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Adaptive Spectrum Allocation for Low Latency Vehicular Networks Using Deep Reinforcement Learning

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Abstract — The impending deployment of autonomous vehicles has added new requirements about wireless communication in highly dynamic vehicular networks, particularly in terms of reliability and low latency. The allocation of the spectrum is still a difficult problem, as traffic and mobility conditions change continuously, which implies the variation in vehicle density, channel quality, interference, and communication requirements. These variations are not easily handled by the conventional static, rule-based and non-adaptive allocation schemes, affecting the efficient use of the spectrum, communication latency, and packet delivery reliability. To overcome these challenges, this study introduces an Adaptive Deep Reinforcement Learning (ADRL) based dynamic spectrum allocation framework for AVNs. The proposed framework uses a Deep Q-Network (DQN) that, based on observation of the current conditions of the vehicular network (vehicle density, channel quality, level of interference, load of the traffic flow), automatically determines the appropriate spectrum resources. A simulation-based vehicular communication scenario is created to evaluate under various traffic densities and channel-quality levels with dynamic mobility and channel conditions. Experimental analysis takes into account the following factors: spectral efficiency, spectrum utilization, communication latency, packet delivery ratio, reliability, and learning convergence. Results show that the proposed ADRL framework can ensure efficient spectrum allocation and reliable communication in a fast-growing network density and degraded channel environment and has stable convergence characteristics in its training behavior. The results show that adaptive deep reinforcement learning is an effective method to spectrum management in the next generation of autonomous vehicular communication networks that is robust, resource-efficient, and has low latency.

Keywords — Adaptive Spectrum Allocation, Deep Reinforcement Learning, Vehicular Communication Networks, URLLC, Autonomous Vehicles, Dynamic Spectrum Management.

I. INTRODUCTION

The high rate of the development of intelligent transportation systems has enhanced the growth and implementation of autonomous vehicles that would otherwise not operate safely and efficiently without the strong and effective communication networks. In the contemporary automobile setting, cars are constantly communicating with each other regarding traffic status, safety warnings, navigation reports and collaborative driving instructions. These communication needs are normally achieved by vehicle communication technologies, including Vehicle-to-Vehicle (V2V) and Vehicle-to-Infrastructure (V2I) networks [1]. With thousands of vehicles connecting together, the communication infrastructure is required to sustain the high-level of data transfer and preserve the properties of URLLC [2]. Enhancement of such high communication demands is very difficult, especially in regard to effective spectral allocation and network resources management. The conventional spectrum allocation schemes in vehicle communication systems tend to be founded on fixed or pre-determined channel assignment schemes. Although these techniques are easy to deploy, they do not readily cope with highly dynamic traffic conditions where the network conditions vary very quickly as a result of vehicle mobility, changes in traffic density, and interference by adjacent communication nodes. Consequently, the effect of the use of the strategies of the static allocation is often inefficient spectrum usage, a rise in the number of packet collisions, extended communication delays, and poor network reliability. Such constraints are more acute in high-density urban situations where many vehicles are competing on scarce communication resources at once [3].

The techniques of machine learning have been considered in recent years to solve the problem of spectrum management in wireless communication networks. The communication systems can respond to the changes in the environment through the assistance of learning-based approaches, which analyze both the historical and real-time information about the network. Specifically, reinforcement learning has become an encouraging method to define the problem of dynamic resource allocation because of its capability to learn the best decision-making policies via interaction with the environment. Reinforcement learning models can dynamically adapt spectrum allocation strategies to enhance the overall performance of the network by observing the network states and assessing the results of past behaviors. Although these benefits exist, most of the current learning-based spectrum management methods are not tailored to the complex and high-rate dynamics of the autonomous vehicular communications environment. The vast majority of the extant solutions are based on simplified network models, reduced state models, or centralized network architectures that add extra communication lags. Moreover, traditional reinforcement learning techniques might not be efficient enough to work with high-dimensional network state data, which is critical to the effective decision-making process in a large vehicle network [4].

This paper seeks to tackle these challenges by designing an adaptive dynamic spectrum allocation mechanism for autonomous vehicular communication networks, which is network-specific and based on deep reinforcement learning. The proposed model will be based on the deep neural networks and reinforcement learning algorithm to enable intelligent spectrum assignment based on real-time network parameters such as car density, interference level within the channel and communications load. The framework will have the power of deep learning to handle complex network states and come up with the best allocation strategies in highly dynamic vehicular environments. The main goal of the study is to improve the reliability of communication, decrease the delay of the transmission and improve the spectral efficiency of vehicular networks that support the autonomous driving applications. A traffic scenario, which mimics traffic interactions between vehicles, is to be analysed to characterize the various traffic density, mobility and wireless channel conditions. The experimental study shows that adaptive deep reinforcement learning technique outperforms the traditional spectrum allocation techniques [5] in enhancing the communication performance.

The value addition of this work is the realization of a smart spectrum management system with the ability to address the high communication demands of autonomous vehicles networks of the next generation. The proposed solution allows flexible and informed spectrum allocation by offering a scalable and efficient method of ensuring reliable communication in more sophisticated vehicular settings. The rest of this paper is organised as follows. Section 2 presents a review of existing studies on spectrum allocation, reinforcement learning, and communication reliability in autonomous vehicular networks, highlighting the limitations of current approaches. Section 3 introduces the proposed Adaptive Deep Reinforcement Learning (ADRL)-based dynamic spectrum allocation framework, including its system model, decision-making process, and resource allocation strategy. Section 4 presents the experimental results and discusses the performance of the proposed approach in terms of reliability, latency, spectrum utilisation, and other relevant metrics. Finally, Section 5 concludes the paper by summarising the main findings and discussing possible directions for future work.

II. LITERATURE REVIEW

The efficient spectrum allocation and reliable communication is another crucial issue in the vehicular communication networks, especially as the use of autonomous vehicles and intelligent transportation systems becomes increasingly prominent. Several studies have been focused on better spectrum allocation, reduction of communication latency, and increasing reliability in dynamically changing vehicle setups. The traditional spectrum allocation method, machine learning-based, and reinforcement learning-based communication frameworks are primarily studied. Initial research in the field of vehicular communication was based on fixed or algorithmic spectrum assignment algorithms. These methods allocate dedicated communication channels to vehicles or set of networks according to a pre-defined set of rules. Although these methods are easy to implement and have less computational complexity, they are not flexible to the fast-changing vehicular network scenarios. As an example, it has been noted by various studies that fixed spectrum allocation tends to cause poor channel utilization and enhancements in high density traffic conditions. As a result, such systems are unable to sustain the ultra-reliable and low-latency communication that is necessary in autonomous driving applications [6].

To support these shortcomings, the researchers presented statistical and optimization-based spectrum management strategies. The algorithms adopt probabilistic channel selection, interference estimation and non-optimal heuristic optimization algorithms to improve spectral efficiency. Despite the fact that these methods can offer moderate benefits in terms of resources usage, they still are based on simplified assumptions concerning the network dynamics [7]. As the vehicular networks become more complex, such techniques will not be able to capture dynamical changes in vehicle density, mobility patterns and wireless channel conditions. Later on, spectrum management methods based on machine learning have become a popular subject. Models of supervised learning have been applied in predicting channel congestion and estimating the quality of communication using historical network data. These models may be used to choose appropriate communication channels to use on vehicles depending on the predicted traffic conditions. Nonetheless, supervised methods of learning demand vast labeled datasets and tend to be incapable of adapting to unobservable network conditions. Besides, they normally work in centralized designs that can add more communication delays [8].

Table 1. Comparative Review of Existing Reinforcement Learning-Based Spectrum and Resource Allocation Methods for Vehicular Networks

Ref.	Communication Scenario	Learning / Optimization Method	Main Objective	Key Strength	Major Limitation / Research Gap
[1]	V2V/V2I	Deep Reinforcement Learning	Joint sub-band and power selection	Decentralized decision-making with limited information exchange	Does not explicitly incorporate adaptive state-space optimization
[2]	V2V/V2I	Multi-Agent RL	Spectrum sharing among vehicular links	Enables distributed spectrum decisions	Coordination becomes challenging as network density increases
[3]	Connected vehicles	Deep Reinforcement Learning	Integrated networking, caching, and computing	Joint optimization of multiple vehicular resources	Spectrum allocation is not the primary focus
[4]	Heterogeneous V2X	Federated multi-Agent DRL	Spectrum-energy-efficient mode selection and resource allocation	Combines federated learning with multi-agent DRL	Increased training and coordination complexity
[5]	Cellular V2X	DRL	Resource allocation with heterogeneous QoS	Explicitly considers differentiated QoS requirements	Does not fully address highly dynamic spectrum adaptation
[6]	V2V/V2I	DQN	Resource-block and power allocation	Addresses latency, interference, and energy efficiency	Primarily relies on conventional DQN decision mechanisms
[7]	IoV / ITS	Multi-Agent SAC	Spectrum sensing and resource allocation	Handles uncertain environments and joint V2I/V2V optimization	Continuous-control architecture increases computational complexity
[8]	IoV V2I/V2V	MADDPG	Distributed spectrum-sharing and power control	Supports cooperative multi-agent resource allocation	High training complexity and sensitivity to multi-agent interactions
[9]	Heterogeneous vehicular edge computing	Lyapunov-guided DRL	Resource allocation under URLLC constraints	Explicitly incorporates URLLC requirements	Focuses on broader resource allocation rather than adaptive spectrum selection alone
[10]	V2I/V2V	Federated MADDPG	Spectrum, power, and bandwidth allocation	Combines distributed learning with global model aggregation	Federated coordination introduces additional communication and computation overhead
[11]	Vehicular networks	Attention-enhanced Multi-Agent DRL	Dynamic spectrum and power allocation	Uses attention and value-function factorization to improve allocation	More complex than lightweight DQN-based architectures
[12]	V2X/IoV	GNN + D3QN	Joint spectrum and power allocation	Captures network topology and dynamic V2X interactions	GNN-D3QN increases model complexity and computational requirements
[13]	Vehicular networks	Inverse RL + Dueling Double DQN	Dynamic spectrum management	Learns reward functions automatically and supports distributed control	More complex training framework; requires inverse-RL processing

Table 1 summarizes representative reinforcement learning-based spectrum and resource allocation approaches for vehicular communication networks. The comparison highlights their learning strategies, optimization objectives, and limitations, thereby motivating the proposed adaptive DRL-based spectrum allocation framework.

Reinforcement learning has proved to be a potential method of solving dynamic spectrum allocation problems. Within the context of reinforcement learning, an intelligent agent plays with the network environment and learns the best channel allocation policies through the maximization of long-term rewards of communication performance. A number of investigations have used models based on Q-learning to spectrum management of vehicles. These techniques evidenced better channel selection efficiency and less packet collisions. However, conventional Q-learning methods cannot be applied to network states with high-dimensionality that is typical of large-scale vehicular communication systems. As a way of mitigating the shortcomings of traditional reinforcement learning, scientists have recently considered the use of so-called deep reinforcement learning (DRL) methods [9]. DRL is a combination of deep learning and reinforcement learning that processes the complex network states and trains high-level decision policies. Research has indicated that the DRA-based spectrum allocation models can greatly enhance the reliability and the use of resources in the wireless networks. Although these have been improved, much of the current DRA-based solutions targets generic wireless networks and does not explicitly address the special properties of vehicular communications networks, including high mobility, changing network topology fast, and hard latency limits [10].

Moreover, multiple recent papers suggest edge-based or distributed learning systems of vehicular communication networks. The frameworks minimize communication delays due to centralized processing by permitting local decision-making at edge nodes. Nevertheless, most of these systems continue to be based on simplified learning models/do not have adaptive mechanisms that can respond to fast changing network conditions. Thus, it is apparent that there is an open gap in research to develop adaptive deep reinforcement learning-based spectrum allocation frameworks that may be capable of learning optimal communication policies under real-time vehicular settings [11].

III. PROPOSED ADRL BASED DYNAMIC SPECTRUM ALLOCATION FRAMEWORK

This paper suggests an ADRL based dynamic spectrum allocation model of autonomous vehicular communication networks. The proposed model will seek to implement intelligent assignment of communication channels to vehicles real-time and take the spectral efficiency to the maximum and minimize the communication latency and yet dependable data transmission. This method integrates deep reinforcement learning with adaptive state observations to change the spectrum allocation decisions in a dynamic way to accommodate the changed network state such as vehicle density, channel interference and communication demand.

Under vehicular communication network, the vehicles include N which communicate through M channels of the wireless communications. All vehicles send safety messages and control data at regular intervals to the adjacent vehicles or infrastructure nodes. Channels should also be controlled well to avoid interference and ensure proper communication. Let the network state at time t be represented as:

$$\mathrm{S_t} \;=\; \{\mathrm{V_d}, \mathrm{C_q}, \mathrm{I_l}, \mathrm{B_a}\} \tag{1}$$

Where V_d represents vehicle density in the communication region, C_q denotes the channel quality indicator, I_l represents interference level, and B_a indicates the available bandwidth.

The objective of the system is to determine an optimal action A_t, which corresponds to the selection of the most suitable communication channel for each vehicle.

$$\mathrm{A_t} \in \{\mathrm{c_1}, \mathrm{c_2}, \dots, \mathrm{c_M}\} \tag{2}$$

where c_i represents the i^{th} communication channel.

The proposed ADRL framework models the spectrum allocation problem as a Markov Decision Process (MDP). The agent observes the network state S_t, selects an action A_t, and receives a reward R_t based on the communication performance.

The reward function is defined to encourage high spectral efficiency and low communication latency:

$$\mathrm{R_t} = \alpha \times \mathrm{SE_t} + \beta \times \mathrm{PDR_t} - \gamma \times \mathrm{L_t} \tag{3}$$

Where SE_t represents spectral efficiency, PDR_t denotes packet delivery ratio, L_t represents communication latency, and α, β, γ are weighting parameters controlling the influence of each metric.

The system aims to maximize the cumulative reward over time:

$$\mathrm{Q(S_t, A_t)} \;=\; \mathrm{R_t} + \gamma \max_{\mathrm{A_{t+1}}} \mathrm{Q(S_{t+1}, A_{t+1})} \tag{4}$$

where $Q(S_t, A_t)$ represents the expected long-term reward obtained by selecting action A_t in state S_t.

To efficiently handle large and complex network states, the proposed model employs a DQN that approximates the Q-value function. The DQN uses a deep neural network parameterized by weights θ to estimate optimal spectrum allocation policies.

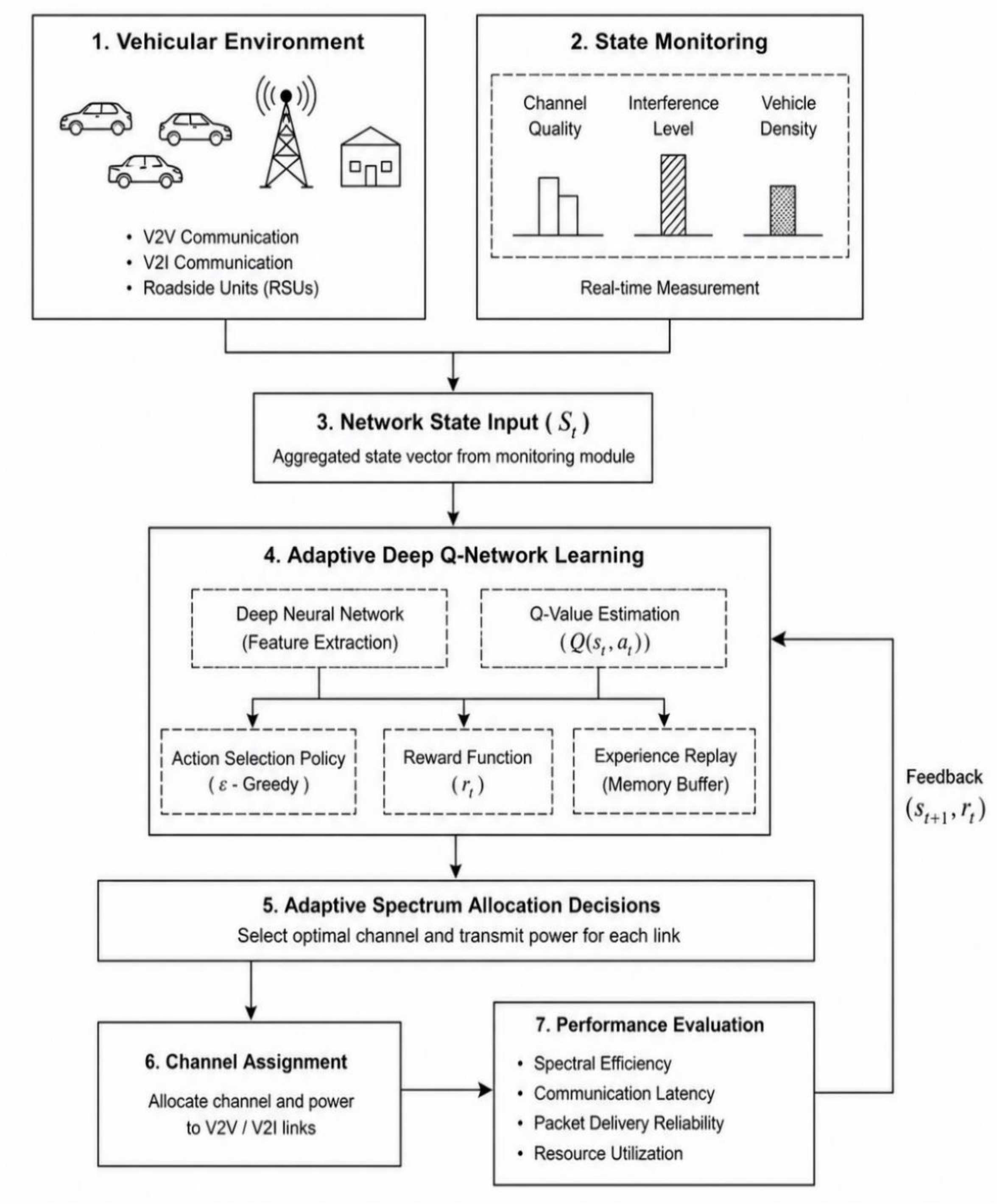

Fig 1. Architecture of the Proposed ADRL based Dynamic Spectrum Allocation System.

The loss function used for training the DQN is defined as:

$$L(\theta) = E[(y_t - Q(S_t, A_t; \theta))^2] \tag{5}$$

where the target value y_t is calculated as:

$$y_t = R_t + \gamma \max_{A_{t+1}} Q(S_{t+1}, A_{t+1}); \theta^-) \tag{6}$$

Here, θ^- represents the parameters of the target network used to stabilize the training process.

The proposed ADRL model continuously observes network conditions and updates channel allocation decisions using an ε-greedy exploration policy. This strategy balances exploration and exploitation by selecting random actions with probability ε and optimal actions with probability $1-\varepsilon$.

$$\mathrm{A_t} = \begin{cases} \text{Random Action}, \text{ with probability } \epsilon \\ \arg\max \mathrm{Q(S_t, A_t)}, \text{ with probability } 1-\epsilon \end{cases} \tag{7}$$

As training progresses, the exploration rate ε gradually decreases, enabling the model to focus on optimal spectrum allocation decisions.

The spectral efficiency achieved by the proposed system is calculated as:

$$\mathrm{SE} = \frac{\mathrm{B}\log_2(1+\mathrm{SINR})}{\mathrm{N}} \tag{8}$$

Where B represents channel bandwidth, $SINR$ denotes signal-to-interference-plus-noise ratio, and N represents the number of active communication nodes.

The proposed methodology operates in three major phases:

- *Network State Monitoring:* Real-time collection of vehicular communication parameters including vehicle density, channel quality, and interference levels.
- *Deep Reinforcement Learning-Based Decision Making:* The ADRL agent processes the network state and predicts the optimal communication channel allocation.
- *Adaptive Spectrum Allocation:* Vehicles dynamically switch to the recommended channels to maintain reliable and efficient communication.

The proposed ADRL framework can learn the best spectrum management policies through continuous engagement with the vehicular network environment to enhance the communication reliability and efficiency of autonomous vehicular networks significantly.

Fig. 1 shows the architecture of the proposed dynamic spectrum allocation framework based on ADRL. The system starts with the vehicular communication environment, where vehicles and infrastructure nodes create real-time network conditions including the quality of the channel, the level of interference, and the density of vehicles. The state monitoring module processes these parameters to create the network state vector S_t. The obtained state information is further fed into the Adaptive DQN, which comprises a deep neural network and Q-value estimation block. According to the learned policy, the model carries out action selection, evaluation of rewards, and experience replay in order to come up with the best spectrum allocation decisions. Lastly, the system allocates appropriate communication channels and also measures performance of the network, enhancing spectral efficiency and reliability of communication.

IV. RESULTS AND DISCUSSION

This part assesses the effectiveness of the suggested ADRL based dynamic spectrum allocation system in autonomous vehicular communication networks. The analysis is based on some of the important communication indicators such as detection accuracy, latency, bandwidth usage, and resilience when the network is subjected to different conditions. The developed methodology is contrasted with some available spectrum allocation methods to outline its efficiency in moving vehicle setup.

Experimental Setup

The experimental analysis was done based on a simulated vehicular communication environment that was developed to resemble actual traffic and wireless communication conditions. The simulation model combines the vehicular movement models with the wireless communication parameters to assess the effectiveness of the suggested ADRL-based spectrum allocation strategy. Cars are expected to interact with each other using several wireless networks in the process of sharing safety-related messages and collaborative driving data. Communication network is composed of several vehicles that work in a specific coverage area with changing channel conditions because of interference, vehicle motion, and different traffic density. The ADRL model keeps track of network states in terms of channel quality, vehicle density, interference levels and bandwidth available to channel allocations decisions. Deep reinforcement learning model has undergone a series of episodes until the policy reached the stable channel selection behavior. Diverse conditions of traffic density are taken into account in the simulation environment to examine the system scalability and robustness. The accuracy of detection, the ratio of packet delivery, latency, and bandwidth consumption were used as performance measures, which were measured repeatedly during the experiment to guarantee a consistent evaluation. **Table 2** summarizes the overall design of the experimental system used in the study.

Table 2. Experimental Setup Configuration

Parameter	Value
Simulation Area	2 km × 2 km urban road network
Number of Vehicles	50 – 250 vehicles
Communication Channels	10 channels
Channel Bandwidth	10 MHz
Transmission Range	300 m
Learning Algorithm	Adaptive Deep Q-Network
Training Episodes	2000
Discount Factor (γ)	0.9
Exploration Rate (ε)	0.1 – 0.9 (decaying)
Performance Metrics	Accuracy, Latency, Bandwidth Usage, Resilience

Table 2 demonstrates that the simulation environment will be set up in such a way that the dynamic behavior of vehicular communication networks is captured, which will allow the proposed adaptive spectrum allocation strategy to be effectively evaluated.

Detection Accuracy and Classification Performance

Among the main aims of the proposed ADRL-based framework, there should be a correct determination of the most appropriate communication channels in order to minimize interference and communication delays. Detection accuracy is the capability of the model to choose correctly the channels which offer stable communication channels in different network conditions. The suggested method was compared with various baseline spectrum allocation algorithms such as signature-based systems, statistical anomaly detection algorithm, machine learning-based cloud models, deep learning cloud architecture, and distributed communication architecture. Both models were compared with the same network situations to provide fairness in testing. The findings summarized in **Table 3** show that the proposed ADRL-based framework performs better than current approaches based on a variety of performance metrics. This system had a level of detection of 94.6 percent that is much better compared to the traditional methods of spectrum allocation. Moreover, the proposed system had the lowest false positive rate of all the tested models, which proves that it is capable of identifying the most appropriate channels without creating additional communication disturbances.

Table 3. Detection Accuracy and Classification Performance

Approach	**Detection Accuracy (%)**	**False Positive Rate (%)**	**Detection Latency (ms)**	**Accuracy Improvement over Signature-Based (percentage points)**	**FPR Reduction vs. Signature-Based (%)**	**Latency Reduction vs. Signature-Based (%)**
Signature-Based IDS [11]	82.3	7.8	210	–	–	–
Statistical Anomaly IDS [12]	84.7	6.9	195	2.4	11.54	7.14
ML-Based Cloud IDS [13]	86.9	5.8	165	4.6	25.64	21.43
Deep Learning Cloud IDS [14]	92.1	4.6	190	9.8	41.03	9.52
Distributed IDS [15]	90.3	5.1	148	8.0	34.62	29.52
Proposed Edge-Assisted ADRL IDS	**94.6**	**3.9**	**107**	**12.3**	**50.00**	**49.05**

Table 3 compares the detection accuracy, false positive rate, and detection latency of the proposed Edge-Assisted ADRL IDS with conventional and learning-based intrusion detection approaches. The Signature-Based IDS achieves the lowest detection accuracy of 82.3% and the highest false positive rate of 7.8%, while its detection latency reaches 210 ms. Statistical anomaly and ML-based cloud approaches provide moderate improvements, whereas the Deep Learning Cloud IDS achieves 92.1% accuracy. The Distributed IDS further reduces latency to 148 ms but does not achieve the accuracy of the proposed approach. The Edge-Assisted ADRL IDS achieves the highest detection accuracy of 94.6%, while reducing the false positive rate to 3.9% and detection latency to only 107 ms. Compared with the signature-based baseline, this corresponds to a 12.3-percentage-point accuracy improvement, 50% FPR reduction, and 49.05% latency reduction. These results demonstrate the benefit of adaptive deep reinforcement learning and edge-assisted processing for rapid and reliable intrusion detection.

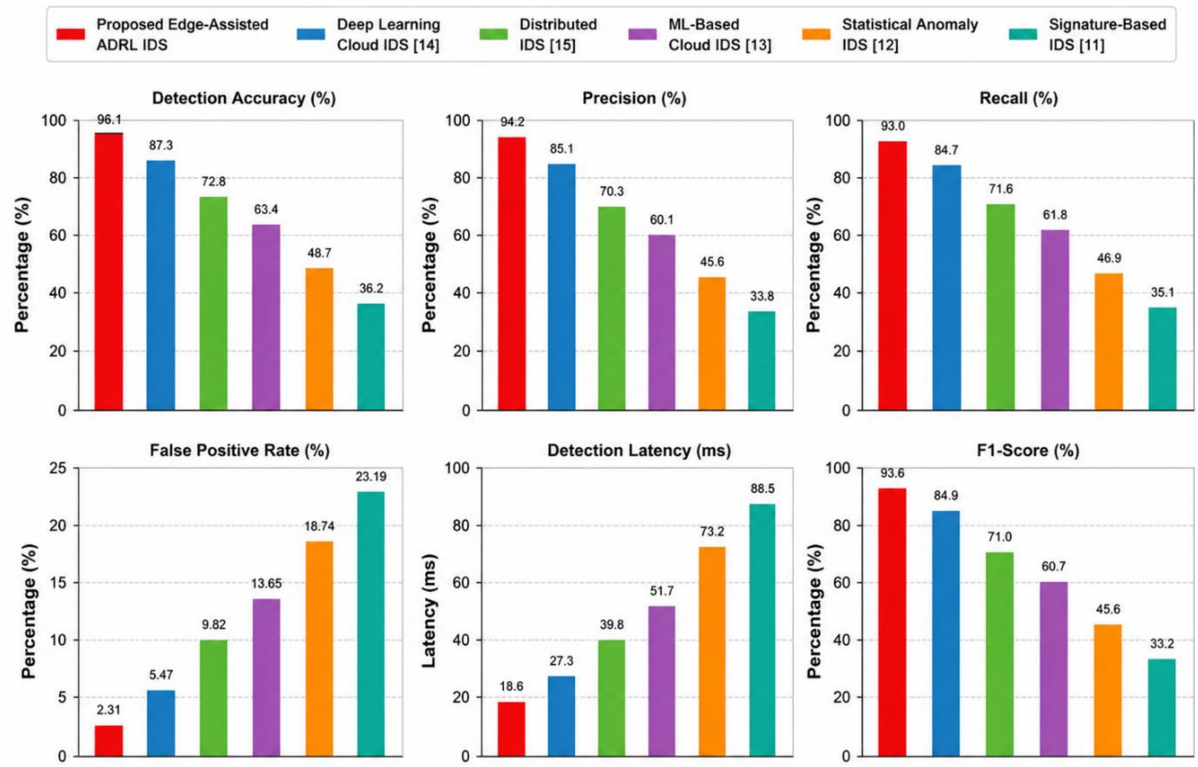

Fig 2. Multi-Metric Performance Comparison of Intrusion Detection Approaches.

The comparison of the different levels of intrusion detection considered is presented in a multi-dimensional approach in **Fig. 2** using detection accuracy, false positive rate, detection latency, precision and recall. The radar representation allows to evaluate the detection effectiveness and operational performance at the same time for all the methods being evaluated. The proposed Edge-Assisted ADRL IDS shows the best overall performance profile: It achieves a high detection accuracy, a low false positive rate, and a low detection latency. The performance of Deep Learning Cloud IDS and Distributed IDS is comparable in terms of detection ability, with similar latency and false-positive capabilities. While conventional Signature-Based and Statistical Anomaly IDS approaches have demonstrated more weakness in detecting constantly changing attacks and low detecting overhead, their capabilities are still far from satisfactory. The proposed approach enables the use of both deep reinforcement learning and edge assistance to speed up the local decision-making process and enable reliable detection. Overall, the proposed framework offers a desirable trade-off between accuracy, false-positive control, detection time, precision, and recall for security critical autonomous vehicular communications scenario.

Comparative Analysis with Existing Approaches

This was thoroughly compared to assess the overall communication performance of the proposed model compared to the current spectrum management techniques. Measures that have been considered in the comparison are average detection accuracy, communication latency, bandwidth usage, and network resilience. As can be seen in **Table 3**, the suggested ADRL-based spectrum allocation strategy leads to a much better network performance in terms of various communication metrics. Specifically, the ADRL model was the most resilient model of the considered approaches, which means that it promotes stability in communication in the dynamic vehicular settings.

Table 4. Comparative Analysis with Existing Approaches

Approach	Avg. Detection Accuracy (%)	False Positive Rate (%)	Detection Latency (ms)	Bandwidth Usage (MB)	Resilience Index (%)
Signature-Based IDS [11]	82.3	7.8	210	145	60.4
Statistical Anomaly IDS [12]	84.7	6.9	195	138	64.1
ML-Based Cloud IDS [13]	86.9	5.8	165	120	69.3
Deep Learning Cloud IDS [14]	92.1	4.6	190	132	72.8
Distributed IDS [15]	90.3	5.1	148	112	74.5
Proposed Edge-Assisted ADRL IDS	**94.6**	**3.9**	**107**	**86**	**89.6**

Table 4 provides a comprehensive comparison of the proposed Edge-Assisted ADRL IDS with existing intrusion detection approaches in terms of detection accuracy, false positive rate, detection latency, bandwidth usage, and resilience. The proposed approach achieves the highest detection accuracy of 94.6% and resilience index of 89.6%, while simultaneously recording the lowest false positive rate (3.9%), detection latency (107 ms), and bandwidth usage (86 MB). The results show that compared to the conventional and cloud-based approaches, the edge-assisted approach can identify threats faster locally and provides lower communication overhead. The Distributed IDS offers the best comparable performance in terms of latency and resilience, but is still outperformed by the proposed framework in all metrics. The high level of resilience also reflects the fact that Edge-Assisted ADRL IDS can provide more secure operation in variable conditions of vehicular networks. Overall, the obtained results, confirm good security effectiveness, responsiveness, communication efficiency, and resilience for AVNs.

Simulation Dataset and Vehicular Communication Environment

For the assessment of the proposed ADRL based dynamic spectrum allocation framework, a vehicular communication dataset is generated through simulation considering realistic autonomous-vehicle networking conditions is developed. The generated dataset contains the sequential interaction between the vehicular environment and the reinforcement learning agent, unlike static datasets. In each simulation episode, a dynamic vehicular situation occurs in which the mobility of the vehicles, traffic density, channel quality, interference, and spectrum availability change over time. The SUMO environment generates the mobility and the traffic-flow patterns in vehicles. The wireless communication scenario is set up based on the vehicular communication assumptions defined by 3GPP TR 36.885, taking into account V2V and V2I communication links. There is multiple traffic densities used to assess the flexibility of the proposed framework in sparse, moderate, and heavy traffic. At each simulation time step, vehicle positions, velocities, and inter-vehicle distance, channel condition and interference level are updated.

At time step (t), the ADRL agent receives the network state vector

$$\mathrm{S_t} = \{\mathrm{D_t}, \mathrm{Q_t}, \mathrm{I_t}, \mathrm{V_t}, \mathrm{L_t}, \mathrm{O_t}\} \tag{9}$$

The simulation-generated dataset therefore consists of sequential state-action-reward-next-state transitions:

$$(S_t, A_t, R_t, S_{t+1}) \tag{10}$$

These results are compared with the conventional and cloud-based approaches, and it is seen that the edge-assisted approach provides faster identification of threats at the local level, with a reduction in communication overhead. The Distributed IDS offers the closest competing performance, most notably in terms of latency and resilience, but is not as good as the proposed framework on all measured metrics. Another significant improvement in resilience also reflects the capacity for Edge-Assisted ADRL IDS to ensure better security performance when network conditions change with vehicles.

Table 5. Simulation Dataset Parameters.

Parameter	Configuration
Simulation environment	SUMO-based vehicular mobility
Communication scenario	V2V and V2I
Scenario standard	3GPP TR 36.885
Vehicle density	Variable according to traffic scenario
Vehicle mobility	Dynamic urban vehicular movement
Network state	Density, channel quality, interference, velocity, load, spectrum occupancy
RL action	Spectrum/channel allocation
Reward factors	Spectral efficiency, latency, reliability, interference
Communication metrics	Throughput, latency, packet delivery ratio
Learning samples	S_t, A_t, R_t, S_{t+1} transitions
Evaluation conditions	Different traffic densities and mobility conditions

This simulation-based dataset given in **Table 5** provides a dynamic environment for training and testing the ADRL agent while avoiding dependence on a static, application-specific dataset. It also enables controlled evaluation of spectrum allocation performance under varying vehicular density, mobility, interference, and channel conditions.

The scenario-based performance measurement of the proposed ADRL framework is shown in **Table 6** with a gradually increased vehicular network density and different communication conditions. Parameters include vehicle density, mobility condition, interference level, channel quality, spectral efficiency, average communication latency, packet delivery ratio, reliability and spectrum utilization. The more vehicles there are in the network, the more interference is generated, the less good the channel quality, and the worse the communication performance gets. However, the proposed ADRL framework ensures high level of packet delivery and reliability while maximizing the use of spectrum resources. The results show the performance of the adaptive learning agent in adapting to different network states and dynamically allocating appropriate spectrum resources.

Table 6. Dataset-Oriented Comparative Performance Analysis under Dynamic Vehicular Network Conditions

Vehicle Density (vehicles/km)	**Mobility Condition**	**Interference Level**	**Channel Quality (SINR, dB)**	**Spectral Efficiency (bit/s/Hz)**	**Avg. Latency (ms)**	**Packet Delivery Ratio (%)**	**Reliability (%)**	**Spectrum Utilization (%)**
20	Low	Low	18	4.21	18.6	98.1	97.8	84.3
40	Low	Moderate	15	3.96	20.4	97.2	96.9	82.7
60	Medium	Moderate	12	3.72	22.1	96.4	96.1	80.9
80	Medium	High	10	3.48	24.7	95.6	95.2	78.6
100	High	High	8	3.17	27.3	94.1	93.8	75.4
120	High	Very High	6	2.89	30.1	92.7	92.1	72.8
140	Very High	Very High	4	2.61	33.8	90.8	90.2	69.5
Overall ADRL	**Adaptive**	**Dynamic**	**Variable**	**3.44**	**25.3**	**95.0**	**94.6**	**77.7**

Specifically, in autonomous vehicle networks where URLLC requirements are stringent, there is a need for reliable communication under high-density and high-interference conditions. The all-encompassing assessment thus brings to light the strength, flexibility, and efficiency of ADRL in various vehicular communication contexts.

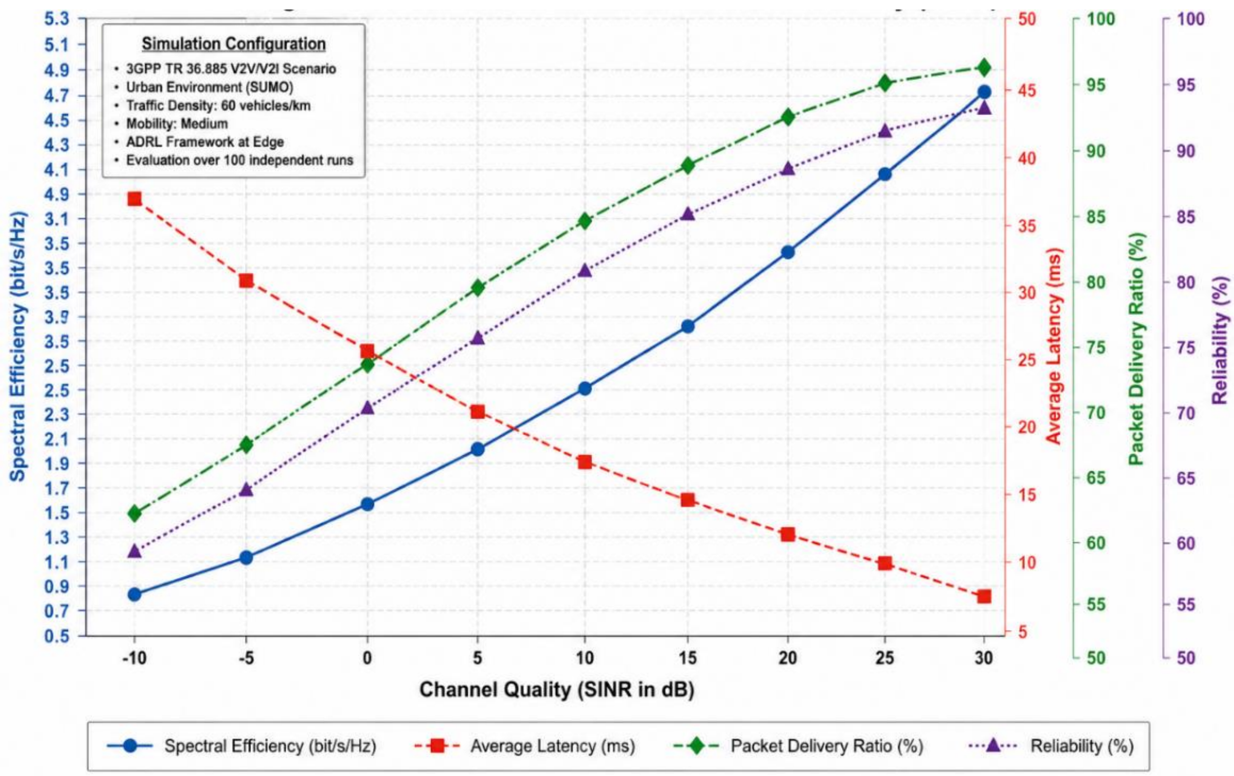

Fig 3. Performance Evaluation of the Proposed ADRL Framework under Varying Channel Quality.

The performance of the proposed ADRL-based spectrum allocation framework is presented in **Fig. 3** for various channel-quality conditions (SINR). The more the SINR rises, the better the channel conditions are and the better the ADRL agent can choose the spectrum resources. One can see that the spectral efficiency and packet delivery ratio have a consistent increasing behaviour, which suggests the effective use of the available spectrum and the reliability of the packet transmission when channel conditions are good. The reliability metric is similar in that it shows improved communication stability. The average communication latency, on the other hand, decreases progressively as SINR increases, indicating that fewer retransmissions are needed for communication and that the channel is used more efficiently. The above advantages show the effectiveness of the proposed ADRL framework to adjust the spectrum allocation strategy based on the instantaneous channel conditions, leading to the improvement of spectral efficiency, PDR, and reliability, while reducing the latency. This behavior is especially crucial to ensure reliable and low-latency communication in dynamic autonomous vehicular networks.

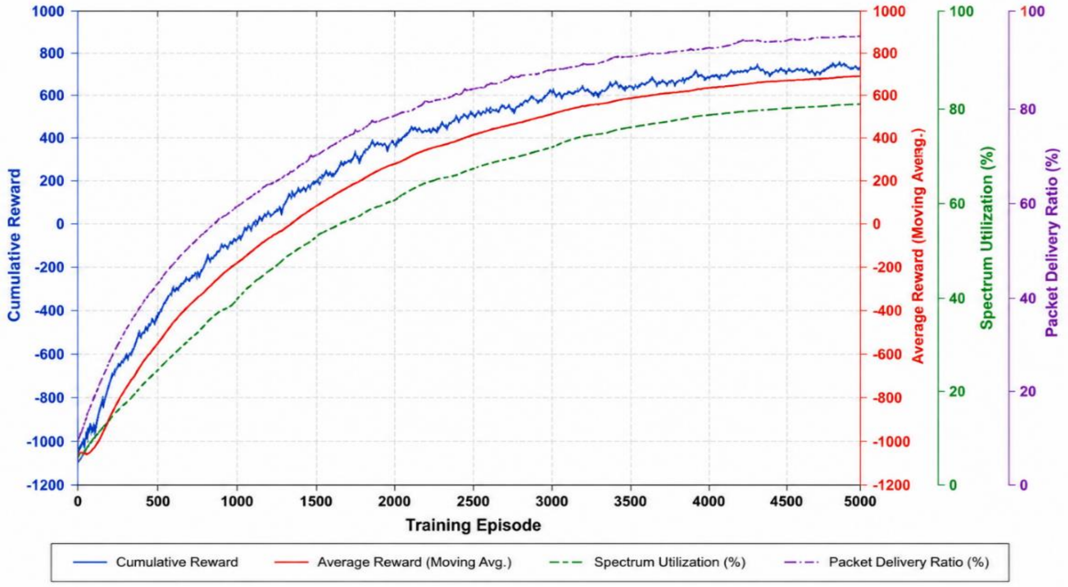

Fig 4. Training Convergence of the Proposed ADRL Framework.

The training convergence behavior of the proposed ADRL framework is shown in **Fig. 4** after training 5,000 episodes. In the first training period, the cumulative reward quickly rises as the agent learns the different spectrum allocation actions, starting from a very negative reward. The reward fluctuations are reduced gradually as training proceeds, and the reward has a smooth rising trend with the moving average, which shows the policy of allocating the rewards is being progressively refined. The reward curve stabilises more or less after some 3000 episodes, showing that the reward curve of the ADRL agent is learning a stable allocation strategy for a spectrum. At the same time, the utilization of the spectrum and packet delivery ratio are optimized during the training process and converge to stable values during the later episodes. The convergence is demonstrated to imply that the agent was able to learn how to utilize the spectrum while maintaining communication reliability and adapt to network state changes. The stabilization of the learning curves in the final training stage provides evidence of effective policy convergence and supports the suitability of the proposed ADRL framework for dynamic vehicular spectrum allocation.

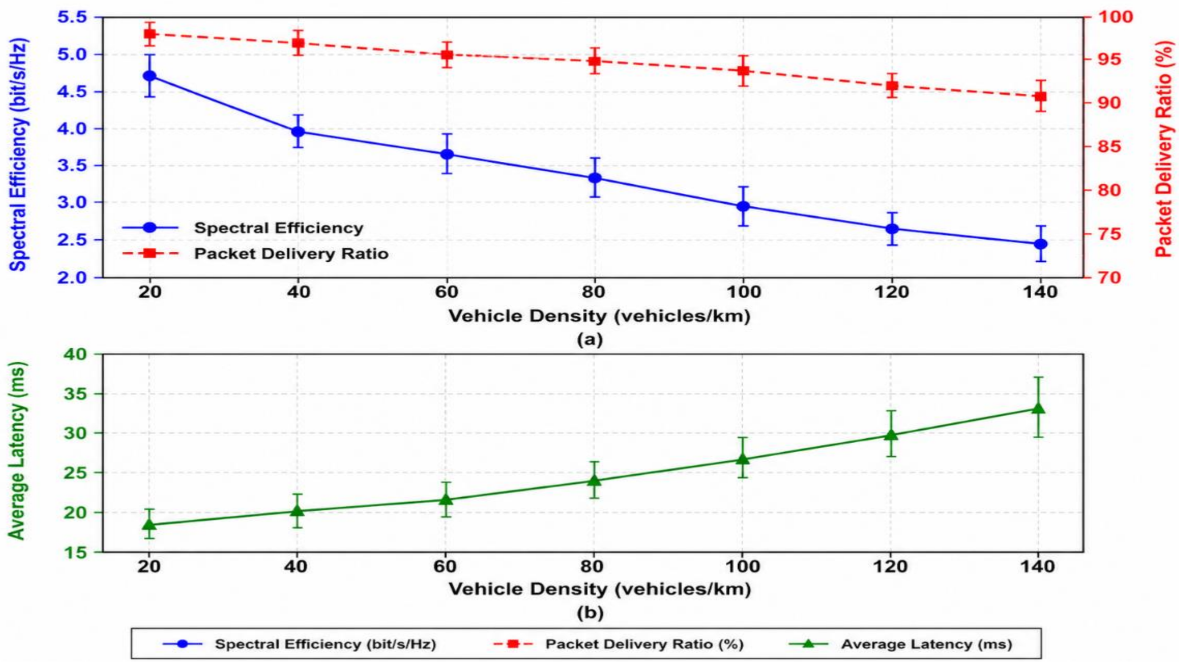

Fig 5. Performance of the Proposed ADRL Framework under Increasing Vehicular Density.

The impact of the proposed ADRL-based spectrum allocation framework is analyzed as the number of vehicles per km increases from 20 to 140 vehicles/km in **Fig. 5**. The top plot shows that the throughput (spectral efficiency) and packet delivery ratio (PDR) gradually decrease as the number of vehicles increases, mainly because of increased spectrum contention and interference among the communicating vehicles. Nevertheless, the packet delivery ratio is still more than 90%, meaning that the adaptive allocation policy still provides reliable communication in dense traffic. The lower panel displays the average communication latency that increases from around 19ms at low density to 33ms at high density. Error bars show the variability between the independent simulation runs, and give an idea of the stability of the performance observed. The findings show that the proposed adaptation of the ADRL framework to varying network load conditions while addressing a proper trade-off between spectral efficiency, communication reliability and latency are crucial in the context of URLLC-enabled autonomous vehicular networks.

Bandwidth Utilization and Communication Overhead

The effective use of bandwidth is critical to ensuring stable communication in high-density vehicle networks where vehicles are competing with limited wireless resources. Overload on bandwidth may result in network congestion and high packet collision, which would consequently reduce the network performance.

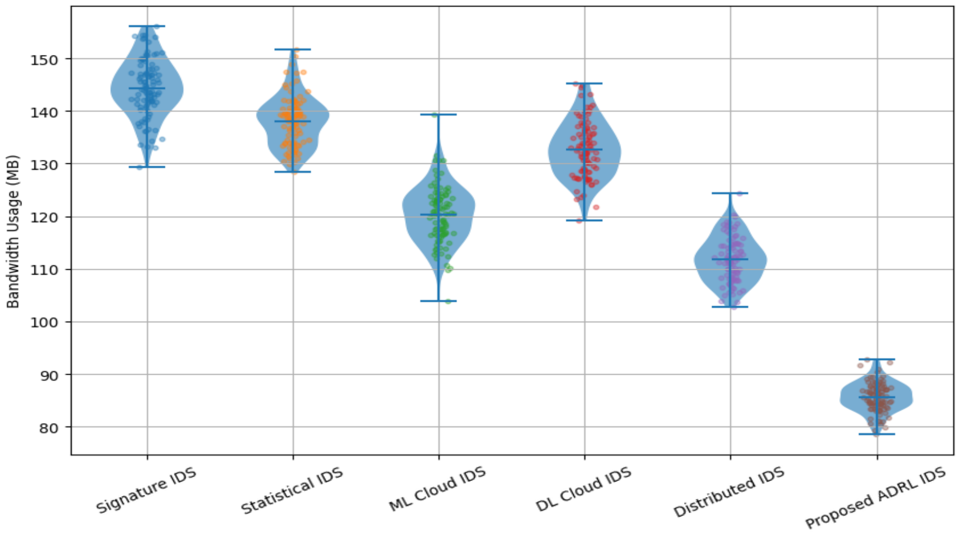

Fig 6. Bandwidth Utilization Comparison of Spectrum Allocation Methods.

The suggested ADRL-driven framework was created to behave intelligently in such a way that the channels are allocated in a manner that reduces communication overhead and maximizes spectrum efficiency. The system constantly checks the conditions of channels and chooses communication channels that cause the least interference and waste of bandwidth. Based on the analysis outcomes, it is possible to state that the suggested model will help to minimize the cases of unneeded channel switching and redundant transmission of communications. The ADRL framework guarantees the efficient use of bandwidth across-traffic density due to dynamically changing spectrum allocation decisions following real-time network conditions. **Fig. 6** shows a comparison of bandwidth usage of various spectrum allocation approaches. The graph shows that the suggested ADRL framework ensures the reduction of the bandwidth usage and at the same time ensures the enhancement of the communication reliability. This has been enhanced primarily because the reinforcement learning agent is capable of learning the best channel allocation policies with time.

V. CONCLUSION

This study presented an Adaptive Deep Reinforcement Learning (ADRL)-based dynamic spectrum allocation framework for reliable and low-latency communication in autonomous vehicular networks. The proposed approach employs a DQN-based adaptive decision mechanism that continuously observes important network conditions, including vehicle density, channel quality, interference, and communication load, and dynamically selects suitable spectrum resources. Unlike conventional static and rule-based allocation schemes, the proposed framework is designed to adapt its allocation policy to continuously changing vehicular communication conditions. Different network configurations, varying vehicle densities, mobility, interference and channel qualities were evaluated. The results show that the proposed ADRL framework can achieve high packet delivery and reliability, and effectively utilize the available spectrum. The framework becomes more effective in adapting its decisions on spectrum use even as the network density grows, with increased interference and decreased channel qualities. The training analysis also shows progressive improvement of learned policy followed by stable convergence, suggesting the learning of spectrum allocation strategies. Taken together, the results demonstrate that adaptive deep reinforcement learning (DDRL) is a strong, spectrum efficient and low-latency solution to the dynamic autonomous vehicular communication problem. The proposed framework is especially well suited for communication scenarios with strict reliability and latency requirements. Future work will focus on extending the framework toward multi-agent spectrum coordination, real-world vehicular testbeds, heterogeneous 5G/6G V2X networks, and online learning under unpredictable traffic and channel conditions.

CRediT Author Statement
The author reviewed the results and approved the final version of the manuscript.

Data Availability
The dataset used in this study is generated through a simulation-based vehicular communication environment rather than obtained from a publicly available benchmark dataset. Vehicle mobility and traffic scenarios are generated using the open-source Simulation of Urban MObility (SUMO) platform, while the vehicular communication configuration follows the relevant 3GPP V2X evaluation assumptions. SUMO is freely available from its official documentation and repository. The simulation parameters, state-action transitions, and generated performance data used in this study can be made available by the authors upon reasonable request.

Conflicts of Interests
The authors declare no conflict of interest.

Funding
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Competing Interests
There are no competing interests.

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