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Threshold-Based Fuzzy Deep Q-Network for Spectrum Management in Cognitive Radio Vehicular Networks

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Abstract – Vehicular Ad Hoc Networks (VANETs), a fast-evolving technology, improves safety and traffic management and acting as the foundation for intelligent transportation systems. Because VANET is linking more vehicles in a larger network, it is a tough challenge to provide bandwidth to all vehicles at all times. Consequently, the effectiveness of transportation is diminished. Cognitive Radio (CR) is a transformative communication paradigm that facilitates the efficient utilization and dynamic access to spectrum. Without knowledge of the signal's fundamental properties, it is a critical operation to sense the unused spectrum in conditions of low SNR and noise uncertainty. The proposed Threshold-based Fuzzy Deep Q-network (T-FuzzyDQN) is a new mathematical framework that has been developed to resolve the aforementioned challenges. This framework is designed to compute the triple threshold using the dynamic threshold factor. Clustering is implemented by the VANET environment vehicles and Roadside Units (RSUs) in accordance with vehicle density. The triple threshold mechanism is used to elect the cluster chief, who will be responsible for estimating the transmission in all clusters. The sensing findings are communicated to the RSU, which receives a fresh state and an incentive for sensing and obtaining the channel if it has not been in use. The RSU dynamically modifies the channel status in accordance with the present reward and condition after the spectrum sensing process. It strategically selects high-reward channels for efficient vehicle communication. This iterative procedure continues until congestion is effectively managed, ensuring reliable and uninterrupted transmission of emergency messages in the vehicular environment. Simulation findings demonstrate that, compared to existing works, the proposed T-FuzzyDQN yields superior results in spectrum management.

Index Terms – Spectrum Management, Cognitive Radio, VANET, Clustering, Road Side Unit, T-FuzzyDQN.

1. INTRODUCTION

Vehicular Ad Hoc Networks (VANETs) are an unavoidable study area since they always include reducing human efforts in traffic control while also allowing vehicles to connect with one another and with Road Side Units (RSUs). In general, the transport system consists of a significant number of vehicles. As part of its standard, the European Telecommunications Standards Institute (ETSI) has classified many uses related to road safety [1]. To meet these objectives, the network needs to have minimal latency and outstanding precision. But scalability and intermittent connection issues are brought on by VANET's dynamic network structure and huge number of mobility vehicles. Clustering is one effective method to address these issues; it essentially arranges automobiles into groupings called clusters [2]. A good clustering algorithm may produce a small number of clusters and maintain the cluster structure solidly without adding a lot of network cost. Further, an effective cluster conservation strategy is required to prevent unnecessary cluster re-formations [3]. VANET facilitates connections between vehicles and infrastructure

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through the utilization of wireless electromagnetic radio frequency. The original standard established to facilitate communication solutions among vehicles within short to medium distances is dedicated short range communications (DSRC). Thus, it is difficult for vehicles to gain access to the spectrum due to the combination of all the aforementioned communications [4]. Spectrum voids, where no permission is required to use radio waves, are home to cognitive radios (CRs), which are intelligent radios [5]. In the context of DSRC, a dedicated spectrum band of 75 MHz has been allocated within the 5.9 GHz frequency range. This specific spectrum allocation serves the purpose of enabling seamless communication for Intelligent Transportation Systems (ITS), with a particular focus on VANETs [6]. Six of the seven channels in total have been allocated for the transfer of operational messages, with one channel serving as the channel for control and being utilized primarily for the dissemination of safety-oriented messages. The number of vehicles on the road increases during peak hours and after accidents, which causes traffic jams. As a result, not enough DSRC channels are available to accommodate all vehicles [7].

Extending the DSRC channels beyond the 5.9 GHz ranges is not feasible due to the current fixed radio frequency allotment. However, there is now what is known as an artificially produced shortage of radio frequency spectrum due to the static allotment of spectrum resources. Comprehensive assessments of spectrum usage and associated efforts have indicated that certain radio frequency bands are heavily utilized, while others are not being used to their full potential [8]. Consequently, there is a necessity for implementing mechanisms to enhance the utilization of underutilized frequency bands, if no interference occurs with the original license holders.

The FCC introduced a proposal for a mechanism aimed at optimizing the utilization of underutilized radio spectrum, and this was achieved through the concept of Dynamic Spectrum Access (DSA). The core principle of DSA is that unlicensed users should be allowed to use channels that were originally meant for licensed users, as long as it doesn't cause adverse effects for the primary owner of the license. Main users (PUs) inside DSA are individuals or organizations having valid licenses, whereas secondary users (SUs) are those without such a license.

The fundamental technology that drives DSA is called CR. One definition of a cognitive radio is a sophisticated software-defined radio (SDR) that can sense its environment and adjust its transceiver settings accordingly [9]. Maximizing the efficient utilization of radio spectrum resources while ensuring the utmost protection for licensed users against communication channel interference is contingent upon the precision of spectrum sensing results. The effectiveness of a spectrum sensing system relies on the assumptions made regarding the primary user activity model. A thorough understanding of PU behaviors is therefore crucial for improving the accuracy of sensing results. The current research has a plethora of models for PU activity [10,11]. A prevalent PU activity model utilized by numerous spectrum monitoring algorithms in VANET environments is the fixed ON/OFF activity model. Nevertheless, it has become apparent that this model proves to be impractical in real-world scenarios due to the perceived randomness in the operation of primary systems [12].

In environments characterized by low Signal-to-Noise Ratio (SNR), where noise levels fluctuate and signal characteristics remain ambiguous, this study introduces an innovative approach aimed at enhancing the robustness of spectrum sensing. The proposed approach selects the cluster head using a triple threshold mechanism that takes into account the vehicle speed, energy level, and data rate. The implementation of Fuzzy DQN results in a hybrid model that merges the interpretative strengths of fuzzy logic with the advanced learning abilities of a deep Q-network. This fusion improves decision-making in complicated and unpredictable settings by providing a more nuanced and adaptable framework for spectrum sensing and communication in VANETs.

The key contributions of the paper are outlined below:

- Triple threshold method:

The use of triple thresholds provides a more nuanced and adaptive approach to decision-making. Adjusting these thresholds based on the characteristics of the observed signals or the operating environment allows for better customization of the detection system to specific requirements, especially in challenging scenarios characterized by low SNR or dynamic conditions.

- Dynamic threshold factor (α'):

It significantly enhances the robustness of spectrum sensing in scenarios characterized by consistently low SNR. By dynamically updating threshold values according to changing SNR conditions, the proposed method maximizes the probability of successful detection, ensuring reliable performance in challenging environments.

- Fuzzy Deep Q-network (Fuzzy DQN):

The incorporation of Fuzzy DQN introduces a hybrid model that combines the interpretability of fuzzy logic with the learning capabilities of a Deep Q-network. This fusion enhances decision-making in complex and uncertain scenarios, offering a more nuanced and adaptive system for spectrum sensing and communication in VANETs. The model addresses a central concern in VANETs by focusing on the efficient utilization of unoccupied spectrum bands initially reserved for PUs. Utilizing the available frequency spectrum

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to its fullest potential, the suggested methodology repurposes these bands through dynamic spectrum management.

1.1. Motivation

CR technology has indeed been a subject of research for a considerable period, but its application in vehicular networks is increasingly relevant, especially in the field of vehicular environments. The dynamic nature of vehicular environments requires adaptive and intelligent communication systems, where CR can enhance spectrum sensing and congestion control to contribute to safer driving conditions. The strategic selection of cluster leaders and effective spectrum allocation are interdependent processes that, when coordinated, can significantly enhance the performance and optimization of Vehicular Ad-hoc Networks (VANETs).

In Section 2, inspiration is presented along with a thorough synopsis of previous works, problems, and reasons for each. The system model and the suggested approach are explained in Section 3, and the findings are thoroughly discussed in Section 5. The study is finally concluded in Section 5, which summarizes important discoveries and possible future paths.

2. LITERATURE SURVEY

Several spectrum sensing methods are examined in this review. Due to the arrival of primary users and unpredictable traffic, unreliable broadcast services occur. Due to this Jahnvi Tiwari *et al.* [13] proposed a MAC protocol, which addressed the issues by incorporating a dynamic contention window back-off mechanism based on a cooperative makeup strategy, resulting in significant improvements. The research emphasizes the importance of analyzing throughput and delay efficiency criteria and selecting appropriate utility and cost functions. Rajesh Natarajan *et al.* [14] underscored the critical role of resolving radio access challenges in 5G vehicle networks for realizing the full potential of connected vehicles and achieving the goals of smart transportation systems. With limited spectrum and dynamic vehicular communication, effective resource allocation strategies are needed to minimize interference, diminish channel congestion, and prioritize services. The 5G Optimization strategy uses Magnified Network for traffic classification and radio access optimization. Rashid Ali *et al.* [15] introduced a driver model for adopting the various challenges in lane detection by considering various road scenarios. The method showed high effectiveness and better feasibility but the difference between the scene and the model acts as a disadvantage. Lingyun Lu *et al.* [16] dwell on the unique challenges posed by high mobility and dynamic topology in vehicular networks by using an innovative approach for spectrum sensing. This study employs CNN and LSTM networks to develop a cooperative spectrum sensing (CSS) technique for multiband spectrum sensing. Eliminating specified choice criteria improves detection accuracy, robustness, and spectrum sensing time compared to conventional approaches. Sunil U. Nyat *et al.* [17] integrated the GPS technology, especially with 4G and 5G infrastructure for enhancing vehicular communication, particularly in emergency message transmission between vehicles and infrastructure environments. This emphasized the importance of utilizing local wireless networks and existing infrastructure for efficient information exchange in dynamic wireless communication scenarios.

In the existing literature, three conventional spectrum sensing techniques have gained recognition: the Energy-based detector, the Cyclostationary feature-based detector, and the Matched filter detector [18]. Furthermore, it is crucial to recognize that the operations of primary users (PUs) are often unknown to cars beforehand, and the PU system itself does not participate in the spectrum sensing procedure [19]. Recent research suggests that cooperative decision-making may address some challenges associated with traditional spectrum sensing techniques [20]. Since SUs simply communicate a binary bit (0 or 1), hard fusion cooperative decisions are easy to implement. Participating automobiles may transmit harmful data that the hard fusion rule cannot identify. This implies the fusion center (FC) cannot distinguish between a valid SU's binary bit and a malignant SU's, which might compromise the cooperative decision process [21,22]. The soft combining strategy in cooperative decision-making needs the FC to receive channel sample measurements from individual SUs to solve some of the constraints of the hard fusion rule. This method improves decision-making by conveying more channel information than a binary bit [23]. Centralized cooperative decision-making systems, unlike hard fusing and soft combining, include a range of methodologies. The Renewal Process Method employs renewal processes to improve the precision of spectrum sensing [24]. It focuses on modelling the renewal process of PU activities to make informed decisions regarding PU occupancy. Covariance Matrix-Based General Likelihood Ratio Test (GLRT) leverages statistical likelihood ratios and covariance matrix information to detect PU signals in the presence of noise and interference, making it a powerful tool for cooperative decision-making [25]. The coordinated Spectrum Sensing approach emphasizes the importance of coordination among participating vehicles in the spectrum sensing process. Vehicles share information and collectively determine PU occupancy, improving overall decision accuracy [26]. The principal aim of the coordinated approach is to surmount the constraints associated with conventional methods through the assignment of a coordinator, which may take the form of a vehicle or an RSU. The coordinator plays a pivotal role in streamlining the cooperative decision process. However, it is important to note that cooperative decision-making in the centralized approach can face challenges related to synchronization, which are often overlooked by the spectrum

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sensing methods discussed earlier [19]. The collective delay caused by numerous vehicles operating in concert can have a substantial influence on the overall efficacy of spectrum sensing. Considering the high velocities of vehicles, there is a likelihood that, by the time the global result from the RSU is ascertained, a vehicle may have transitioned into an area outside the coverage of the RSU. This could lead to missed opportunities in the spectrum. To mitigate the challenges linked to synchronization, one potential solution is to explore the utilization of an asynchronous approach, as suggested in the study by [26].

For distributed cooperative decision-making, a dedicated infrastructure support functioning as an FC is absent. Consequently, vehicles engage in an ad hoc collaboration to collectively achieve consensus on the sensing results. A range of distributed cooperative sensing decision algorithms has been proposed in the current literature, primarily categorized as follows: consensus-based [27,28], belief propagation [29], and weighted [30,31].

The large bandwidth requirement needed to allow vehicle-to-vehicle information sharing for a worldwide result is often overlooked. The requirement for automobiles to communicate across the common channel drives this need. In low vehicle density scenarios, distributed cooperative decision-making algorithms perform poorly, making them unsuitable for suburban regions with sparse vehicle populations. Malignant assaults can provide erroneous data into the distributed collaborative decision strategy, causing cars to disseminate disinformation and impairing the cooperative choice process [27]. In a second study, Reinforcement Learning (RL) was used to solve cooperative overhead concerns such sensing latency while reporting local judgments. However, RL algorithms in VANET have yet to reach their full potential. This work uses RL to help the RSU comprehend PU activity pattern behavior. Predicting which licensed channels cars may use during congested scenarios is the goal. The RL model optimizes output depending on reward. PUs that transmit on a channel for a long time may earn a low reward as a penalty. Conversely, if the PU stays dormant for a long period, the linked PU channel is more likely to get a large payout, making it a good DSA pick. Thus, RL is used to constantly improve the PU activity model, a key spectrum sensing component. The PU model, updated by RL, is used to predict future channels. This projection is based on past and present incentives, making spectrum management more efficient and forward-looking [32]. This study [33] demonstrates how fuzzy logic improves cognitive radio network performance. Cognitive radio's flexibility and fuzzy logic's uncertainty management create a compelling framework for spectrum use, interference control, and network performance. Cognitive radio networks require more study on fuzzy logic-based methods that can adapt to complex and unpredictable situations. This work introduces a novel time slot framework that substitutes the conventional spectrum sensing phase with the reception of spectrum information, resulting in a notable decrease in vehicle energy consumption. A new hybrid access mode is introduced, which combines overlay and underlay approaches. This allows for flexible adjustments under varying network conditions and significantly improves spectrum access effectiveness [34]. Table 1 provides a summary of the most relevant work conducted in the same field.

Table 1 Prior Research was Discussed by Different Authors in the Field

Author	Technique Used	Pros	Cons
X. Qian and L. Hao [35]	Cooperative sensing Binary Decision Making	Collaborative sensing techniques (soft fusion and hard fusion) improve detection performance in extremely dynamic vehicular settings.	It potentially requires a substantial allocation of computational resources.
Pal *et al.* [36]	Regional Super Cluster-Based Optimum Channel Selection	Minimized interference, leading to improved network metrics.	Sensing data overhead and the complexity of data processing.
Zanin *et al.* [37]	long short-term memory	Improved Cluster Head (CH) stability, reduced overhead, and spectrum sensing based on trust.	The rate of misclassification is elevated.
Chembe *et al.* [38]	Adaptive Spectrum Sensing	Autonomous modelling of PU traffic patterns for enhanced	Elevated computational complexity, which could

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		channel prediction.	restrict practicality in resource-constrained situations.
Hossain *et al.* [39]	Segment-based spectrum sensing	Selects sensing techniques dynamically.	Managing dynamic segmentation involves high complexity.

2.1. Challenges

Nevertheless, proper resolution of the remaining obstacles to spectrum sensing in the domain of vehicular communication is imperative before the full implementation of cognitive radios for spectrum administration in VANETs. Significantly, one of the primary obstacles in spectrum sensing for VANET environments is related to the mobility of vehicles [40]. In the context of vehicular communication, a critical requirement is the rapid detection of available spectrum gaps within a limited timeframe before the vehicle relocates to areas where such spectrum openings may no longer be accessible. Conversely, the mobility of vehicles can be harnessed to potentially secure spectrum opportunities at future times and locations, provided that the vehicle's speed and trajectory are well understood [41]. Furthermore, the Doppler Effect contributes to radio signal fading, resulting in a reduction of the SNR between the SU and the source of the PU. Multiple solutions have been proposed to tackle some of these challenges [42]. The T-FuzzyDQN-based CR-VANET model presents an innovative and promising solution to the spectrum management challenges in VANETs. Through robust spectrum sensing, reward-driven channel selection, and adaptive network coordination, this model strives to create a more efficient and congestion-free wireless communication environment.

3. SYSTEM MODEL OF THE VANET NETWORK

The road model, as depicted in the figure 1, presents a simulation profile situated within an urban environment. The road network is comprised of four primary roads, each designated as WW', XX', YY', and ZZ', and is equipped with two lanes for vehicular traffic.

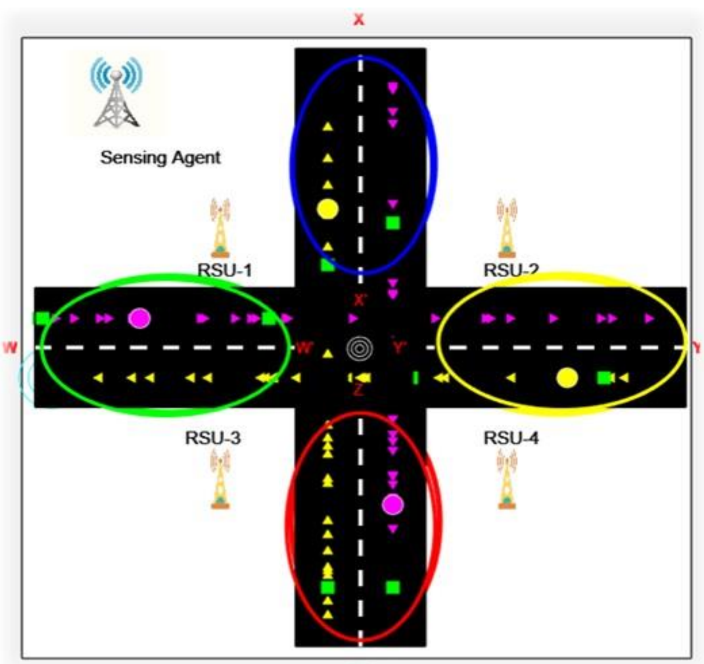

Figure 1 System model of VANET Environment

Notably, the segment between roads W' and X' features a single lane, which distinguishes it from the other roads within this urban setting. This road configuration is emblematic of the diversity and intricacies often encountered in urban traffic scenarios, where multiple lanes and varying lane configurations are essential to accommodate the flow of vehicles and address the specific traffic dynamics of this environment.

4. PROPOSED METHODOLOGY

The system model represents a pivotal advancement in the realm of VANETs. Initially, the vehicle density is estimated

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to manage the number of vehicles in a specific area and if the density is beyond the threshold, then the prediction of the channel is performed else the density will be evaluated again. Clustering is performed using Intelligent Bald Eagle Optimization [42]. Here, the channel prediction is performed using the proposed Threshold-based Fuzzy Deep Q-Network (T-FuzzyDQN), and after the prediction spectrum sensing is performed to analyze the availability and usage of the radio frequency spectrum. If there is an available channel then the communication is enabled otherwise, a request for the new channel will be generated. The overall schematic representation of the proposed model is shown in figure 2.

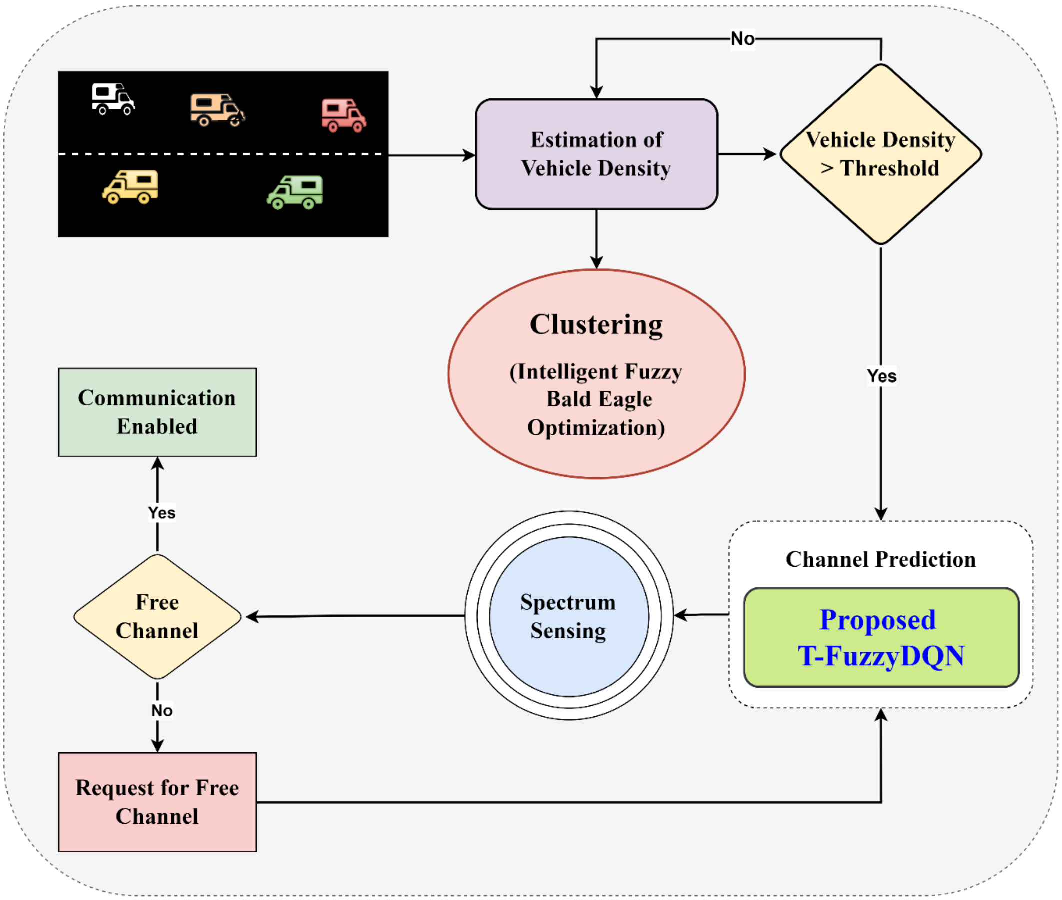

Figure 2 Schematic Representation of the Proposed Model

The model integrates several components, including sensing units and RSUs, to facilitate dynamic and adaptive spectrum management. In considered VANET model, there are N vehicles in the VANET, each with a unique role in the network. To initiate this network, the clusters vehicles into distinct clusters, denoted as C_1, C_2, C_3, and so on, up to C_n. In the context of the VANET environment with predefined parameters, this operational sequence outlines the spectrum sensing and decision-making process for an individual vehicle, denoted as $X_n(t)$. The vehicle commences by receiving signals, which are indicative of local spectrum conditions, and initiates local spectrum sensing. During this process, it calculates two critical threshold values, β_1 and β_2, based on specific statistical parameters, signal-to-noise ratios, and probabilities of false alarm and detection. Depending on the relationship between the received signal strength (T_s) and these thresholds, the vehicle classifies the channel as either occupied (S_1) or unoccupied (S_0). When the received signal strength falls between β_1 and β_2, a secondary assessment involving β_3 and $\Delta\beta$ is employed to make the final determination. Subsequently, the vehicle utilizes a Fuzzy-DQN to compute the final spectrum sensing result and communicates it to an RSU, which is responsible for allocating spectrum channels to the vehicles based on these determinations, thus effectively managing spectrum resources in the VANET.

4.1. Estimation of Vehicle Density

These factors include the total number of vehicles within a given area and the distances between these vehicles in corresponding RSU. Continuously, the RSU estimates the vehicle density within each cluster. When the vehicle density surpasses a predefined threshold (VD_{th}), the system activates R-DQN, a robust approach for spectrum sensing and congestion control in equation (1).

$$f(x) = \begin{cases} T\_FuzzyDQN\ , & VD \geq VD_{th} \\ No\ action, & VD < VD_{th} \end{cases} \tag{1}$$

where $T\_FuzzyDQN$ denotes the proposed method and VD notifies the vehicle density. VD_{th} is the vehicle density threshold. It should be remembered that when there is congestion, more spectrum is required. In high-density traffic jams, vehicles travel at very low speeds of 0 to 10 km/h, and up to 45 km/h in medium-density traffic. As a result, the T-FuzzyDQN protocol approach is only used when there is heavy traffic on the road. Each frame in the frame-by-frame structure of VANET communication contains the sensing time and transmission time.

4.2. Proposed T-FuzzyDQN

Combining the principles of the Triple Threshold Method and Fuzzy Logic with the capabilities of DQN, the T-FuzzyDQN shown in the figure 3 aims to enhance the adaptability and precision of channel predictions in dynamic environments. By incorporating triple thresholds, the model can categorize channel conditions into distinct states, facilitating a nuanced understanding of spectrum availability. The integration of fuzzy logic enables the system to handle uncertainties inherent in real-world scenarios, while the deep Q-learning aspect allows for the learning of optimal strategies over time. This amalgamation creates a sophisticated framework capable of making informed decisions regarding communication channel selection based on both crisp and fuzzy inputs, contributing to improved reliability and efficiency in vehicular communication systems.

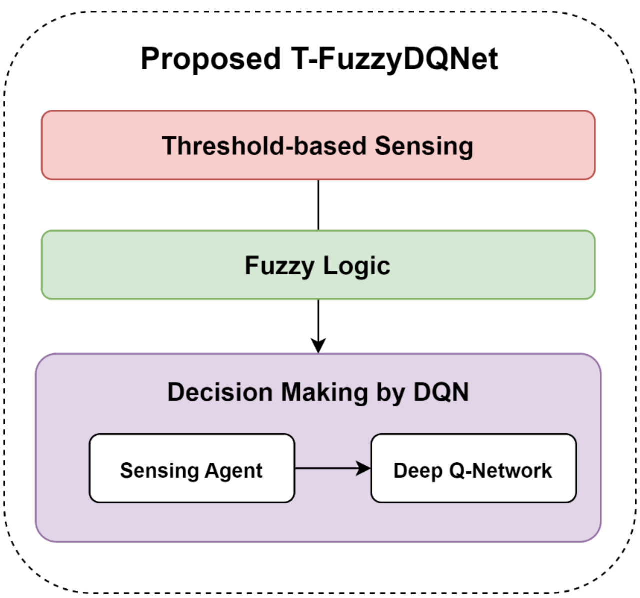

Figure 3 Proposed T-FuzzyDQN

4.2.1. Triple Threshold Method

Each vehicle in the VANET environment uses an energy detector to perceive its surroundings by the hypothesis S_o and S_1, so that the signal received at the nth sensing vehicle is given in equation (2).

$$X_n(t) = \begin{cases} n(t), & for\ S_o \\ A(t) + n(t), & for\ S_1 \end{cases} \tag{2}$$

Where, A is amplitude of received signal, $S_{snr}(t)$ is SNR signal originating from the PU transmitter. S_1 indicates that the PU signal is occupied, and S_o indicates that there is no PU signal at all, indicating that just noise is present.

The test statistic(T_s) for K sensing samples of the PU signal is given by equation (3),

$$T_s = \sum_{t=0}^{K} |X_n(t)|^2 \tag{3}$$

In the absence of noise uncertainty, the central limit theorem provides performance analysis probabilities for detection and false alarm as depicted in equation (4) and (5).

$$P_{f_{wo}} = Q\left(\frac{\beta - K\sigma_n^2}{\sqrt{2K}\sigma_n^2}\right) \tag{4}$$

$$P_{d_{wo}} = Q\left(-\frac{\beta - K\sigma_{tot}}{\sqrt{2K}\sigma_{tot}}\right) \tag{5}$$

Where, $\sigma_{tot} = \sigma_x^2 + \sigma_n^2 . \sigma_x^2$ is power variance transmitted by PU signal, σ_n^2 is variance of AWGN noise n(t) distorted by PU signal and β is the detection threshold, Q (…) is the standard generalized Marcum Q-function. From equation (3), threshold β_1 is calculated and it is given in equation (6).

$$\beta_1 = \sigma_n^2\left(\sqrt{2K}Q^{-1}\left(P_{fwo}\right) + K\right) \tag{6}$$

From equation (4), threshold β_2 is calculated and it is given in equation (7),

$$\beta_2 = K(\sigma_n^2 + \sigma_x^2) - \sqrt{2K}(\sigma_n^2 + \sigma_x^2)Q^{-1}(P_{dwo}) \tag{7}$$

Above mentioned thresholds β_1 and β_2, is compared to energy statistic T_s observed from sensing to detect the occupancy state of the PU signal. If the test result is smaller than β_1, the conclusive determination about the occupancy status of the PU signal will be S_o. If the test statistic is larger than or equal to β_2, the final conclusion about the occupancy condition of the PU signal will be S_1 as given in equation (8).

$$P_D = \begin{cases} S_0, & P(T_S < \beta_1 \\ S_1, & P(T_S \geq \beta_2 \end{cases} \tag{8}$$

However, if the test statistic falls within the test static, this threshold is not fit. Also, the selection of threshold by each SU becomes critical in conditions of low SNR and unknown noise, in order to prevent missed detection or triggered false alarm. The detection scheme's sensing capabilities fails in such a case; therefore, noise uncertainty and dynamic threshold are updated to improve the probability of detection.

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The noise uncertainty factor α in the noise model and the dynamic threshold factor α′ in the detection probabilities should be taken into account after the probabilities of detection in equation (4) and false alarm in equation (5) have been adjusted and given as equation (9) and equation (10) respectively,

$$P_{f_w} = Q\left(\frac{\alpha'\beta - K\alpha\sigma_n^2}{K\alpha\sigma_n^2}\right) \quad (9)$$

$$P_{d_w} = Q\left(-\frac{\frac{\beta}{\alpha'} - K(\sigma_x^2 + \frac{\sigma_n^2}{\alpha})}{\sqrt{2K}(\sigma_x^2 + \frac{\sigma_n^2}{\alpha})}\right) \quad (10)$$

The distributed in the interval of noise uncertainty factor and dynamic threshold factor is [σn2/α, ασn2] and [β/α′, βα′] respectively. In this section, considering simplicity and sensing time, a novel threshold factor β_3 has been presented in equation (11)

$$\beta_3 = \left(\frac{\beta_1 + \beta_2}{2}\right) \times (\Delta\beta) \quad (11)$$

$$\Delta\beta = \alpha'\left(1 - \frac{\alpha}{\alpha'}\right) \quad (12)$$

where, Δβ is given in equation (12) the change in thresholds β_1 and β_2 due to noise uncertainty factor and dynamic threshold factor α′ and α′ respectively. The updated occupancy condition is given in equation (13).

$$P_{FA-TDQNet} = \begin{cases} S_0, & P(T_s < \beta_3) \\ S_1, & P(T_s \geq \beta_3) \end{cases} \quad (13)$$

The next level involves employing Fuzzy DQN agent-based reinforcement learning to let SA decide on its own. These results from the dual validating sensing technique offer improved performance and reliability in CR-VANET.

4.2.2. Fuzzy Deep Q Network

A Fuzzy Deep Q Network is a hybrid model that combines elements of fuzzy logic and deep reinforcement learning, specifically using a Deep Q Network.

4.2.2.1. Deep Q Network

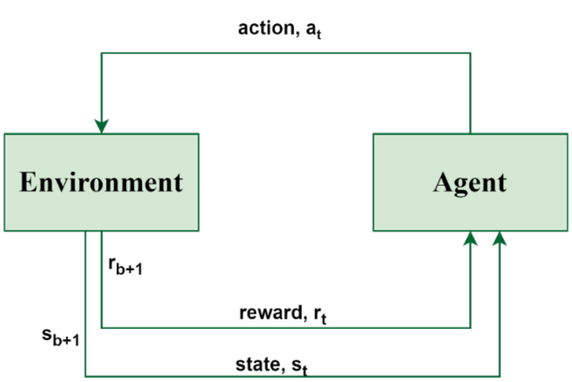

Figure 4 Interaction Between Agent and Environment in DQN

DQNDQN, a reinforcement learning method, approximates the Q-function with a neural network to determine each state's action quality. Addressing channel assignment complexities and uncertainty improves performance and spectrum management. Deep reinforcement learning creates several actions in state Q and selects the best channel selection action. State, reward, and action interactions guide the agent's decision-making to improve performance and spectrum use. DQN architecture, displayed in figure 4, shows agent-environment interaction.

4.2.2.2. Fuzzy Logic

Fuzzy logic is employed in channel prediction to handle uncertainties and imprecise information inherent in vehicular environments. Linguistic variables, such as traffic density, interference levels, and signal quality, are defined with associated linguistic terms like Good, Fair, and Worst. Membership functions capture the degree to which input values belong to these linguistic terms. Fuzzy rules are established, connecting input variables to output linguistic terms. This linguistic approach enhances interpretability and adaptability, allowing the system to make nuanced predictions even in scenarios with incomplete or uncertain information. The fuzzy logic acts as an intelligent decision-making component, refining channel predictions.

- Fuzzification

Here, each linguistic variables are associated with a corresponding membership function. In the initial stage, the assessment involves evaluating the triangular membership functions for each input. The characteristics of these triangular membership function is defined in equation (14).

$$\mu(\varsigma) = \begin{cases} 0, & \varsigma \leq a \\ \frac{\varsigma - a}{b - a}, & a \leq \varsigma \leq b \\ \frac{c - \varsigma}{c - b}, & b \leq \varsigma \leq c \\ 0, & c \leq \varsigma \end{cases} \quad (14)$$

The membership function μ(ς), denoted as, quantifies the degree of membership.

- Fuzzy Rules

Fuzzy rules, employing the Mamdani method, guide decision-making in prediction. For clarity, the limit values good, fair, and worst are used. Three instances exemplify the rules: good chance for minimum traffic density, and minimum interference level; worst chance for maximum traffic density, and maximum interference level and fair chance for moderate traffic density and moderate interference level. These rules form the channel.

- Defuzzification

The defuzzification process involves two sequential steps. Initially, the membership function depicted in Figure 5 is

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evaluated at the values obtained in the second stage. Subsequently, a singular numerical value is derived. This two-step process refines the fuzzy logic output, converting it into a crisp, numerical result. It enables the extraction of a clear and actionable decision from the fuzzy system, facilitating straightforward implementation and further analysis. This defuzzification step is crucial in translating fuzzy logic-based assessments into precise, understandable outcomes with VANET.

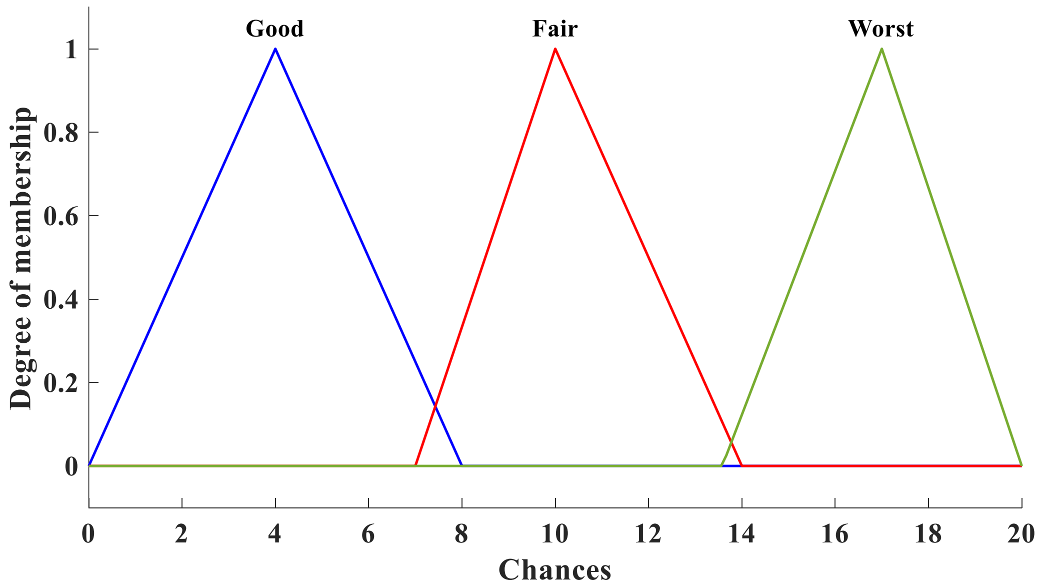


Figure 5 Defuzzification

4.2.2.3. Integration

The integration of the output from the fuzzy logic layer with the learned predictions from the DQN involves a sophisticated weighted fusion approach. This process combines the interpretability of fuzzy logic with the learning capabilities of the DQN algorithm, creating a hybrid decision-making system. The weighted fusion considers the confidence levels of both the fuzzy logic and DQN components, ensuring a balanced integration of their outputs. This synergistic fusion approach harnesses the strengths of both fuzzy logic and deep learning, providing an intelligent and responsive system capable of making informed decisions in complex and dynamic environments. The final decision, whether the spectrum is accessible, is decided by SSA in accordance with the FuzzyDQN as given in equation (15) and the cooperative decision.

$$\mathrm{DM}(\mathrm{SA_n}) \in \{\mathrm{S_0}, \mathrm{S_1}\} \quad (15)$$

This choice is then conveyed to the cluster's RSU for optimal network operations. The RSU allocates channels to SUs for data transmission. Vehicles can use assigned channels to send data. The pseudo code is shown in algorithm 1.

1. Start
2. create VANET environment with specified parameters
3. clustering
4. get the received signal from sensing vehicle $X_n(t)$
5. // Local Spectrum sensing
6. find $\beta_1 = \sigma_n^2\left(\sqrt{2K}Q^{-1}(P_{fwo}) + K\right)$
7. find $\beta_2 = K(\sigma_n^2 + \sigma_x^2) - \sqrt{2K}(\sigma_n^2 + \sigma_x^2)Q^{-1}(P_{dwo})$
8. if $T_s < \beta_1$:
9. detect as S_0 (Absence of PU)
10. else if $T_s \geq \beta_2$:
11. detect as S_1 (Presence of PU)
12. else if $\beta_1 < T_s < \beta_2$
13. find $\Delta\beta = \alpha'\left(1 - \frac{\alpha}{\alpha'}\right)$
14. find $\beta_3 = \left(\frac{\beta_1+\beta_2}{2}\right) \times (\Delta\beta)$
15. if $T_s < \beta_3$:
16. detect as S_0 (Absence of PU)
17. else if $T_s \geq \beta_3$:
18. detect as S_1 (Presence of PU)

```
end
end
// Decision making
compute DM(SA_n) ∈ {S_0, S_1} , by DQNet
send sensing result to RSU
RSU allocate channel to vehicle
End
```

Algorithm 1 T-FuzzyDQN

5. RESULTS AND DISCUSSION

This section delves into the operation of the proposed T-FuzzyDQN system for CR-VANET across various parameters. It also provides insights into the configuration of the experimental environment.

Table 2 Simulation Parameters for the Proposed Model

Parameter	Specific Value
Road length	100km
Road width	7m
Number of lanes	4
Number of RSU	4
Simulation time	100s
Vehicle Speed	10-70km/h
RSU transmission range	1000m
Bandwidth	10MHz
Frequency of operation	5.9GHz

The simulated road segment spans 100 kilometers with a width of 7 meters, accommodating four lanes for vehicular traffic. In this environment, four strategically placed RSUs are present. The simulation runs for 100 seconds, during which vehicles exhibit speeds ranging from 10 to 70 kilometers per hour.

Each RSU has a transmission range of 1000 meters, ensuring comprehensive coverage. The available bandwidth for communication is set at 10 megahertz, and the system operates at a frequency of 5.9 gigahertz. These parameters collectively define the conditions under which the T-FuzzyDQN is evaluated, providing a comprehensive perspective on its performance in a realistic vehicular network setting.

5.1. Simulation Environment

MATLAB simulator was utilized for simulations to assess the effectiveness of the proposed method. The performance of the Threshold-based Fuzzy Deep Q-Network approach was evaluated by comparing it against four existing techniques: BDM [32], RC-based sensing [33], LSTM-based VANET [34], RL-ASS [35], and Seg-CR-VANET [36].

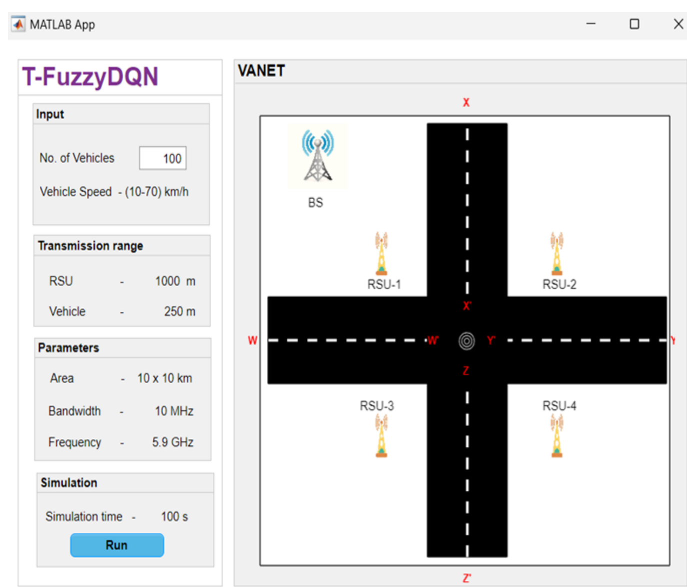
Various metrics, including Delay, Jitter, Packet Loss Ratio (PLR), Packet Delivery Ratio (PDR), Probability of Detection, and Throughput, were employed for performance evaluation. Table 2 outlines the simulation parameters for the proposed Robust Deep Q-Learning Network (T-FuzzyDQN), encompassing specific values and conditions.

5.2. Experimental Results

In the context of VANETs, the dynamic nature of vehicle speeds underscores the need for adaptive mechanisms in protocol design, moving beyond static criteria.

Figure 6 displays the Graphical User Interface (GUI) created in MATLAB, depicting the VANET environment featuring clustering and spectrum sensing components. Triangles symbolize vehicles, and round shapes represent clustering heads elected by the Intelligent Bald Eagle Optimization [42].

This visual representation captures the adaptability required to address the changing conditions in VANETs and highlights the role of clustering for effective communication and spectrum management.



(a)

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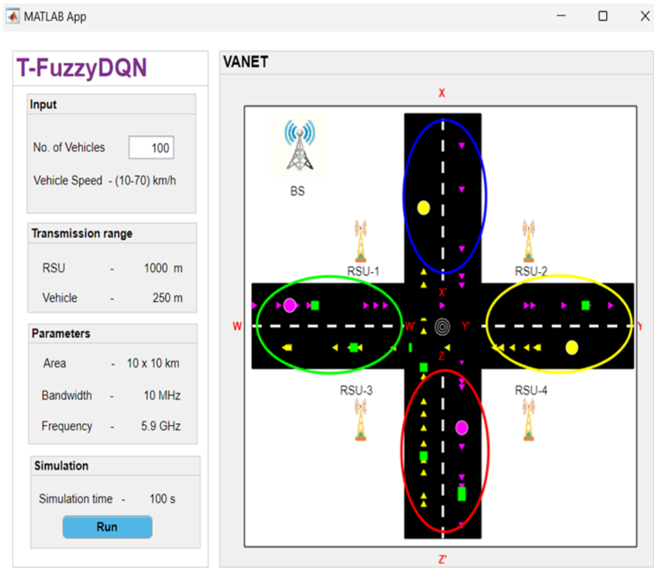
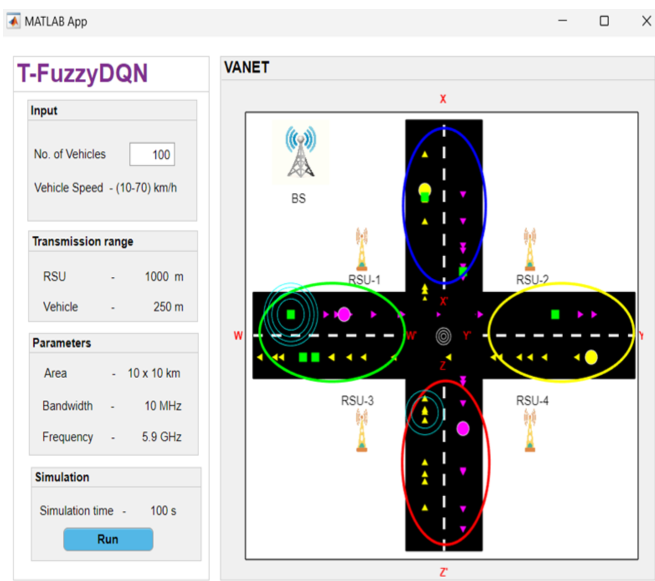


(b)



(c)

Figure 6 Experimental Results (a) Environment (b) Clustering (c) Sensing

5.3. Performance Evaluation

The proposed T-FuzzyDQN diminishes jitter, lowers the packet loss ratio, reduces delay, and improves the probability of detection in comparison to existing methods. Accuracy is characterized as the ratio of correctly identified outcomes, encompassing both positives and negatives as given in equation (16).

$$Accuracy = \frac{P_T+N_T}{P_F+N_F+P_T+N_T} \tag{16}$$

Where P_T represents number of true positives, N_T represents number of true negatives, P_F represents number of false positives and N_F represents number of false negatives. Precision, on the other hand, in equation (17), represents the ratio of genuine positives among positive outcomes.

$$Precision = \frac{P_T}{P_T+P_F} \tag{17}$$

Meanwhile, Recall in equation (18) denotes the fraction of properly detected positive outcomes.

$$Recall = \frac{P_T}{P_T+N_F} \tag{18}$$

When compared to the existing methods, the proposed T-FuzzyDQN demonstrates an average improvement of 0.05% across all three parameters shown in figure 7.

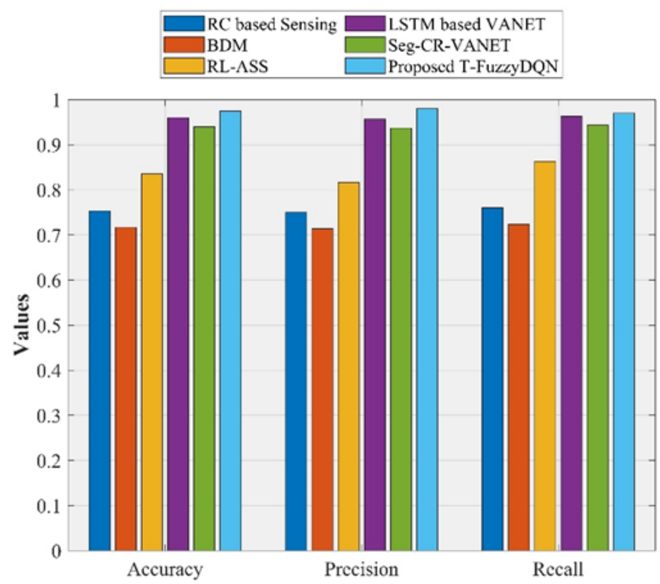


Figure 7 Comparative Analysis of Accuracy, Precision and Recall

5.3.1. Relying on Delay

Figure 8 compares packet transmission latency over a network. T-FuzzyDQN reduces latency by reducing calculation time. Delays are measured in milliseconds. The proposed solution cuts the latency to 14 milliseconds, a big improvement.

5.3.2. Relying on Jitter

The jitter is the fluctuation in the transmission delays experienced by data packets. A measure of how inconsistent or out of the ordinary the packet arrival timings are. The quality of streaming or real-time applications can be negatively impacted by jitter, leading to delays or

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interruptions in the transmission of data. The formula in equation (19) is to calculate jitter and is typically expressed as the difference between the inter-arrival times of consecutive packets.

$$Jitter = |I_t - E_t| \tag{19}$$

Where I_t is the time between packet n and packet n-1 and E_t is the expected time between packet n and packet n-1. The results demonstrate that the proposed mechanism reduces jitter by 50% than the existing mechanisms. Figure 9 illustrates the comparative analysis of jitter with existing methods.

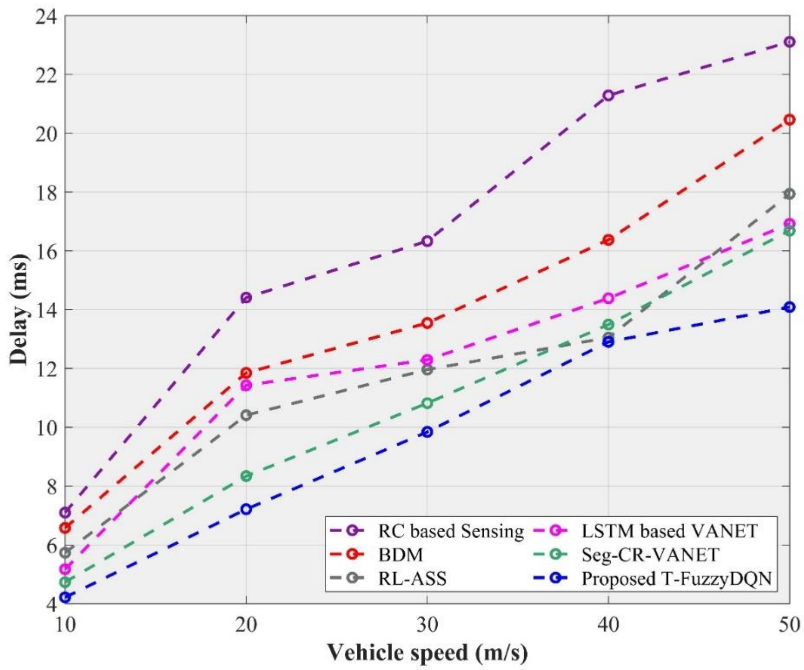

Figure 8 Vehicle Speed vs Delay

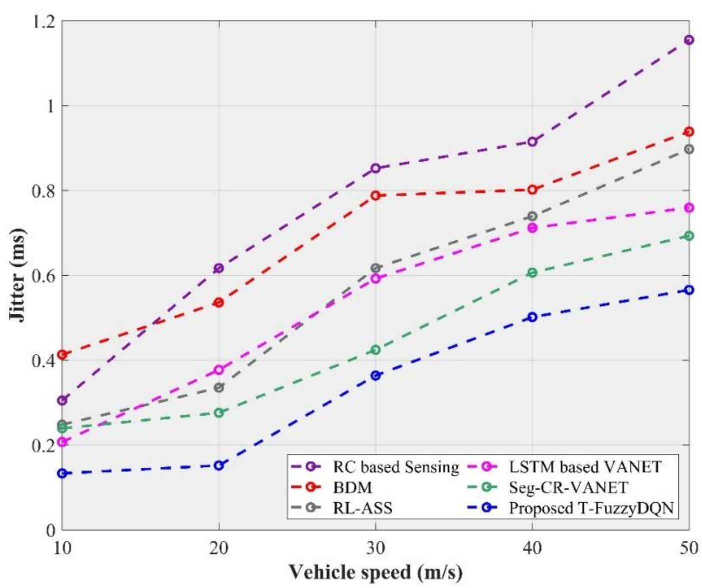

Figure 9 Vehicle Speed vs Jitter

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5.3.3. Packet Loss Ratio

Packet Loss Ratio (PLR) in equation (20) is a network performance metric that quantifies the proportion of data packets transmitted over a network that do not reach their intended destination, or are lost during transmission. It is typically expressed as a percentage and is used to assess the reliability and effectiveness of data transmission within a network.

$$Packet\ Loss\ ratio = \frac{Number\ of\ lost\ packets}{Total\ number\ of\ packets\ sent} \times 100 \quad (20)$$

A lower PLR indicates a more reliable network with fewer lost data packets, while a higher PLR suggests a less reliable or congested network where a significant number of packets fail to reach their destination. In the proposed method, the PLR is significantly reduced, measuring at only 5%. Figure 10 depicts the comparative analysis of packet loss ratio.

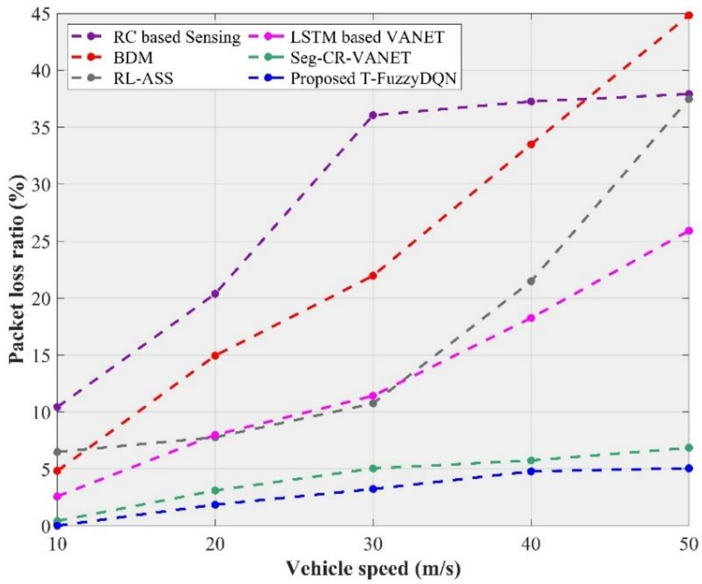

Figure 10 Vehicle Speed vs PLR

5.3.4. Packet Delivery Ratio

Figure 11 depicts the comparative analysis of packet delivery ratio. As a network performance metric, Packet Delivery Ratio (PDR) indicates the percentage of packets of information that are delivered effectively from the original location to the destination during a network's interaction process. It is usually expressed as a percentage and is used to assess the efficiency and effectiveness of data transmission in a network. The proposed T-FuzzyDQN indicates that 95% of the data packets sent using the proposed method successfully reach their intended destination, which is a higher PDR compared to other existing methods.

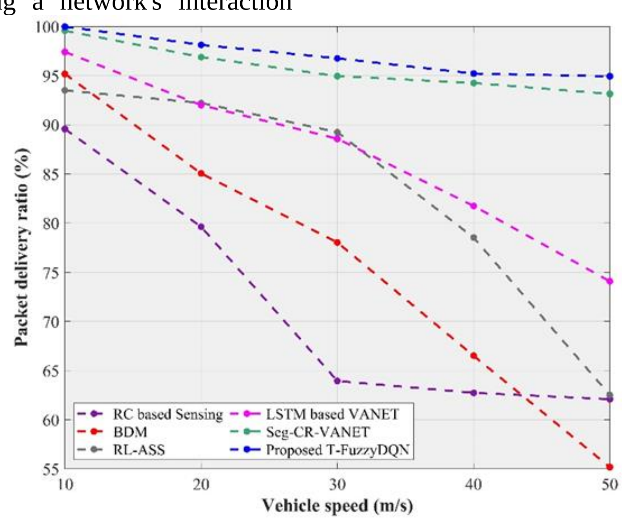

Figure 11 Vehicle Speed vs PDR

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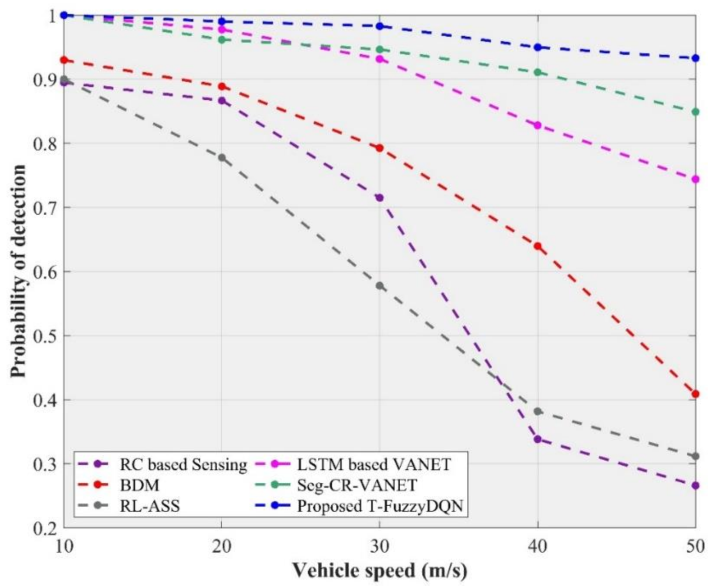
5.3.5. Probability of Detection

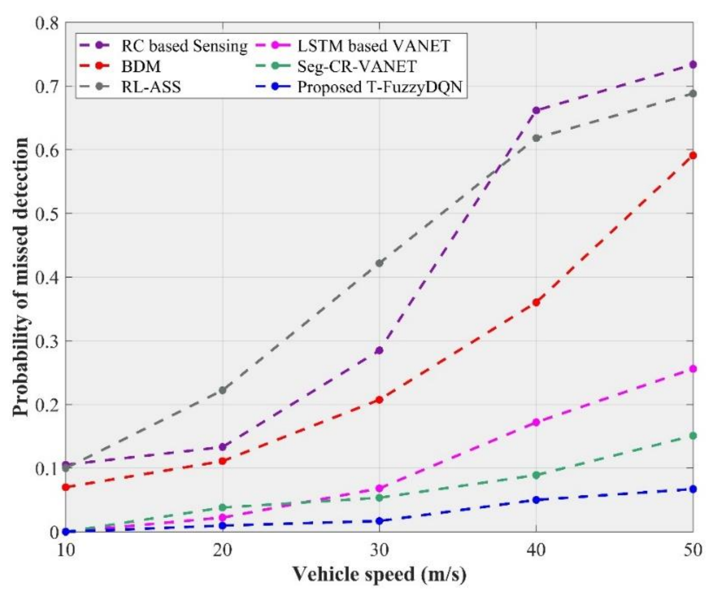
In CR- VANET, Probability of Detection (PD) is a crucial performance indicator that analyses a cognitive radio system's capability to properly detect the existence of principal users or signals within the radio spectrum, as provided in equation (21). It quantifies the likelihood of the system successfully detecting the primary user's signal when it is present.

$$Probability\ of\ detection = \frac{P_T}{P_T+N_F} \tag{21}$$

True Positives (P_T) represent the number of instances in which the system correctly detects the primary user's signal when it is present. False Negatives (N_F) represent the number of instances in which the system fails to detect the primary user's signal when it is present. The proposed T-FuzzyDQN exhibits a significant increase in the Probability of Detection while also demonstrating a noteworthy decrease in the Probability of Missed Detection (PMD). Figure 12(a), 12(b) depicts the comparative analysis of PD and PMD respectively.



(a)



(b)

Figure 12 Vehicle Speed Versus (a) PD, (b) PMD

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5.3.6. Throughput

Throughput analysis is shown in figure 13. It is a network performance indicator that measures the rate at which information is effectively transported from source to destination inside a network, as defined in equation (22). It represents the amount of data that can be transferred in each period and is often expressed in bits per second (bps) or megabits per second (Mbps). The proposed T-FuzzyDQN can transmit data at a rate of 18 megabits per second, which is higher than the data transfer rates achieved by other existing methods.

$$Throughput = \frac{Amount\ of\ data\ transferred}{time\ taken} \quad (22)$$

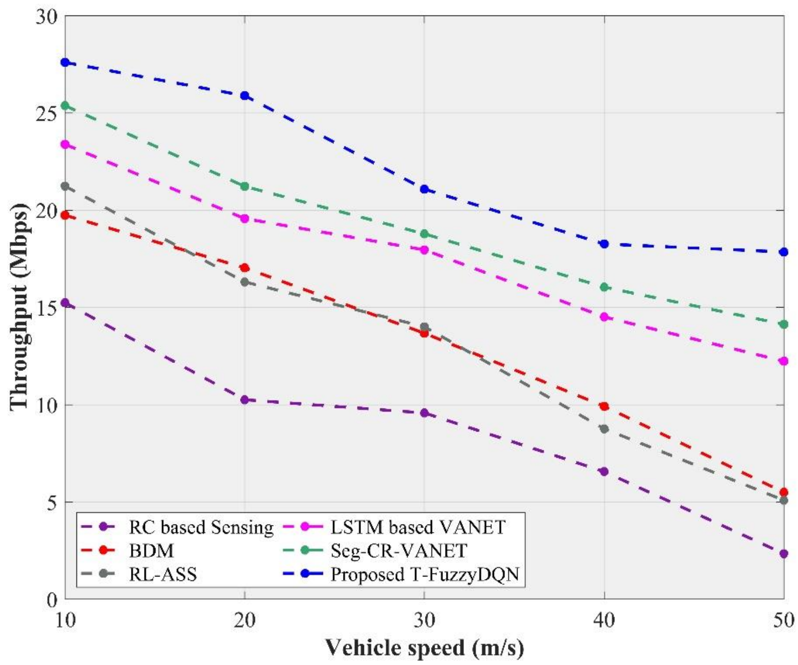

Figure 13 Vehicle Speed vs Throughput

5.4. Comparative Discussion

The F1 Measure is a performance statistic employed to evaluate the accuracy and efficacy of classification or detection systems, including those utilized in CR-VANETs. It is the harmonic mean of accuracy and recall, offering a balanced assessment of a system's capability to accurately categorize positive cases while reducing false positives and false negatives. The False Positive Rate (FPR), or Type I Error Rate, is the ratio of negative events misclassified as positive. In the context of CR-VANETs, it may denote the frequency at which secondary users are erroneously identified as primary users. The False Negative Rate (FNR), or Type II Error Rate, measures the percentage of positive cases misclassified as negative. In CR-VANETs, this may represent the rate at which primary users are erroneously missed or not detected. Table 3 provides a comparison of the F1 Measure, FPR, and FNR for various existing methods and the proposed T-FuzzyDQN.

Table 3 Comparative Discussion

Techniques	Accuracy	Precision	Recall	Specificity	F1 Measure	FPR	FNR
RC-based Clustering	0.7533	0.75	0.76	0.7467	0.755	0.2467	0.24
BDM	0.7167	0.7138	0.7233	0.71	0.7185	0.2833	0.2767
RL-ASS	0.835	0.817	0.8633	0.8067	0.8395	0.165	0.1367

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LSTM based VANET	0.96	0.9567	0.9631	0.957	0.9599	0.04	0.0369
Seg-CR-VANET	0.94	0.9371	0.9433	0.9367	0.9402	0.06	0.0567
Proposed T-FuzzyDQN	0.975	0.9799	0.9702	0.9799	0.975	0.025	0.0298

Based on the results presented in table 3, the performance of the proposed T-FuzzyDQN is enhanced in spectrum-scarce scenarios. The network model is continually updated with the assistance of adaptive threshold parameters, improving the effectiveness of spectrum sensing through the accumulation of historical sensing patterns.

6. CONCLUSION

Finally, the suggested Threshold-based Fuzzy Deep Q-network (T-FuzzyDQN) provides a new solution to spectrum management difficulties in Vehicular Ad Hoc Networks. Using cognitive radio engineering, the model applies a triple threshold framework with a dynamic threshold factor to improve robustness and detection probability, especially in low Signal-to-Noise Ratio (SNR) and noise uncertainties. The clustering-based technique to grouping cars and Roadside Units (RSUs) allows for precise channel prediction, making it easier to strategically pick high-reward channels for successful communication. The integration of the output from the fuzzy logic layer with the learned predictions from the DQN involves a sophisticated weighted fusion approach. This process combines the interpretability of fuzzy logic with the learning capabilities of the DQN, creating a hybrid decision-making system. Simulation results showcase T-FuzzyDQN superior performance, achieving an accuracy of 97.5% and surpassing existing methods, holding promise for optimizing spectrum utilization and enhancing communication reliability in VANETs. As a direction for future work, focusing on security aspects, particularly incorporating machine learning models, can further enhance the robustness and resilience of the proposed solution in dynamic vehicular environments.

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