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An Adaptive Mac Protocol (DQ-MAC) for Efficient Dynamic Spectrum Access in Cognitive Radio Networks

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Abstract: Cognitive Radio Networks (CRNs) require dynamic spectrum access as a way to maximize the use of inadequate spectrum resources with minimal interference from licensed primary users. MAC protocols of a traditional nature frequently fail to respond effectively in real-time to changing channel availability, resulting in poor spectrum utilization and high rates of collisions. This work presents a new Deep Q-Network (DQN)-based MAC protocol that learns and adapts to the shifting spectrum environment, allowing secondary users to make insightful, instantaneous channel access choices. The development and assessment of the protocol occurred across different environments–urban, rural, and indoor–representing unique ranges of spectrum availability and interference issues. The simulations ran on MATLAB, utilizing actual user mobility, Rayleigh fading, interference, and noise conditions in the real world. Results show that the DQN-based MAC protocol markedly outperforms traditional random channel selection across major performance assessments, realizing up to 71% higher throughput, 58% less collisions, and improved equity within user interactions. The results show improvement in the spectrum efficiency and user performance in real time.
Keywords: Cognitive radio networks, dynamic spectrum access, reinforcement learning, MAC protocol, spectrum management

Introduction

The proliferation of wireless communication has led to an unprecedented need for radio spectrum, a scarce resource that is traditionally managed through fixed allocation policies [1, 2]. However, such policies have resulted in total underutilization of the spectrum. CRNs have been proposed as a reformative way to improve spectrum efficiency by allowing wireless radios to use their transmission parameters dynamically in response to environment [3].

CR is a wireless technology with a potential outlook that can look into the scarcity problem spectrum by enabling the un-licensed users (SUs) to have access to spectrum holes or white spaces that are not being used by the licensed users (PUs) [4]. CR is an adaptive and intelligent wireless device that can scan the environment for spectrum, it has the ability to learn from the network changes, and adjust its transmission parameters accordingly. However, cognitive radio (CR) also poses new challenges while designing and implementing MAC protocols, which are responsible for coordinating how channel can be accessed among the un-licensed users (SUs) and avoiding the interference with the licensed users (PUs) [5]. Some of the challenges faced include the dynamic and heterogeneous spectrum availability, the spectrum sensing and sharing overhead, exploration and exploitation trade-off, and the fairness and cooperation among the SUs [6].

To cope with these challenges, different MAC protocols have been suggested for CR. However, most of these protocols are based on fixed or predefined rules or parameters, which may not be adaptable to the varying spectrum, network conditions leading to suboptimal spectrum utilization [7]. Moreover, some of these protocols rely on centralized or global information, which may not be available or scalable in decentralized or distributed CR networks. Therefore, there is a need for a more adaptive and decentralized MAC protocol that can learn from the local and online feedback and optimize the channel access strategy for each secondary user (SU).

Reinforcement Learning (RL) offers a gripping framework for developing adaptive MAC protocols that can learn and optimize their performance in complex environments [8]. Deep Reinforcement Learning (DRL), an extension of RL that uses deep neural networks, has shown great potential in solving high-dimensional control problems [9]. Q-learning is a reinforcement learning technique that allows an agent to learn the optimal policy from its own actions and rewards, without requiring a model of the environment. While, Deep Q-Network (DQN) is a deep neural network that approximates the Q-function, and can handle high-dimensional and continuous state and action spaces.

Deep Q-Networks (DQNs) combine Q-learning with deep neural networks, allowing agents to approximate an optimal action-value function and make informed decisions across vast state spaces [9].

Thus, this research proposes the development of an adaptive Q-learning MAC protocol for CRNs that incorporates DQNs to efficiently manage spectrum access. The proposed protocol uses Q-learning to learn an optimal channel selection for each SU, and DQN to approximate the Q-values for each state-action pair. The proposed protocol also uses abetter channel observation scheme to optimize decision-making in real-time with efficient assessment of channel states. This maximizes spectrum utilization, minimizes interferences while ensuring an acceptable Quality of Service (QoS) requirements.

Cognitive radio networks are advanced wireless technology systems that can interact with the environment and adjust their operating parameters based on how they interact with the environment. They have the ability to sense the radio frequency (RF) spectrum, make their own decisions based on what they learn from the environment to optimize the use of available spectrum [10]. The need for dynamic spectrum access (DSA) protocols in cognitive radio networks arises from the growing needs for wireless communication services and the shortage of available spectrum. DSA protocols allow the efficient management and utilization of the spectrum by allowing cognitive radio devices to access underutilized or unused spectrum bands without interfering with licensed users (Pus) [11]. These protocols are essential for improving spectrum efficiency, increasing network capacity, and enabling the primary and secondary users to exist in a shared spectrum [12]. Dynamic spectrum access comprises techniques such as sharing of spectrum, assigning of channel, management of interference, as well as control, and can take advantage of software radio to change parameters dynamically at once. The advancement of DSA techniques is long formed in the field of CRN and is of important interest for various applications, including industrial IoT, wireless sensor networks, and 5G communications [12].
Recent research has examined alternative approaches to traditional methods of dynamic spectrum access, such as dynamic spectrum access (DSA), which is reinforcement learning base frameworks for cognitive radio sensor networks [13]. These frameworks can help overcome the constraints of traditional methods and better the performance of CRN. Additionally, research has focused on the development of scalable and energy-efficient Q-learning-based MAC protocols for dynamic spectrum access in cognitive radio networks. These protocols aim to improve system performance, reduce transmission delay, and save energy in wireless systems.

Materials and Methods

This section details the methodology used for designing, simulating, and evaluating the proposed Deep Q-Network-based MAC protocol for Cognitive Radio Networks (CRNs). The methodology is divided into several phases that involve developing a near-real-world CRN topology, integrating dynamic spectrum access mechanisms, and evaluating the performance under various conditions, including urban, rural, and indoor environments.
The proposed adaptive Q-learning MAC protocol for CRN is based on the idea of using Q-learning to learn the optimal channel access strategy for each secondary user (SU) in a dynamic spectrum environment. Q-learning is a reinforcement learning technique that allows an agent to learn from its own actions and rewards, without requiring a model of the environment. The Q-learning algorithm maintains a Q-table that stores the Q-values for each state-action pair, where the state represents the current channel availability and the action represents the channel selection. The Q-values are updated iteratively according to the rule given in equation 1.

$$Q(s,a) \leftarrow Q(s,a) + \alpha\left[r + \gamma\, max_{a'}\, Q\,(s',a') - Q(s,a)\right] \quad (1)$$

Simulation or experimental environment

MATLAB is proposed as the main simulation tool for the proposed adaptive Q-learning MAC protocol for cognitive radio networks. The CRN simulation is designed to mimic real-world environments and incorporate key features such as user mobility, channel fading, and interference. Three distinct network environments are simulated: urban, rural, and indoor. The simulation parameters for each topology are provided in Table 1.

Table 1: Simulation parameters

Parameter	Urban Setup	Rural Setup	Indoor Setup
Number of Primary Users	20	10	5
Number of Secondary Users	50	20	15
Number of Channels	15	10	8
Simulation Time (seconds)	500	500	500
Grid Size (units)	100x100	500x500	50x50
Mobility Speed (units/second)	1.0	0.5	0.3
Channel Model	Rayleigh Fading	Rayleigh Fading	Rayleigh Fading
Interference Factor	0.1	0.05	0.2
Noise Power (AWGN)	0.01	0.01	0.01

The Fig. 1 above shows the spectrum usage pattern of primary users across ten channels over the same 100-second period. Black represents channel occupancy by a primary user, while white indicates availability. The heatmap reveals a dynamic and non-uniform pattern of primary user activity across channels and time. Some channels experience higher occupancy rates than others, and the occupancy pattern is not consistent over time. This highlights the unpredictable nature of primary user behaviour in a cognitive radio environment.

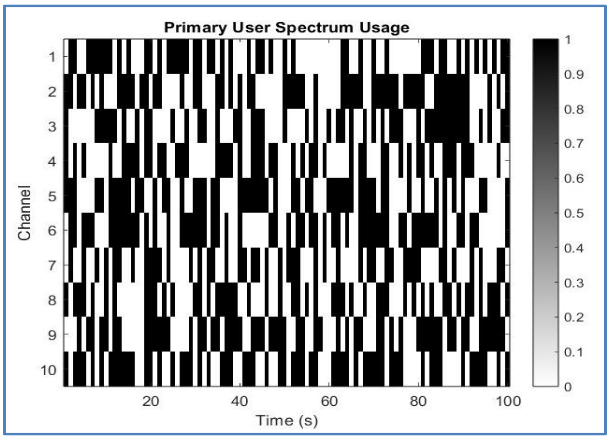

Figure 1: Primary user spectrum usage heatmap

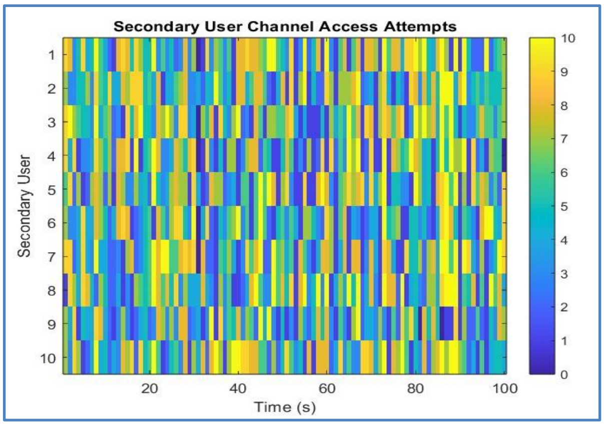

Figure 2: Secondary user channel access attempts heatmap

Figure 2 depicts the heatmap representing the channel access attempts made by ten secondary users over a time period of 100 seconds. The colour intensity represents the number of attempts on a given channel at a specific time. The heatmap reveals a dynamic pattern of channel access attempts, with varying levels of activity across different users and time slots. This non-uniformity suggests that the algorithm is adapting its channel selection strategy over time.

Results and Discussion

The primary focus is on evaluating the network throughput for the three outcomes (indoor, rural, and urban) environments.

A. Urban scenario

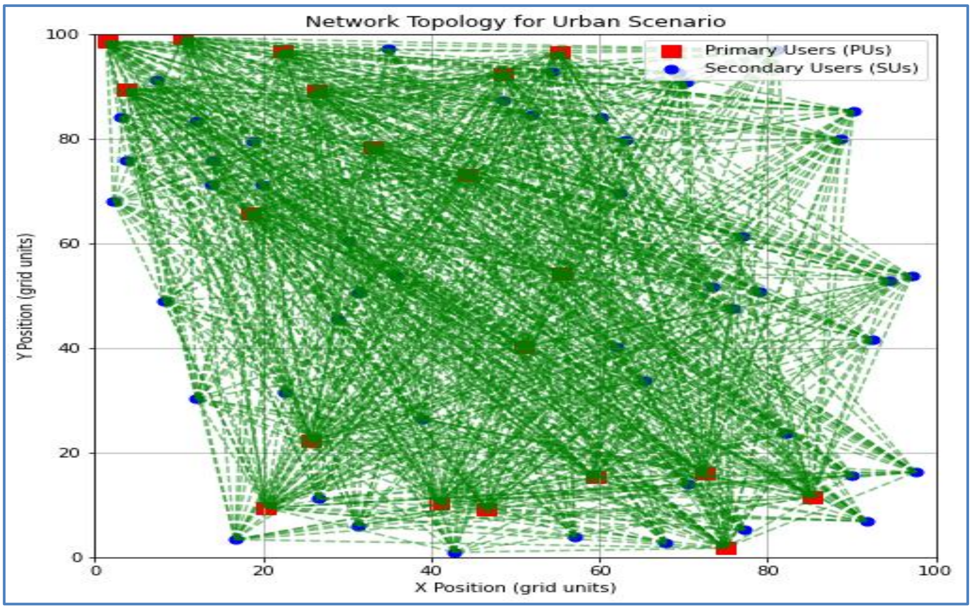

Figure 3: Network topology for urban scenario

Figure 3 illustrate the urban topology with 50 secondary users, 20 primary user, and 15 channels. The throughput is notably high due to the DQN's ability to learn and adapt in a highly congested environment. However, the presence of a large number of users results in fierce competition for channels. The DQN-based MAC protocol significantly outperforms the random channel selection protocol, with about 71% higher throughput. The DQN effectively identifies idle channels, minimizing interference with primary users.

B. Rural scenario

Figure 4 depicts the rural network scenario with fewer users (20 secondary users and 10 channels); the throughput is generally higher per user as there is less competition for available channels. Remarkably, the DQN-based MAC protocol demonstrates about 29% higher throughput compared to the random channel selection, benefiting from less congestion and more efficient channel access.

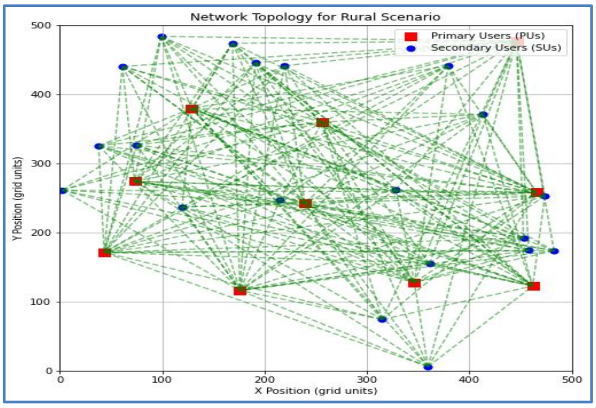

Figure 4: Network topology for rural scenario

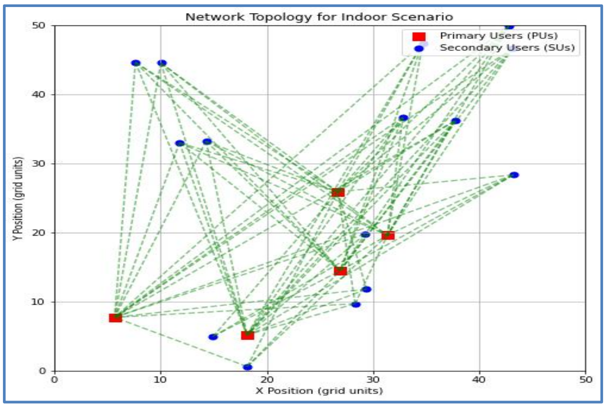

Figure 5: Network topology for indoor scenario

C. Indoor scenario

Figure 5 below depicts the indoor topology (IoT, Smart devices), with its smaller grid size and fewer users, presents a unique challenge due to interference from closely spaced devices. However, the DQN still manages to outperform the baseline protocol. The DQN-based MAC protocol shows 42% improvement in throughput in indoor environments compared to random selection.

Figure 6 represents the throughput performance evaluation using DQN-MAC protocol against the random selection approachacross the three scenarios (urban, rural, and indoor). The results show that our proposed DQN-MAC protocol outperforms the random channel selection method in all the three outcomes.

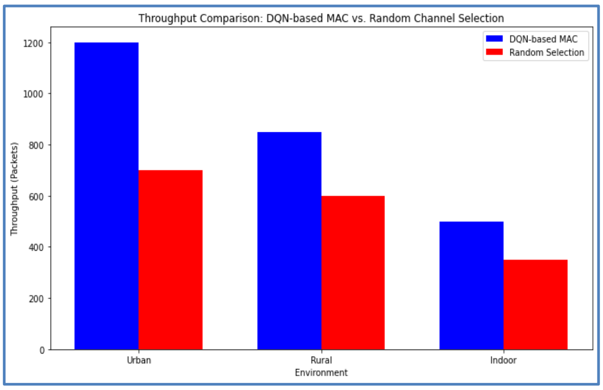

Figure 6: Throughput performance comparison for DQN-based MAC and random channel selection

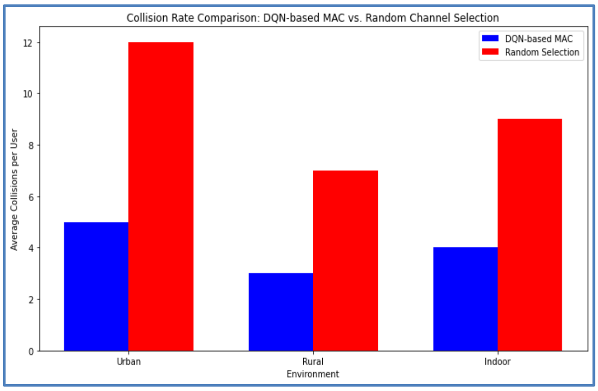

Figure 7: Collision rate comparison

Figure 7 illustrate the collision rates of the three scenarios (urban, rural, and indoor). The DQN demonstrates a substantial reduction rate in collisions across all environments (5, 3, and 4%), especially in the rural setting compare to the random selection approach (12, 7, and 9%). This underscores the algorithm's effectiveness in coordinating channel access and avoiding simultaneous transmissions. While the collision rate reduction is most significant in the urban environment, the DQN still outperforms random selection in rural and indoor settings. This indicates the effectiveness of the DQN's learning mechanism in adapting to varying environmental conditions.

Conclusion

The research conducted in this study successfully demonstrates the effectiveness of a Deep Q-Network (DQN)-based MAC protocol for Cognitive Radio Networks (CRNs). The DQN-based protocol achieves significant improvements in throughput, collision avoidance, and transmission quality (SINR) compared to traditional random channel selection. By enabling secondary users to learn from the spectrum environment and optimize their channel access strategies, the DQN-based MAC protocol provides a scalable and adaptive solution for dynamic spectrum access. The results of this research have important implications for the design and deployment of future wireless networks, particularly in scenarios where spectrum resources are scarce, and user density is high.

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