Deep Reinforcement Learning for Real-Time Safety Warning Dissemination in Cooperative Driving Environments

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***Abstract*- The rapid development of connected and autonomous vehicles much more complex on vehicular communication particularly in "Vehicular Ad Hoc Networks (VANETs)" in a high traffic dense area. Reliable security messages and Low-latency are challenging to deliver on these networks because of their high mobility, dynamic topological changes and heterogenous communication infrastructures. Real-time safety warning dissemination plays an important role for supporting critical driving functions such as intersection coordination, overtaking assistance, lane keeping and pedestrian collision avoidance. However, existing VANET-based Vehicle-to-Everything (V2X) communication models suffer from limited overtaking decision support, increased end-to-end latency, simplified pedestrian interaction modelling, Scalability and robustness issues in large-scale vehicular networks. To address these problems, the research proposes VANET a unified method for rapidly disseminating safety alerts in cooperative driving scenarios. The proposed method incorporates Adaptive Network Selection-V2X (ANS-V2X) mechanism to minimize communication delay by efficiently utilizing heterogeneous radio access technologies, including 5G NR-V2X and DSRC. The "Deep Reinforcement Learning" (DRL)-based "Deep Deterministic Policy Gradient" (DDPG) algorithm is used to generate optimal acceleration and steering commands for dynamic overtaking manoeuvres and stable lane keeping. The complex interactions between vehicles and pedestrians "Deep Multi-agent Reinforcement Learning (DMARL)" framework is provided for capturing adaptive decision-making behavior in dynamic traffic scenarios. The adaptive federated "multi-agent reinforcement learning (AF-MARL) strategy" is used to enhance scalability and robustness. The proposed framework jointly optimizes communication latency, driving safety, pedestrian interactions and system scalability in VANET environments. The proposed model result minimized end-to-end latency, enhances overtaking performance, increases pedestrian safety, and improves scalability and robustness.**

Index Terms*- *Vehicle Ad Hoc Network (VANET), ANS-V2X, Deep Reinforcement Learning (DRL), AF-MARL, DDPG, Decision modeling

I. INTRODUCTION

VANETs are mobile ad hoc networks that can operate with a diversity of models, such as the V2I and V2V model [1]. As an essential component of Intelligent Transportation Systems (ITS), connected and autonomous vehicles (CAV) mean of reducing traffic accidents, easing traffic congestion, and enhancing traffic performance [2]. Vehicles can interact directly with their neighboring vehicles to CAV V2V communication, which extends perception and permits explicit vehicle cooperation [3]. The technique for exchanging information on the roads is V2X connectivity. It is used to connect vehicles to vehicles [4]. Vehicle-to-infrastructure (V2I) communication lines will be used by the roadside unit (RSU) to collect state data, such as each participating vehicle's position, velocity, acceleration, and the heading angle [5]. Due to the local perspective of vehicle autonomy, RSUs make decision from a global perspective that allows for a more thorough assessment of the traffic situation and a more effective optimisation of overall system performance [6]. Preventing collisions requires detecting a vehicle's "position, speed, acceleration, and other attributes". In order to collect information about the driving environment, such as position, obstacle distance, and vehicle status, sensors are crucial [7]. A high-level DRL collision avoidance controller is triggered when it identifies vulnerable road users close to the vehicle. This controller slows down or changes the vehicle's path to help it avoid potential collisions [8]. One of the most significant concerns in high-level decision-making is lane maintenance, which has a big impact on traffic efficiency and safety in VANET [9]. In order to properly execute a full traditional overtaking process, it is necessary to have control of the vehicle, a method for making decisions about overtaking [10]. The ability to navigate through traffic competitively is essential when driving in congested traffic conditions [11]. Due to the extremely joining of lanes and high traffic density on congested roads, it is difficult for autonomous vehicles to make joining of lanes without causing disruption. The number of times autonomous vehicles have been able to merge on these types of lane-changing is limited because of how little time is available for an autonomous vehicle to merge before hitting another vehicle. [12]. Vehicle trajectory planning and signal adjustment mechanisms are examples of effective advanced traffic management methods which help to reduce congestion and improve the safety of all road users by considering pedestrian activity, vehicle density, speed, etc. [13]. The goal of cooperative driving at signal-free junctions is to facilitate the safe and effective passage of vehicles through conflict areas by coordinating their movement in various directions. A chain collision between several vehicles could occur if other vehicles lack the distance to stop the failing vehicle [14]. Pedestrian behaviour can be unexpected and vary based on a number of factors, including surroundings, and distractions, as demonstrated by vehicle-pedestrian conflict interactions [15]. pedestrian zones that restrict or prohibit specific vehicle groups from using particular road spaces during particular hours [16]. congestion, which can result in air pollution, more fuel use, and traffic delays [17]. The high-level model minimises the overall vehicle delay and the number of vehicles that change lanes by optimising traffic signal features, CAV arrival time at the intersection, and arrival lane assignment [18]. The increasing number of vehicles on the roadways adversely affects ecology, latency, safety, and traffic efficiency [19]. To improve traffic efficiency by facilitating traffic management and control [20]. High vehicle density, limited overtaking assistance, robustness and scalability issues, and complexity of pedestrian decision-making are the challenges that occurred. To overcome these challenges, the proposed model introduces ANS-V2X with DENM, DDPG, MARL and AF-MARL frameworks.

A. Motivation & Objectives

In multi-access vehicular communication systems, safety messages are transmitted through various access technologies to support cooperative driving functions such as “lane keeping, overtaking, pedestrian crossing, and collision avoidance”. Even though existing V2X communication frameworks enable interactions, they face significant performance issues in high-density traffic and network changeover scenarios. The most critical issues are described below:

- **Increased End-to-End Latency:** Increased “end-to-end delay” and decreased communication efficiency are caused by high vehicle density and network changeovers between multiple-access points.
- **Limited Overtaking Assistance:** The current system can only specify whether overtaking is safe, without providing assistance with proper speed and steering guidance for effective collision avoidance and stable lane keeping.
- **Simplified Pedestrian Modelling:** Existing pedestrian crossing models do not adequately account for dynamic traffic conditions and the complexities of pedestrian decision-making behaviour.
- **Scalability and Robustness Issues:** Existing systems can degrade in expanded urban areas due to limited robustness and scalability.

This research aims to reduce end-to-end latency and improve safety warning dissemination in multiple-access VANET environments for cooperative autonomous driving. The other objectives are as follows:

- To reduce the delay with multiple-access points during handover situations and confirm safety message dissemination.
- To improve overtaking assistance by providing active steering and speed direction for reliable lane maintenance and efficient collision avoidance.
- To increase the safety of pedestrian crossings by developing and modelling adaptive vehicle-pedestrian interactions in highly dynamic traffic situations.
- To enhance the scalability and robustness of the system in expanding urban environments with growing vehicle density and frequently changing network topology.

B. Research Contribution

These are illustrations of the research study's highlights:

- Consuming the ANS-V2X algorithm integrates with DENM to “minimize end-to-end delay” through the integration of multiple access points in changeovers and enhances the safety warning dissemination in high-density vehicular networks.
- By using the DDPG algorithm based on DRL, enhance overtaking performance through optimizing steering control and speed control systems, improve lane keeping, and avoid collisions effectively.
- To use the MARL approach to increase pedestrian safety while crossing roads through developing an adaptive model of pedestrian-vehicle interactions, allowing for accurate prediction of risk.
- Utilize the AF-MARL framework to greatly increase scalability and robustness to faults in large urban regions.

C. Paper organization

The remainder of this research is as follows: Provides an explanation of Section II of a survey of previous work. Section III states the main issue with the current methods. Section IV defines the system model. Then Section V presents the study approach for the suggested model, appropriate diagrams, mathematical representations and pseudocode. In Section VI, the suggested and current methodology is compared and experimental results are explained. The proposed model conclusion and future work are explained in Section VII.

II. LITERATURE SURVEY

The article presents performance accuracy of “V2V communication” using the 5G NR system this study suggests “intelligent driver model-lane changes (IDM-LC) and intelligent driver model-avoidance (IDM-A) models”. In this instance, various “road scenarios – such as square, hexagon, heptagon, and triangle” – are used to assess the realism of the vehicle movement models. While the proposed model is meant to represent real-world environment conditions, due to isolated constraints on what it was built on, there is some space between the simulated condition and real-world performance deployment issues [21]. In this article, the author provides a unique intelligent 5G-assisted "Software-Defined Networking-based Collision Avoidance (SDNCA) framework". SDNCA primarily uses federated learning across vehicles to train the "proposed Risk Severity-Artificial Neural Network (RS-ANN) model", which is the first algorithm to reliably predict the "Risk Severity (RS)". The second algorithm is used by the SDNCA framework to accomplish three primary goals. Although this research does not assess performance based on a large-scale network with thousands of controllers [22]. To increase safety, effectiveness, and ride comfort, this work suggests an "intelligent speed control strategy for AVs in CVIS" utilizing DRL. First, using vertical comfort evaluation, the maximum tolerable speeds on segments are used to depict the variable and changing road profiles with uneven surfaces. Then, using road and traffic data, a "DRL-based speed control" model is created. This work only considers linear driving situations and does not involve multi-vehicle interactions or lane changing [23]. In this research, an approach to decrease latency in VANETs by combining pattern discovery techniques with cluster-based routing protocols. Four modules make up the suggested method's outline: pattern extraction and route discovery for vehicles; data transmission routing and vehicle grouping; main details preparation and analysis; and major data collection and analysis. When estimating the route pattern of automobiles on silent highways, the suggested method's accuracy will be reduced [24]. This study proposes a "traffic density-based congestion control algorithm (TDCCA)". Because the experiment only uses "one-fourth of the congestion window", the updated mathematical method outperforms earlier studies in terms of overall packet latency. To make the model parameters more effective, it incorporates a "congestion management" technique that modifies the "rate of CAM delivered across the host controller". The approach takes into account a range of situations, including sparsely distributed and teemed networks, as well as non-saturated and significantly saturated networks. Because the system must constantly analyse the traffic, the suggested system requires more calculation time [25].

This study suggests "CARAC (Cluster-based Ant Colony Routing with Adaptive Cluster Head), a hybrid routing protocol that combines "Ant Colony Optimization (ACO) and dynamic clustering" utilizing the K-medoids method to enhance data delivery performance, scalability, and route stability. Through the use of relative velocity and physical closeness, CARAC creates mobility-aware clusters. Nevertheless, controlled-environment simulations fall short in accurately simulating actual mobility situations. Unpredictable changes in the terrain, actual driver behavior, and obstructions may affect performance [26]. This article suggests a "deep deterministic policy gradient-based sequential decision algorithm" that instructs the self-driving automobile to stay in its lane by acting as a learning agent, pass stationary and moving vehicles, and steer clear of frontal and right-side collisions. The proposed system does not take into consideration changes in the weather, road conditions, traffic light directions, lighting levels, etc. [27]. This article proposes an effective safety message distribution system that targets "urban areas with high vehicle density and mobility". By taking into account "frequent cluster departures and subscriptions" using an effective "cluster management strategy", the suggested scheme lowers packet loss. There are two types of safety message distribution in a vehicle-to-vehicle setting: inter-cluster emergencies, in addition to a general safety message dissemination method. However, this proposed work does not take into account important real-world factors that could impact "V2V communication performance", such as road volume, quantity of lanes, vehicle characteristics, landscape, obstacles, speed limitations, etc. [28]. In this paper, a novel framework for "combining Network Functions Virtualization (NFV) and Software-Defined Networking (SDN)" as embedded functions in connected automobiles is proposed. However, the proposed system requires optimization, because it introduces a processing delay at the SDN gateway [29]. This study provides an offloading approach for heterogeneous VECN that takes into account "mobility, contact, and computational load". The "MCLA scheme" optimizes performance by integrating "Mode-1 and Mode-2 of the 5G-NR-V2X standard, as well as mmWave communications". Although frequent message exchanges between the edge server and the vehicle's OBU can result in higher delay and communication overhead [30]. In this study, they suggest a "pedestrian protection" mechanism that relies on "vulnerable road users and smart vehicles communication". They used "NS-3" to simulate various traffic scenarios. It assessed key network metrics like average "throughput, processing delay, and network load". Nevertheless, it might not accurately reflect the variety of pedestrian behaviors, abrupt direction changes, and interactions with the surroundings that occur [31].

This study suggests a seamless changeover system that uses the Media-Independent-Changeover (MIH) Framework and Software-Defined Networking (SDN) to execute dynamic topology changes in VANETs. The VANETs both contribute positively to the handover scheme. Nevertheless, variable density will produce greater amounts of packet loss, with changes in vehicle speed causing problems with a low packet ratio being one area of concern [32]. The author presents V2X communications; this study proposes a Double Deep Q-Network (DDQN)-based dual connectivity controller that uses RSU cooperation to intelligently coordinate handover choices and interface selection. Proactive handover decisions are made possible by the suggested solution's introduction of a thorough 10-dimensional state representation that explicitly incorporates RSU proximity, RSRP, SINR, cluster dynamics, and handover history. Through explicit handover cost penalties and ping-pong detection procedures, an advanced multi-objective reward function strikes a balance between handover frequency and performance benefits. Despite having excellent functionality, these systems are still facing major limitations due to coordinating distributed RSUs, backhaul restrictions, integration of heterogeneous RSU capabilities, and scalability issues with respect to large quantities of vehicles & secure handover integration [33]. The research paper presents “services for in-vehicle communication"; this study incorporates two “vehicular communication technologies—dedicated short-range communication (DSRC) and C-V2X”—into a framework known as “cluster-based traffic differentiated hybrid routing (CTDHR)”. They propose a hierarchical clustering-based vehicle clustering method to address issues. The generated clusters were used to simulate the CTDHR framework, and an objective equation was developed. Lastly, we suggest a heuristic technique to tackle this optimization problem because the derived nonlinear integer programming problem is the objective equation. In the simulation trials, CTDHR outperforms the current “DSRC and C-V2X hybrid models” in terms of communication. While CTDHR is within an acceptable range; it is marginally less effective. It is evident that CTDHR’s throughput remains low after the aforementioned optimizations [34]. This paper presents a study for evaluating how reliable VANET to connect based on both patterns of node movement and methods of failure, including hardware and software failure, out of power, attacks, and isolated nodes. Additionally, they introduce an algorithm for identifying the most optimal routing paths, as well as describe our approach to VANET connectivity in order to verify the connectivity of the VANET. However, the approach is constrained by using a binary communication paradigm for determining link reliability in VANETs, such that it fails to factor in the impact that the interaction between link throughput and capacity has on the information processing workload required by the respective nodes [35]. This study suggests a versatile and embeddable stochastic intention vector creation method to better reflect the stochastic characteristics of pedestrian behaviour and predict abrupt changes in pedestrian intentions in real-world scenarios. Firstly, in order to dynamically combine past trajectory data with random variables to explicitly characterize the direction and velocity changes brought on by “random pedestrian intentions”. The second is a “new intention loss function” that is used to dynamically depict “pedestrian intention changes” by guiding the system to understand the possibility of purpose alterations in an adaptive way. Any baseline pedestrian trajectory prediction system can incorporate our generalizable approach as an embeddable module. Even so, this approach suffers from the simplicity of its representation of the scene information, which does not allow for a full representation of the variety and complexity of pedestrian movements [36]. In Table 1, the summary of Existing works is presented.

Table 1
Summary of Existing works

References	Objectives	Algorithms or methods used	Limitations
[21]	The 5G NR infrastructure to increase the accuracy and performance of V2V communication.	“IDM-LC and IDM-A” for V2V communication.	• Real-world performance deployment issues occur.
[22]	Federated learning across vehicles is training the model.	The SDNCA framework assisted 5G.	• It does not assess performance based on a large-scale network with thousands of controllers.
[23]	Road and traffic data: the model is utilised to create safe, effective, and comfortable automobile following behaviour.	DRL-based intelligent speed control method for AVs in CVISs	• The model does not consider multi-vehicle interactions or lane changing.
[24]	To decrease latency, the data collection, analysis and vehicle grouping are used.	Cluster-based routing protocols and pattern discovery techniques.	• The estimation of the route pattern of automobiles on silent highways, the method accuracy will be reduced.
[25]	The back-off values for high-standard results analysis based on vehicle ID	“Traffic density-based congestion control algorithm (TDCCA)” for increasing the effectiveness.	• The model does not constantly analyse the traffic, and the proposed model needs more calculation time.
[26]	To improve traffic safety and mobility by designing ITS for real-time vehicle communication.	CARAC is used for higher route discovery success and lower latency.	• Unpredictable changes in the terrain, actual driver behavior, and obstructions may affect performance.
[27]	The intelligent agent is capable of observing and perceiving the dynamic and complex road environment.	Sequential decision algorithm for lane maintenance and overtaking with collision avoidance based on deep deterministic policy gradients.	• Limited by does not take into consideration changes in the weather, road conditions, traffic light directions, lighting levels, etc.
[28]	The proposed method is used to reduce the packet loss through an efficient cluster management technique.	An efficient safety message dissemination scheme reduces the processing request and duplicate messages.	• The proposed method does not consider V2V communication performance such as vehicle characteristics, speed limitations, and quantity of lanes.
[29]	The model is used for efficient management of data, networks and identities.	The NFV and SDN method for virtualised and distributed 5G VANET.	• Nevertheless, the model requires optimization, because it introduces a processing delay at the SDN gateway.

[30]	The model takes into account the vehicles' movement, contact, and computing burden when deciding how to offload tasks.	MCLA task offloading scheme for reducing communication latency.	• The message exchange between the edge server and the vehicle's OBU can result in a higher delay.
[31]	Pedestrian safety system with two-way communication based on VANET	Pedestrian protection mechanism for empowering pedestrian safety.	• It does not reflect the variety of pedestrian behaviours and abrupt direction changes.
[32]	To enhance network performance, when handover occurs.	MIH and SDN framework to execute dynamic topology changes in VANET.	• Nevertheless, variable density occurs with a greater amount of packet loss.
[33]	The intelligent handover and urban V2X dual connectivity network.	Double Deep Q-Network (DDQN) for enhanced V2X communication.	• Limited by backhaul restrictions and scalability issues
[34]	The model is used to design and provide services for in-vehicle communication.	CTDHR is used for better communication.	• It is evident that CTDHR's throughput remains low after the aforementioned optimizations.
[35]	To perform various communication latency and search and rescue operations.	Routing path identification algorithm, connective reliability of VANET	• The model fails to link throughput and capacity to the information processing workload required by the respective nodes.
[36]	To better reflect stochastic characteristics of pedestrian behavior and predict abrupt changes in pedestrian intentions in real-world scenarios	Flexible and embeddable stochastic intention vector construction strategy, pedestrian trajectory prediction	• It does not allow a full representation of the variety and complexity of pedestrian movements.

III. PROBLEM STATEMENT

The numerous existing works and their associated responses are arranged in sequence of publication in this section. Furthermore, this study offers the research solutions for the mentioned issues.

Specific research work & Issues: This article suggests a decision tree-based autonomous and intelligent technology selection method. The program gathers characteristics, including inter-vehicular "Cooperative Intelligent Transport Systems (C-ITS) Cooperative Awareness Messages (CAMs)". The "decision tree" that chooses the "best technology (DSRC, C-V2X PC5, or 5G) for the next planned C-ITS message transmission" uses these statistics as input [37]. This study presents an approach to modeling a vehicle's "Adaptive cruise control and overtakes assist (ADAS)" functions. The self-interest vehicle uses a longitudinal "Model Predictive Controller (MPC)". This setup models the physical structure for "adaptive cruise control (ACC)". The MPC determines a safe distance using an appropriate time interval and compares it with the relative separation, switching between distance and speed control as needed [38]. Some of the problems detected in these papers are the following:

- High vehicle density and frequent DENM message transmissions lead to increased congestion in the network and subsequently result in more one-way end-to-end latency.
- However, the existing system simply tells the driver if the overtaking is safe. Based on research on a vehicle's longitudinal and lateral dynamics, the system might recommend any necessary speed changes as well as the steering angle to execute the overtake.

In article [39], to provide a new visual collision cue-based model for the beginning of crossing decisions in order to propose time-dynamic crossing decisions. A traffic gap approach is used to describe and simulate "pedestrian" coming up behavior in "traffic flow" in light of the risk-aversion hypothesis. In article [40], the author proposes In VANETs, this article suggested "a cluster-based enhanced authentication and communication protocol for an intelligent transportation system". Improving vehicle communication through resource sharing optimization is our main goal. By implementing "cluster-based routing protocols for V2V and Vehicle-to-Infrastructure (V2I) communications", they improved the stability and dependability of "fast-moving VANETs".

Some issues are focused in this research include:

- However, there might be more complex pedestrian decision-making patterns in the traffic flow in the proposed system.
- Although the urban area can be expanded, the proposed method doesn't evaluate the scalability and robustness.

Research solution: this mainly focusing to mitigate the above determined existing challenges. So, we proposed method which is given below:

In situations with a high vehicle density, the ANS-V2X algorithm fully minimizes the one-way "end-to-end latency" and decreases congestion by optimizing message scheduling and resource allocation. During overtaking, the DRL-based method employing the DDPG algorithm is used to control vehicle steering and speed. It offers proper guidance for collision avoidance and lane keeping, instead of only specifying whether overtaking is safe. A DMARL technique can be employed to model pedestrians in terms of intelligent learning agents, thereby allowing the modeling to enable the capture of complex, adaptive decision-making behaviors. To enhance the scalability and robustness in growing urban areas using the AF-MARL approach.

IV.SYSTEM MODEL

A. Network Construction Model:

The cooperative vehicular networks, vehicles exchange safety messages through wireless communication links to support real-time decision making. The vehicular network can be represented as dynamic graph $G = (V, E)$, where V represents set of vehicles and E represents the communication links established between neighboring vehicles. The communication flow between vehicles depends on their transmission range and relative positions. The distance between two vehicles i and j is defined as:

$$d_{ij} = \sqrt{(x_i - x_j)^2 + (y_i - y_j)^2} \quad (1)$$

Where d_{ij} represents Euclidean distance between vehicles i and j, While $(y_i)$and $(y_j)$is a spatial coordinate. The communication data flow between vehicles can be expressed as

$$F_{ij} = B_{ij} log\,_2(1 + SNR_{ij}) \quad (2)$$

Where F_{ij} denotes achievable communication flow rate between vehicles i and j. B_{ij} represents available channel bandwidth. SNR_{ij} denotes "signal-to-noise ratio" of the wireless link. The network flow formulation enables efficient dissemination of safety messages among neighboring vehicles.

B. Latency Model:

Low communication latency is important for safety message delivery in vehicular environments. The "end-to-end communication delay" mainly consists of "transmission and propagation delay". The transmission delay is defined as

$$D_{tx} = \frac{S}{B} \quad (3)$$

T_{tx} represents the time required to transmit a packet, S denotes packet size in bits and B is a communication bandwidth. The propagation delay between vehicles is expressed as

$$D_{prop} = \frac{d_{ij}}{C} \quad (4)$$

Where T_{prop} represents the signal propagation delay, d_{ij} is the communication distances between vehicles and C is the speed of electromagnetic wave propagation. The overall latency directly affects the responsiveness of cooperative safety applications.

C. Dynamic Overtaking decision model:

In self-driving vehicles, dynamically deciding whether or not to overtake another vehicle is vital to operating well within dense traffic. Every vehicle will consider whatever is around it in its environment to decide if an overtaking operation will be done safely or not. The relative velocity of two vehicles is expressed as:

$$v_r = v_i - v_j \quad (5)$$

Where v_i and v_j denote velocities of the ego vehicle and the preceding vehicle and v_r represent relative velocity, respectively. The safety distance required for overtaking is expressed as

$$d_s = v_i T_r + \frac{v_i^2}{2a} \quad (6)$$

Where T_r represents the driver or system reaction time, D_s denotes minimum safe overtaking distance, v_i is a velocity of the vehicle and a denotes vehicle deceleration capability. The model ensures overtaking manoeuvres are performed only when sufficient safety distance is available.

D. Multi-Agent interaction Modeling:

In cooperative driving environments, multiple vehicles interact simultaneously. The interaction can be modelled using a "multi-agent framework" where each vehicle as an autonomous agent. The state of an agent time t is defined as

$$\mathcal{S}_t = \{p_i, v_i, a_i\} \quad (7)$$

Where p_i, v_i, a_i is denoted as "position, velocity and acceleration" of vehicle i. The reward function guiding cooperative behaviour is expressed as:

$$\mathbb{R}_i = w_1 \mathbb{S}_i + w_2 E_i - w_3 C_i \quad (8)$$

w_1, w_2, w_3 are represented as weighting parameters, and $\mathbb{R}_i$ a reward of a vehicle i. $\mathbb{S}_i$ denotes safety performance and E_i driving efficiency. The formulation encourages cooperative decision-making among multiple vehicles.

E. Scalability and Robustness-Awareness Optimization

A large-scale vehicular network for maintaining reliable operations has a scalability and robustness optimization feature. The optimization allows for the system to continue performing reliably under conditions of increased numbers of vehicles. The scalability performance of the network can be defined by

$$\eta = \frac{T_{base}}{T_{system}} \quad (9)$$

η represents scalability efficiency, T_{system} denotes system processing time under increased network load and T_{base} denotes baseline processing time. Robustness against communication uncertainty is expressed as

$$R = 1 - P_{loss} \tag{10}$$

Where R is a robustness level of the network and what P_{loss} denotes the packet loss probability during communication. These optimization mechanisms enhance reliability and scalability of cooperative vehicular communication systems.

V. PROPOSED METHODOLOGY

This paper proposes a framework for minimizing end-to-end delay by integrating multiple access points to facilitate assistance for overtaking, to support lane keeping, to assist in avoiding accidental collisions, to enhance safety for pedestrians, and to provide greater scalability for the system. The overall proposed architecture is shown in Fig 1. The suggested work includes five sequential works as follows,

- Network Construction & Data Collection
- Latency-aware warning dissemination
- Dynamic overtaking decisions
- Vehicle interaction and Decision modeling
- Scalability-and Robustness-Aware Optimization

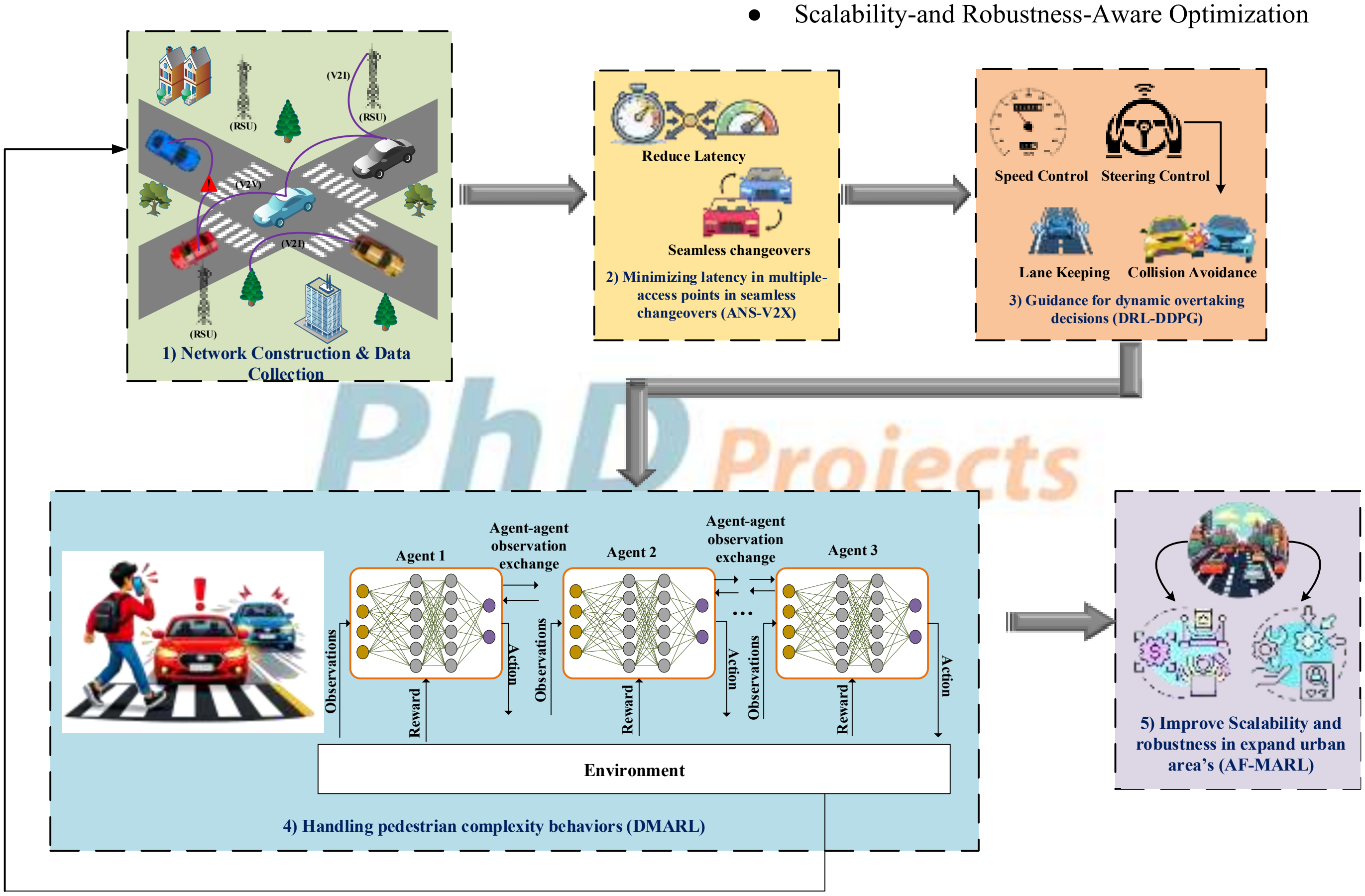

Fig 1. Overall Proposed architecture

A. Network Construction & Data Collection

The network's architecture is a multi-access V2X network made up of V2V, V2I, and V2N communications. All vehicles have OBUs that support both 5G NR-V2X that is standardized by 3GPP, as well as DSRC (802.11p). The infrastructure layer consists of RSUs, 5G base stations, and cloud servers. A multi-RAT mechanism allows for the dynamic switching of 5G and DSRC to provide low-latency and reliable communication through high-density urban traffic. A collection of 2300 records collected in a variety of cooperative autonomous driving situations using a V2X-enabled VANET system. The data includes multiple types of agent sensor data as well as different types of network metrics, including latency, packet delivery ratio, etc. Specifically, under simulated conditions of delay as a result, they are suitable for evaluating both collision detection and decision-making accuracy as well as intelligent driving with knowledge of communication requirements within the proposed framework.

B. Latency-aware warning dissemination: -

The approach integrates the protocol for distributed safety warnings using Decentralized Environmental Notification Message (DENM) with a multi-Radio Access Technology (RATs) network for an "Adaptive Network Selection framework tailored for latency-aware density scenarios". V2X systems (ANS-V2X) under varying vehicle and network" density scenarios. In Fig 2. Latency-aware warning dissemination is presented. Vehicles integrate multiple access points (5G, DSRC) that decrease the overall end-to-end delay, including transmission and changeover delays, and prioritize DENM messages as latency-critical traffic. To prevent congestion using bandwidth and computation constraints, while seamless changeovers across multiple overlying access points provide low-latency communication in high-density scenarios. The proposed integrated framework jointly models latency-aware safety warning dissemination and deep reinforcement learning based cooperative vehicle control in a unified mathematical structure. The overall one-way end-to-end delay experienced by a safety message is defined as

$$D_{e2e} = D_{tx} + D_{queue} + D_{prop} + D_{proc} + D_{ho} \tag{11}$$

Where D_{tx} denotes transmission delay, D_{queue} represents queuing delay caused by buffer congestion, D_{prop} corresponds to propagation delay across a wireless medium, D_{proc} indicates processing delay at intermediate infrastructure nodes such as RSUs or base stations, and D_{ho} represents handover delay introduced during switching between heterogeneous radio access technologies (RATs). This additive decomposition enables analytical evaluation of delay contributions from each network component and forms the basis for latency minimization in time-critical vehicular safety and expressed as,

$$D_{tx} = \frac{L}{R} \tag{12}$$

Where R is the current achievable rate of sending data in bits per second and L is the size of a safety packet in bits. The length of time that data can be sent will increase or decrease as a result of how many packets are being sent or how much bandwidth the channel has available. The following is the maximum rate possible through a wireless channel:

$$R = B\log_2(1 + SINR) \tag{13}$$

Where $SINR$(Signal-to-Interference-plus-Noise Ratio) represents the ratio of the reference signal to the total interference and noise when measured with respect to a specific frequency (bandwidth). The effects of physical layer spectral regulation (spectrum allocation), fading and interference are included via the formulation to capture their impact on network latency. The delay due to propagation can be expressed as shown below:

$$D_{prop} = \frac{d}{c} \tag{14}$$

Where C denotes physical distance between transmitter and receiver, then c is a speed of electromagnetic wave propagation. This component becomes more important in V2N scenarios involving cloud servers, even if it is usually minimal in urban terrestrial networks. Under stochastic traffic arrivals, queueing delay is modeled as

$$D_{queue} = \frac{\lambda}{\mu(\mu-\lambda)} \tag{15}$$

Where λ denotes "packet arrival rate" and μ is the service rate of the communication node. Congestion-induced latency escalation is caused by high vehicle density and frequent DENM transmissions, as evidenced by the traffic intensity ratio λ/μ approaching unity and the rapid growth of queue delay. The handover delay between heterogeneous access technologies is represented as

$$D_{ho} = T_{scan} + T_{auth} + T_{assoc} \tag{16}$$

Where T_{scan} is network scanning time, T_{auth} and T_{assoc} is authentication and association time. Particularly in dense urban deployments, frequency mobility-driven handovers lower reliability and increase delay variance. The reliability of safety message dissemination is defined as

$$\mathcal{P}_s = 1 - P_{loss} \tag{17}$$

Where $\mathcal{P}_s$ represents the probability of successful message delivery and P_{loss} is "packet loss probability due to collisions", fading and interference. The optimal radio interface selection minimizing delay while preserving reliability is formulated as

$$r^* = arg\ min_{r\in R}\, D_{e2e}(r)\ \ P_s(r) \geq \gamma \tag{18}$$

Where r^* is the candidate RAT set and what γ denotes minimum acceptable reliability While exceeding the safety criteria, this limited optimisation ensures that the lowest-latency interference is chosen. $\mathcal{P}_s$ is a successful probability. The cooperative driving control problem is modelled as an MDP

$$M = (\mathcal{S}, A, \mathbb{P}, \mathbb{R}, \gamma) \tag{19}$$

Where S is the state space capturing vehicle and network conditions, A is the continuous action space, P is a state transition dynamic, $\mathbb{R}$ is a reward function and γ is it a discount factor. The formulation enables optimal sequential decision-making under uncertainty. The state vector at time t is,

$$\mathcal{S}_t = [d_{rel}, v_{rel}, e_{lane}, D_{e2e}, \rho] \tag{20}$$

Where d_{rel} is relative inter-vehicle distance, v_{rel} is relative velocity, e_{lane} is lateral lane deviation, D_{e2e} represents current communication delay, and ρ denotes traffic density. Including D_{e2e} ensures that control policies adapt to network conditions. The longitudinal velocity update is

$$v_{t+1} = v_t + a_t \Delta t \tag{21}$$

Where v_t is current velocity, a_t is acceleration control input, and Δt is sampling interval. The discrete-time kinematic model approximates vehicle motion under moderate speeds. The longitudinal position update follows

$$x_{t+1} = x_t + v_t \Delta t + \frac{1}{2} a_t \Delta t^2 \tag{22}$$

Which models forward displacement under constant acceleration during the sampling interval. The lateral motion is described as

$$y_{t+1} = y_t + v_t \sin(\delta_t) \Delta t \tag{23}$$

Where δ_t denotes steering angle. This captures lane-changing and overtaking behavior. Collision imminence is quantified using Time-to-Collision (TTC):

$$TTC = \frac{d_{rel}}{v_{rel}} \tag{24}$$

Which estimates time remaining before collision, assuming constant relative velocity. The collision risk C_{risk} metric is defined as

$$C_{risk} = \frac{1}{TTC} \tag{25}$$

Which indicates that risk increases inversely with available safety margin. The deterministic actor policy is

$$a_t = \mu(S_t \mid \theta^{\mu}) \tag{26}$$

Where θ^{μ} denotes actor network parameters and a_t consists of acceleration and steering commands. The mapping determines real-time control actions. The critic value function is

$$Q(s_t, a_t) = E[\sum_{k=0}^{\infty} \gamma^k \mathbb{R}_{t+k}] \tag{27}$$

$Q(s_t, a_t)$ is an additional value function (Q-value) $E[.]$ is an expectation operator. $\mathbb{R}_{t+k}$ is a reward received at time $t+k$. The temporal-difference learning target:

$$y_t = \mathbb{R} + \gamma Q'(s_{t+1}, \mu'(s_{t+1})) \tag{28}$$

Where Q' and μ' are targets, networks providing stable gradient updates. The latency-aware reward formulation is:

$$\mathbb{R}_t = -\alpha D_{e2e} - \beta C_{risk} - \lambda e_{lane}^2 + \eta V_{prog} \tag{29}$$

Where weighting coefficients $\alpha, \beta, \lambda, \eta$ regulate trade-offs between communication delay, collision risk, lane stability and overtaking progress. V_{prog} is a vehicle progress. Finally, the overall optimization objective is

$$\min E[\sum_{t=0}^{T} (\alpha D_{e2e} + \beta C_{risk} + \lambda e_{lane}^2)] \tag{30}$$

Optimizing autonomous control performance and communication efficiency in cooperatively networked vehicle contexts can lead to so called "real-time delivery of safety alerts". The combined approach ensures that both latency and safety risk associated with a stochastic network and traffic dynamics are minimized over a period T.

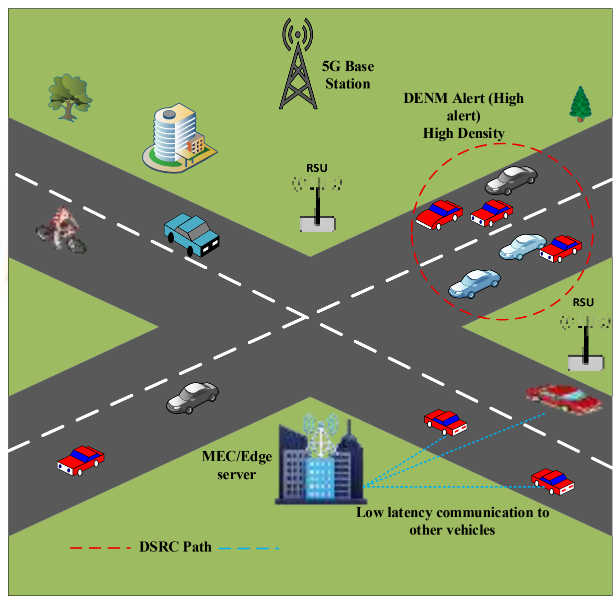

Fig 2. Latency-aware warning dissemination

B. Dynamic overtaking decisions:

After minimizing end-to-end latency, the proposed system utilizes a "deep reinforcement learning (DRL)-based deep deterministic policy gradient (DDPG) method". An objective of the model is not only to indicate whether it is safe to perform the overtaking maneuver but also to provide optimal acceleration and steering angle commands by taking into account both longitudinal and lateral vehicle dynamics. The agent learns a series of continuous control actions to safely perform the overtaking maneuver and maintain stable lane keeping and avoid collisions based upon relative distance, velocity, and lane position of the vehicle. In Fig 3. Dynamic overtaking decisions is shown.

The dynamic overtaking decision mechanism is integrated with a DRL-based "Deep Deterministic Policy Gradient (DDPG)" algorithm to generate continuous acceleration and steering commands under real time traffic and communication constraints. Unlike conventional rule-based overtaking systems that only classify maneuvers as safe or unsafe, the proposed approach formulates overtaking as a "continuous time optimal control problem" within a Markov Decision Process (MDP). The Agent observes the relative kinematic state, lane geometry and communication parameters and produces optimal control inputs that guarantee safe overtaking, lane-keeping stability and efficient overtaking. The overtaking "decision-making problem" can be considered an MDP in equation (19).

The state vector at time $t$is defined as

$$\mathcal{S}_t = [d_{rel}, v_{rel}, d_{opp}, v_{opp}, e_{lane}] \tag{31}$$

Where d_{rel}, v_{rel} represented as relative distance and velocity with respect to the preceding vehicle, $d_{opp}$and v_{opp} denotes distance and velocity of oncoming(opposite) vehicles in the opposite lane, and e_{lane} is lateral deviation from lane center. The continuous action generated by the agent is

$$a_t = [a_t^{acc}, \delta_t] \tag{32}$$

Where a_t^{acc} is longitudinal acceleration and δ_t is steering angle. These continuous control inputs allow smooth overtaking maneuvers. The deterministic policy function in the DDPG framework is expressed as

$$a_t = \mu(\mathcal{S}_t \mid \theta^{\mu}) \tag{33}$$

Where μ denotes the actor network and θ^{μ} represents its parameters. This mapping directly produces optimal acceleration and steering actions. Vehicle longitudinal velocity dynamics are modelled as

$$v_{t+1} = v_t + a_t^{acc} \Delta t \tag{34}$$

Where v_t is current velocity and Δt is sampling interval. This discrete time kinematic model governs speed variation during overtaking. The longitudinal position update is given by

$$x_{t+1} = x_t + v_t \Delta t + \frac{1}{2} a_t^{acc} \Delta t^2 \tag{35}$$

Where x_t represents longitudinal position. It ensures smooth acceleration based overtaking transitions. The lateral vehicle motion during lane change is approximated by,

$$y_{t+1} = y_t + v_t sin\,(\delta_t) \Delta t \tag{36}$$

Where y_t represents lateral position and δ_t steering input. This model smooth lateral displacement into the adjacent lane. Collision risk with the preceding vehicle is quantified using Time-To-Collision (TTC):

$$TTC_{lead} = \frac{d_{rel}}{v_{rel}} \tag{37}$$

Where smaller TTC_{lead} indicates imminent collision risk. Similarly, collision risk with an oncoming vehicle is expressed as

$$TTC_{opp} = \frac{d_{opp}}{v_t + v_{opp}} \tag{38}$$

Which measures available time before frontal conflict during overtaking. The safety risk metric combining both interactions is defined as

$$C_{risk} = \frac{1}{TTC_{lead}} + \frac{1}{TTC_{opp}} \tag{39}$$

TTC_{lead} denotes Time-to-collision with lead vehicle, Which increases as available safety margins decrease. The action-value function is defined as

$$Q(\mathcal{S}_t, a_t) = E[\sum_{k=0}^{\infty} \gamma^k r_{t+k}] \tag{40}$$

Representing expected cumulative discounted reward. The Bellman target for critic update is

$$y_t = \mathbb{R}_t + \gamma Q'(\mathcal{S}_{t+1}, \mu'(\mathcal{S}_{t+1})) \tag{41}$$

Where Q' and μ' are target, networks ensuring stable convergence. The dynamic overtaking reward function is formulated as

$$\mathbb{R}_t = -\alpha C_{risk} - \beta e_{lane}^2 - \lambda \mid a_t^{acc} \mid + \eta V_{prog} \tag{42}$$

Where $\alpha, \beta, \lambda, \eta$ are weighting coefficients; C_{risk} penalizes unsafe proximity; e_{lane}^2 penalizes lane deviation; $\mid a_t^{acc} \mid$ discourages excessive acceleration; and V_{prog} rewards forward progress. Finally, the overall overtaking optimization objective over horizon T is

$$min\ E[\sum_{t=0}^{T} (\alpha C_{risk} + \beta e_{lane}^2 + \lambda a_t^2)] \tag{43}$$

The integrated DRL system is used as the basis for optimizing the driver and vehicle during overtaking through the use of online full-state feedback. The actor-critic structure ensures optimum steering/acceleration inputs in real-time while maintaining safety distances from both lead and approaching vehicles, and the system continually fine-tunes these inputs as needed by applying predictive control so that both the vehicle and driver are able to overtake in the safest manner possible with the lowest collision risk, stable over time under a variety of conditions, and operated in a manner that minimizes the amount of control action required. The pseudocode for Deep Deterministic policy Gradient is presented in algorithm 1.

Algorithm 1: Deep Deterministic Policy Gradient (DDPG) Method

Input: Real-time vehicle state S_t(relative distance, velocity, lane deviation, oncoming vehicle state)

1. Initialize network parameters θ^{μ} and critic network parameters θ^{Q}
2. Initialize target networks $\theta^{\mu'} \leftarrow \theta^{\mu}$, $\theta^{Q'} \leftarrow \theta^{Q}$
3. Observe current stateS_t from vehicle sensors and V2X communication
4. Compute Time-to-collision (TTC) with leading and oncoming vehicles
5. Form state vector including longitudinal and lateral safety constraints
6. Generate continuous action $a_t = (accleration, steering)$ using actor network
7. Apply action a_t to vehicle kinematic model
8. Update vehicle position and velocity using motion
9. Calculate collision risk and lane deviation error
10. Compute reward based on safety, lane stability and overtaking progress
11. Store transition (S_{t+1}) in replay buffer
12. Sample mini-batch from replay buffer for training
13. Update critic network using temporal difference loss
14. Update network using policy gradient
15. Soft-update target networks and repeat until overtaking maneuver completes
16. **End**

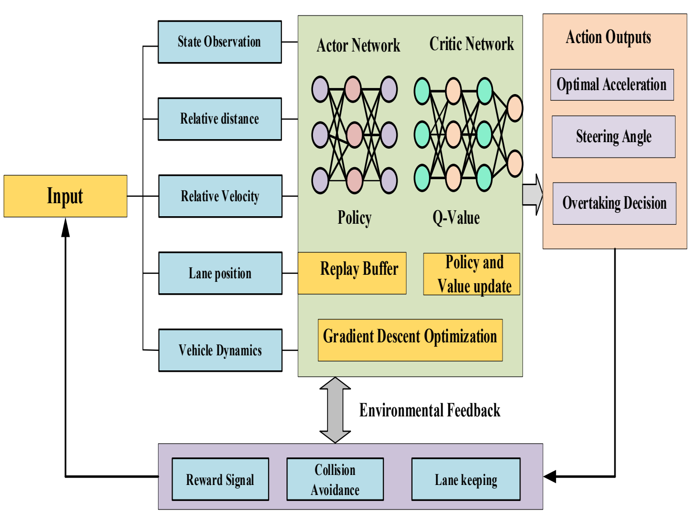

Fig 3. Dynamic overtaking decisions

D. Vehicle interaction and decision modeling

The Deep Multi-Agent Reinforcement Learning (DMARL) method is used in the proposed system to identify intricate pedestrian decision-making patterns after providing the guide assistance for overtaking maneuvers. By detecting traffic density, vehicle speed, and accident risk, pedestrians and vehicles are modeled as intelligent agents who acquire adaptive crossing behaviors. The system learns dynamic pedestrian behaviors and enhances traffic flow stability and safety by rewarding safe crossing and collision avoidance while penalizing dangerous activities. The Deep Reinforcement learning for real time safety warning dissemination in cooperative driving environments, vehicle interaction and decision modelling is formulated as a coupled stochastic dynamic optimization problem in which each connected autonomous vehicle (CAV) operates as an intelligent agent interacting with surrounding vehicles through physical motion dynamics and cooperative safety awareness. In Fig 4. Vehicle interaction and decision modeling is presented. The theoretical foundation is established by modeling the environment as a "Multi-Agent Markov Decision Process (MAMDP)" is expressed in equation (19),

The global system state at time t is defined as,

$$\mathcal{S}_t = \{\mathcal{S}_t^1, \mathcal{S}_t^2, \dots, \mathcal{S}_t^N\} \tag{44}$$

Where s_t^i denotes local state vector of vehicle i. The individual vehicle state is expressed as

$$\mathcal{S}_t^i = [x_t^i, y_t^i, v_t^i, a_t^i, \psi_t^i] \tag{45}$$

Where x_t^i and y_t^i denotes longitudinal and lateral positions in a global coordinate frame, v_t^i denotes longitudinal velocity, a_t^i is an acceleration and ψ_t^i is heading angle. The spatial coupling between vehicles i and j using "Euclidean distance"

$$d_{ij}(t) = \sqrt{(x_t^i - x_t^j)^2 + (y_t^i - y_t^j)^2} \tag{46}$$

Since the risk of a collision increases with decreasing distance, this parameter has a direct impact on contact intensity. The relative speed can be determined using:

$$v_{ij}(t) = v_t^i - v_t^j \tag{47}$$

Which describes closing speed. If $v_{ij} > 0$, vehicle j, increasing collision likelihood; if negative, vehicles are separating. Vehicle motion evolves according to discrete time kinematic dynamics. The longitudinal velocity is update is

$$v_{t+1}^i = v_t^i + a_t^i \Delta t \tag{48}$$

The longitudinal position update is

$$x_{t+1}^i = x_t^i + v_t^i \Delta t + \frac{1}{2} a_t^i \Delta t^2 \tag{49}$$

Second-order integration of motion equations. These equations guarantee smooth acceleration-based trajectory generation. The lateral motion influenced by steering control δ_t^i:

$$y_{t+1}^i = y_t^i + v_t^i sin\,(\delta_t^i)\Delta t \tag{50}$$

It relates steering angle to lateral displacement to simulate lane-keeping or lane-change actions. Time-To-Collision (TTC), which is defined as

$$TTC_{ij} = \frac{d_{ij}}{max\,(v_{ij},\epsilon)} \tag{51}$$

Where $\in> 0$ prevents division by zero. TTC represents remaining time before impact assuming constant relative velocity. To convert temporal safety margin into risk metric suitable for optimization, interaction risk is defined as

$$C_{ij} = \frac{1}{TTC_{ij}} \tag{52}$$

C_{ij} is a Collision risk cost between vehicle i and vehicle j. The cumulative interaction risk experienced by vehicle i is

$$C_i = \sum_{j\neq i}^{i} w_{ij} C_{ij} \tag{53}$$

The normalized weighting coefficient w_{ij}represent the degree to which a vehicle is affected by properties of surrounding vehicles through their proximity or alignment to one another. The aggregation of all surrounding vehicles contributes to the overall effects of all surrounding vehicles on the control policy of vehicle i, which is determined by a deterministic function.

$$a_t^i = \mu^i(\mathcal{S}_t^i \mid \theta^i) \tag{54}$$

Where μ^i represents neural network parameterized by θ^i. The output action $a_t^i = [a_t^{acc}, \delta_t^i]$ includes acceleration and steering commands, enabling continuous control. The joint system action is

$$a_t = \{a_t^1, \dots, a_t^N\} \tag{55}$$

Which simultaneously determines the next global state via coupled vehicle dynamics. The expected cumulative reward for vehicle i is

$$Q^i(\mathcal{S}_t, a_t) = E\left[\sum_{k=0}^{\infty} \gamma^k r_{t+k}^i\right] \tag{56}$$

Which quantifies long-term performance of policy μ^i. The Bellman consistency condition is

$$Q^i(\mathcal{S}_t, a_t) = r_t^i + \gamma E[Q^i(s_{t+1}, a_{t+1})] \tag{57}$$

Ensures recursive optimality in value estimation. The reward function balancing safety, comfort and efficiency is formulated as

$$\mathbb{R}_t^i = -\alpha C_i - \beta e_{lane,i}^2 - \lambda (a_t^i)^2 + \eta v_t^i \tag{58}$$

Where C_i penalizes cumulative interaction risk, $e_{lane,i}$ represents lane deviation error ensuring lateral stability, $(a_t^i)^2$ penalizes aggressive acceleration for passenger comfort, and v_t^i rewards forward mobility. The coefficient $\alpha, \beta, \lambda, \eta$ define the relative importance of each objective. The interaction confidence factor is defined as

$$\phi_{ij} = \mathcal{P}_{s,ij} e^{-D_{e2e,ij}} \tag{59}$$

Where $\mathcal{P}_{s,ij}$ denotes successful safety message delivery probability and $D_{e2e,ij}$ denotes communication delay. The adjusted communication interaction risk becomes

$$\tilde{C}_{ij} = C_{ij}(1 - \phi_{ij}) \tag{60}$$

It supports conservative management measures and raises risk in the event of inconsistent communication. The worldwide joint goal for all vehicles is

$$J = \sum_{i=1}^{N} E\left[\sum_{t=0}^{T} \gamma^t r_t^i\right] \tag{61}$$

Which maximizes collective efficiency and safety. J is a total objective function. Finally, the optimal policy set satisfies

$$\{\mu^{1*}, \dots, \mu^{N*}\} = arg\ max\ J \tag{62}$$

The cooperative equilibrium strategy will both decrease the likelihood of crashes (or accidents) and provide a consistent flow of traffic by ensuring that there is a sufficient distance between vehicles in order to increase that flow, by providing all vehicles the opportunity not just to have their travel times optimized, but also to have a stable flow over time. The methodology to develop these strategies will rely on an analytical framework that will integrate agents, stochastic control systems, non-linear dynamics, proximity-based interaction models, communication-aware adaptations of risk, and deep reinforcement learning optimization. The optimal action for each vehicle/agent will be determined through a continual evaluation of the following: The degree of "spatial coupling" of the vehicles; The predicted time until a collision occurs between any two vehicles and the reliability of the information cooperatively shared between the vehicles. The establishment of a rigidly defined procedure for establishing this analytical framework will provide the stability required for convergence to a safe, cooperative equilibrium as well as real-time adaptability of all vehicles.

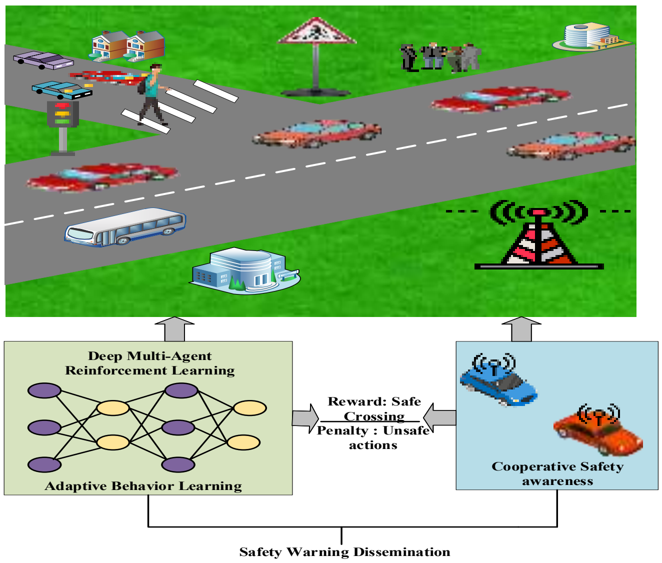

Fig 4. Vehicle interaction and decision modeling

E. Scalability and Robustness Aware Optimization:

Using the previously established MARL framework for intricate pedestrian behavior decision-making, extending that model through the inclusion of Adaptive Federated Learning (AdFL) into adaptive federated multi-agent reinforcement learning (AF-MARL) makes it more scalable and robust across larger-scale urban directional environments. The semi-synchronous federated aggregation combined with CVAE-based representations increases stability and adaptability of the learning process to dynamic, non-IID traffic conditions through training quality. The proposed real time safety warning dissemination and cooperative driving framework is modelled as unified stochastic optimization problem integrating latency-aware communication, continuous vehicle control, pedestrian interaction modelling and scalability robustness enhancement within deep reinforcement learning. The entire system is formulated as a MAMDP in equation (19), The global state at time t is defined as

$$\mathcal{S}_t = \{x_i^t, v_i^t, \theta_i^t, d_{ij}^t, \rho_t, D_t\} \tag{63}$$

Where x_i^t and v_i^t is the longitudinal position and velocity of vehicle i, θ_i^t represents its heading angle, d_{ij}^t indicates the relative inter-vehicle distance between vehicles i and j, ρ_t denotes traffic density at time t, and L_t is the experienced communication latency. The end-to-end delay experienced by safety messages is modelled as

$$D_{total} = D_{tx} + D_{queue} + D_{handover} \tag{64}$$

Where D_{tx} denote transmission delay over wireless channel, D_{queue} is the queueing delay due to network congestion, and $D_{handover}$ is the delay incurred during network switching between heterogeneous radio access technologies. The transmission delay is given by

$$D_{tx} = \frac{S}{B} \tag{65}$$

Where S represents the safety packet size in bits and B denotes available communication bandwidth in bits per second. The queueing delay under assumption is expressed as

$$D_{queue} = \frac{1}{\mu - \lambda} \tag{66}$$

Where λ denotes packet arrival rate and μ represents service rate, with the stability condition $\mu - \lambda$. The handover delay is modelled as

$$D_{handover} = T_{scan} + T_{auth} \tag{67}$$

Where T_{scan} denotes channel scanning time and T_{auth} is authentication delay during network reassociation. The latency aware optimization objective is therefore formulated as

$$min_{\ \pi_{net}} E[D_{total}] \tag{68}$$

Where π_{net} denotes the policy governing radio access selection and $E[.]$ represents expectation over stochastic traffic and channel variations. D_{total} is a total delay system. The optimal network selection decision is determined through an action-value function as

$$a_t^{net} = arg\ max_{\ k \in K}\, Q(s_t, k) \tag{69}$$

Where K is the set of available communication technologies and $Q(s_t, k)$ estimates the long-term performance of selecting technology k under state s_t. The longitudinal vehicle motion is governed by the kinematic equations

$$\dot{x}_i = v_i \tag{70}$$

and

$$\dot{v}_i = a_i \tag{71}$$

Where $\dot{x}_i$ and v_i represent time derivatives of position and velocity, and a_i is a longitudinal acceleration control input generated by the learning agent. $\dot{v}_i$ is a Time derivative of velocity of vehicle i. The lateral vehicle dynamics are represented using the bicycle model.

$$\dot{\theta}_i = \frac{v_i}{L} tan\,(\delta_i) \tag{72}$$

Where L is the vehicle wheel base and δ_i is the steering angle control input. The continuous action applied to vehicle i is defined as

$$a_t = [a_i, \delta_i] \tag{73}$$

Where a_i corresponds to acceleration and δ_i corresponds to steering command. The actor network that produces deterministic control actions is represented as

$$a_t = \mu(s_t \mid \theta^{\mu}) \tag{74}$$

Where $\mu(.)$ is the policy function parameterized by θ^{u}. The critic network estimating action-value function is expressed as:

$$Q(s_t, a_t \mid \theta^{Q}) \tag{75}$$

Where θ^{Q} represents critic parameters. The critic is trained by minimizing temporal-difference loss

$$L(\theta^{Q}) = E[(y_t - Q(\mathcal{S}_t, a_t))^2] \tag{76}$$

The target value is computed as

$$y_t = r_t + \gamma Q'(\mathcal{S}_{t+1}, \mu'(\mathcal{S}_{t+1})) \tag{77}$$

Where r_t denotes immediate reward, γ is a "discount factor" and Q', μ' represents target networks for stability. The reward function guiding learning formulated as

$$r_t = w_1 \mathbb{R}_{safe} + w_2 \mathbb{R}_{lane} - w_3 D_{total} - w_4 C_t \tag{78}$$

Where R_{safe} quantifies safety margin and collision avoidance performance, R_{lane} measures lane-keeping stability, C_t is a collision indicator variable equal to 1 when collision occurs and 0 otherwise and w_1, w_2, w_3, w_4 re positive weighting coefficients balancing objectives. Pedestrian interaction behavior is modelled probabilistically as

$$\mathcal{P}_{cross} = \sigma(W^T s_t) \tag{79}$$

Where P_{cross} denotes pedestrian crossing probability, W is a learned parameter vector, s_t is an environment state, and $\sigma(x) = \frac{1}{1+e^{-x}}$ is the sigmoid activation function mapping values to $[0,1]$. To enhance scalability and robustness in large-scale urban environments, federated parameter aggregation across distributed edge nodes is performed as

$$\theta_{global} = \sum_{k=1}^{K} \frac{n_k}{n} \theta_k \tag{80}$$

Where θ_k denotes local model parameters at node k, n_k represents the size of local dataset at node $k, n = \sum_{k=1}^{K} n_k$ is a total sample size and K (Number of participating nodes). Finally, overall integrated optimization objective of the scalability and robustness- aware DRL framework is defined as

$$max_{\pi,\theta} \, E[\textstyle\sum_{t=0}^{T} \gamma^t r_t] \tag{81}$$

Where π denotes the joint communication and control policy, θ represents all learnable parameters of federated components and the objective maximizes expected cumulative discounted reward while inherently enhancing safety, minimizing latency, improving lane stability, modeling pedestrian interactions and ensuring scalable learning under high density vehicular network conditions. The pseudocode for Adaptive federated multi-agent reinforcement learning (AF-MARL) is presented in algorithm 2.

Algorithm 2: Adaptive federated multi-agent reinforcement learning (AF-MARL)

Input: Distributed vehicle-pedestrian datasets: $\mathcal{D}_k$, initial global parameters θ_0

1. **Initialize** global critic parameters θ_g at central server
2. Distribute θ_g to edge nodes $k = 1,2, \dots, K$
3. For each edge node k, collect local traffic state and communication data $\mathcal{D}_k$
4. Encode non-IID traffic patterns using CVAE-based feature representation.
5. Initialize local AF-MARL agent with parameters $\theta_k \leftarrow \theta_g$
6. Perform local multi-agent interaction and compute reward based on safety, latency and stability
7. Update local critic networks using temporal difference learning
8. Apply communication delay penalty in reward for robustness adaptation
9. Perform semi-synchronous federated aggregation scheduling
10. Send updated local parameters θ_k to central aggregator
11. Compute weighted federated averaging $\theta_g = \sum(n_k/n)\theta_k$
12. Broadcast updated global parameters θ_g to all nodes
13. Evaluate global stability using cumulative safety and latency metrics
14. If convergence criteria stop training
15. Output optimized scalable and robust joint policy π^*
16. **End for**

VI. EXPERIMENTAL RESULT

A. Simulation setup

The section proposes Deep Reinforcement learning for cooperative driving Environments. . To simulate the proposed research method, the OMNET++ 6.3.0 is used. Table 2 displays the System specification.

Table 2
System specifications

Hardware specifications	Hard disk	512 GB
	RAM	16 GB
Software specifications	Simulation tools	OMNET++ 6.3.0
	OS	Ubuntu 22.04 (64-bit)

B. *Comparative analysis*

The proposed method is evaluated by comparing with many existing methods in the following domains: Number of Vehicles Vs End-to -End delay(ms), Number of Vehicles Vs Packet delivery Ratio (%), Number of Vehicles Vs Communication Overhead (%), Number of Vehicles Vs Energy Consumption (KJ**)**, Number of Episodes Vs. Average reward (%),Number of Episodes Vs. Accuracy(%) Compared to existing method such as AI-DTSA (Autonomous Intelligent-Decision Tree Selection Algorithm) [37] , DDQN (Double Deep Q-Network) [33], MSCA (Multi sensing communication approach) [5], IRQ (Intersection-based Routing method using Q-learning) [13], the proposed model perform good and accurate.

a. *Number of Vehicles Vs. End-to-End Delay (ms)*:

End-to-End delay (ms) defines how communication latency communication latency changes with increasing vehicle density in the VANET network. Lower End-to-End delay better network performance and faster safety message dissemination.

Table 3
Number of vehicles Vs End-to-End Delay(ms)

X-axis (Number of vehicles)	Y-axis (End-to-end delay(ms))		
	Proposed	AI-DTSA	DDQN
10	12	16	28
20	15	21	33
30	18	26	38
40	22	31	43
50	26	37	49

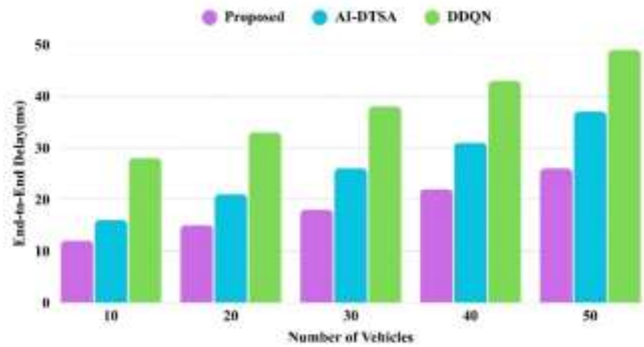

Fig 5. Number of Vehicles Vs End-to-End Delay(ms)

In Fig 5. and Table 3, the Number of Vehicles Vs End-to-End Delay(ms) is presented. Initially, with 10 vehicles, the proposed model has "End-to-End delay" of 12 ms, which is better than the AI-DTSA 16 ms and DDQN 28 ms, showing that the proposed method reduces communication latency effectively. Finally, with 50 vehicles, the proposed method achieves 16 ms , whereas AI-DTSA (37 ms) and DDQN (49 ms). The proposed method ensures lower delay and faster message dissemination.

b. Number of Vehicles Vs Packet Delivery Ratio (%)

Packet Delivery Ratio shows the reliability of message transmission as vehicle density increases in VANET network. A higher packet delivery ratio indicates better communication reliability and efficient safety message dissemination.

Table 4
Number of vehicles vs Packet delivery ratio (%)

X-axis (Number of vehicles)	Y-axis (Packet delivery ratio(%))		
	Proposed	AI-DTSA	DDQN
10	100	75	60
20	95	73	55
30	90	71	50
40	80	70	45
50	85	65	40

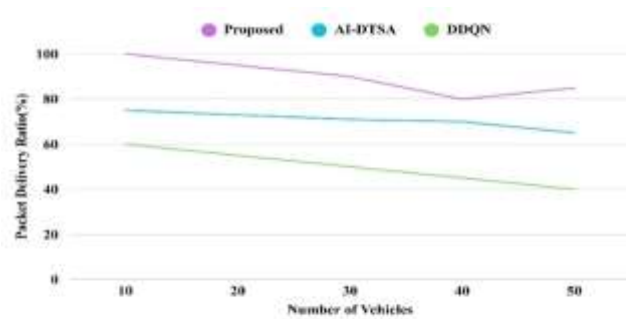

Fig 6. Number of Vehicles Vs Packet Delivery Ratio (%)

In Fig 6. and Table 4, Number of vehicles Vs packet delivery ratio (%) is presented. At initial stage, with 10 vehicles, the proposed model reaches 100%, which is higher than AI-DTSA (75%) and DDQN (60%), showing improved communication reliability. Finally, with 50 vehicles, the proposed model achieves 85%, whereas AI-DTSA (65%) and DDQN (40%). The proposed method ensures better message delivery performance.

c. *Number of Vehicles Vs. Communication Overhead (%)*

Communication overhead (%) defines additional communication required for message exchange in the network. Lower communication overheads indicate a more efficient and optimized network performance.

Table 5
Number of Vehicles Vs Communication Overhead (%)

X-axis (Number of vehicles)	Y-axis (Communication Overhead (%))		
	Proposed	AI-DTSA	IRQ
10	9.0	10	15
20	8.9	11	16
30	8.7	12	17
40	8.8	13	18
50	8	14	19

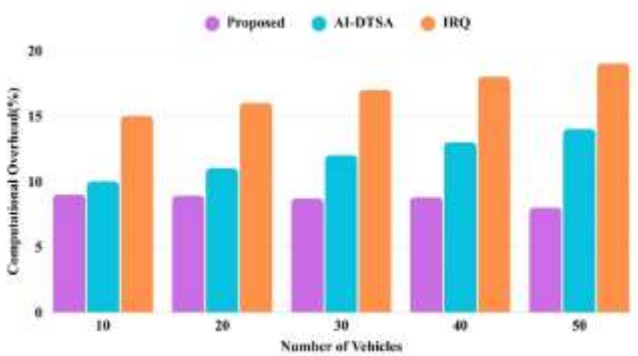

Fig 7. Number of Vehicles Vs Communication overhead (%)

In Fig 7. and Table 5, the number of vehicles Vs Communication overhead (%) is presented. Initially, with 10 vehicles, the proposed model has communication overhead of 9%, which is lower than the IRQ (15%) and AI-DTSA (10%) which indicates efficient communication management. Finally, with 50 vehicles, the proposed model achieves 8%, whereas AI-DTSA (14%) and IRQ (19%). The proposed method achieves reduced communication overhead and efficient network utilization.

d. *Number of Vehicles Vs. Energy Consumption (KJ)*

Energy consumption (KJ) defines the amount of energy required for communication and processing in the vehicular network as the number of vehicles increases. Lower energy consumption indicates better efficiency of the proposed system.

Table 6
Number of Vehicles vs Energy consumption (KJ)

X-axis (No.of. Vehicles)	Y-axis Energy consumption (KJ)		
	Proposed	AI-DTSA	IRQ
10	0.0126	0.0130	0.0140
20	0.0225	0.0235	0.0245
30	0.0200	0.0210	0.0220
40	0.0175	0.0190	0.0220
50	0.0120	0.0150	0.0170

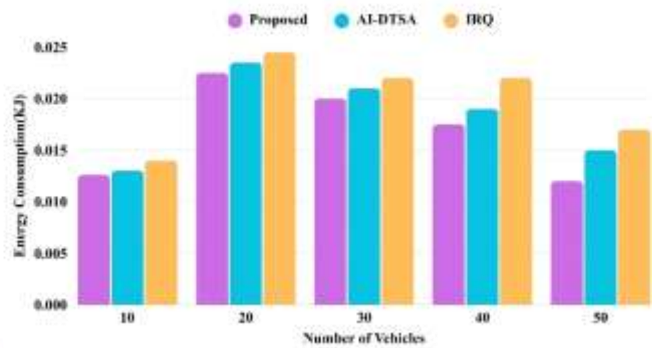

Fig 8. Number of Vehicles Vs Energy Consumption (KJ)

In Fig 8. and Table 6, the Number of Vehicles Vs Energy consumption (KJ) is presented. Initially, with 10 vehicles, the proposed model consumes 0.0126 KJ, which is lower than AI-DTSA (0.00130 KJ) and IRQ (0.0140 KJ), represents improved energy efficiency. Finally, with 50 vehicles, the proposed model consumes (0.0120 KJ), whereas AI-DTSA (0.0150 KJ) and IRQ (0.0170 KJ). The proposed method achieves lower energy consumption in vehicular communication networks.

e. *Number of Episodes Vs. Average reward (%):*

Average reward represents the learning model improve its decision- making performance during training. Higher average reward indicates better learning and optimization performance.

Table 7
Number of Episodes Vs Average reward (%)

X-axis (Number of Episodes)	Y-axis (Average reward (%))		
	Proposed	AI-DTSA	DDQN
20	100	80	50
40	95	75	45
60	85	70	40
80	75	65	35

100	65	60	30

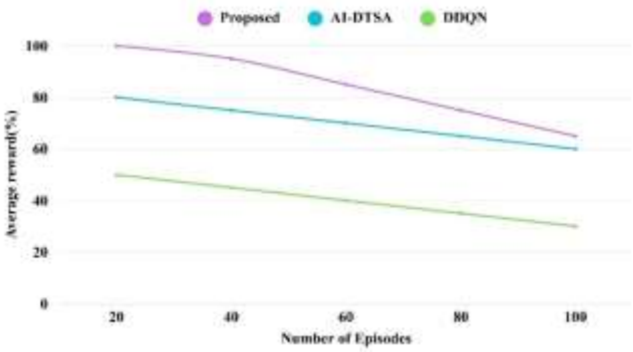

Fig 9. Number of Episodes Vs Average reward (%)

In Fig 9. and Table 7, Number of Episodes vs average Reward (%) is shown. Initially, with 20 episodes, the proposed model reaches “Average reward” of 100%, which is higher than AI-DTSA (80%) and DDQN (50%), showing better learning performance. Finally, at 100 episodes, the proposed model achieves 65%, whereas AI-DTSA (60%) and DDQN (30%). The proposed model ensures improved reinforcement learning performance.

f. Number of Episodes Vs. Accuracy (%):

Accuracy (%) defines how the prediction performance of the model improves as the training process progresses. Higher accuracy represents better model learning and reliable decision making.

Table 8
Number of Episodes Vs Accuracy (%)

X-axis (Number of Episodes)	Y-axis (Accuracy(%))		
	Proposed	AI-DTSA	MSCA
20	85	35	15
40	87	40	17
60	89	45	19
80	91	50	21
100	95	65	25

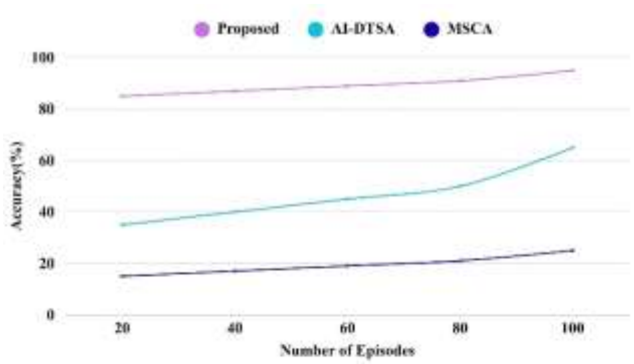

Fig 10. Number of Episodes Vs Accuracy (%)

In Fig 10. and Table 8, Number of Episodes Vs Accuracy(%) is presented. At the initial stage with 20 episodes, the proposed model achieves an accuracy of 85%, which is significantly higher than AI-DTSA(35%) and MSCA(15%), indicates better prediction performance. Finally, at 100 episodes, the proposed method reaches 95%, Whereas AI-DTSA (65%) and MSCA(25%). The proposed method ensures higher accuracy and reliable decision making.

C. Research Summary

Initially, we create a V2X-capable VANET (Vehicular Ad-hoc Networks) consisting of multiple vehicles, two Road Side Units (RSUs), a base station, and a cloud server, which will utilize both 5G NR-V2X and DSRC communications. We then gather data from cooperative driving scenarios simulated by reticulating vehicles. We utilize DENM messages along with an Adaptive Network Selection (ANS-V2X) mechanism to improve the efficiency of safety warnings sent via DENM in regards to time delay between the time the safety message is sent until the time the recipient receives the message while under highly congested vehicle traffic conditions. We then employ a Deep Reinforcement Learning-based Deep Deterministic Policy Gradient (DDPG) approach to generate dynamic decision-making for overtaking based upon how much steering and acceleration is required for each particular safe lane change scenario. Moving forward, we employ Deep Multi-Agent Reinforcement Learning (DMARL) to represent the interactions of drivers and pedestrians based upon how each driver and pedestrian adaptively decision-makes during varying traffic scenarios in real-time. Lastly, we apply Adaptive Federated Multi-Agent Reinforcement Learning (AF-MARL) to facilitate increasing the scalability and reliability of a large vehicular network. Performance metrics including end-to-end delay, packet delivery ratio, communication overhead, energy consumption, average reward, and accuracy were utilized to measure system performance and demonstrate improved performance compared to previous methods.

VII. CONCLUSION

This paper proposed an intelligent communication and decision-making architecture to enhance the dissemination of safety messages in VANET using Vehicle-to-Everything (V2X). The integrated system combines Adaptive Network Selection (ANS-V2X) with Decentralized Environment Notification Messages (DENM) to disseminate safety alerts among vehicles as efficiently as possible. The dynamic identification of network will provide most efficient delivery, increasing transmitting reliability for high-density vehicle traffic. In addition, to support cooperative driving behaviours e.g., overtaking, the framework employs Deep Deterministic Policy Gradient (DDPG)-based Reinforcement Learning (RL) to generate the optimal turning. To further assist vehicle & pedestrian interaction complexity, the architecture employs DMARL (Deep Multi-Agent Reinforcement Learning) by enabling multi-agent collaboration towards decision-making within the traffic management. The architecture uses the AF-MARL (Adaptive Federated Multi-Agent Reinforcement Learning) approach to support scalability and maintain data privacy through distributed training where no raw data is exchanged among participants. Experimental result shows improved end-to-end delay, packet delivery ratios, communication overhead, Energy Consumption, accuracy and average reward to use of existing approaches. In future work, Combined use of edge computing together with other advanced technologies supporting V2X communications might increase further scalability of the overall system.

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