Cognitive and QoS-Oriented Approach Routing Protocol for CRAHN Using Machine Learning

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Abstract— **Current network control systems struggle to adapt to changing conditions. Integrating machine learning (ML) at the network layer can improve Quality of Service (QoS) by dynamically adjusting protocol parameters. This paper presents an ML-enhanced Cognitive QoS On-Demand Routing Protocol for Cognitive Radio Ad-Hoc Networks (CRAHNs), focusing on modifying AODV protocol parameters to better handle network dynamics. The proposed DQN-QoS-CAODV protocol uses reinforcement learning to select efficient routes with minimal delay and high throughput, even under channel switching and user mobility. Simulations show that it outperforms both QoS-CAODV and ML-AODV in terms of overhead, packet delivery ratio, interference, throughput, delay, and packet loss.**

Keywords—Cognitive Radio Ad-Hoc Networks (CRAHNs), QoS, Machine Learning (ML), Ad-Hoc On-Demand Distance Vector (AODV), QoS-AODV, DQN-QoS-CAODV.

I. INTRODUCTION

The detection of unused spectrum in Cognitive Radio (CR) systems has gained significant interest due to its potential to enhance wireless communication. CR enables unlicensed users to access licensed bands opportunistically without interfering with primary users (PUs). Wireless ad hoc networks offer a strong architecture for studying CR- based routing, leading to the development of various protocols for Cognitive Radio Ad Hoc Networks (CRAHNs) [1] [2] [3] [4].Each routing protocol in CRAHN aims to achieve different goals, such as minimizing delay, reducing hops, and ensuring PU protection. CRAHN routing can follow proactive or reactive strategies, and integrating Quality of Service (QoS) is critical for meeting application demands [4] [5] [6].

The convergence of CR with Machine Learning (ML) marks a major advancement in wireless networks. ML-enabled CR supports dynamic adaptation in environments like IoT, vehicular networks, and UAV communications. These intelligent systems help optimize energy use, reduce interference, and improve latency, throughput, and security. The fusion of ML-based CR with these evolving wireless networks holds the promise of creating intelligent, efficient, and universally accessible wireless communication systems tailored to the spectrum demands of next-generation applications and services [11].

This work reviews the role of AI in cognitive radios, distinguishing between supervised learning (which uses prior knowledge) and unsupervised learning (ideal for unknown RF environments). Both are crucial for enabling real cognitive decision-making in dynamic spectrum contexts. We conduct a comprehensive review of diverse learning approaches proposed for cognitive radios, categorizing them into supervised and unsupervised learning paradigms. Unsupervised learning is introduced as an independent learning mechanism well-suited for unfamiliar radio frequency (RF) environments, while supervised learning methods leverage prior information available to cognitive radios during the learning process[8] [9].

II. RELATED WORK

The Ad hoc On-Demand Distance Vector (AODV) protocol is widely used in mobile ad hoc networks (MANETs) due to its reactive nature, which establishes routes only when needed. This on-demand mechanism minimizes control overhead and adapts well to highly dynamic network topologies.

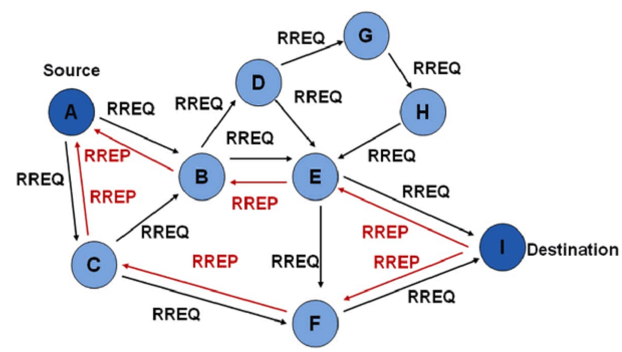

Fig. 1. Illustration of the AODV Route Discovery Mechanism

Despite its efficiency and simplicity, AODV lacks native support for Quality of Service (QoS) metrics such as delay, bandwidth, packet loss, and throughput—factors crucial for real-time or high-priority applications. To address this, several enhancements have been proposed to integrate QoS considerations into AODV, enabling the protocol to make routing decisions based on performance requirements. Building on these principles, the Cognitive AODV (CAODV) protocol was developed to meet the unique needs of Cognitive Radio Ad Hoc Networks (CRAHNs).

CRAHNs allow nodes to dynamically sense and utilize underused spectrum bands, requiring routing protocols that can adapt to both network topology and spectrum availability. CAODV extends AODV by incorporating spectrum-related information into the RREQ messages.

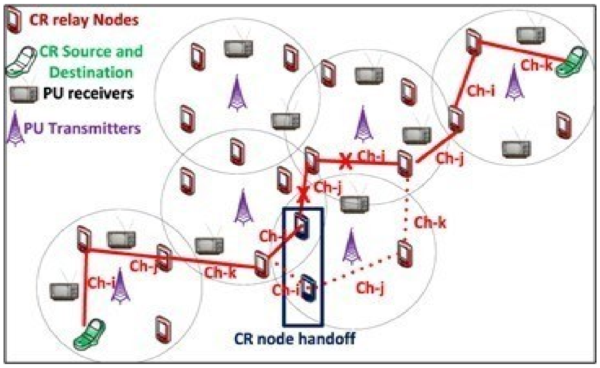

Fig. 2 Cognitive AODV routing protocol.

A. Literature review of QoS in Cognitive Radio Ad Hoc Networks

The creation of QoS-supporting routing protocols is the contribution of the CRAHN routing protocol design. Different QoS is required by the applications running in CRAHNs, including bandwidth, jitter, latency, delay, and package loss [10][11][12]. They may require all of the services, or only one of them. For voice communication, the routing protocol with QoS support might identify the application service requirements and select the path with the least amount of jitter, end-to-end latency, and delay variation. In the absence of QoS support, the routing protocol could not be able to meet application needs since it would assign the path and spectrum only according to its routing metric.

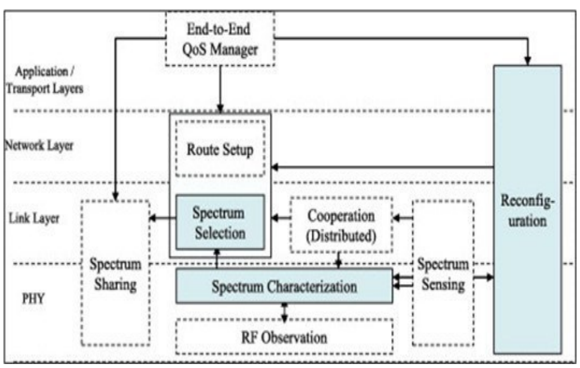

Fig. 3. QoS-Based Path Establishment in Cognitive Radio Ad Hoc Networks

In [13], the authors introduced three QoS metrics—blocking, dropping, and failure probabilities—to evaluate network performance but overlooked the impact of primary users (PUs). Although a power control method was proposed, network performance remained limited. Performance improves when secondary users (SUs) quickly access spectrum and reduce switching time. However, the proposed QoS-based routing lacked explicit throughput consideration, focusing instead on bandwidth and latency. A K-shortest Q-Routing approach was suggested to reduce delay, but the shortest path is not always optimal.

III. MACHINE LEARNING

Cognitive Radio Ad Hoc Networks have attracted growing interest for applications like disaster response and military operations. AODV is a widely used reactive routing protocol in MANETs, but it faces challenges such as high overhead, discovery delays, and limited scalability. To overcome these issues, researchers have explored enhancements, including machine learning (ML)-based approaches. This review examines how ML can improve AODV's performance in CRAHNs. ML-based AODV approaches apply machine learning to improve routing decisions by learning from past network behavior. These techniques help predict link quality, assess node mobility, and optimize route selection, enhancing AODV's performance in CRAHNs[21].

One of the early works in this domain is the ML-AODV approach proposed by Li et al. (2011). They employed a support vector machine (SVM) algorithm to predict link quality based on features such as signal strength and packet loss rate. The predicted link quality was then used to select the most reliable route for data transmission. The results showed that ML-AODV outperformed traditional AODV in terms of packet delivery ratio and end-to-end delay.

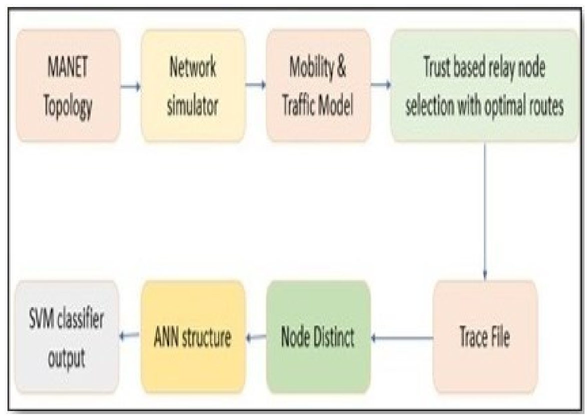

Fig.4 ML-AODV Routing Performance

Another ML-based AODV approach was introduced by Sharma and Jain (2013), where they applied a decision tree algorithm to estimate node mobility. By con- sidering factors like speed, direction, and acceleration, the decision tree algorithm predicted the future location of nodes, enabling proactive route maintenance and improved routing decisions. The experimental evaluation demonstrated that the proposed approach achieved better performance in terms of route stability and packet delivery ratio compared to traditional AODV. Furthermore, Chen et al. (2017) proposed an ML-based AODV approach that utilized a random forest algorithm to predict the optimal route for data transmission. The random forest model was trained using historical data on network conditions, includ- ing link quality, node mobility, and traffic load. The experimental results showed that the ML-AODV approach significantly reduced the control overhead and improved the overall network performance[21] .

Several studies have evaluated and compared different ML-based AODV approaches to assess their effectiveness in enhancing the performance of MANETs. For instance, Kumar et al. (2019) conducted a comparative analysis of various ML algorithms, including SVM, decision tree, and random forest, applied to the AODV routing protocol. Their results indicated that the random forest algorithm outperformed the other algorithms in terms of packet delivery ratio, end-to-end delay, and energy consumption. Similarly, Sharma et al. (2020) evaluated the performance of ML-AODV approaches using different ML algorithms, such as k-nearest neighbors (KNN), naive Bayes, and artificial neural networks (ANN). Their findings revealed that ANN- based ML-AODV achieved the highest packet delivery ratio and lowest end-to-end delay compared to other ML algorithms [21].

This is mainly due to fluctuations in node speeds, energy consumption, and network congestion. In the ML-AODV architecture, each mobile node maintains a list of immediate (1-hop) neighbors via periodic HELLO packets. The source node checks its routing table for a route to the destination. If found, it begins data transmission; if not, it broadcasts a RREQ packet to its 1-hop neighbors. Upon receiving the RREQ, a node checks if it is the destination; if not, it calculates a trust value and compares it to a threshold. If the trust value exceeds the threshold, it is saved in the RREQ packet. The RREQ packet structure includes additional fields beyond the standard AODV protocol. In a MANET, the lack of centralized control requires mobile nodes to act as routers, relying on mutual trust for data exchange. When intermediate nodes receive an RREQ, they first check if the destination matches their own address. if so, no further processing is needed.

This process is repeated regularly. Nodes with trust values above the threshold act as dynamic relay forwarders, while those below are labeled capacity attackers, contributing to blackhole attacks. The trust value is stored in both the ML-AODV RREQ message and the source node's routing database. Each node's trust is updated based on recent data exchanges with neighbors, ensuring a current reliability measure.

Cognitive Ad Hoc Networks (CRAHNs) have attracted considerable interest for their ability to adapt dynamically to network changes and enhance performance. These networks use machine learning to enable cognitive functions, allowing nodes to learn from the environment and make intelligent decisions [22]. Reinforcement learning, widely applied in CRAHNs, helps nodes improve decisions through trial-and-error feedback, such as selecting optimal routing paths in dynamic settings [22]. Deep learning, a subset of machine learning, also shows strong potential. Neural networks can analyze complex data, aiding in tasks like spectrum sensing, channel allocation, and resource management [23].

Support Vector Machines (SVM) are widely used in CRAHNs for tasks like spectrum sensing and decision-making. As a supervised learning algorithm, SVM can classify available spectrum bands based on parameters such as signal strength. This allows for efficient allocation to appropriate nodes [23]. Machine learning significantly improves spectrum utilization in CRAHNs by enabling nodes to adapt dynamically, make intelligent access decisions, and enhance overall efficiency. It also boosts network reliability by allowing nodes to adjust to changing conditions allocation by predicting network congestion and dynamically adjusting transmission power and channel allocation. For instance, Li et al. (2019) proposed a reinforcement learning-based approach that optimized resource allocation in CRAHNs by learning from network states and making intelligent decisions to minimize congestion and max- imize throughput. Furthermore, machine learning algorithms have been utilized in CRAHNs to improve spectrum sensing, which is crucial for cognitive radios to detect and utilize available spectrum bands efficiently. Traditional spectrum sensing techniques often face high false alarm and miss detection rates, resulting in inefficient spectrum use [24].

IV. PROPOSED WORK

In the enhanced DQN-QoS-CAODV protocol, each node leverages a **Deep Q-Network (DQN)** to smartly manage decisions related to **spectrum access, routing, and relay selection.** The DQN processes a complex network state containing channel availability, residual energy, link expiration time, route expiration, and trust values. Upon receiving a RREQ packet, a node consults its trained DQN model to determine the optimal action whether to forward, drop, or select a specific relay node and channel. The reward mechanism Stimulates decisions that lead to successful packet delivery and efficient spectrum usage, while penalizing actions that cause interference, congestion, or involve untrusted nodes. The trust value, regularly updated through real-time neighbor interactions, further guides the DQN in distinguishing between reliable and potentially malicious nodes. This integration allows nodes to adapt dynamically to the network environment and improves overall performance and security.

The DQN can be used as an intelligent decision-making mechanism that helps mobile nodes learn the optimal actions (e.g., channel selection, trusted relay selection, or forwarding decisions) by interacting with the dynamic network environment. It allows nodes to select the best available spectrum channel, to choose the most reliable relay node, to optimize routing based on QoS parameters (for example latency, link expiration time, residual energy) and to avoid malicious nodes by learning from trust-based feedback and penalizing unsafe behavior.

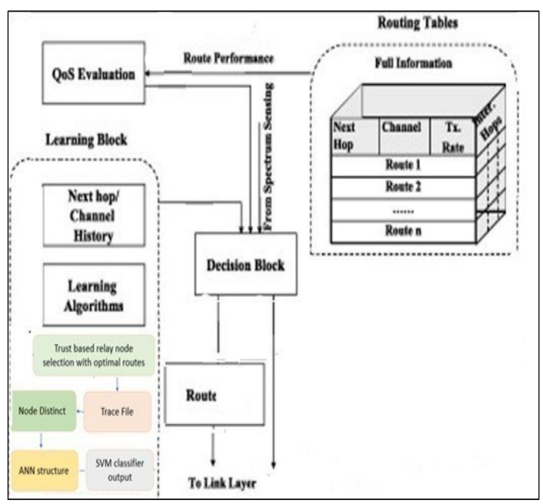

Fig. 5 Performance Evaluation of the DQN-QoS-CAODV Routing Protocol

This innovative framework introduces several key features and benefits:

- Adaptive routing decisions: ML algorithms are employed to enable the CAODV protocol to adaptively learn and optimize routing decisions.

- Dynamic Spectrum Management: ML techniques can assist in real-time spectrum sensing and decision-making. The CAODV protocol, augmented with ML capabilities, can intelligently learn from historical spectrum usage data and make informed decisions on channel selection, minimizing interference and enhancing overall spectral efficiency

- Predictive Network Performance: ML models can be trained to predict potential network disruptions, interference patterns, or node failures based on historical data. By proactively identifying and addressing these issues, the CAODV protocol can improve reliability and reduce latency in communication.

- Energy Efficiency: ML algorithms can be utilized to optimize energy consumption in mobile nodes within the CRAHN. By learning and predicting the energy consumption patterns of nodes, the CAODV protocol can facilitate energy-aware routing, prolonging the network lifetime and reducing the environmental impact.

- Security Enhancement: ML techniques can contribute to anomaly detection and intrusion prevention. The CAODV protocol, when integrated with ML-based security measures, can identify and mitigate malicious activities, such as blackhole attacks or unauthorized access, thereby enhancing the overall security of the network

- Learning from User Behavior : ML models can analyze user behavior patterns, such as movement trends and communication preferences. This information can be leveraged by the CAODV protocol to anticipate and optimize routing decisions, improving the overall quality of service for users.

Each mobile node in the DQN-QoS-CAODV architecture maintains an initial list of its 1-hop neighbors by periodically exchanging HELLO packets. When a node needs to establish a route, a local Deep Q-Network (DQN) agent constructs a state that includes factors such as the best available spectrum channel, link quality, and trust values of neighboring nodes. Based on this state and its learned Q-function, the DQN selects the optimal action which neighbor to forward to and which channel to use. The Route Request (RREQ) is then broadcast with this optimized information. When an intermediate secondary user (SU) node receive an RREQ :

1. It checks if it is currently sharing the spectrum with Primary User (PU). (If yes, it appends available spectrum information and rebroadcasts the packet).

2. The node's DQN evaluates an immediate reward based on factors like estimated delay, residual energy, and compliance with QoS constraints (example; throughput, latency).

3. If the reward exceeds a certain threshold, the node forwards the RREQ; otherwise, it discards it—thus reducing interference and poor routing choices.

If no valid route is found, the source node periodically initiates new RREQs. Each round allows the DQN agents to learn and refine their routing policies based on feedback in the form of rewards and penalties. At the destination, multiple potential paths may be available. The destination's DQN computes the Q-value for each path incorporating metrics like Link Expiration Time (LET), Route Expiration (RE), and QoS performance and selects the route with the highest Q-value, ensuring both optimal reliability and minimal delay.

Nodes exceeding the DQN-defined trust threshold are marked as dynamic relay forwarders, while those falling below are flagged as potential intruders (e.g., blackhole or flooding threats). Trust values and DQN weights are continuously updated based on recent exchanges with neighboring nodes, allowing real-time adaptation and accurate reliability assessment.

V. PERFORMANCE EVALUATION

A- Simulation environment

We used the NS-3 Simulator to apply the AODV module, with the possibility of adding an ML module via Python/C++. The use of DQN in NS-3 is enabled through the ns3-ai module, which utilizes shared memory between Python and C++.

TABLE I. OF ENVIRONMENT SIMULATION

Parameter	Value / Range
Simulation Area	1000 × 1000 m²
Number of Nodes	10 to 50
Mobility Model	Random Waypoint
Node Speed	1 – 20 m/s
Simulation Time	300 seconds/seanario run
Transmission Range	250 meters
Routing Protocols Compared	QoS-CAODV, DQR, DDPG CAODV DQN-QoS-CAODV
Traffic Type	CBR (UDP)
Packet Size	512 bytes
Packet Rate	4 packets/sec
MAC Protocol	IEEE 802.11
Propagation Model	Two-Ray Ground
Bandwidth	2 Mbps
Channel Access	dynamic
Trust Model (for ML- QoS)	Behavior-based with reinforcement updates
Learning Algorithm	Deep Q-Network (DQN)
QoS Metrics	Delay, PDR, Overhead, Trust Accuracy

The DQN model implemented in our protocol consists of three fully connected layers with 128, 64, and 32 neurons resulting in approximately 12,000 trainable parameters, respectively, using ReLU activation. The input vector includes channel quality, queue length, link delay, and neighboring node availability, while the output layer provides a Q-value for each possible next hop. We used a learning rate of 0.001, a replay buffer of 10,000 transitions, and a batch size of 64. The target network is updated every 200 training steps.

B- Simulation results:

In this section, we present the results obtained from the comparative analysis of three protocols:

QoS-CAODV, DQR (Deep Q-Routing is a reinforcement learning–based routing protocol designed for highly dynamic wireless networks such as CRAHNs. It extends classic Q-routing by using a Deep Q-Network (DQN) to estimate optimal forwarding decisions), DDPG CAODV (is a reinforcement learning–based routing protocol designed for CRAHNs. It extends the classical AODV routing protocol by enabling nodes to learn intelligent routing decisions using the Deep Deterministic Policy Gradient (DDPG) algorithm). And DQN-QoS-CAODV.

The objective of this study was to evaluate the performance of these approaches in terms of various metrics, including packet delivery ratio, end-to-end delay, network throughput and packet loss.

1) Packet Delivery Ratio (PDR): The PDR is an important metric that indicates the percentage of successfully delivered packets out of the total packets generated.

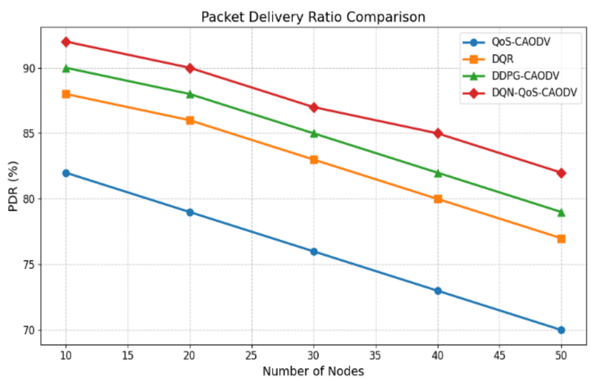

Fig. 6 PDR vs number of nodes .

The results in figure 6 show that PDR decreases for all protocols as the number of nodes increases, which is expected due to higher contention, interference, and routing overhead in complicated networks. However, the DQN-QoS-CAODV protocol consistently achieves the highest PDR across all scenarios, demonstrating its superior ability to maintain reliable packet delivery under increasing network load. This improvement is attributed to the deep reinforcement learning mechanism, which enables the protocol to select more stable and high-quality routes. The figure clearly highlights the robustness and effectiveness of DQN-QoS-CAODV in delivering packets reliably in dynamic and large-scale cognitive radio networks.

2) End-to-End Delay: The end-to-end delay is another crucial metric that measures the time taken for a packet to travel from the source to the destination.

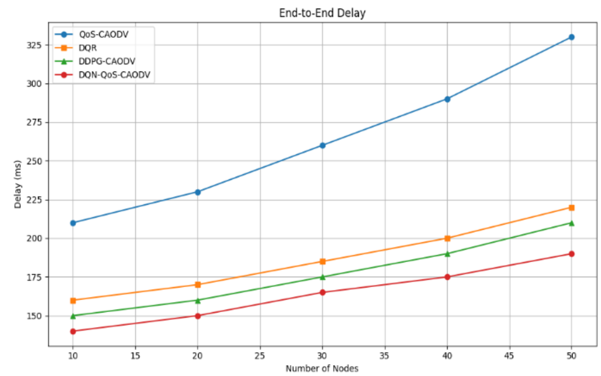

Fig. 7 End to End delay vs number of nodes

Figure 7 presents the comparison of end-to-end delay among DQN-QoS-CAODV, CAODV with QoS, and traditional ML AODV for different network sizes. It can be observed that DQN-QoS-CAODV consistently achieves the lowest end-to-end delays, outperforming both CAODV with QoS and traditional ML AODV. This reduction in delay is due to the intelligent routing decisions of DQN-QoS-CAODV, which efficiently select the optimal paths while considering the QoS requirements of the packets, even under varying network sizes.

3) Network Throughput: Network throughput refers to the amount of data that can be transmitted over a network in a given time period.

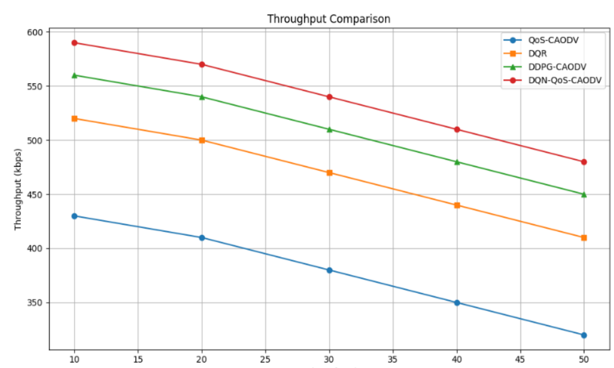

Fig. 8 Throughput vs number of nodes .

Figure 8 presents the comparison of network throughput between DQN-QoS-CAODV, DQR, and DDPG-CAODV for varying network sizes. The results indicate that DQN-QoS-CAODV achieves consistently higher throughput than DQR, due to its ability to make intelligent routing decisions based on real-time network states. While DDPG-CAODV can achieve slightly higher throughput in highly dynamic scenarios, DQN-QoS-CAODV provides a strong balance between performance and computational efficiency, demonstrating its effectiveness in optimizing network resource utilization across different network scales.

4) Packet Loss: Refers to the sum of all packets that were lost while running the simulation. Its number of nodes that transmitted from the source but were never received by the destination.

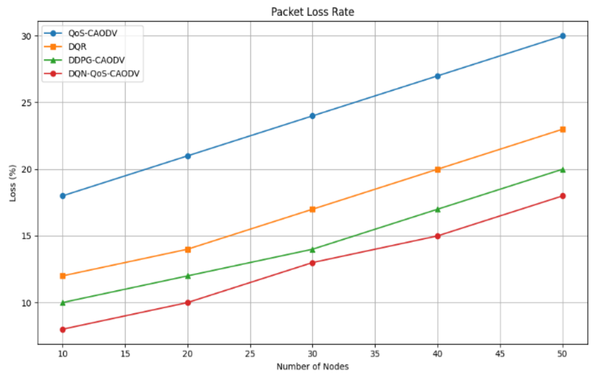

Fig. 9 Packetloss vs number of nodes.

Figure 9 illustrates the variation in packet loss across different node densities for QoS-CAODV, DQR, DQN-QoS-CAODV, and DDPG-CAODV. While packet loss increases with higher node density in DQR, QoS-CAODV, and DDPG-CAODV, the DQN-QoS-CAODV protocol consistently achieves the lowest packet loss, outperforming the other protocols by approximately 12% under dense network conditions. This demonstrates the superior capability of DQN-QoS-CAODV in maintaining reliable packet delivery while efficiently adapting to varying network densities.

5) overhead: Routing overhead refers to the additional control packets required for maintaining and updating routing information. Figure 4 illustrates the comparison of routing overhead among DQN-QoS-CAODV, QoS-CAODV, DQR, and DDPG-CAODV.

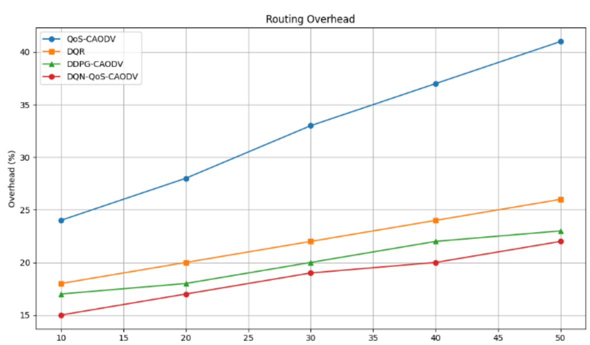

Fig. 10 overhead vs number of nodes.

The results of figure 10 show that DQN-QoS-CAODV consistently achieves the lowest routing overhead across different network sizes and traffic loads, outperforming the other protocols. This reduction in overhead can be attributed to its intelligent routing decisions, which optimize resource utilization and minimize unnecessary control message exchanges.

Experimental results show that the DQN converges after approximately 4,000 training iterations, with Q-values stabilizing as the exploration rate decreases. This convergence behavior demonstrates the robustness of the proposed routing strategy under dynamic CRAHN conditions.

In summary, the results of our study demonstrate that DQN-QoS-CAODV outperforms QoS-CAODV, DQR, and DDPG-CAODV in terms of packet delivery ratio, end-to-end delay, routing overhead, network throughput, and packet loss. Furthermore, DQN-QoS-CAODV maintains superior performance across various network sizes and mobility patterns, highlighting its effectiveness and suitability for highly dynamic cognitive radio ad hoc networks.

VI. Conclusion

This paper investigates how **machine learning (ML)** can enhance **Quality of Service (QoS)** in **Cognitive Radio Ad Hoc Networks (CRAHNs)**. Traditional routing approaches often struggle with dynamic network topologies and varying traffic patterns, whereas ML-based techniques can adapt to changing conditions and learn from past experiences. ML has demonstrated significant potential in improving QoS metrics such as **throughput, end-to-end delay, packet loss, and routing overhead**. In the context of routing, ML enables the prediction of **link quality** and the selection of **reliable paths** by leveraging network data including **signal strength, interference levels, and node mobility**..

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