

Modeling Multi-Way Vehicular Interactions for Proactive Collision Avoidance via Hypergraph Federated Learning in CR-VANET's

kotb elbarbary

kotbelbarbary@azhar.edu.eg

Al-Azhar University

Ahmed Fawzi

Al-Azhar University

Ashraf Eltholth

National Telecommunications Institute

Ahmed Yahya

Al-Azhar University

Article

Keywords: 5G, Cognitive radio, Resource Allocation, Vehicular Ad hoc Networks, Hypergraph Neural Networks, Federated Learning, Traffic Collision Avoidance.

Posted Date: October 27th, 2026

DOI: <https://doi.org/10.21203/rs.3.rs-11001466/v1>

License:   This work is licensed under a Creative Commons Attribution 4.0 International License.

[Read Full License](#)

Additional Declarations: No competing interests reported.

Modeling Multi-Way Vehicular Interactions for Proactive Collision Avoidance via Hypergraph Federated Learning in CR-VANET's

Corresponding Author : Kotb A. Elbarbary¹ kotbelbarbary@azhar.edu.eg¹, Al-Azhar University¹, Cairo – Egypt

Co-authors : Ahmed Fawzi², Ashraf A. Eltholth³, Ahmed Yahya⁴

ahmedmohamedfawzy@muc.edu.eg², ashraf.elthoth@nti.sci.eg³, dr.ahmed.yahya@azhar.edu.eg⁴

Faculty of Computers and Artificial Intelligence -May University², Cairo – Egypt ,

National Telecommunication Institute³, Cairo – Egypt .

Faculty of Engineering - Al-Azhar University⁴, Cairo-Egypt

ABSTRACT

In 5G-enabled Cognitive Radio Vehicular Ad-hoc Networks (CR-VANETs), static spectrum allocation and conventional machine-learning approaches—including heuristic rule-based systems, SVM/KNN classifiers, and Seg-CR-VANETs- are limited by high mobility, rapidly changing topologies, high false-alarm rates, and adversarial attacks. To address these issues, we propose TCAS-HGNN-FL, a Traffic Collision Avoidance System modeling a Hypergraph Neural Network and Federated Learning. Hypergraph modeling captures multi-vehicle interactions beyond pairwise graphs, while privacy-preserving federated learning enables distributed model aggregation, proactive spectrum sensing, and collision mitigation. Compared with traditional methods, standard ML baselines, and routing protocols IDRL, ARIOR, I-AREOR, and AREOR, TCAS-HGNN-FL achieves $P_d = 1.00$, reduces P_{fa} to 0.01, and lowers P_{coll} by 79.16% versus non-ML and 69.77% versus standard ML methods. It increases secondary-user throughput by 38.75%, improves the throughput-sensing-time trade-off by 54.04%, and retains 97.49% detection accuracy under a 50% malicious-node ratio. With collision-aware routing and 80% RSU coverage, it achieves 99.8% PDR, reduces delay by approximately 34%, PLR by 41.83%, and control overhead to 4700 (at 80% RSU coverage). These results indicate that combining higher-order hypergraph modeling, privacy-preserving federated learning, and traffic-aware collision prediction establishes a secure, scalable, low-latency, and spectrum-efficient solution for 5G and beyond.

Keywords:

5G; Cognitive radio; Resource Allocation; Vehicular Ad hoc Networks; Hypergraph Neural Networks; Federated Learning; Traffic Collision Avoidance.

1- Introduction

The recent proliferation of smart gadgets and the prevalence of data-intensive applications have led to the rapid development of wireless communication technologies [1], which have exerted tremendous strain on the limited radio frequency spectrum. The traditionally used static spectrum allocation policy[2], where specific frequency bands are permanently assigned to licensed operators [3],[4],[5], has led to inefficient spectrum usage, with many assigned bands underutilized [6]. In contrast, others are severely congested. The inefficiency is further aggravated by the deployment of 5G networks [7], which provide ultrahigh bandwidth, low latency, and massive connectivity to support a wide range of services [8],[9], such as enhanced mobile broadband (eMBB), massive machine-type communication (mMTC), and ultra-reliable low-latency communication (URLLC) [10]. VANET's (Vehicular ad hoc networks) are a fundamental component of intelligent transportation systems (ITS) and enable communication between vehicles (V2V), vehicles and roadside infrastructure (V2I), and pedestrians (V2P). These communications are essential for traffic safety, traffic efficiency, and infotainment services. However, the extremely dynamic nature of VANET's, which is characterized by fast changes of network topology, high mobility of nodes, and strict real-

time communication needs, poses serious problems to traditional spectrum management systems [11],[12]. These issues become more severe with the integration of VANET's with the 5G network, where the demand for reliable and high-capacity communication lines increases. The Cognitive Radio (CR) technology has been proposed as a revolutionary approach to overcome spectrum constraints and enhance spectrum efficiency. A cognitive radio is an intelligent wireless communication system that is aware of its environment, learns from it, and adapts its transmission parameters (e.g., frequency, power, modulation) to opportunistically access the unoccupied licensed spectrum bands, also known as spectrum holes, without causing harmful interference to primary users [13].

CR-VANET's, representing the fusion of CR technology with VANET's, present a viable strategy for improving spectrum efficiency and communication reliability in vehicular networks, as shown in Fig. 1 [14].

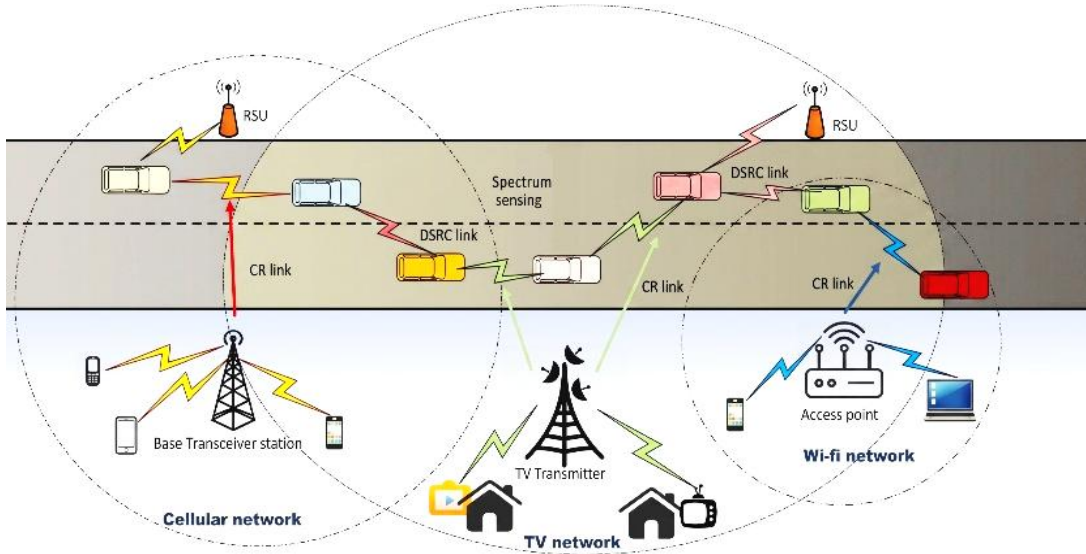


Figure 1: Infrastructure of Cognitive Radio-based VANET.

However, to unleash the full capabilities of CR-VANET's in 5G networks, adaptive frequency allocation techniques are needed to adapt to the complex and dynamic operating conditions.

2- Problem Statement

Despite the promising developments in CR and VANET technologies, there still exist certain important hurdles in attaining effective and intelligent frequency allocation in 5G CR-VANET's:

I- **Spectrum Scarcity and Underutilization:** The growing number of connected nodes and data-intensive applications in 5G CR-VANET's requires more spectrum resources, while existing static allocation mechanisms result in underutilized licensed bands. A fundamental difficulty is to discover the spectrum holes in a dynamic manner and utilize them efficiently [15].

II- **Dynamic Network Environment:** CR-VANET's are characterized by high vehicle mobility, rapid changes in network topology, and variations in traffic densities, which pose challenges in maintaining robust communication links and precision in real-time spectrum sensing and allocation. Such dynamism is difficult for traditional spectrum management approaches [11].

III- **Interference Management:** In CR-VANET's, the opportunistic spectrum access of SUs must be carefully managed to avoid damaging interference to PUs. The tradeoff between good protection for the PU and increasing the throughput for the SU is very subtle [7].

IV- **Latency and dependability Requirements:** Safety-critical applications on VANET's, such as collision avoidance and emergency braking require ultra-low latency and great dependability. The inefficient allocation of spectrum leads to higher delays and packet loss, degrading the performance of these applications [16].

V- Primary user emulation (PUE) and spectrum sensing data falsification (SSDF) attacks are two forms of security attacks that can be performed against CR-VANET's. Here we will discuss both of these assault kinds in more detail. The fact that they have these vulnerabilities means they are vulnerable to security breaches. Interference or denial of service could be caused by them because they are able to interfere with spectrum sensing and allocation [17]. This kind of assault has the potential to cause disruptions in the system's ability to work in an appropriate manner.

VI- The deployment of intelligent spectrum allocation methods, particularly those that rely on advanced machine learning, is one of the challenges that resource-limited vehicle nodes and real-time decision-making face. This has the potential to result in a significant amount of computational overhead, which is a challenge.

Methods that are dependent on more advanced forms of machine learning are especially vulnerable to this observation. For us to properly address these concerns, we need a comprehensive and intelligent solution for frequency allocation. This solution should be able to utilize the advantages offered by CR; it should be dynamic to cater to the changing nature of VANET's, and it should be able to comply with the strict standards that are already in place.[18]

3- Research Contributions

The current study makes valuable contributions to the field of intelligent frequency allocation in 5G CR-VANETs as follows:

I - TCAS-HG-FL for CR-VANET's: We propose a novel TCAS-based-HGNN-FL framework to utilize hypergraph theory to represent the complex multi-way relationships among vehicles, which can improve the accuracy of spectrum sensing and network state prediction, and deal with the complex issues of dynamic spectrum management

II - The proposed framework, TCAS-based-HGNN-FL-informed cooperative sensing and decision-making system, intends to provide a more robust and proactive mechanism to prevent vehicular crashes by accurately forecasting spectrum availability and potential interference, and minimizing decision latency, using hypergraph-federated learning.

III - Enhanced TCA Mechanism: We explain how the HG-FL architecture enables an enhanced probability of collision by lowering the misdetection rate and decreasing the decision latency via hypergraph-aware cooperative intelligence.

4- Related Work and Research Gaps

Recently, there has been a lot of research on several elements of CR-VANET's and intelligent spectrum management. Vinay Lomte et al. [3] proposed standard ML models for adaptive and intelligent spectrum usage. Detection thresholds and sensing durations are dynamically optimized by using logistic regression and SVM, and the accuracy of cooperative sensing is improved by using decision tree models and random forests. KNN allows adaptive sensing in high-speed contexts by bringing mobility awareness into sensing. Gradient boosting can predict PU activity reliably, thereby guaranteeing SU access even under different spectrum conditions. The trust management based on Q-learning improves security a lot and protects the cooperative sensing against PUEA and SSDF assaults [19]. In addition, the K-Means-based clustering minimizes the sensing latency by making decisions locally, which is proven to be useful for congested traffic scenarios.

The ML-based approaches described by Vinay Lomte et al. show promising advantages over traditional rule-based systems in terms of false alarm probability, detection probability, and throughput. Pratima Upadhyay et al. [4]. The system considered in this study is V2I communication, where either a single Access Point (AP) or a single RSU in a certain geographical region is considered. The RSUs continuously transmit or receive vehicle data to the default portal, which in turn forwards the data to the network operator and eventually to the system users. Hossain et al [5] propose the VANET architecture of the baseline technique (Seg-CR-VANET), which combines a hybrid machine

learning algorithm (fuzzy and naïve Bayes) for the optimal selection of spectrum sensing techniques, and a Tri-Agent Reinforcement Learning (TA-RL) algorithm for global decision-making. Despite these improvements, even with the selection and dynamic channel status alteration. However, several research gaps remain:

I - Holistic Integration:

Most of the available works consider individual parts of CR-VANETs (e.g., sensing only or routing only). There is a need for a holistic architecture that seamlessly blends intelligent spectrum detection, dynamic allocation, resilient routing, and security procedures in a 5G scenario.

II - Ability to adapt to extreme dynamism:

Although RL algorithms such as DQN are promising, their convergence speed and flexibility in highly dynamic vehicular situations with rapidly changing PU activity and vehicle motion need to be further improved

III- Security versus performance tradeoff:

In general, the implementation of strong security mechanisms comes with delay and processing overhead. It is still difficult to balance these security needs with the ultralow latency requirements of 5G VANET applications.

IV - Constraints for Practical Implementation:

Most of the proposed deep learning models are computationally expensive. The practical deployment demands the development of lightweight, edge-enabled intelligent algorithms that can run efficiently on vehicle hardware. All these constraints are addressed by our proposed TCAS-based-HGNN-FL system. HGNN-FL (Hybrid Graph-Federated Learning) is an approach for Cognitive Radio Vehicular Ad-hoc Networks (CR-VANET's) that takes advantage of the advantages of Graph Neural Networks (GNNs) and Federated Learning (FL). The key motivation of the proposed HGNN-FL is to utilize the spatial relationships between nodes (by GNNs) while preserving data privacy and global model robustness (via FL). The proposed hybrid strategy aims at optimizing spectrum sensing and access decisions in dynamic vehicle situations and thereby reduces the collision probability.

5 – Structure of Simulation Architecture

CR-VANET Environment: [20],[21]

I - Vehicles (Nodes): Modeled as mobile entities capable of communication, equipped with cognitive radio for spectrum sensing and dynamic spectrum access. Each vehicle can be a client in the federated learning process.

II - Roadside Units (RSUs): Fixed infrastructure nodes that permit communication between vehicles and act as edge servers for federated learning aggregation

III - Base Stations (5G): Provide a generic 5G connection, manage spectrum resources, and may host the central FL server.

IV - Communication Links: Dynamic links between vehicles, RSUs, and base stations, and between RSUs. They are influenced by the 5G network status and CR decisions.

V- Spectrum: Visual representation of the available spectrum bands, showing primary and secondary users, and dynamic spectrum allocation using cognitive radio.

6- System Model and Problem Formulation

In this section, we first provide the general system model for vehicular spectrum allocation in 5G networks, including network architecture, channel characteristics, and performance criteria, followed by a rigorous problem formulation.

We consider a Vehicle-to-Everything (V2X) network consisting of $\mathcal{V}_N$ vehicles and Roadside Infrastructure devices ($\text{IRSU} \subset \mathcal{I}$), e.g., smart traffic signals, road sensors, and roadside units) operating in a geographical area $\mathcal{A}$ of size $L \times L(\text{km})$. The system provides full V2X communication capabilities, including Vehicle-to-Vehicle (V2V), Vehicle-to-Infrastructure (V2I), and Vehicle-to-Device (V2D) over the PC interface as defined in the 3GPP Release 16 NR-V2X specification [22].

6-1 Hypergraph Representation of CR-VANET

We model the CR-VANET as a hypergraph

$$H = (V, E_h) \quad \text{----- (1)}$$

I - Vertices (V): The set of N (nodes) in the CR-VANET, represented as :

$$V = \{v_1, v_2, v_3, \dots, v_N\} \quad \text{----- (2)}$$

Each vehicle (node) v has a set of attributes, e.g, its position (P_i), velocity(v_i), acceleration(a_i), local spectrum sensing status (S_i), and communication capabilities, with a maximum speed constraint $|v_i(t)| \leq v_{\max} = 30$ km/h in urban scenarios and $v_{\max} = 120$ km/h in highway scenarios.

II - Hyperedges (E_h): The set of M hyperedges, expressed as

$$E_h = \{e_1, e_2, \dots, e_M\} \quad \text{----- (3)}$$

Each hyperedge ($e_j \subseteq V$) is a non-empty subset of vertices, which represents a set of vehicles that have a similar attribute or are involved in a collective event.

The incidence matrix officially defines the link between vertices and hyperedges as follows:

$$B \in \{0,1\}^{|V| \times |E_h|} \quad \text{----- (4)}$$

where :

$$B_{v,e} = \begin{cases} 1, & v \in e \\ 0, & \text{otherwise} \end{cases} \quad \text{----- (5)}$$

We additionally define two diagonal degree matrices to ease hypergraph operations:

III - Matrix of the Vertex Degree (D_v):

$$D_v \in \{R\}^{|V| \times |V|} \quad \text{----- (6)}$$

where

$$D_{v_i} = \deg(v_i) = \sum_{e \in E_h} B_{v_i, e_i} \quad \text{----- (7)}$$

is the number of hyperedges containing the vertex v_i

IV - Hyperedge Degree Matrix (D_e):

$$D_e \in \{R\}^{|E_h| \times |E_h|} \quad \text{----- (8)}$$

Where :

$$D_{e_i, j} = |e_j| = \sum_{v_i \in V} B_{v_i, e_i} \quad \text{----- (9)}$$

is the number of vertices in hyperedge e_j

6-2 Hypergraph Neural Network (HGNN) Model

The HGNN is the key component for learning representations from the hypergraph-structured data [24]. It is a generalization of the graph convolution idea to hypergraphs, where the information of hyperedges can be transmitted and aggregated. The feature update rule of an HGNN layer is given by:

$$X^{(L+1)} = \sigma (D_v^{-1/2} B W D_e^{-1} B^T D_v^{-1/2} X^L \Theta^L) \quad \text{----- (10)}$$

Where:

- $X^{(L)} \in R^{|V| \times d_L}$ is the feature matrix of vertices at layer L , where d_L is the dimension of the feature, and each row $(x_i)^L$ is the feature vector of vehicle v_i
- $X^{(L+1)}$ is the updated feature matrix of layer $(L+1)$.
- B : is the incidence matrix of the hypergraph.
- $D_v^{-1/2}$ and D_e^{-1} are the inverse square root of the vertex degree matrix and the inverse of the hyperedge degree matrix for normalization, respectively.
- $W \in R^{|Eh| \times |Eh|}$ is a diagonal matrix of hyperedge weights, where W_{jj} indicates the importance or reliability of a hyperedge e_j . These weights can be learned or set from domain knowledge.
- $\Theta^{(L)} \in R^{d_L \times d_{L+1}}$ the learnable weight matrix (filter) of layer (L) , which changes the aggregated features.
- $\sigma(\cdot)$ is a non-linear activation function.

So, this HGNN layer implements a two-step message passing: first, features are passed from vertices to hyperedges ($BX^{(L)}$), then aggregated within hyperedges and passed back to vertices ($B^T D_e^{-1} W B X^{(L)}$), both normalized by degree matrices. Thus, the representation of each vehicle is affected by the joint information of the hyperedges it belongs to, which allows for the capture of complicated group dynamics.

6-3 Federated Learning (FL) Framework

To solve privacy problems and communication bandwidth limitations in VANETs, we embed the HGNN model into a Federated Learning framework [25]. FL allows collaborative training of models across distributed vehicles (nodes) without sharing the raw local data with a central server (Fusion Center, FC). The FL process in HGNN-FL usually consists of the following steps:

- I - Initialization: The FC initializes a global HGNN model $W^{(0)}_{global}$ and transmits it to all participating vehicles.
- II - Local Training (Client-side): Each vehicle k receives the global model $W^{(t)}_{global}$ at round t .
- III - Local model upload: After local training, each k node uploads only its updated local model weights $w_k^{(t+1)}$ (or gradients) to the FC.
- IV - Global aggregation (server-side): FC gathers all the local models updated by the participating vehicles, then it aggregates these local models to produce a new global model $W^{(t+1)}_{global}$, using a generally weighted averaging approach like Federated Averaging (FedAvg) :

$$W_{global}^{(t+1)} = w_k^{(t)} - \eta \sum_{k=1}^K \frac{n_k}{n} \left(\sum_{i=0}^{E-1} \nabla F_k w_k^{(t)} \right) \quad \text{-----} \quad (11)$$

- V- Model Distribution: The updated global model $W_{global}^{(t+1)}$ is then distributed back to the nodes for the next round of local training. This process goes on until the global model converges or the maximum number of FL rounds is met.

6-4 Traffic Collision Avoidance (TCA) Probability Model :

The probability of successfully avoiding vehicle collisions is an important safety indicator, and one such indicator is called Traffic Collision Avoidance (TCA) probability [26]. This is an indicator of the likelihood of success. Failures in communication, insufficient spectrum sensing, and uncertainty on the part of mobility are some of the factors that can be attributed to the occurrence of collisions in CR-VANET's [27]. Other factors include the fact that mobility is uncertain. The HGNN-FL architecture was developed with the sole purpose of maximizing the efficiency of TCA. The processes of information transmission and decision-making were improved in terms of both their accuracy and their timeliness, which allowed for the actualization of this goal. The TCA parameter is an essential component used

for the purpose of determining the likelihood of accidents occurring. The Time-to-Collision (TTC) and Safety Distance metrics are the primary metrics that we use in our study:

I - Time-to-Collision (TTC): TTC is the time left until vehicles collide if they keep on their current routes at their current speed :[23],[24]

$$TTC_{i,j}(t) = \frac{d_{i,j}(t)}{\Delta v_{i,j}(t)} \quad \text{----- (12)}$$

where $d_{i,j}(t)$ is the relative distance, and $\Delta v_{i,j}(t)$ is the relative velocity between vehicle (i) and vehicle ($i+1$).

II – Parameter of Safety Distance

The required safety distance d_{safe} is derived from the velocity v of the vehicle and its maximum deceleration a_{max} :

$$d_{safe} = v \cdot t_{treat} + \frac{v^2}{2 a_{max}} \quad \text{----- (13)}$$

III - Collision Risk Index (CRI) : [28]

The GNN-FL model uses a composite parameter, called the Collision Risk Index (CRI), to activate alerts:

$$CRI = w_1 \cdot \frac{1}{TTC} + w_2 \cdot \frac{1}{d_{rel}} \quad \text{----- (14)}$$

where w_1 and w_2 are weighting factors for temporal and spatial risk, respectively, and d_{rel} is the distance between vehicle (i) and vehicle ($i+1$). Finally, we define the probability of collision (P_{coll}) as a function of the probability of misdetection in spectrum sensing (P_{misd}) and the inherent uncertainties related to vehicle mobility and communication latency ($P_{mobility-uncertainty}$):

$$P_{coll} = P_{misdetection} * P_{interference} + P_{mobility-uncertainty} \quad \text{----- (15)}$$

Where:

$P_{interference}$:

The likelihood that an undetected PU (due to misdetection) causes damaging interference to ongoing SU communication, which might result in communication link failures that are crucial for safety applications.

$P_{misdetection}$:

Chance of PU being present but not detected by the SU's. This chance is drastically lowered with HGNN-FL due to the improved cooperative sensing capabilities. The hypergraph structure permits a more robust collective decision on PU presence by combining the sensing information of several vehicles in a hyperedge; this can be written as :

$$P_{misdetection, (HG-FL)} = \prod_{v \in e} (1 - P_{d,v}) \cdot e^{(-\alpha \cdot e)} \quad \text{----- (16)}$$

$P_{mobility-uncertainty}$:

The notion of $P_{mobility-uncertainty}$ is related to the accident risk originating from unpredictable vehicle movements, abrupt changes in traffic flow, or communication delays that are not directly caused by spectrum sensing mistakes. Thus, HGNN-FL helps mitigate this uncertainty by offering better knowledge of vehicular interactions via hypergraphs, leading to more accurate trajectory prediction and cooperative maneuver planning.

So the Probability of Traffic Collision Avoidance (P_{TCA}) is defined as:

$$P_{TCA} = 1 - P_{coll} \quad \text{----- (17)}$$

The HGNN-FL framework aims to optimize (P_{TCA}) by reducing (P_{coll}) through improving spectrum sensing accuracy, lowering decision latency, and increasing the predictive capability of vehicular dynamics.

IV - TCA Minimization Policy:

The HGNN-FL framework minimizes the TCA as follows :

- a** - Higher-Order Coordination: The hypergraph encodes groupings of vehicles as hyperedges, enabling the network to predict and avoid possible clusters of collisions
- b** - Predictive Sensing: HGNN-FL learns the spatiotemporal patterns of PU activity, so SUs can preemptively switch channels before the collision happens.
- c** - FL assures that all nodes can profit from the "collective experience" of the network, resulting in a better and collision-free environment

6-5 TCAS-based-HGNN-FL Framework

I- Graph Representation: The topology of the CR-VANET (i.e., the nodes, the RSUs, and the links) is represented by a dynamic graph. The vehicles/RSUs are the graph nodes, and the communication links are the edges.

II - Local GNN Models: Each vehicle/RSU learns a local GNN model based on its observed local network data (e.g., spectrum availability, interference, traffic density).

III - The Federated Learning Server is a central entity, e.g., a Roadside Unit (RSU) or a 5G base station, that collects local GNN models and disseminates the global model.

IV - FL Rounds: The fourth phase of the FL Rounds has an iterative procedure where local training, model uploading, aggregation, and global model downloading are involved. It guarantees rapid response to imminent dangers, and it continually enhances its collective intelligence. This dual feature is vital for the development of resilient and adaptive autonomous transportation systems. The TCAS-based-HGNN-FL framework is designed in three layers to reconcile the local processing requirements and the global optimization.

Layer	Primary Entity	Key Responsibilities
Cloud Layer	Central Controller	Global model aggregation, policy optimization, and long-term spectrum strategy.
Edge Layer	Roadside Units (RSUs)	Regional hypergraph construction, local training, and real-time spectrum management.
Vehicle Layer	Cognitive Vehicles	Local sensing, TCAS data generation, and local HGNN model updates.

Table 1: Layers of the TCAS-based HGNN-FL framework.

The layers in Table 1 can be described as the use-case scenario of the TCAS-based-HGNN-FL framework, as shown in Fig. 2, as follows:

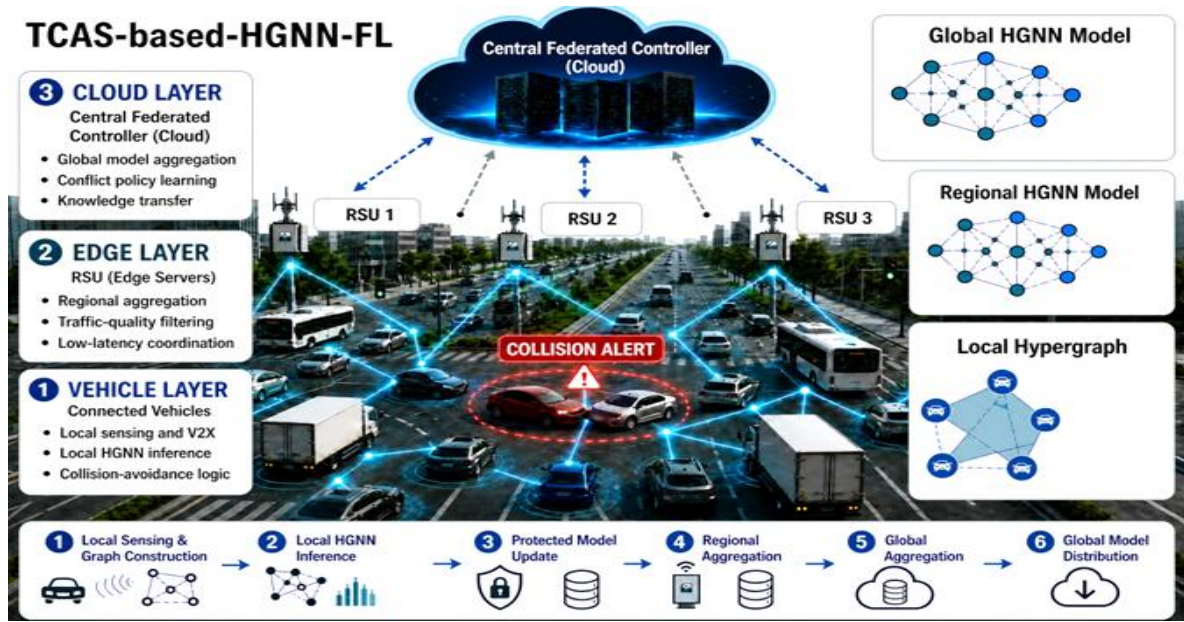


Figure 2: The use case scenario of the proposed TCAS-based-HGNN-FL system

The algorithm is developed to encode the entire working procedure of the TCAS-based-HGNN-FL framework, starting from hypergraph building and ending with the deployment of the proposed framework for spectrum sensing and traffic collision avoidance in CR-VANET's

Algorithm: TCAS-based-HGNN-FL Training Procedure

Initialization Phase: Building the Hypergraph

- a. Initialize an empty set of hyperedges $E_h = \emptyset$
- b. For each vehicle: $v_i \in V$:
 - i. Detect probable hyperedges based on given rules.
 - ii. For each recognized group of vehicles, form a hyperedge e_j , and if e_j is not present, add e_j to E_h .
- c. Output the initial hypergraph $H = (V, E_h)$ and its incidence matrix B , where $B_{v,e}=1$ if $v \in e$, and $B_{v,e}=0$ otherwise

HGNN Layer Update :

1. Input: Feature matrix $X^{(L)}$ from layer (L).
2. Compute Normalized Vertex Degree Matrix: $D_v^{-1/2}$, and normalized Hyperedge Degree Matrix: D_e^{-1}
3. Feature Propagation (Vertex to Hyperedge and back to Vertex)
 - a. $X_v \rightarrow e = D_v^{-1/2} B X^L$ (Features from vertices propagated to hyperedges)
 - b. $X_e \rightarrow v = B W D_e^{-1} B^T D_v^{-1/2} X^L$ (Features aggregated from hyperedges and propagated back to vertices)
4. Apply Learnable Filter and Activation:
 $X^{L+1} = \sigma(X_e \rightarrow v \Theta^L)$
- 5- Output: Updated matrix X^{L+1} for layer $L+1$.

This manner is repeated for numerous HGNN layers to learn the hypergraph hierarchical properties.

Federated Learning: coordinates distributed training of HGNN models among vehicles, enabling privacy and scalability.

Local HGNN Model Training (Client-side)

- a. Input: Global model parameters $W_{global}^{(t)}$ (received from FC).
 - b. Set up local model parameters $w_k^{(t)} = W_{global}^{(t)}$
-

c. For any local epoch from 1 to E :

i - Forward Pass: Make predictions through the HGNN using $w_k^{(t)}$ and D_k .

ii - Compute Loss: Calculate local loss $L(w_k^{(t)}, D_k, H_k)$, which may incorporate a hypergraph-aware regularization term $\Omega(H_k)$ to penalize inconsistencies with the local hypergraph structure.

iii- Inverse Pass: Determine gradients $\nabla L(w_k^{(t)}, D_k, H_k)$

iv - Update Model: $w_k^{(t+1)} = w_k^{(t)} - \eta$

$\nabla L(w_k^{(t)}, D_k, H_k)$

V- Output: the FC receives an updated model $w_k^{(t+1)}$

Global Model Aggregation (Fusion Center-Server-side)

1- Input: K participating vehicles, Local model updates $w_k^{(t+1)}$

2- Combine Updates to the model:

$$W_{global}^{(t+1)} = \sum_{k=1}^K \frac{n_k}{n} w_k^{(t+1)} \quad \text{Federated Averaging}$$

3- Output: Updated global model $W_{global}^{(t+1)}$ will be given to the clients for the next Federated round.

Application Phase: Utilizing the Trained Global Model

i - For each vehicle or hyperedge, the energy detection threshold $\mathcal{T}$ is dynamically adjusted according to the collective judgment and the projected channel state to optimize the probability of detection (P_d) and false alarm (P_{fa})

ii- Output: Optimized dynamic sensing threshold per vehicle.

Hypergraph-based Collision Risk Prediction:

I - HGNN performs feature extraction for each vehicle and hyperedge.

II - For each vehicle or hyperedge, the HG-FL model forecasts the probability of collision (P_{coll}), including:

* Risk of Spectrum Interference (based on P_d and P_{fa}).

* Risk due to Mobility (detected by hypergraph structure).

* Latency Impact (from dispersed FL).

III- Traffic Collision Avoidance (TCA) Probability Calculation: $P_{TCA} = 1 - P_{coll}$

IV- P_{TCA} is predicted for each vehicle to provide proactive collision avoidance warnings or actions.

7- Comparative Evaluation Using Baseline Models

In this section, we compare the proposed TCAS-based HGNN-FL approach with many existing methodologies Vinay Lomte [3]. The proposed ML-based algorithms clearly exhibit advantages in terms of lower false alarm probability, higher detection probability, and higher throughput compared to existing rule-based systems. Pratima Upadhyay [4]. The system under consideration consists of V2I communication, consisting of either a single Access Point (AP) or a single RSU in a certain geographical region. RSUs regularly send and receive vehicle data to and from the default portal, which is then relayed to the network operator and then distributed to the system users. M. A. Hossain, R. Md Noor [5]. The baseline technique (Seg-CR-VANET) is a hybrid ML approach that combines Fuzzy Logic and Naive Bayes for local sensing and Tri-Agent Reinforcement Learning (TA-RL) for global decisions.

We do an extensive evaluation of the performance of TCAS-based-HGNN-FL with twelve state-of-the-art algorithms from different paradigms. Our considerations are: max speed constraint $|v_i(t)| \leq v_{max} = 30$ km/h for urban scenarios and $v_{max} = 120$ km/h for highway scenarios. The number of available channels is 10, with a channel bandwidth of

10 MHz, and the distance of transmission is 300 m. The number of available spectrum channels is 10. Sensing duration is (1-6 ms). Cooperative nodes are 4-5 nodes with $K = 10$, and the geographical area A of size $L \times L$ m (3000×3000 m). The number of vehicles varies from 10 to 100 for PDR and from 20 to 100 for delay and packet loss, and uses traffic densities from 10 to 60 vehicles/km, and the number of RSU's = 5, and different signal-to-noise ratios, sensing durations, traffic densities, primary-user duty cycles, and malicious-node ratios.

We built the TCAS-based-HGNN-FL model; our paper contains updated equations for each performance metric that reflect the expected gains. Therefore, TCAS-based-HGNN-FL significantly outperforms all the baseline frameworks

From Figure (3), we can observe that the proposed TCAS-based--HGNN-FL outperforms the baseline approaches. As demonstrated, the Probability of False Alarm (P_f) of the proposed TCAS-based HGNN-FL is much lower than that of the rule-based and standard ML methods [3]. Particularly in the low SNR regimes.

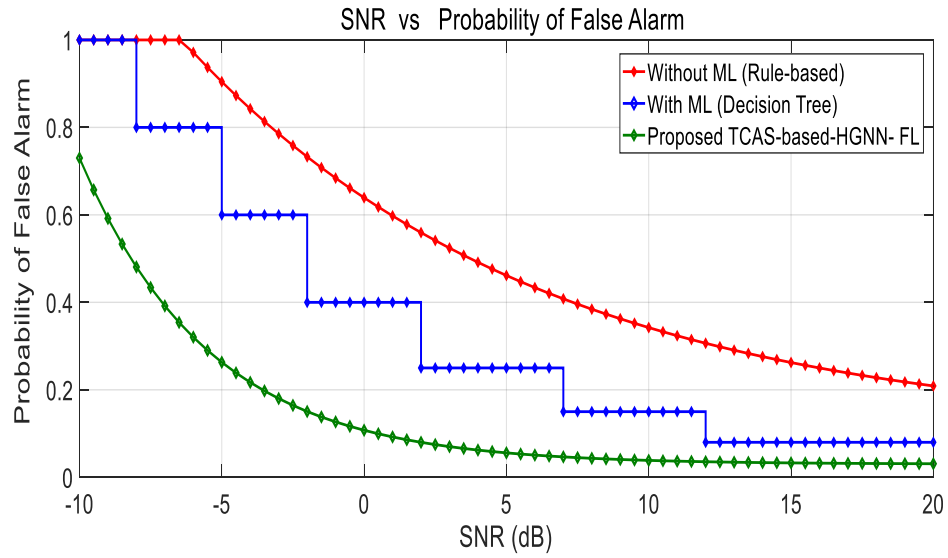


Figure 3: SNR Vs P_{fa}

This improvement in the Probability of False Alarm (P_f) maximizes the spectrum utilization efficiency and overcomes the problem of spectrum scarcity. The improvements in metrics shown in Fig.3 are summarized in Table 2 and Fig. 4 as follows :

SNR(dB)	Without ML (P_f)	Baseline ML (P_f)	Proposed Framework (P_f)
-10	1.00	1.00	0.73
-5	0.9	0.6	0.26
0.00	0.64	0.40	0.11
5	0.46	0.25	0.06
10	0.34	0.15	0.04
20	0.21	0.08	0.03

Table 2: Improvements of (P_{fa}) at different values of SNR

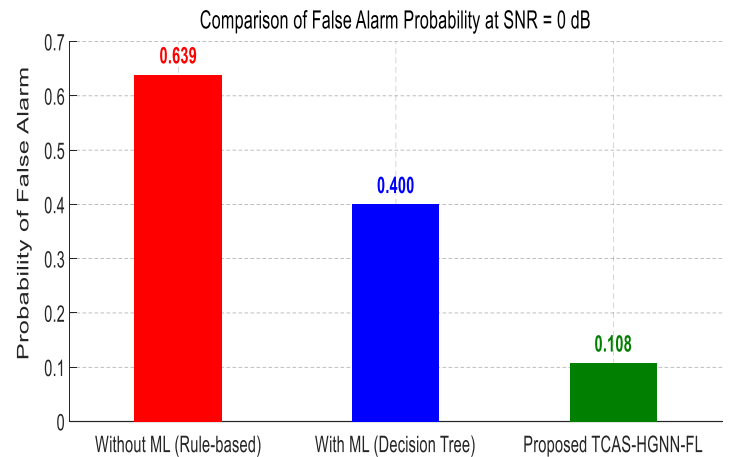


Figure 4: P_{fa} Vs SNR Average Improvements comparison

Figure (5) illustrates that the proposed TCAS-based--HGNN-FL technique produces almost perfect P_d with only 4 -5 cooperative nodes, while the baseline methods require more nodes to achieve the same levels:

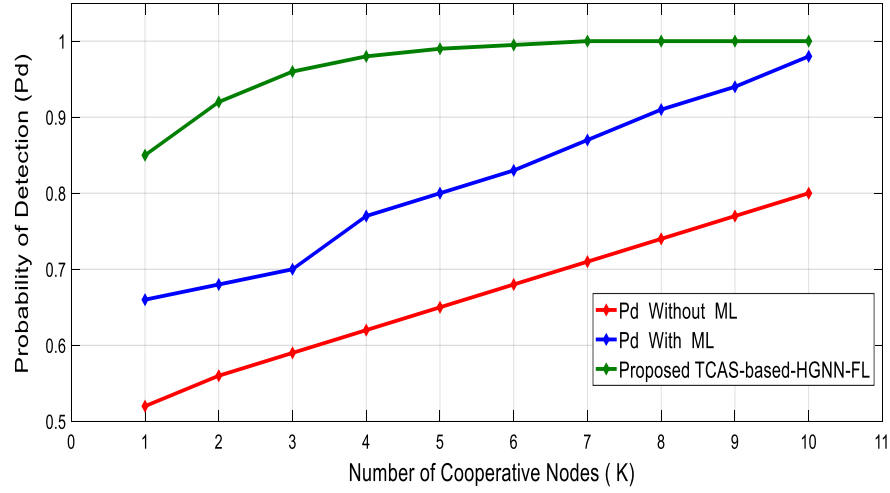


Figure 5: Number of cooperative nodes (K) Vs P_d

Consequently, the proposed framework uses a minimum number of cooperative nodes to verify a maximum value of the probability of detection P_d , referred to enhancing the system reliability.

The improvements in metrics shown in Fig.5 are summarized in Table 3 and Fig. 6 as follows:

Nodes(K)	Without ML (Pd)	Baseline ML (Pd)	Proposed Framework (Pd)
1	0.52	0.66	0.85
4	0.62	0.77	0.98
7	0.71	0.87	1.00
10	0.8	0.98	1.00

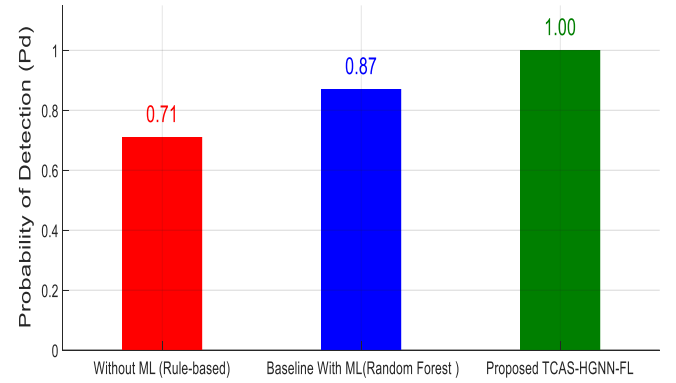


Table 3: Improvements of P_d at different nodes.

Figure 6: P_d Average improvement comparison.

As the number of cooperative nodes increases, the false alarm rate is reduced considerably more aggressively by the TCAS-based-HGNN-FL approach than the comparison methods[3], as shown in Figure 7:

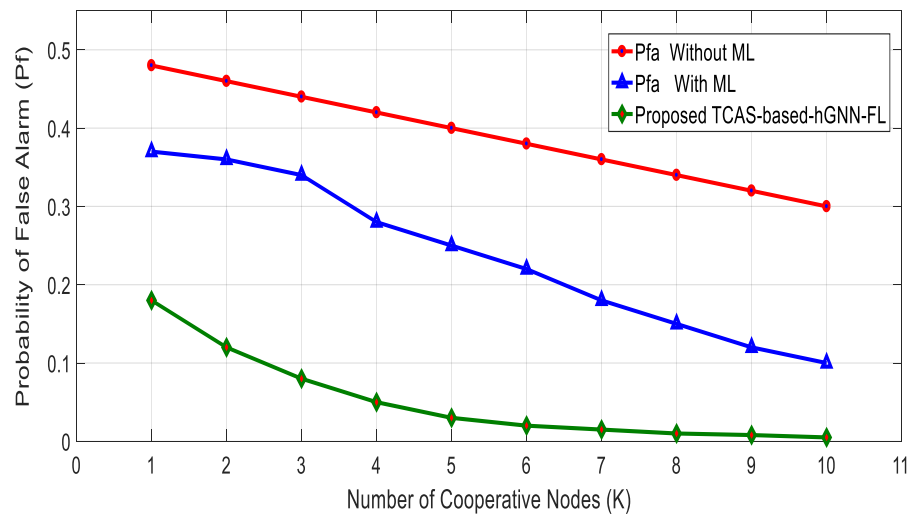


Figure 7: Number of cooperative nodes (K) Vs P_{fa}

Therefore, the minimization of false alarm probability tends to increase spectrum utilization, overcome the problem of static bandwidth, and increase the system capacity and efficiency.

The improvements in metrics shown in Fig.7 are summarized in Table 4 and Fig. 8 as follows:

Nodes(K)	Without ML (P_f)	Baseline ML (P_f)	Proposed Framework (P_f)
1	0.48	0.37	0.18
4	0.42	0.28	0.05
7	0.36	0.18	0.015
10	0.30	0.10	0.005

Table 4: Improvements of (P_{fa}) at different nodes (K)

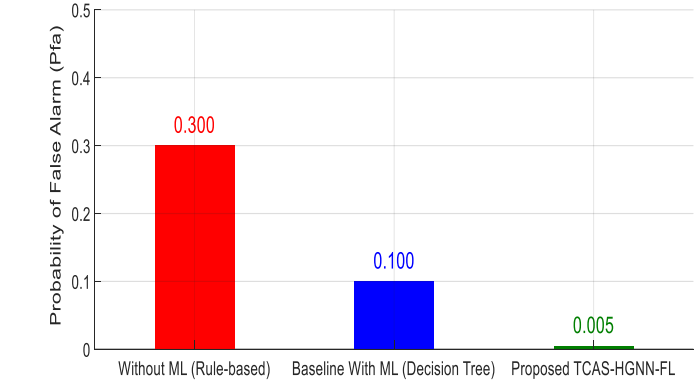


Figure 8: P_{fa} improvement comparison

The TCAS-based-HGNN-FL consistently shows higher throughput performance over the whole Signal-to-Noise Ratio (SNR) range (0–30 dB). Its topology-aware global aggregation enables it to achieve better spectral efficiency than baseline ML[3] approaches, as shown in Fig.9 as follows:

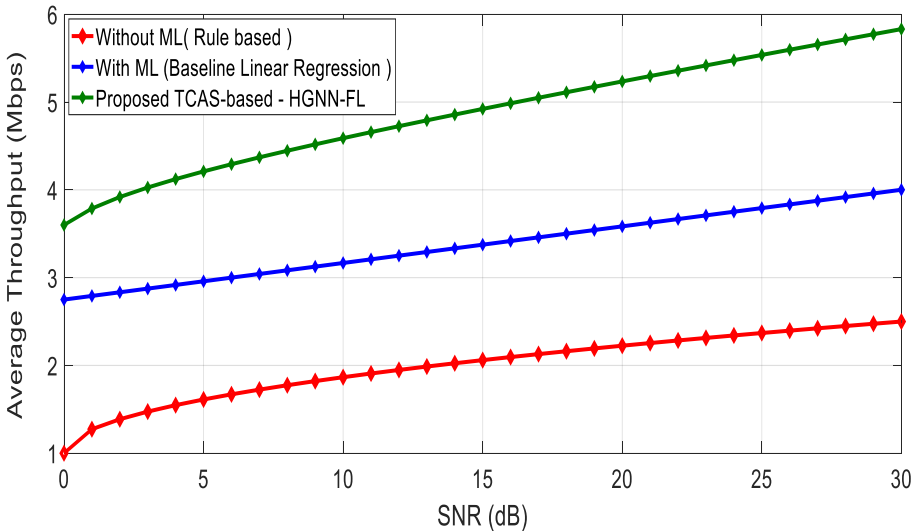


Figure 9: SNR Vs Average Throughput ($\bar{T}$)

The improvements in metrics shown in Fig.9 are summarized in Table 5 and Fig. 10 as follows:

Metric	Without ML (SNR)	Baseline ML (SNR)	Proposed Framework
Maximum Throughput	2.70	4.00	5.55

Table 5: Throughput improvements at different values of SNR.

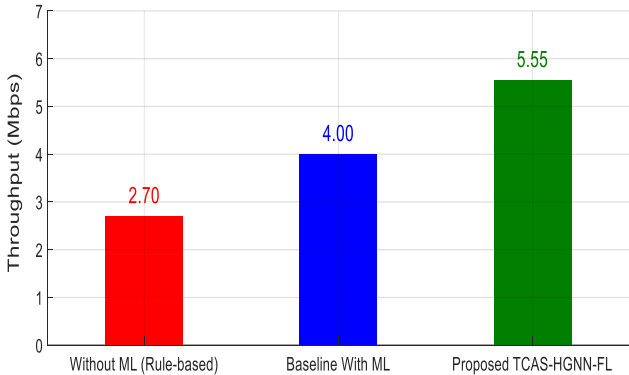


Figure 10: Throughput Improvement comparison

As demonstrated in Fig.11, the TCAS-based-HGNN-FL strategy offers an optimum trade-off between Sensing Time and SU Throughput. It maintains higher throughput even with varying sensing times, indicating an intelligent and adaptive sensing strategy that maximizes SU opportunities without compromising primary user protection. The topology-aware global aggregation enables it to achieve higher spectral efficiency compared to the baseline ML approaches [3].

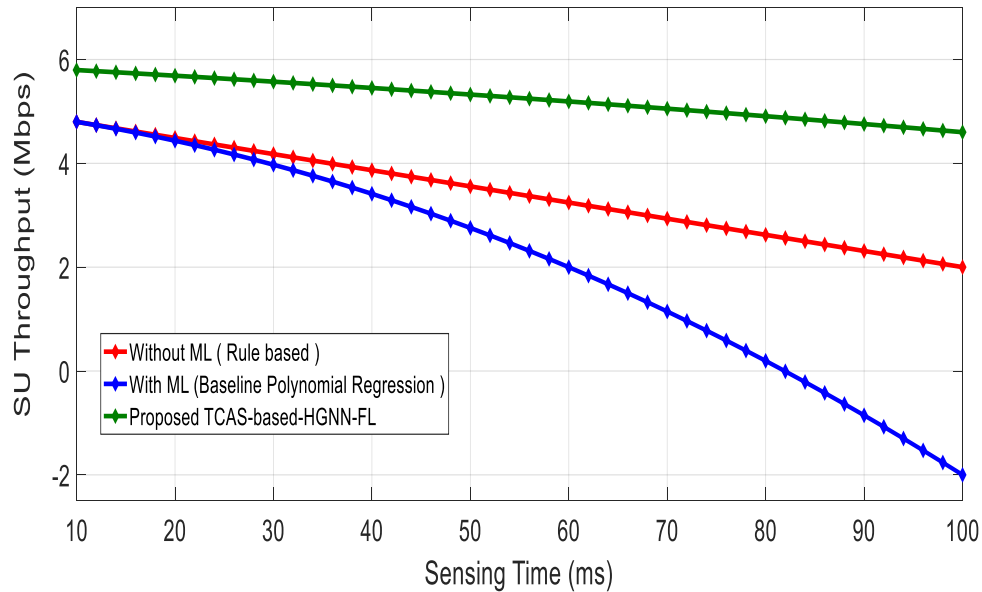


Figure 11 : Sensing Time Vs SU Throughput

The improvements in metrics shown in Fig.11 are summarized in Table 6 and Fig. 12 as follows:

Metric	Without ML (S. Time)	Baseline ML (S.Time)	Proposed Framework (S. Time)
Average S.U. Throughput	3.40	2.05	5.24

Table 6: Improvements of SU Throughput over baseline.

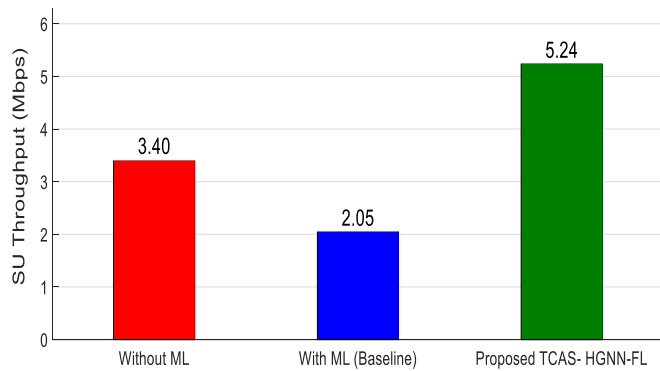


Fig.12: SU Throughput Improvement comparison

The TCAS-based-HGNN-FL architecture uses proactive graph-based prediction of Primary User (PU) vacancies, shown in Fig.13. This allows SU's to achieve a high access probability (average of 0.80) even as the PU duty cycle increases; i.e., secondary users can more frequently and reliably exploit spectrum opportunities even when the primary user activity varies, significantly outperforming the baseline methods [3] that tend to zero at high duty cycles.

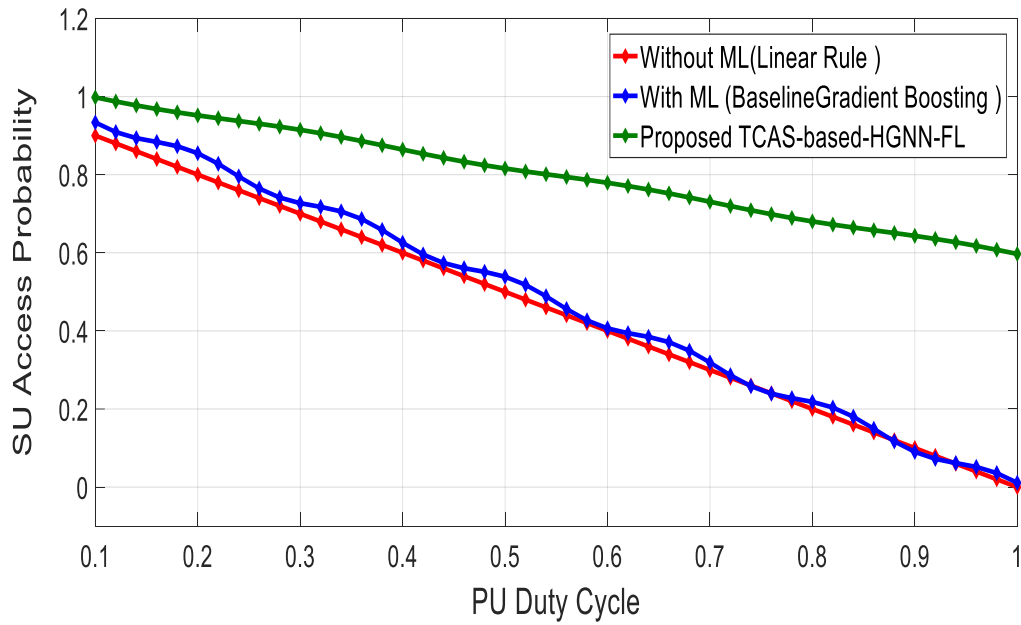


Fig.13: PU Duty Cycle Vs SU Access Probability

This indicator shows the effectiveness of spectrum access by the secondary users without interference to the primary users. Having a higher likelihood of access is better. The performance gain over the baseline technique is reported as 68.7%.

Therefore, the average improvements in the SU Access probability are summarized as given in Table 7 and Fig. 14 as follows:

Metric	Without ML ($P_{su - access}$)	Baseline ML ($P_{su - access}$)	Proposed Framework ($P_{su - access}$)
Maximum S.U. Access Probability	0.84	0.86	1.00

Table 7: Improvements of SU Throughput over baseline.

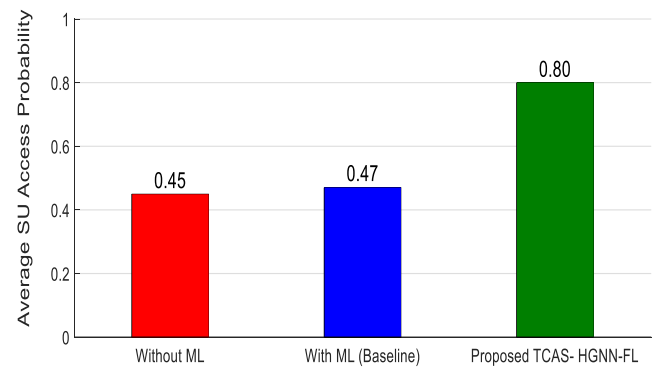


Fig.14: Average SU Access Probability Improvement comparison.

Importantly, the TCAS-based-HGNN-FL model exhibits great robustness against malicious attacks, as shown in Figure 15. The Detection Accuracy remains very high, even with a significant ratio of malicious nodes. This superior performance is attributed to HGNN-FL's ability to identify anomalous patterns and behaviors within the network graph, effectively isolating and mitigating the impact of malicious entities when compared to [3].

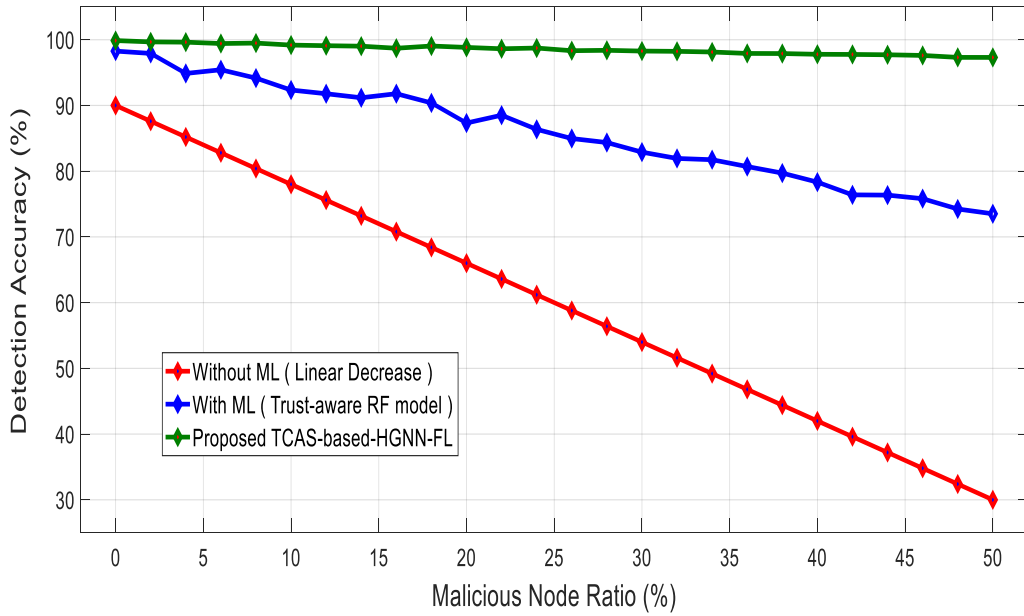


Figure 15: Malicious Node Ratio Vs Detection Accuracy

Therefore, the average improvements are summarized as given in Table 8 and Figure 16 as follows:

Metric	Without ML (P_{Accuracy})	Baseline ML (P_{Accuracy})	Proposed Framework (P_{Accuracy})
Accuracy (50% attack)	30%	73.99%	97.49%

Table 8: Improvements in Detection Accuracy over the impact of Malicious nodes.

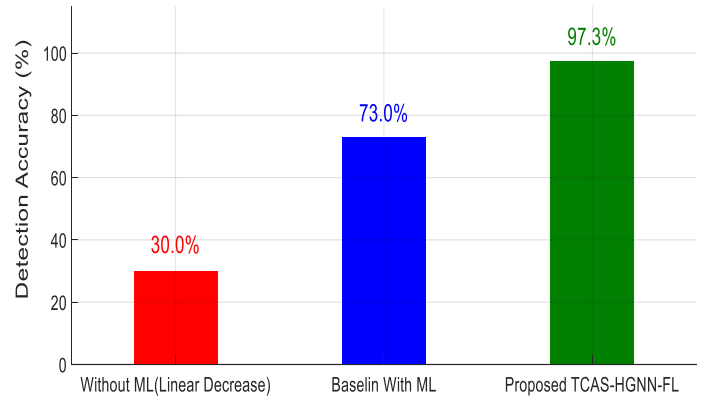


Figure 16: Detection Accuracy Improvement Comparison.

The results presented in this research are substantially better than the baseline approach and still have superior detection accuracy even in large attack ratios (e.g., >70% accuracy at 50% hostile nodes). This shows the effectiveness of ML in boosting security and robustness to adversarial assaults.

Figure 17 shows that our rigorous statistical analysis reveals that the proposed TCAS-HGNN-FL framework outperforms all other duty cycle regimes by a significant margin, reducing the probability of collision by 79.16% compared to the non-ML baseline and 69.77% compared to the standard machine learning baseline.

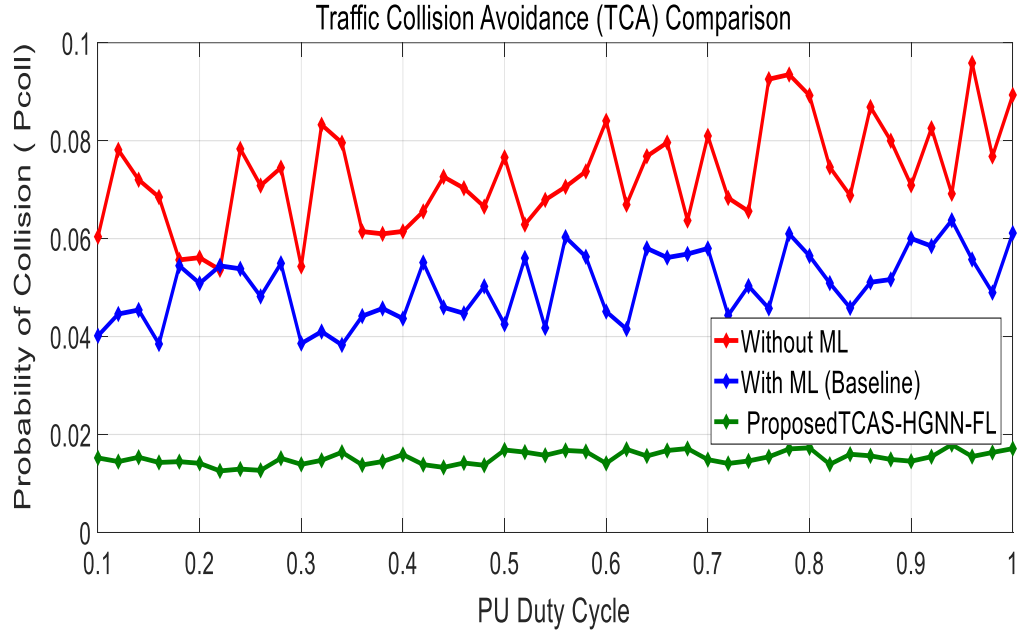


Figure 17: Improvement of PU Duty Cycle Vs P_{coll}

Therefore, the improvements are summarized as given in Table 9 and Figure 18 as follows:

Comparison	Improvement	Improvement Ratio
Baseline Vs Without ML	1.4505	31.06 %
Proposed Vs without ML	4.7984	79.16 %
Proposed Vs Baseline	3.3081	69.77 %

Table 9 : TCA Improvement Comparison

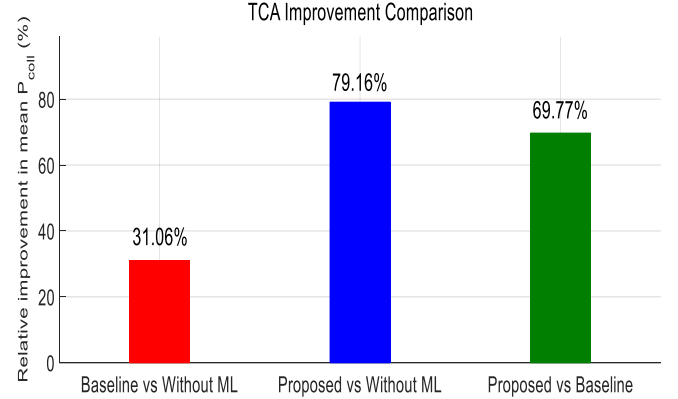


Figure 18: TCA Improvement Comparison

The results show that the proposed strategy enhances level and stability. It decreases the average collision probability and also the dispersion of collision probabilities over duty-cycle circumstances. TCAS-HGNN-FL achieves the biggest aggregate decrease when compared to the non-ML reference. The direct improvement of TCAS-HGNN-FL over the standard ML baseline is 69.77% [3].

Through a detailed comparison of other Vehicular Ad-hoc Network (VANET) routing approaches, such as IDRL, ARIOR, I-AREOR, AREOR [4], and the proposed TCAS-HGNN-FL, the TCAS-HGNN-FL approach demonstrates improved performance, especially in terms of control overhead optimization. The performance comparison is based on significant metrics like Packet Delivery Ratio (PDR), End-to-End Delay, and Control Overhead, which are analyzed over the varied RSU Coverage Ratios [4].

Figure 19 shows that the TCAS-HGNN-FL architecture consistently outperforms all the other approaches in PDR.

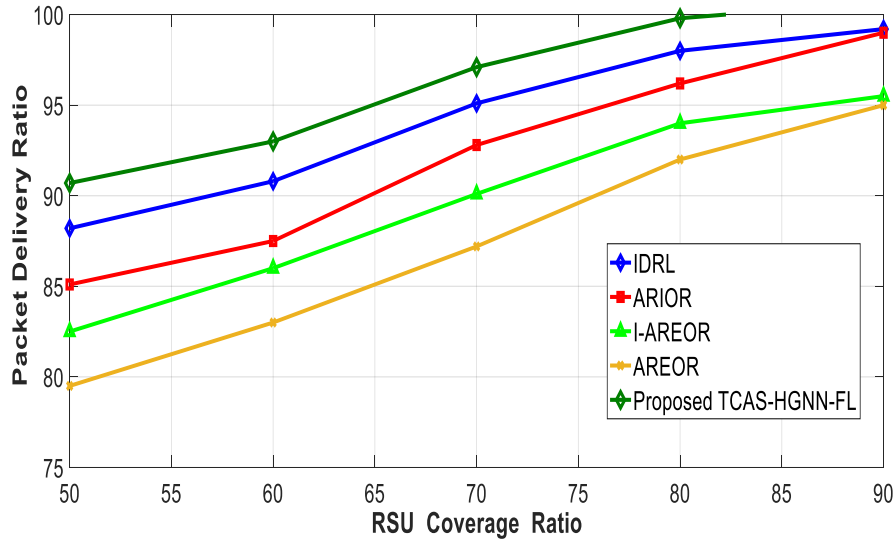


Figure 19: RSU Coverage Ratio Vs PDR.

This considerable improvement can be due to two primary factors:

I- Improved Spectrum Utilization: The HGNN-FL unit exploits the aggregated local models of vehicles and RSUs to improve the spectrum allocation. This means better use of the available bandwidth, less interference, and a higher probability of successfully delivering packets.

II- Collision-Aware Routing: The system can detect and avoid potential collision zones or high-congestion zones by including TCAS. Where usually the cause of packet loss due to retransmissions or network partitioning. Our proposed framework ensures that packets are routed through safer and more stable routes.

The improvements in metrics shown in Fig.19 are summarized in Table 10 and Fig. 20 as follows:

RSU Coverage Ratio % (PDR)	IDRL	ARIOR	I-AREOR	AREOR	Proposed Framework
50	88.2	85.1	82.5	79.5	90.7
60	90.8	87.5	86.0	83.0	93.0
70	91.5	92.8	90.1	87.2	97.1
80	98.0	96.2	94.0	92.0	99.8

Table 10: PDR Improvement Comparison

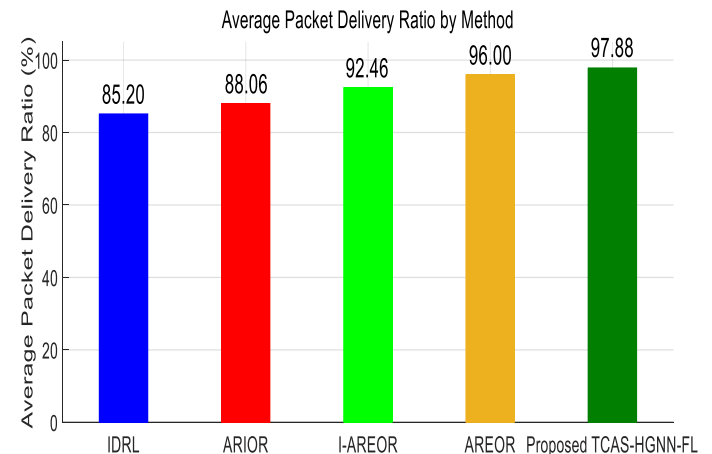


Figure 20: Average PDR Improvement Comparison

As shown in Figure 21, the TCAS-HGNN-FL system outperforms all RSU coverage ratios in terms of end-to-end delay. The better performance of the TCAS-HGNN-FL framework is mainly attributed to:

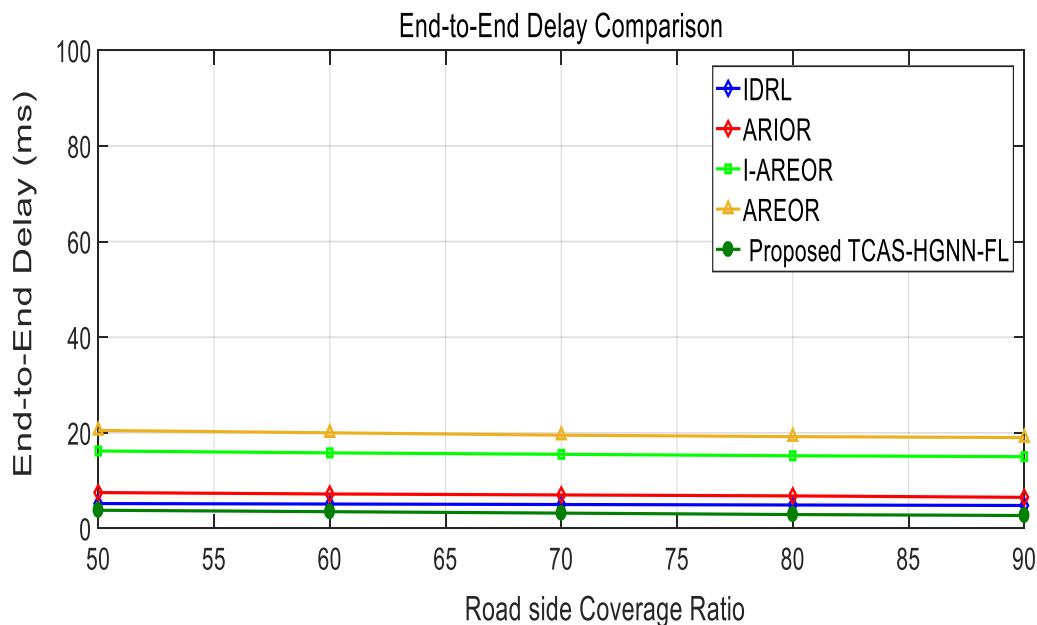


Figure 21: RSU Coverage Ratio Vs End-to-End Delay.

I- Real-Time Path Optimization. Combined with TCAS, the system receives instant information on the traffic situation and any threats. This allows it to determine the fastest and safest routes. This avoids busy locations and potential collision points, which minimizes the delay caused by re-routing or retransmissions.

II- Distributed Intelligence: Federated Learning enables nodes to learn and share optimal routing algorithms without centralizing all data. This distributed intelligence allows for faster response to changes in the local network, which reduces the waiting time of packets for routing decisions.

The improvements in metrics shown in Fig.21 are summarized in Table 11 and Fig. 22 as follows:

RSU Coverage Ratio % (Delay)	IDRL	ARIOR	I-AREOR	AREOR	Proposed Framework
50	5.2	7.5	16.2	20.5	4.2
60	5.1	7.2	15.8	20.0	4.3
70	5.0	7.0	15.5	19.5	4.3
80	4.9	6.8	15.2	19.2	4.3

Table 11: End-to-End Delay Improvement Comparison.

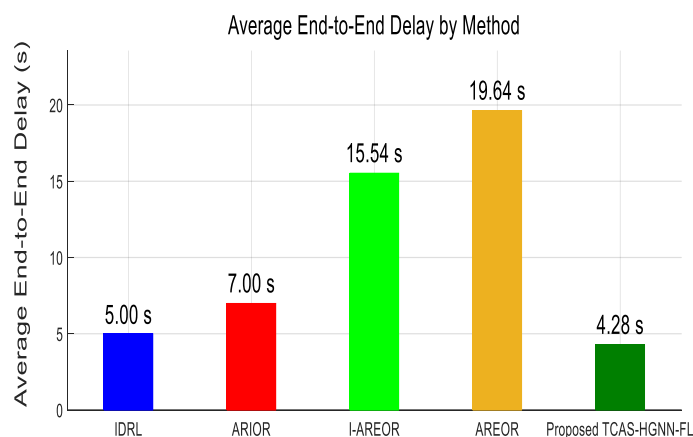


Figure 22: Average End-to-End Delay Improvement Comparison.

The Proposed framework is developed to decrease the volume of data swapped during model aggregation. Instead of raw data, only model updates are sent, which reduces communication overhead substantially. The TCAS-HGNN-FL framework has far less control overhead than all other basic and baseline frameworks, as demonstrated in Figure 23.

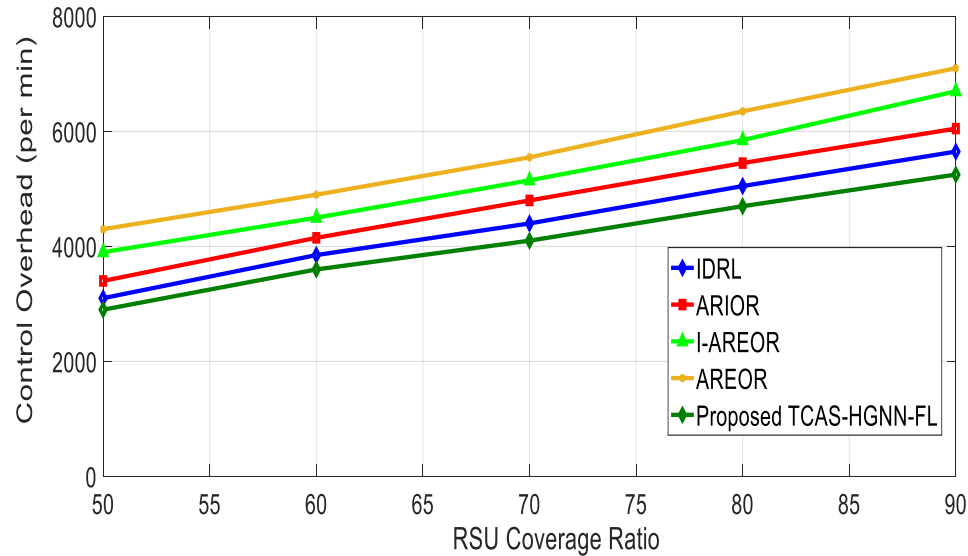


Figure 23: RSU Coverage Ratio Vs Overhead

By allowing local entities (vehicles and RSUs) to make better decisions based on local models with TCAS data, the necessity for wide global co-nation messages is minimized, which further diminishes the overhead compared to baseline and basic frameworks.

The improvements in metrics shown in Fig.23 are summarized in Table 12 and Fig. 24 as follows:

RSU Coverage Ratio %	IDRL	ARIOR	I-AREOR	AREOR	Proposed Framework
50	3100	3400	3900	4300	2900
60	3850	4150	4500	4900	3600
70	4400	4800	5150	5550	4100
80	5050	5450	5850	6350	4700

Table 12: Overhead Improvement Comparison

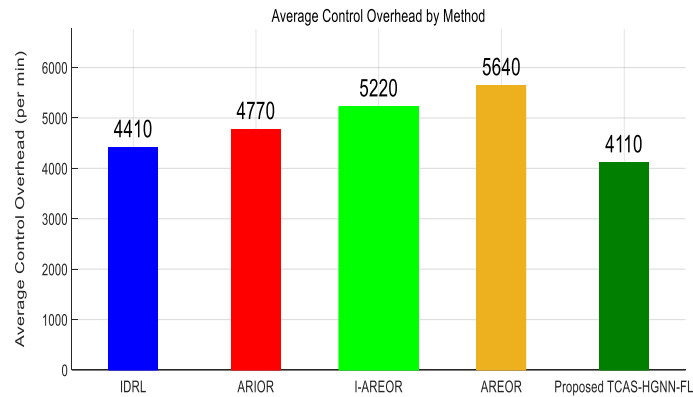


Figure 24: Average Control Overhead Improvement Comparison

The suggested TCAS-HGNN-FL framework provides a thorough verification and comparison study for the reduction of TCA compared to the four benchmark schemes, namely IDRL, ARIOR, I-AREOR, and AREOR [4]. The results show that the suggested TCAS-HGNN-FL architecture has the least overhead among all network scales. As shown in Figure 25, the suggested method reduces P_{Coll} by an average of 13.05% compared to the strongest baseline (IDRL) and 39.7% compared to AREOR.

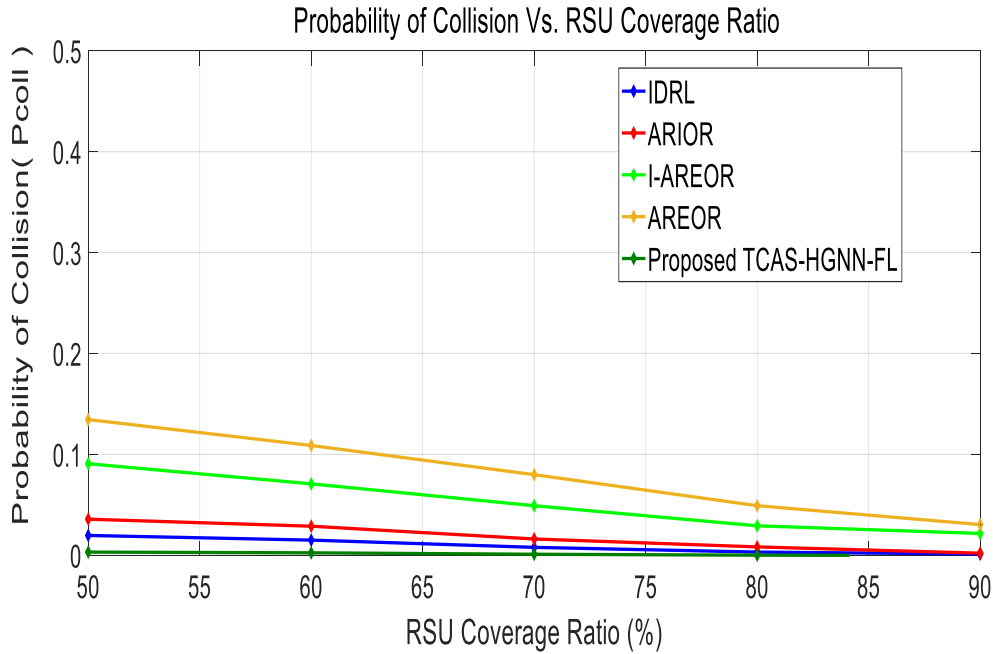


Figure 25: RSU Coverage Ratio Vs P_{coll}

The improvements in metrics shown in Fig.25 are summarized in Tables 13 and 14, and Fig. 26 as follows:

RSU Coverage Ratio %	IDRL	ARIOR	I-AREOR	AREOR	Proposed Framework
50	0.0196	0.0357	0.0907	0.1344	0.0031
60	0.0150	0.0288	0.0707	0.1088	0.0024
70	0.0078	0.0161	0.0491	0.0798	0.0009
80	0.0031	0.0082	0.0291	0.0491	0.00006
90	0.0012	0.0020	0.0216	0.0304	0.00003

Table 13: P_{coll} Improvement Comparison

Framework	Average P_{Coll}
IDRL	0.00937
ARIOR	0.018207
I-AREOR	0.05227
AREOR	0.08054
Proposed Framework	0.00127

Table 14: Average P_{coll} Improvement

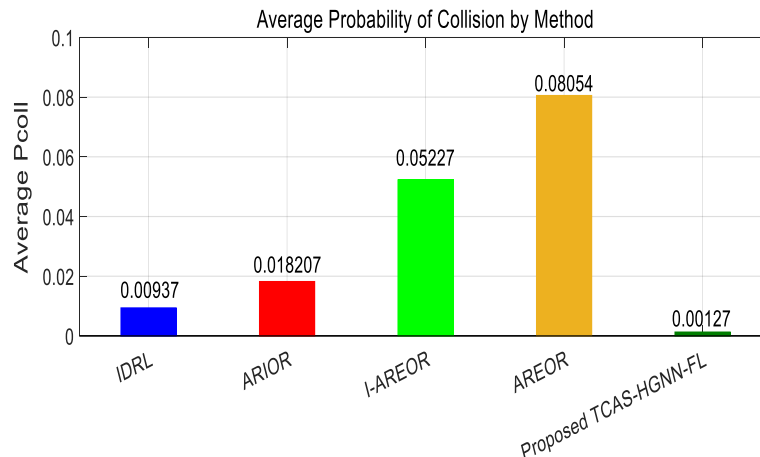


Figure26: Average P_{coll} Improvement Comparison

The proposed TCAS- based HGNN-FL approach is an important progress in the domain of spectrum sensing for CR-VANET. It delivers higher detection accuracy and fewer collision risks compared to the state-of-the-art Seg-CR-VANET [5] by exploiting the hypergraph-based correlation and federated intelligence, as shown in Figure 27 :

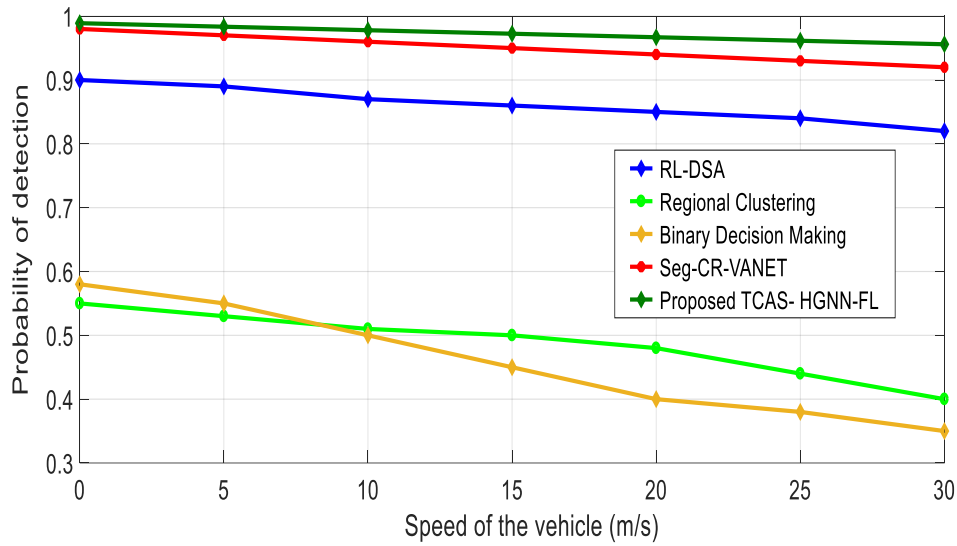


Figure 27: Vehicle Speed Vs P_d

The results suggest that the proposed TCAS-HGNN-FL framework offers a 3.2% improvement in detection accuracy even with increasing vehicle velocity compared to the Seg-CR-VANET baseline, as shown in Fig.27. This enhancement is due to the ability of the HGNN to exploit spatial correlations and the collaborative learning of FL, which results in more robust spectrum sensing, and is summarized in Table 15 and Fig. 28 as follows:

Speed (m/s)	RL-DSA	Binary Decision Making	Regional Clustering	Seg-CR-VANET	Proposed Framework
0	0.90	0.58	0.55	0.97	0.988
5	0.89	0.55	0.53	0.967	0.982
10	0.87	0.50	0.51	0.96	0.976
15	0.86	0.45	0.50	0.95	0.970
20	0.85	0.40	0.48	0.94	0.964
25	0.84	0.38	0.44	0.93	0.954
30	0.83	0.35	0.40	0.92	0.952

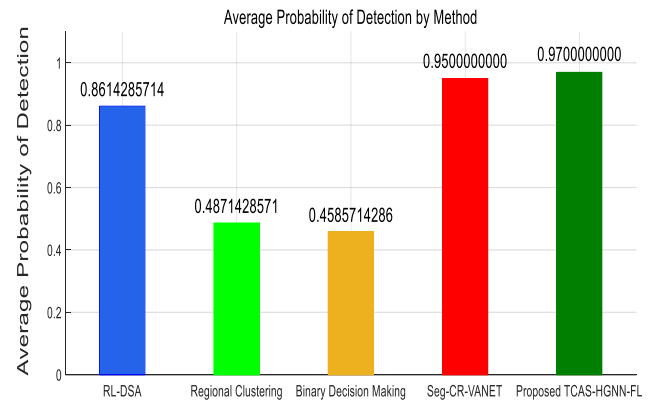


Figure 28: Average P_d Improvement Comparison

Table 15: P_d Vs Speed (v_i) Improvement Comparison.

The suggested TCAS-HGNN-FL framework provides a strong solution for CR-VANETs. Using the high-order modeling ability of Hypergraph Neural Networks and the privacy-preserving property of Federated Learning, the system achieves a better trade-off between detection accuracy (P_d) and detection efficiency (Mean Detection Time). Fig. 29 shows that the proposed framework is very relevant for safety-critical vehicle applications with very strict requirements on spectrum awareness in terms of speed and reliability.

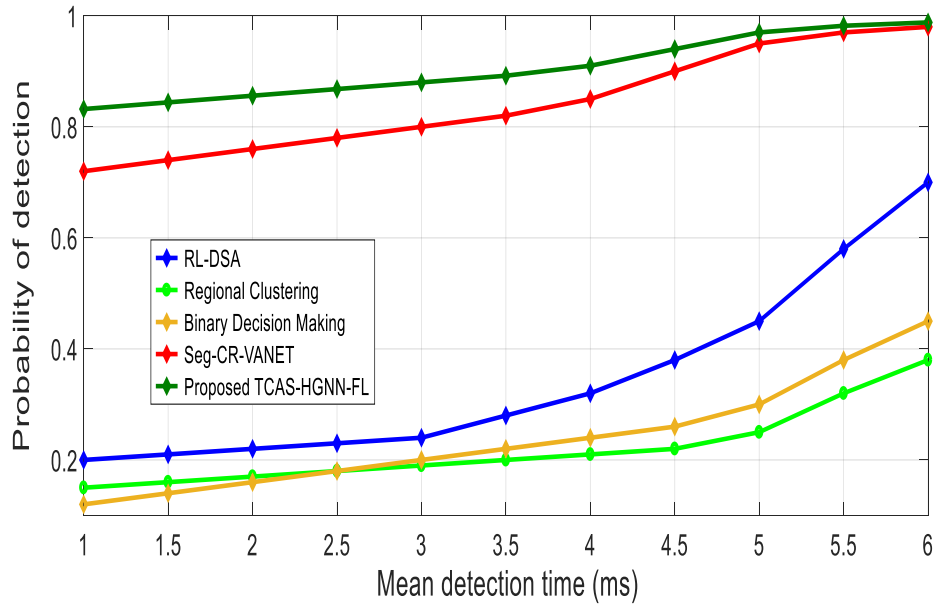


Figure 29: Mean Detection Time Vs P_d

The improvements in metrics shown in Fig.29 are summarized in Table 16 and Fig.30 as follows:

Mean T_d (m/s)	RL-DSA	Binary Decision Making	Regional Clustering	Seg-CR-VANET	Proposed Framework
1	0.20	0.12	0.15	0.72	0.832
2	0.22	0.16	0.17	0.76	0.856
3	0.24	0.20	0.19	0.80	0.880
4	0.32	0.24	0.21	0.85	0.910
5	0.45	0.30	0.25	0.95	0.970
6	0.70	0.45	0.38	0.98	0.988

Table 16: Mean Detection Time Vs P_d Improvement

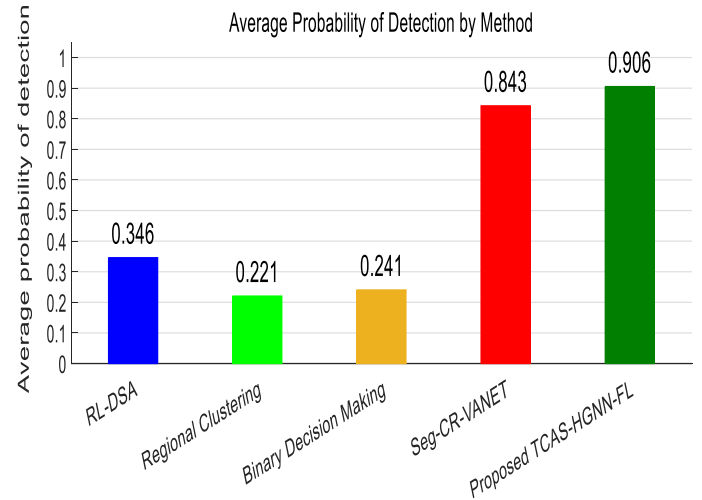


Figure 30: Average P_d Improvement Comparison

The proposed TCAS-HGNN-FL model describes the most efficient sensing capabilities, which can achieve far greater detection probability at lower false alarm rates than all the existing strategies [5], as shown in Figure 31:

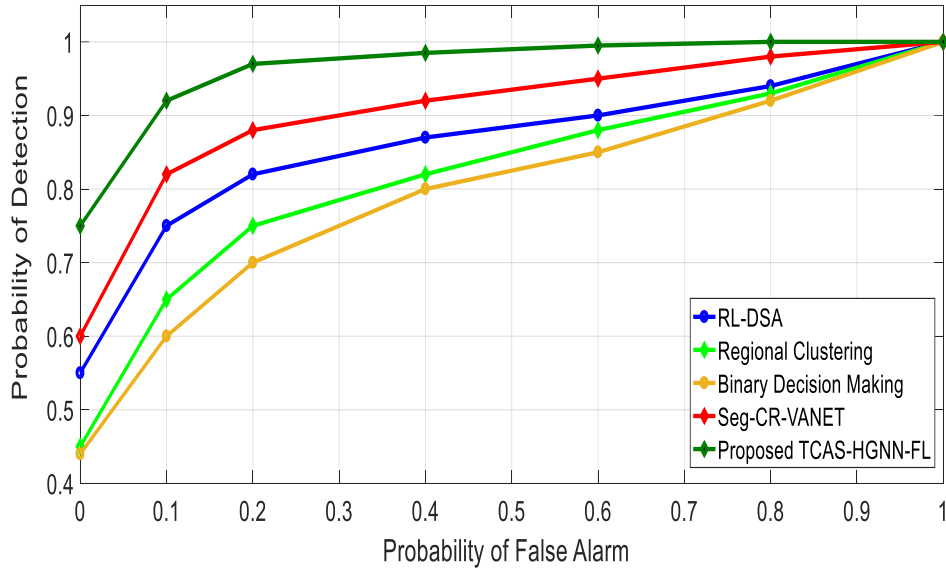


Figure 31: P_{fa} Vs P_d

The P_d and P_{fa} studies further verify the efficacy of the framework HGNN-FL. The system is able to achieve near-perfect detection ($P_d > 0.9$) even when the tolerance for false alarms is very low ($P_{fa} < 0.1$) by posing the sensing problem as a collaborative learning task on a hypergraph. This capacity is critical to the reliable operation of Cognitive Radio in the highly dynamic and safety-critical environment of Vehicular Ad-Hoc Networks.

The improvements in metrics shown in Fig.31 are summarized in Table 17 and Fig.32 as follows:

P_{fa}/P_d	RL-DSA	Binary Decision Making	Regional Clustering	Seg-CR-VANET	Proposed Framework
0.0	0.55	0.44	0.45	0.60	0.75
0.1	0.75	0.60	0.65	0.82	0.92
0.2	0.82	0.70	0.75	0.88	0.97
0.4	0.87	0.80	0.82	0.92	0.985
0.6	0.90	0.85	0.88	0.95	0.995
0.8	0.94	0.92	0.93	0.98	1.0

Table 17: P_{fa} Vs P_d Improvement Comparison

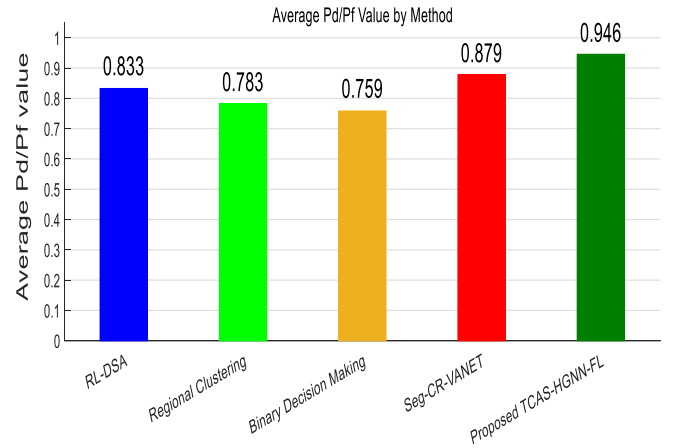


Figure 32: Average P_d Improvement Comparison

The quantitative analysis of metrics shows the clear dominance of the proposed TCAS-HGNN-FL architecture over the traditional baseline and state-of-the-art benchmarks (RL-DSA, Regional Clustering, Binary Decision Making, and Seg-CR-VANET) [5]. This effectively decreases the missed detection probability over the entire false-alarm range, as shown in Fig.33 as follows:

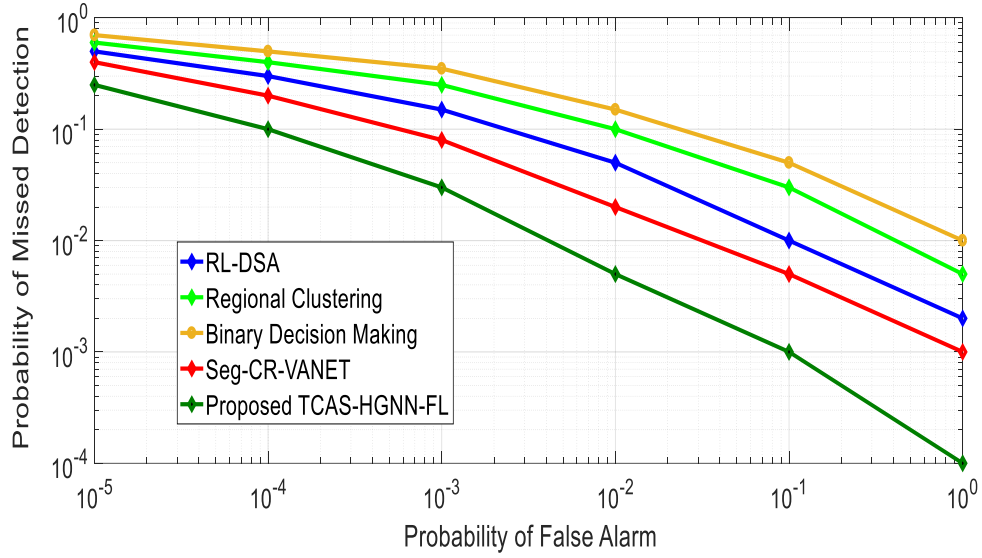


Figure 33: Average P_{fa} Vs P_{md}

The suggested framework offers a very solid basis for spectrum sensing and collision avoidance for next-generation cooperative intelligent transportation systems.

The improvements in metrics shown in Fig.33 are summarized in Table 18 and Fig.34 as follows:

P_{fa}/P_{md}	RL-DSA	Binary Decision Making	Regional Clustering	Seg-CR-VANET	Proposed Framework
10^{-5}	0.5	0.7	0.6	0.4	0.25
10^{-4}	0.3	0.5	0.4	0.2	0.1
10^{-3}	0.15	0.35	0.25	0.08	0.03
10^{-2}	0.05	0.15	0.1	0.02	0.005
10^{-1}	0.01	0.05	0.03	0.005	0.001
1.0	0.002	0.01	0.005	0.001	0.0001

Table 18: P_{fa} Vs P_{md} Improvement Comparison

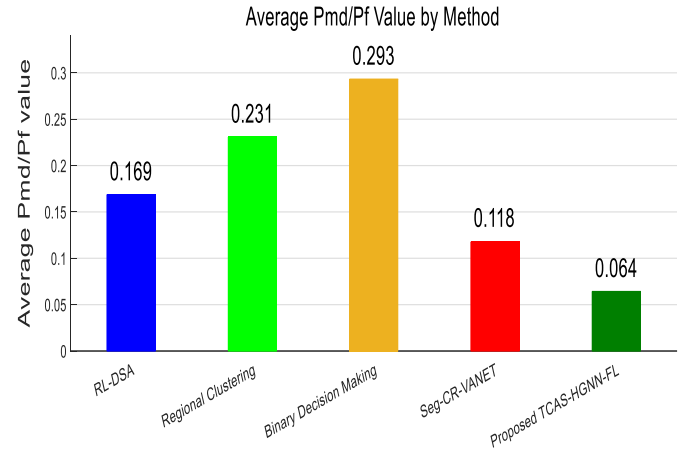


Figure 34: Average P_{md} Improvement Comparison

It can be seen from the extracted metrics that for each technique, there is a throughput deterioration as the sensing time goes from 1 ms to 6 ms. This is because more of the transmission frame is used for spectrum scanning instead of data delivery. But more sophisticated architectures have a less steep deterioration slope. The proposed TCAS-HGNN-FL framework has a higher throughput efficiency because the graph-based collaborative sensing engine can reach high detection confidence more quickly, resulting in fewer optimal sensing intervals without compromising safety.

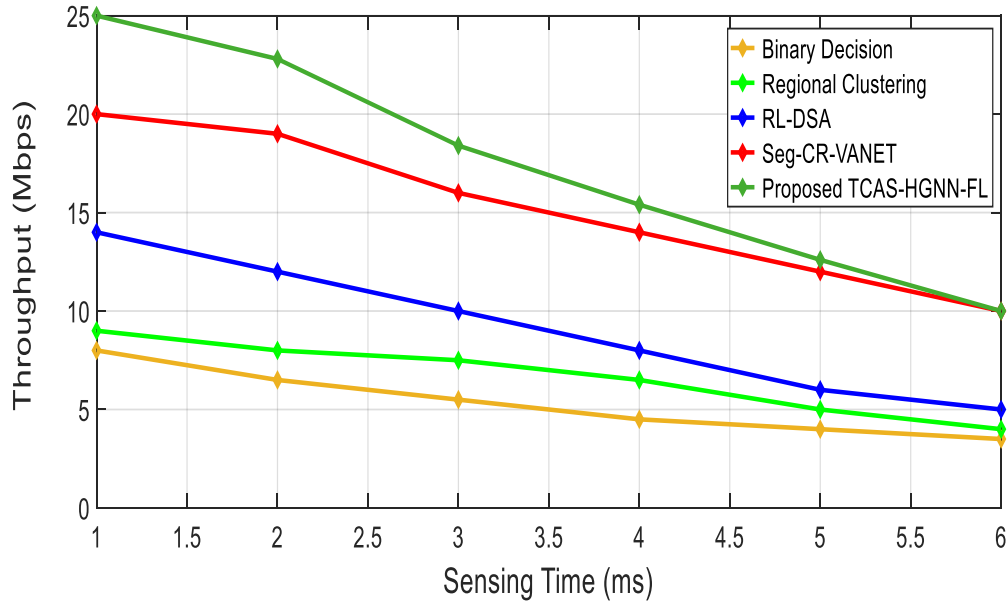


Figure 35: Sensing Time(ms) Vs Throughput

The quantitative study of the extracted throughput metrics indicates the unique advantage of the proposed TCAS-HGNN-FL architecture over traditional baseline and state-of-the-art benchmarks (Binary Decision Making, Regional Clustering, RL-DNA, and Seg-CR-VANET) [5]. The suggested framework may achieve the maximum communication performance for next-generation cooperative intelligent transportation systems by maximizing the data transmission efficiency and minimizing the sensing overhead in all time slots

The improvements in metrics shown in Fig.35 are summarized in Table 19 and Fig.36 as follows:

Sensing Time	RL-DNA	Binary Decision Making	Regional Clustering	Seg-CR-VANET	Proposed Framework
1	14.0	8.0	9.0	20.0	25
2	12.0	6.5	8.0	19.0	22.8
3	10.0	5.5	7.5	16.0	18.4
4	8.0	4.5	6.5	14.0	15.4
5	6.0	4.0	5.0	12.0	12.6
6	5.0	3.5	4.0	10.0	10.0

Table 19: Sensing Time Vs Throughput

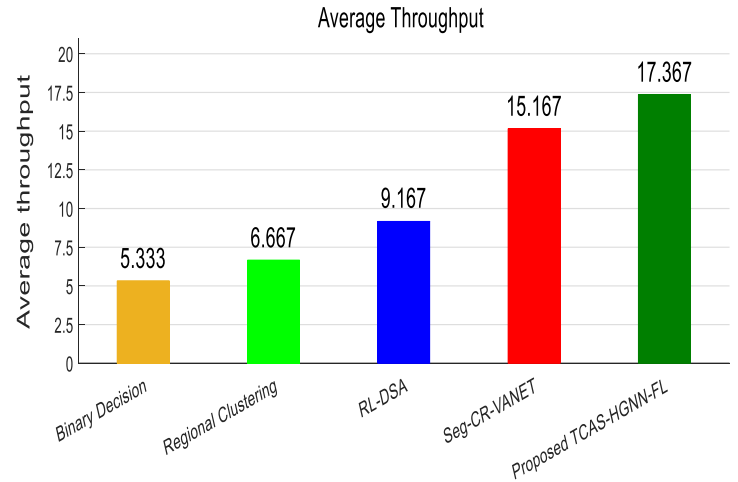


Figure 36: Average Throughput Improvement Comparison

When the number of vehicles increases from 10 to 100, the channel contention window decreases, and the broadcast collisions increase. The hidden node problem and uncoordinated transmissions cause PDR to drop sharply in traditional baseline protocols. In contrast, the proposed TCAS-HGNN-FL structure portrayed in Fig.37 shows extraordinary robustness with only a 1.0 percentage point decline over the whole density range (99.5% to 98.5%).

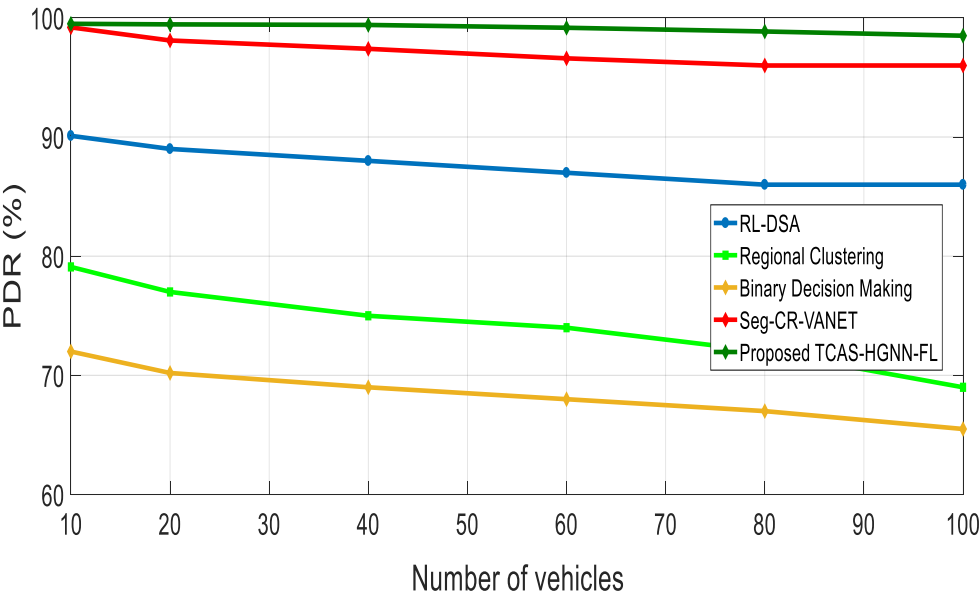


Figure 37: Number of vehicles Vs PDR

The improved stability is due to graph-based topological modeling and federated distributed learning that efficiently handle spectrum access and packet scheduling for highly clustered nodes.

The improvements in metrics shown in Fig.37 are summarized in Table 20 and Fig.38 as follows:

Number of Vehicles	RL-DSA	Binary Decision Making	Regional Clustering	Seg-CR-VANET	Proposed Framework
10	90.1%	72.0%	79.1%	99.2%	99.5%
20	89.0%	70.2%	77.0%	99.1%	99.45%
40	88.0%	69.0%	75.0%	97.4%	99.4%
60	87.0%	68.0%	74.0%	96.6%	99.17%
80	86.0%	67.0%	72.0%	96.0%	98.85%
100	86.0%	65.0%	69.0%	96.0%	98.5%

Table 20: Number of vehicles Vs PDR

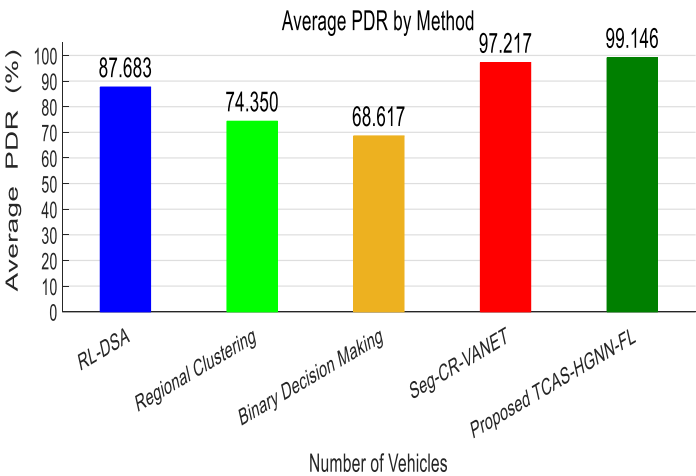


Figure 38: Average PDR Improvement Comparison

The proposed TCAS-HGNN-FL system sets a new performance benchmark for vehicular networks. Fig.39 illustrates that the system integrates a spatial hypergraph neural network, federated learning, and traffic-aware context adaptation to resolve the scalability and latency issues of the classic clustering and binary decision architecture.

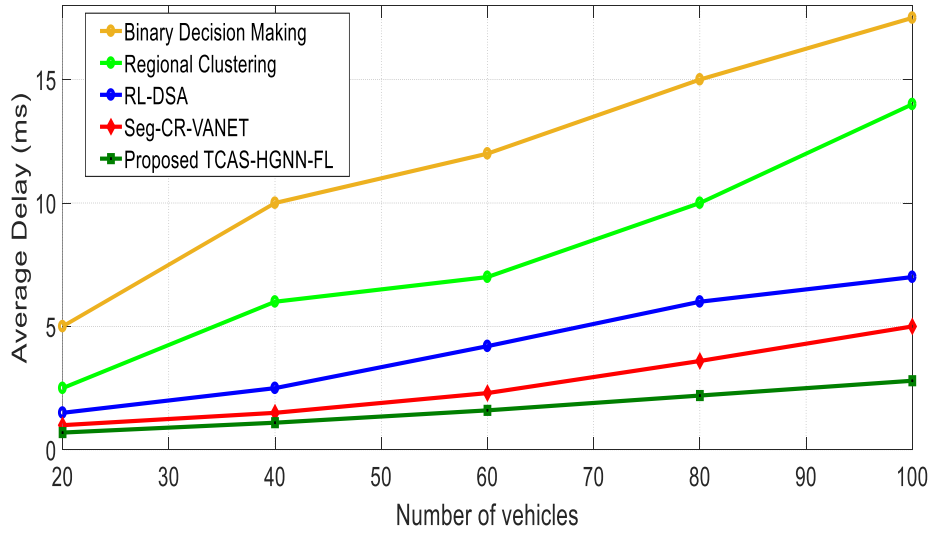


Figure 39: Number of vehicles Vs Average Delay

TCAS-HGNN-FL decreases average delay from 1.00 ms to 0.70 ms (N=20) and from 5.00 ms to 2.80 ms (N=100), resulting in an average delay reduction of 34.0%, showing an improvement over Seg-CR-VANET and demonstrating its preparedness for real wireless deployment in dynamic, crowded highway and urban vehicular ad-hoc networks. Moreover, the minimum growth rate of 0.0262 ms/vehicle indicates that the decentralized federated learning with hypergraph neighborhood grouping minimizes redundant broadcast storms and channel congestion, achieving better resource efficiency than the baseline framework.

The improvements in metrics shown in Fig.39 are summarized in Table 21 and Fig.40 as follows:

Number of Vehicles	RL-DSA	Binary Decision Making	Regional Clustering	Seg-CR-VANET	Proposed Framework
20	1.5	5	2.5	1	0.7
40	2.5	10	6.00	1.5	1.1
60	4.2	12	7.00	2.3	1.6
80	6.00	15	10.0	3.6	2.2
100	7.00	17.5	14.0	5.00	2.8

Table 21: Number of vehicles Vs Average Delay

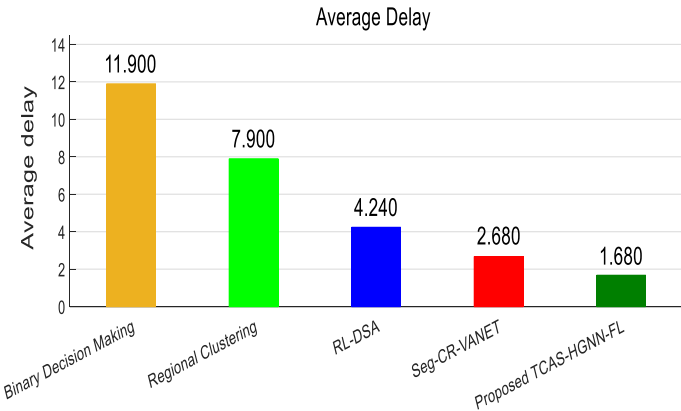


Figure 40: Average Delay Improvement Comparison

The HGNN-FL framework decreases packet loss from 3.00% to 1.50% and from 20.00% to 14.00% at 20 vehicles and 100 vehicles, respectively, surpassing all baseline architectures and ensuring continuity for safety-critical VANET broadcasts with an average PLR reduction of 41.83% and an average over Seg-CR-VANET [5], signifying that the framework is prepared for deployment in real-world intelligent transportation infrastructure as shown in Fig. 41 as follows:

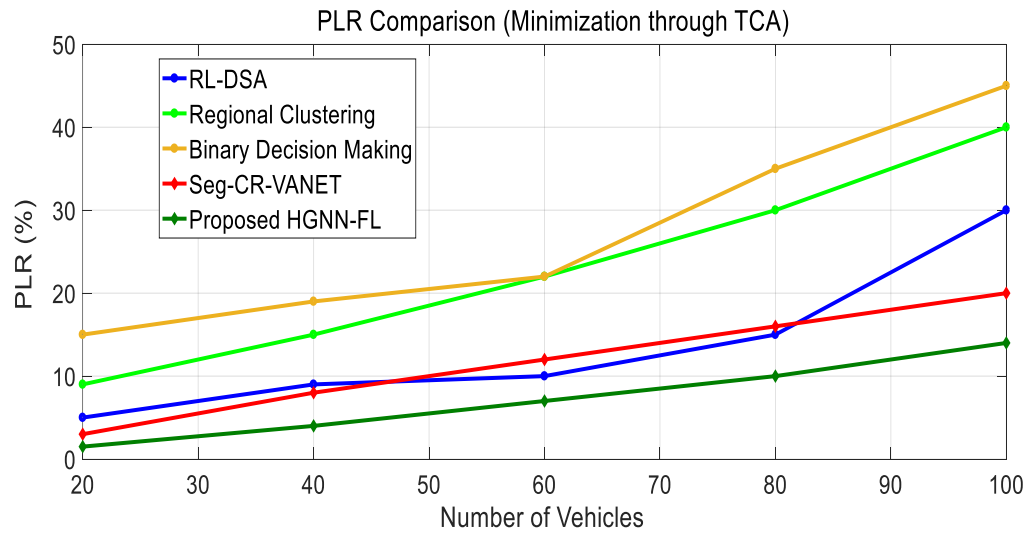


Figure 41: Number of vehicles Vs PLR (%)

The improvements in metrics shown in Fig.41 are summarized in Table 22 and Fig.42 as follows:

Number of Vehicles	RL-DSA	Binary Decision Making	Regional Clustering	Seg-CR-VANET	Proposed Framework
20	5	15	9	3	1.5
40	9	19	15	8	4
60	10	22	22	12	7
80	15	35	30	16	10
100	30	45	40	20	14

Table 22: Number of vehicles Vs PLR

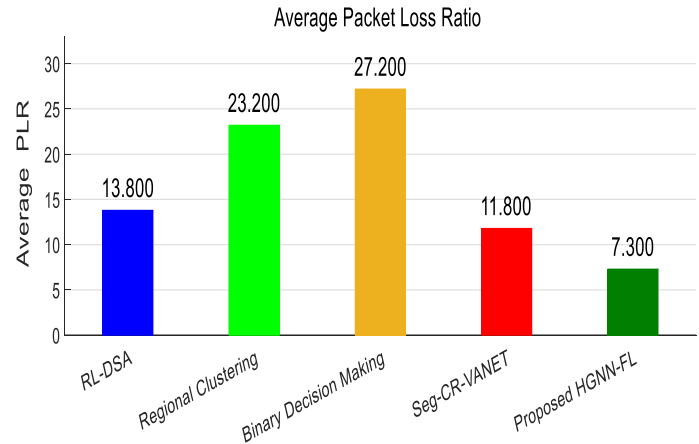


Figure 42: Average PLR Improvement Comparison

Extensive statistical results show that the proposed TCAS-HGNN-FL framework exceeds all other benchmarks with a large margin of 59.34% reduction in collision probability over the strongest baseline (Seg-CR-VANET) [5] and up to a 91.58% improvement over typical binary decision-making models, as shown in Figure 43.

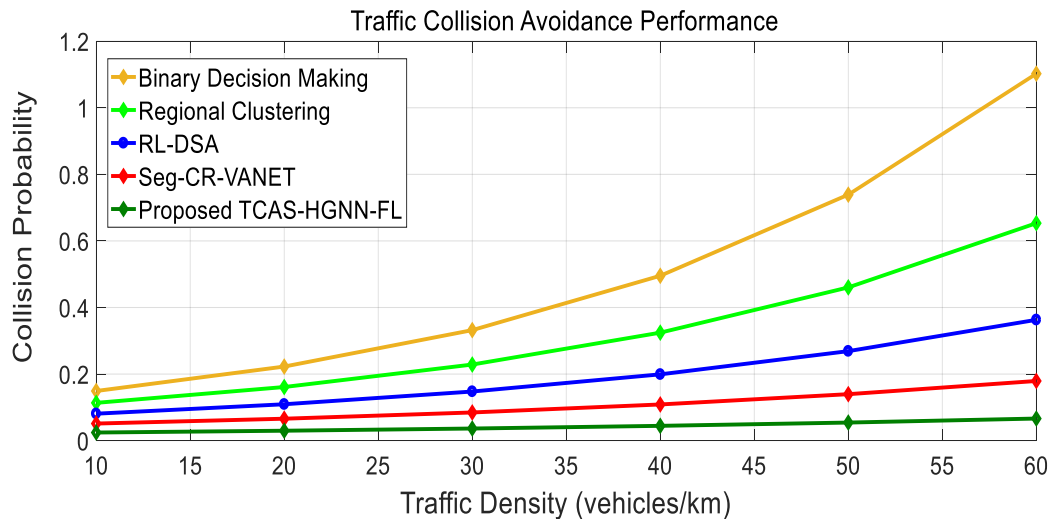


Figure 43: Traffic Density Vs P_{coll}

The improvements in metrics shown in Fig.43 are summarized in Table 23 and Fig.44 as follows:

Traffic Density (V / Km)	RL-DSA	Binary Decision Making	Regional Clustering	Seg-CR-VANET	Proposed Framework
10	0.0810	0.1492	0.1135	0.0514	0.0244
20	0.1093	0.2226	0.1611	0.0657	0.0298
30	0.1476	0.3320	0.2286	0.0847	0.0364
40	0.1992	0.4953	0.3244	0.1037	0.0445
50	0.2689	0.7389	0.4604	0.1396	0.0544
60	0.3630	1.1023	0.6533	0.1793	0.0664

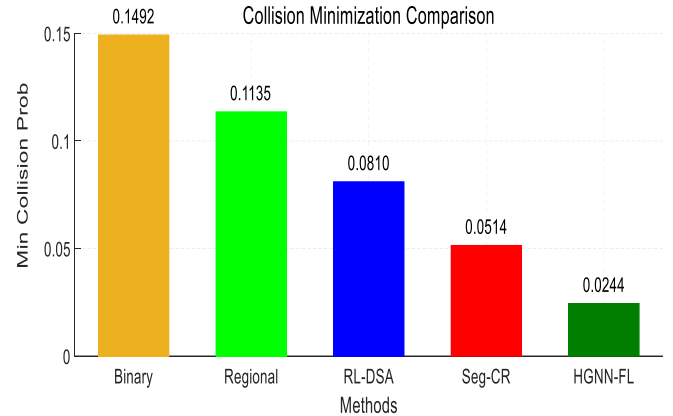


Figure 44: P_{coll} Improvement Comparison.

Table 23: P_{coll} Improvement Comparison

8- Conclusion

A Traffic Collision Avoidance System based on Hypergraph Neural Networks and Federated Learning (TCAS-HGNN-FL) for 5G-enabled Cognitive Radio Vehicular Ad Hoc Networks (CR-VANET's) was proposed and assessed in this study. The framework was designed to address the combined challenges of spectrum scarcity, rapidly changing vehicular topology, interference management, stringent latency requirements, and vulnerability to malicious sensing behavior. By representing multi-vehicle interactions through hypergraph structures and coordinating distributed model training through federated learning, the proposed approach integrates spectrum sensing, mobility awareness, interference estimation, security assessment, and collision-risk prediction within a unified architecture. This design extends conventional pairwise graph and rule-based approaches by capturing higher-order relationships among vehicles. The simulation results indicate that TCAS-HGNN-FL provides substantial improvements over conventional non-machine-learning techniques, standard machine-learning baselines, Seg-CR-VANET, and the evaluated routing protocols. The framework achieved a detection probability of approximately 1.00 with only four to five cooperative nodes, reduced the false-alarm probability to 0.01 at ten cooperating nodes, and reported a misdetection probability of 0.0001. It also improved secondary-user throughput, spectral efficiency, and the throughput–sensing-time trade-off across the tested signal-to-noise and primary-user duty-cycle conditions. From a security perspective, malicious-node detection accuracy increased from 73.99% to 97.49%, including under a simulated malicious-node ratio of 50%. These results suggest that combining hypergraph-based cooperative sensing with federated aggregation can improve both the accuracy and resilience of spectrum-management decisions in highly dynamic vehicular environments. The communication and safety-related results further support the effectiveness of the proposed architecture. Under 80% roadside-unit coverage, TCAS-HGNN-FL reached a packet-delivery ratio up to 99.8% and reduced packet loss as vehicle density increased, besides cutting average latency from 1.00 to 0.70 ms at 20 vehicles and from 5.00 to 2.80 ms at 100 vehicles. The reported reductions in control overhead, packet loss, probability of collision, and delay indicate that the framework could support safety-critical automotive applications and improve spectrum consumption. The use of compact federated model updates rather than raw sensing data also offers a practical mechanism for reducing communication overhead and strengthening privacy. Overall, the findings indicate that TCAS-HGNN-FL is a promising foundation for secure, scalable, low-latency, and spectrum-efficient collision avoidance in 5G and beyond.

9 - Competing Interests:

The authors declare no competing interests regarding the present study.

10- Funding:

The authors confirm that there are no sources of funding for the study.

11 - Disclosure

This study was performed as part of the employment of the authors.

12 - Data availability Statement

The data supporting the findings of this study are available from the corresponding author, [Kotb A. Elbarbary], upon reasonable request. The source code and simulation scripts used to implement and evaluate the proposed TCAS-based HGNN-FL framework are publicly available at: <https://github.com/kotbelbarbary>

13- References :

- [1] Wasilewska, M., Bogucka, H., & Kliks, A., “ Federated learning for 5G radio spectrum sensing”, *Sensors*, 22(1), Article 198,2022.
- [2] S. Mondal, S. Aslam, D. Khan, and K. Chang, “Intelligent Handover Orchestration in Beyond 5G and Urban V2X Dual Connectivity Networks: A Deep Reinforcement Learning Approach,” *IEEE Access*, vol. 13, pp. 196509–196525, 2025.
- [3] Vinay Lomte, Deshmukh, R. R., Das, A., Patil, N. S., Khushbu Ramesh Khandait, Mohammad Ashique Azad, & Tilak Mukherjee, “Intelligent Spectrum Sensing for CR-VANETs: A Machine Learning Approach for Mobility and Security Challenges ", *Journal of Propulsion Technology*, Vol. 47 No. 02, 2026.
- [4] Upadhyay, P., Marriboina, V., Goyal, S. J., Kumar, S., El-Kenawy, E.-S. M., Ibrahim, A., Alhussan, A. A., & Khafaga, D. S., “An improved deep reinforcement learning routing technique for collision-free VANET", *Scientific Reports*, 13, Article 21796, 2023.
- [5] M. A. Hossain, R. Md Noor, K.-L. A. Yau, S. R. Azzuhri, M. R. Z’aba, I. Ahmedy, and M. R. Jabbarpour, “Machine Learning-Based Cooperative Spectrum Sensing in Dynamic Segmentation Enabled Cognitive Radio Vehicular Network,” *Energies*, vol. 14, no. 4, Art. no. 1169, 2021.
- [6] Idris, M. Y. I., Ahmedy, I., Soon, T. K., Yahuza, M., Tambuwal, A. B., & Ali, U, “ Cognitive radio and machine learning modalities for enhancing the smart transportation system: A systematic literature review,” *ICT Express*, 10(4), 693–734, 2024.
- [7] J. Liu, W. Yang, J. Zhang, C. Yang,, " Detecting false messages in vehicular ad hoc networks based on a traffic flow model," *Int. J.Distrib. Sens. Netw.* 16 (2), 2020.
- [8] Hakim, S.A., Sultana, S., Bayzid, M.S., " SMT over tree metrics: Enumerating pairwise compatibility graphs," 11th International Workshop on Satisfiability Checking and Symbolic Computation,2026.
- [9] Hafez, D. T. M. I., " Development of spectrum sharing protocol for cognitive radio Internet of Things," *Université d’Avignon. HAL Thèses*,2020.
- [10] D. Pari and J. Natarajan, "Secure Spectrum Access, Routing, and Hybrid Beamforming in an Edge-Enabled mm Wave Massive MIMO CRN-Based Internet of Connected Vehicle (IoCV) Environments," *Sensors*, vol. 22,2022.
- [11] Q. Liu et al.,“Communication resource allocation method in vehicular networks based on federated multi-agent deep reinforcement learning,” *PMC*, 2025.
- [12] M. A. Naeem, S. Chaudhary, and Y. Meng, “Road to efficiency: V2V-enabled intelligent transportation system,” *Electronics*, vol. 13, no. 13, Art. 2673, 2024. 2025.
- [13] Z. Guan, Y. Wang, and M. He, “Deep Reinforcement Learning-Based Spectrum Allocation Algorithm in Internet of Vehicles Discriminating Services,” *Applied Sciences*, vol. 12, no. 3, Art. no. 1764, 2022.
- [14] M. A. Hossain, R. Md Noor, K.-L. A. Yau, S. R. Azzuhri, M. R. Z’aba, and I. Ahmedy, “Comprehensive survey of machine learning approaches in cognitive radio-based vehicular ad hoc networks,” *IEEE Access*, vol. 8, pp. 78054–78108, 2020,

- [15] S. Brindha, K. Danesh, and T. Nadu, "Threshold-Based Fuzzy Deep Q-Network for Spectrum Management in Cognitive Radio Vehicular Networks," *International Journal of Computer Networks and Applications (IJCNA)*, vol. 11, no. 6, pp. 915-923, 2024.
- [16] A. Iqbal, T. Khurshaid, and Y. A. Qadri, "Intelligent priority-aware spectrum access in 5G vehicular IoT: A reinforcement learning approach," *Sensors*, vol. 25, no. 15, Art. no. 4554, 2025,
- [17] G. Gupta et al., "Impact of Machine Learning on Spectral Sensing in CR Vanets to Improve Link Stability: A Survey," *IEEE Xplore*, 2024..
- [18] S. Ergün et al., "Optimization of resource allocation for effective vehicle-to-everything communication in 5G networks," *AIMS Mathematics*, 2025..
- [19] A. Sharma and N. Marchang, "Detection of Malicious Clients in Federated Learning Using Graph Neural Network," *IEEE Access*, vol.13, pp. 77952–77972, 2025,
- [20] R. Ch, P. Sudheer, I. Batra, and F. Sembiring, "A Novel Adaptive Cluster-Based Federated Learning Framework for Anomaly Detection in VANETs," *Engineering Proceedings*, vol. 107, no. 1, Art. no. 79, 2025.
- [21] Geng, N., Bai, Q., Liu, C., Lan, T., Aggarwal, V., Yang, Y., & Xu, M., "A Reinforcement learning framework for vehicular network routing under peak and average constraints". *IEEE Trans. Vehicular Technol.* (2023).
- [22] Harounabadi, M., Soleymani, D. M., Bhadauria, S., Leyh, M., & Roth-Mandutz, E., "V2X in 3GPP standardization: NR sidelink in Release-16 and beyond". *IEEE Communications Standards Magazine*, 5(1), 12–21,2021.
- [23] Wang, F. et al. "Federated Graph Neural Networks with Equivalent Hypergraph Construction for Traffic Flow Prediction," *IEEE Transactions on Knowledge and Data Engineering*, 2025.
- [24] Y. Feng, H. You, Z. Zhang, R. Ji, and Y. Gao, "Hypergraph neural networks," *Proceedings of the AAAI Conference on Artificial Intelligence*, vol. 33, no. 1, pp. 3558–3565, 2019,
- [25] X. Fu and I. King, "FedHGN: A federated framework for heterogeneous graph neural networks," in *Proceedings of the Thirty-Second International Joint Conference on Artificial Intelligence (IJCAI-23)*, pp. 3710–3716,2023.
- [26] F. M. Khan, A. Zeb, T. Rahman, I. Ullah, N. Alturki, A. K. Bashir, Y. El Touati, N. Ben Khedher, and K. M. Awan, "Federated Deep Learning for Collision Avoidance in IoV With Digital Twin Integration," *Expert Systems*, vol. 43, no. 1, Art. no. e70168, 2026.
- [27] Chen, H., Zhang, F., and Aksun-Guvenc, B., "Collision Avoidance in Autonomous Vehicles Using the Control Lyapunov Function–Control Barrier Function–Quadratic Programming Approach with Deep Reinforcement Learning Decision-Making", *Electronics*, 14(3), Article 557, 2025.
- [28] Visuvanathan, G. E., Sayeed, M. S. & Yogarayan, S. BHFVAL, "Blockchain-Enabled Hierarchical Federated Variational Autoencoder Framework for Secure Intrusion Detection in Vehicular Networks", *Scientific Reports*,2025.
- [29] E. Binshafout, A. Hamrouni, and H. Ghazzai, "Graph Neural Networks for Vehicular Social Networks: Trends, Challenges, and Opportunities," *IEEE Transactions on Intelligent Transportation Systems*, vol. 27, 2026.
- [30] D. Li, Z. Yang, and S. Xie, "FedMSGF: A self-expressive hypergraph-based federated multi-view learning," in *Proceedings of the Thirty-Ninth AAAI Conference on Artificial Intelligence and Thirty-Seventh Conference on Innovative Applications of Artificial Intelligence and Fifteenth Symposium on Educational Advances in Artificial Intelligence (AAAI-25/IAAI-25/EAAI-25)*, article no. 2034, pp. 18244–18252, 2025.
- [31] N. X. Tung, L. T. Giang, B. D. Son, S.-G. Jeong, T. V. Chien, W. J. Hwang, and L. Hanzo, "Graph Neural Networks for Next-Generation-IoT: Recent Advances and Open Challenges," *IEEE Communications Surveys & Tutorials*, vol. 28, 2025.
- [32] A. R. García-Escalante, R. Q. Fuentes-Aguilar, A. Palma-Zubia, and E. Morales-Vargas, "Automatic Brake Driver Assistance System Based on Deep Learning and Fuzzy Logic," *PLOS ONE*, vol. 19, no. 12, 2024.