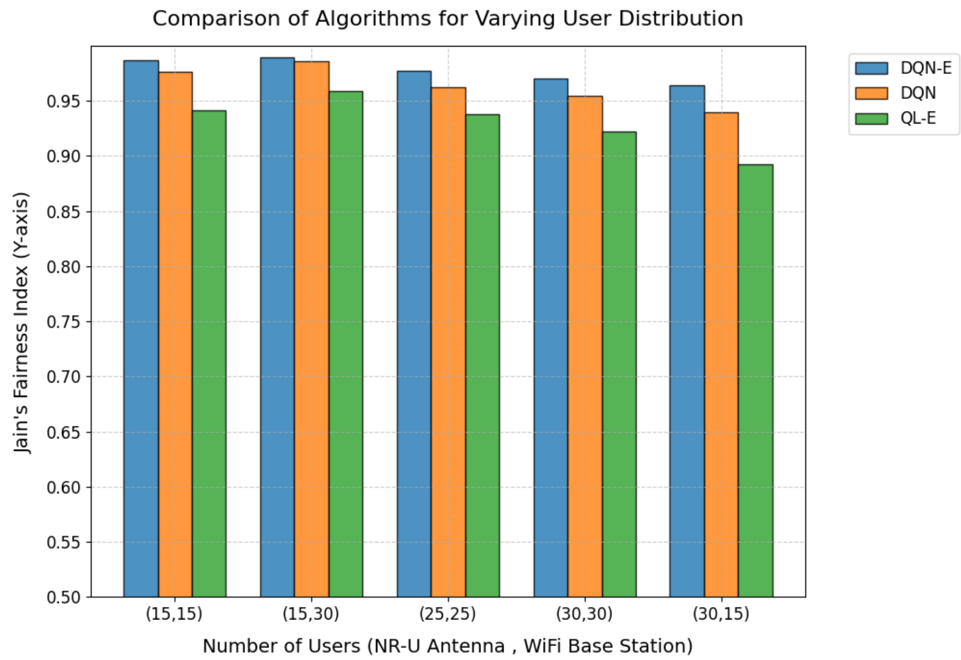

Figure 1: Fairness comparison among DQN, QL-E, and DQN-E.

4.2.2 Throughputs

- **LTE Throughput:** DQN-E achieved the highest NR-U throughput while maintaining stable Wi-Fi performance.

- **Wi-Fi Throughput:** DQN-E's efficient resource allocation ensured Wi-Fi throughput equal to that of QL-E and higher than DQN, demonstrating minimal degradation and superior performance compared to DQN.

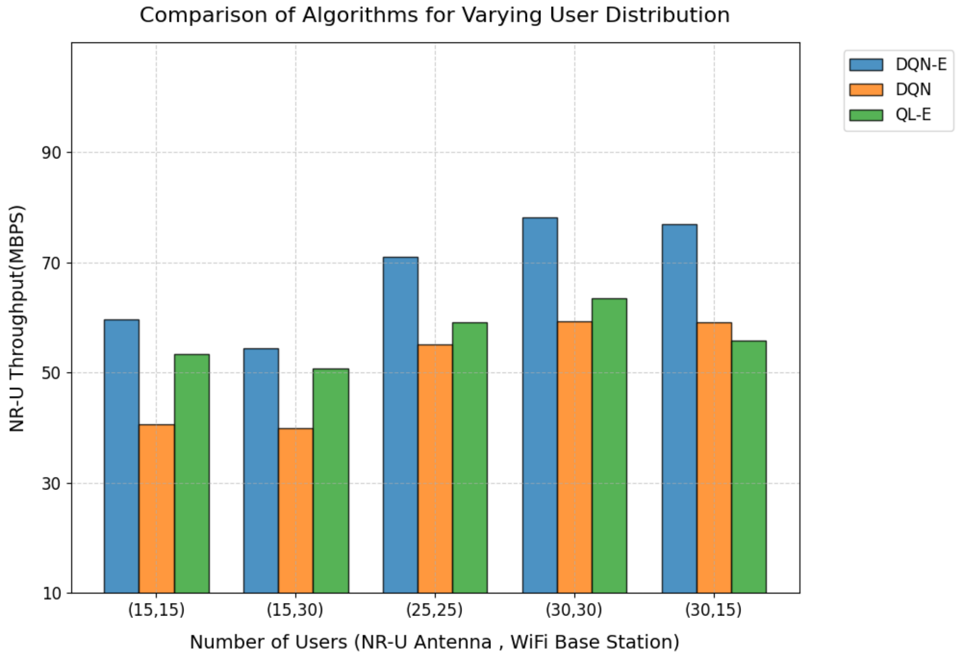

Figure 2: NR-U (LTE) throughput comparison.

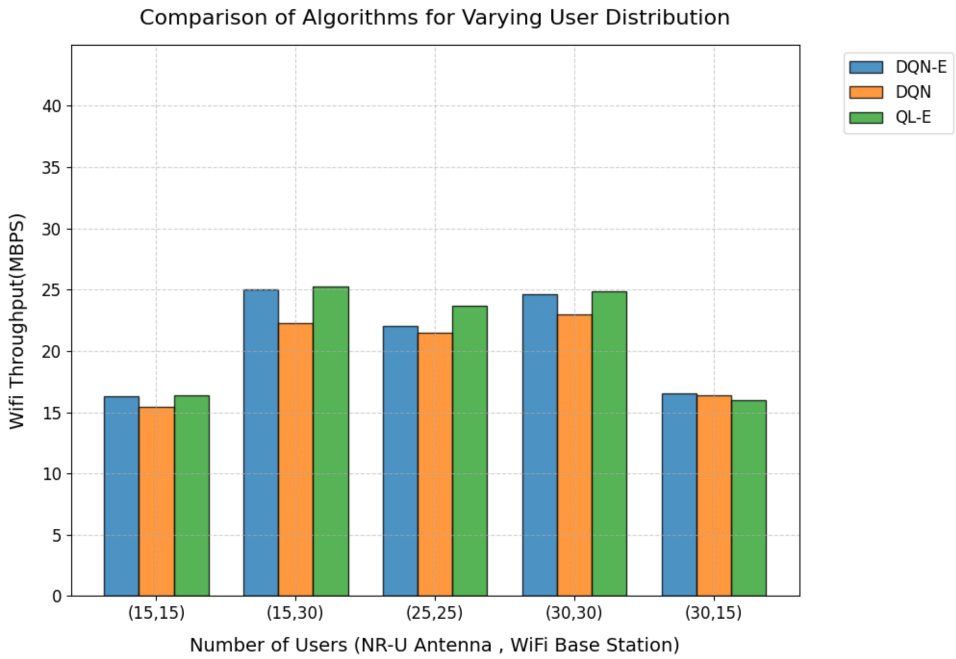

Figure 3: Wi-Fi throughput comparison.

4.2.3 Utilizations

High utilization rates were observed for both NR-U and Wi-Fi networks with DQN-E, indicating efficient use of network resources.

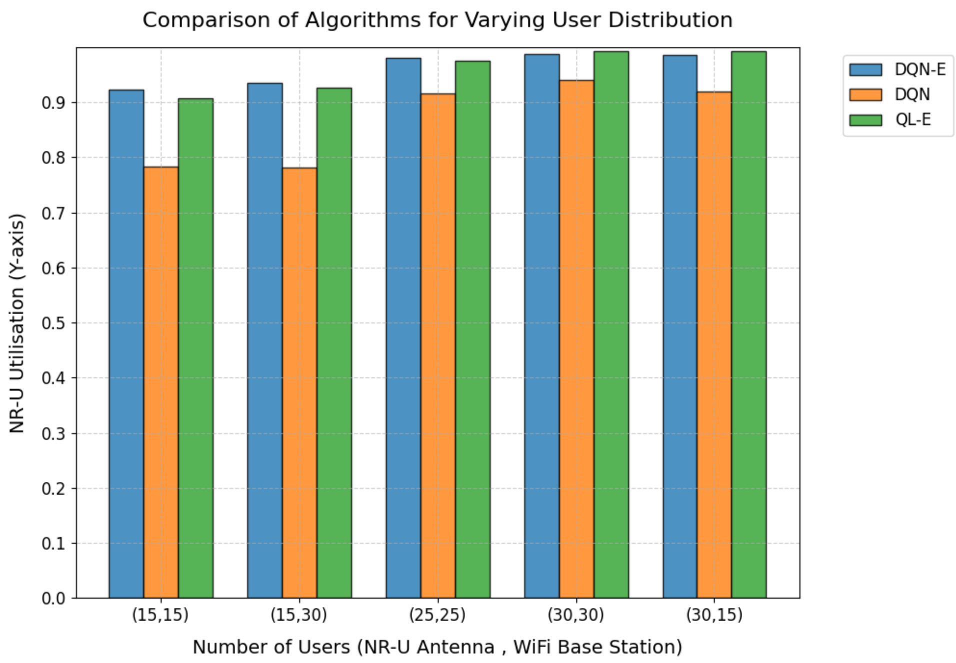

Figure 4: NR-U utilization comparison.

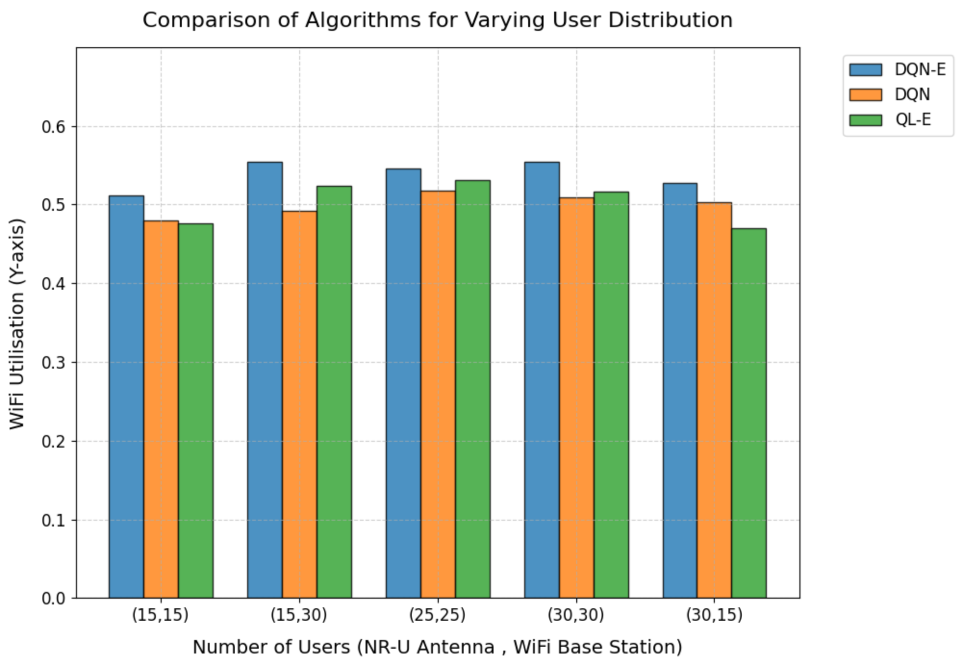

Figure 5: Wi-Fi utilization comparison.

4.2.4 User Satisfaction

DQN-E demonstrated a notable improvement in user satisfaction for both NR-U and Wi-Fi users compared to the other algorithms.

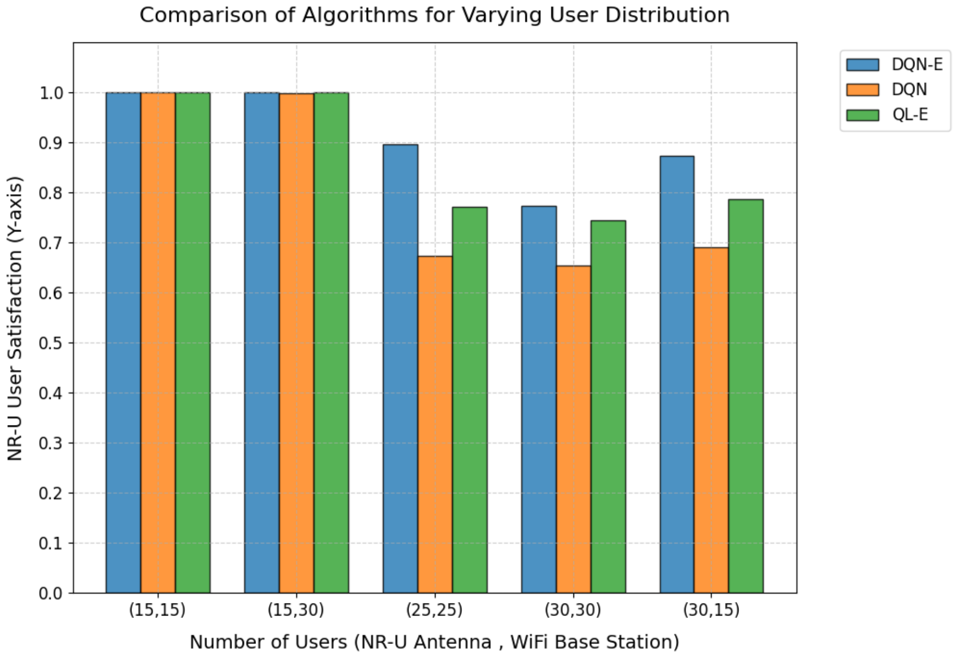

Figure 6: NR-U user satisfaction comparison.

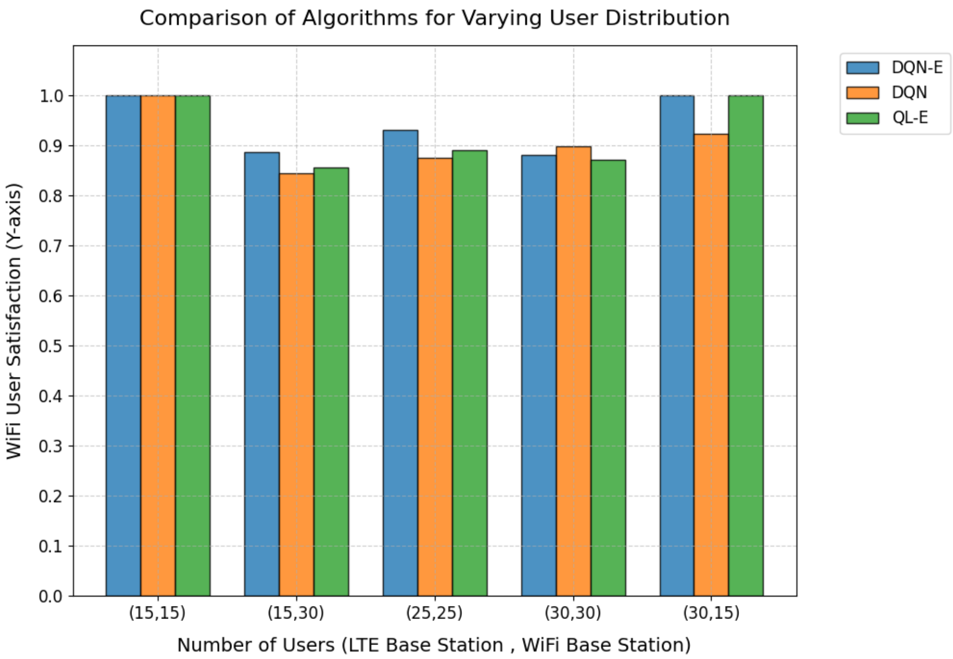

Figure 7: Wi-Fi user satisfaction comparison.

4.2.5 Power Consumption and Energy Efficiency

- **NR-U Power Consumption:** DQN-E optimized energy usage across the three NR-U antennas, resulting in high throughput. Although it consumes more power compared to DQN and QL-E, this is justified by the significant increase in NR-U throughput. The higher power consumption is offset by the improved network performance, ensuring that the overall system benefits from better resource utilization.

- **Energy Consumption Ratio (ECR):** DQN-E achieved a lower Energy Consumption Ratio (ECR) compared to DQN and QL-E, reflecting its energy-efficient operations despite higher power consumption. The trade-off between power consumption and throughput highlights the efficiency of the DQN-E approach in optimizing the coexistence of NR-U and Wi-Fi.

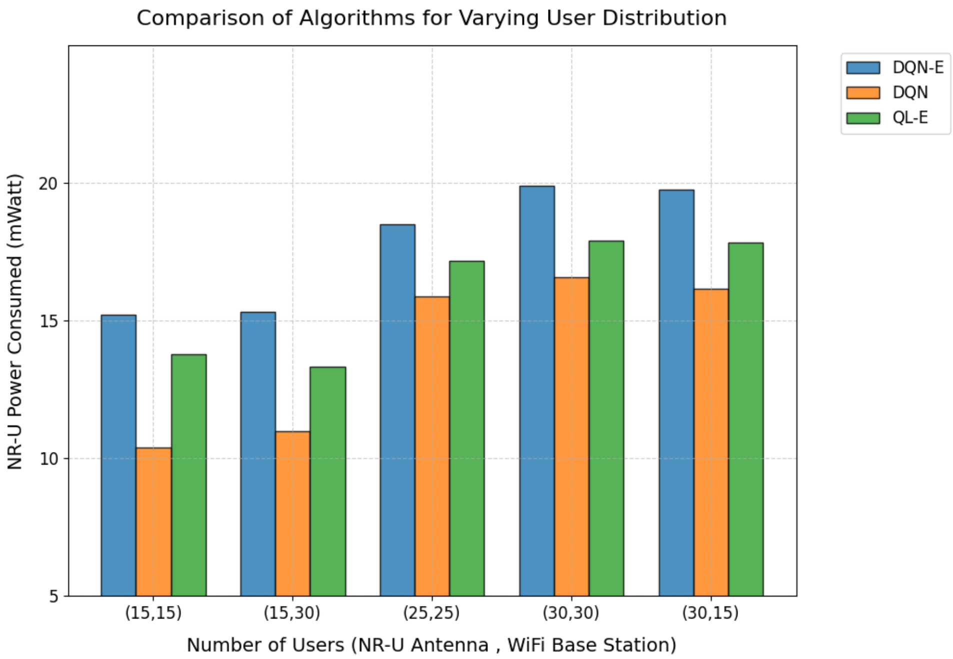

Figure 8: NR-U power consumption comparison.

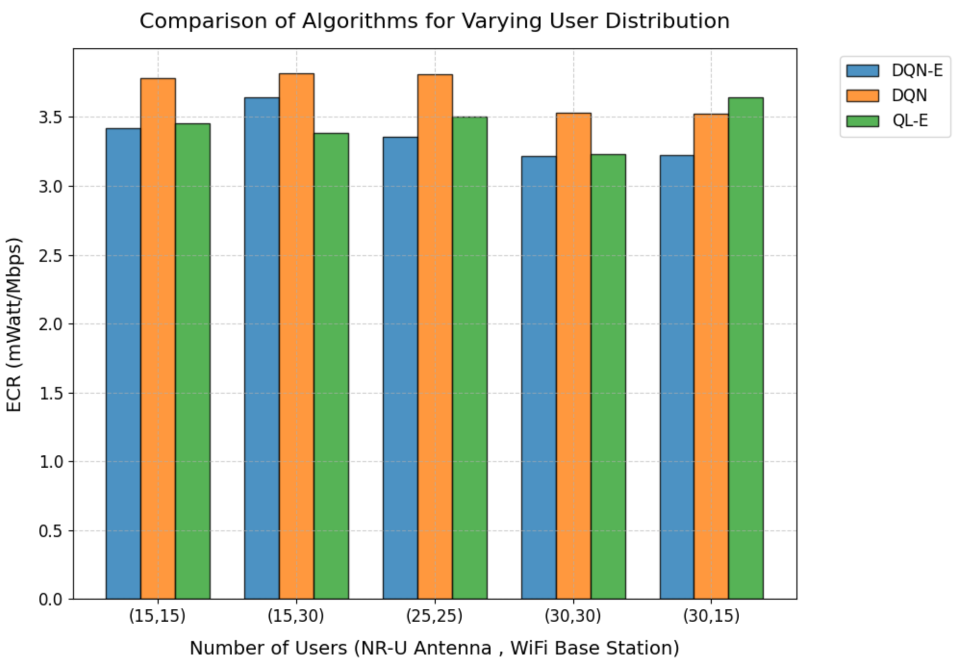

Figure 9: Energy Consumption Ratio (ECR) comparison.

4.3 Summary of Results

DQN-E consistently outperformed both DQN and QL-E across all metrics, demonstrating its capability to optimize NR-U and Wi-Fi coexistence effectively. The integration of energy optimization into the deep Q-learning framework proved critical in achieving superior performance.

5 Future Scope

- **Multi-agent Learning:** Extend the approach to scenarios with multiple NR-U base stations and Wi-Fi access points.
- **Federated Learning:** Explore the use of federated learning to enable decentralized training of the algorithm across multiple network nodes. This approach would allow the model to be trained on local data at each base station or Wi-Fi access point without sharing sensitive data, promoting privacy while improving model performance across diverse environments.
- **Transfer Learning:** Apply the trained model to similar coexistence problems with minimal retraining.
- **Real-world Validation:** Test the algorithm in practical deployments to evaluate scalability and robustness.

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