Hybrid Routing Protocol with Neural Network-Driven Decision-Making in VANET

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***Abstract*— Vehicular Ad-Hoc Networks (VANETs) play a critical role in intelligent transportation systems by facilitating real-time communication between vehicles and infrastructure to improve road safety, traffic management, and driver experience. However, VANETs face challenges due to high node mobility and varying network densities, which impact reliable and efficient communication. Traditional routing protocols, such as proactive, reactive, and hybrid approaches, struggle to adapt to these dynamic conditions, resulting in increased latency, packet loss, and inefficient resource usage.**

In recent years, there has been a notable shift toward the integration of neural networks into routing protocols to confront these challenges. This survey explores the evolution of hybrid routing protocols enhanced by neural network-driven decision-making, facilitating the dynamic adaptation of network topology based on real-time data. By leveraging neural networks, particularly Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) models, these advanced protocols can predict link stability, assess traffic patterns, and optimize routing paths more effectively than traditional methods.

The transition to neural network-driven topologies is motivated by the need to enhance the resilience and scalability of VANETs, especially in environments with high vehicle density and fluctuating connectivity. This survey provides a comprehensive overview of the state-of-the-art techniques, evaluates their performance in various network scenarios, and discusses the future directions in this rapidly evolving field. The findings suggest that neural network-driven hybrid routing protocols offer significant potential in addressing the inherent challenges of VANETs, paving the way for more reliable and intelligent vehicular communication systems.

Keywords: VANETs, Hybrid, Road Side Units, On Board Units, Routing, Protocol, Intelligent Transportation System, Neural Networks, V2V, V2I, V2X, Intersections, Q-Learning

I. INTRODUCTION

Smart transportation, also known as smart mobility, uses automation and data collection to improve the way people move around cities. These systems use up-to-date data and vehicle-to-everything (V2X) communication to enable vehicles to interact with each other and infrastructure to improve traffic management, reduce congestion, and avoid collisions. Smart transportation help in reducing the impact of "human factor" [1] in the accidents since computers cannot get distracted or fatigued. They are capable of identifying problems on the go and provide solutions to fix them so the driver's journey isn't halted. Smart transports are

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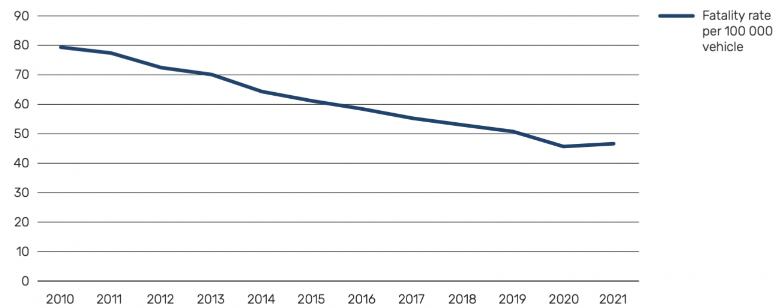

Fig. 1: WHO estimated global road traffic fatality rates per 100,000 vehicles [3], 2010–2021

cost efficient in the way that they enable more efficient and better use of resources by cutting down maintenance costs, fuel consumption, etc.

Several major cities around the globe like London, Paris, Amsterdam have invested in smart transportation to upgrade the cities to "smart cities" [2]. This shows that smart transportation not only helps an individual on a personal level but massively impacts the community as a whole. For a community has a whole, it also helps in solving the problem of Parking, by installing sensors in parking lots to detect open spaces ahead of time so the driver can go directly to the spot. Smart public transportation is something which helps millions of people depending on public transportation daily to communte to their jobs, etc. Citizens can have real-time information about arrival and departure of their choice of commute.

The Global Status Report on Road Safety 2023 [3] by the World Health Organization (WHO) presents alarming statistics on road traffic injuries and fatalities. There were an estimated 1.19 million road traffic deaths in 2021; this corresponds to a rate of 15 road traffic deaths per 100 000 population. Based on 2019 data on the age distribution of all-cause mortality, road traffic injury remains the leading cause of death for children and young people aged 5–29 years and is the 12th leading cause of death when all ages are considered. Globally, users of powered two- and three wheelers represent 30% of fatalities; followed by four-wheel vehicle occupants who represent 25% of fatalities; and pedestrians who make up 21% of fatalities. Cyclists account for 5% of fatalities. Occupants of vehicles carrying more than 10 people, heavy goods vehicles, "other" users and "unknown" user types comprise the remaining 19% of deaths. The global inventory of motor vehicles, presently surpassing one billion units, is expected to undergo a

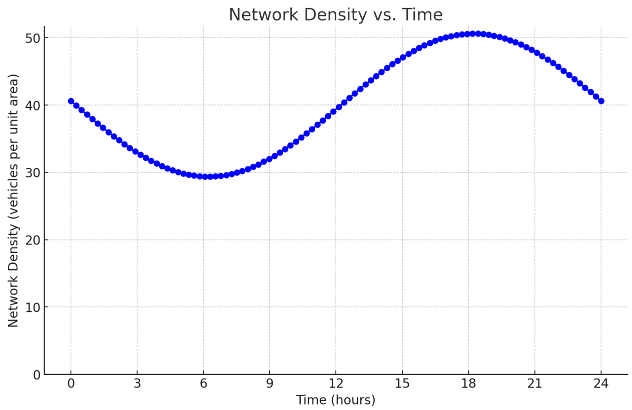

Fig. 2: The graph above shows the change in traffic over a 24-hour period, showing how vehicle speeds change at different times of the day. Morning and afternoon congestion is common and affects traffic patterns. These changes highlight the importance of creating adaptive systems that adapt to different network congestions.

twofold increase in the period leading up to 2030. The data gathered for this report shows that around 10% of road traffic fatalities are attributed to drunk driving, which aligns with self-reported rates of 16–21% of individuals admitting to driving under the influence (DUI) in a survey conducted by the European Survey Research Association (ESRA) [3, 4]. These surveys also indicate that nearly 50% of drivers across 48 countries admit exceeding the speed limit. Furthermore, over half of the surveyed individuals admit to using communication devices while driving. It's crucial to address these statistics as we strive for advancements in smart transportation.

VANET plays a significant role in the development of intelligent transportation by enabling vehicles to communicate wirelessly with each other and with infrastructure. Such communication has proven useful in improving road safety, traffic management, and supporting applications such as real-time navigation, collision avoidance, and emergency assistance. The IEEE Committee has developed the IEEE 802.11p standard specifically for VANETs [5]. The US Federal Communication Commission (FFC) has also designated 75 MHz of bandwidth at 5.9 GHz for short-range communication between vehicles (V2V) and between vehicles and infrastructure (V2I).

However, the dynamic and highly mobile nature of VANETs presents unique challenges. Traditional routing protocols, whether proactive or reactive, often struggle to maintain reliable communication in the face of VANETs' rapidly changing network topology. High mobility leads to frequent disconnections and reconnections, while varying vehicle densities create periods of congestion and sparsity, further complicating routing decisions. To address these challenges, recent researches have focused on hybrid routing protocols that combine the strengths of both proactive and reactive approaches.

Moreover, the integration of machine learning, particularly neural networks, into routing protocols has emerged as a promising approach to enhancing decision-making processes in VANETs. Neural networks can be trained to predict link stability, assess network conditions, and optimize routing paths based on real-time data. One critical aspect of VANETs that must be considered in the design of routing protocols is network density, which can vary significantly over time. Network density, defined as the number of vehicles per unit area, directly impacts the performance of routing protocols. In densely populated areas, the network can become congested, leading to increased packet collisions and delays. Conversely, in sparsely populated areas, maintaining stable communication links can become difficult due to the lack of nearby vehicles.

II. Overview of VANETs

Vehicular Ad-Hoc Networks (VANETs) are a specialized subset of Mobile Ad-Hoc Networks (MANETs) designed specifically for vehicle-to-vehicle (V2V) and vehicle-to-infrastructure (V2I) communication. The primary components of a VANET architecture [6] include:

- **Nodes**: In VANET (Vehicular Ad-hoc Network), nodes refer to the individual entities or devices that participate in the network. These can be the vehicles, roadside units (RSUs), or any device capable of communication within the network.
- **On-Board Units (OBUs)**: Each vehicle is installed with sensors to record traffic and driving data which can then be sent to other vehicles (V2V communication) or RSUs (V2I communication) or satellite navigation systems. OBUs are the mobile nodes in vehicles.
- **Roadside Units (RSUs)**: RSUs are fixed infrastructure units deployed along roadsides that facilitate communication between vehicles and provide access to broader networks, such as the traffic management systems or the internet. RSUs are the stationary nodes along the road like traffic signals, road signs, etc.

VANETs offer 3 types of communication modes, namely :

- **Vehicle-to-Vehicle (V2V)**: Direct communication between vehicles, enabling the exchange of information such as speed, location, steering angle, brake status, traffic conditions, etc. V2V communications allows a vehicle to sense threats with an awareness of position of other vehicles.
- **Vehicle-to-Infrastructure (V2I)**: Communication between vehicles and roadside units, allowing vehicles to access services like traffic management systems, navigation assistance, and internet connectivity. Communication between vehicles and RSUs increases the range of communication. The transfer of information between the vehicle and RSU is highly secure due to the unique key provided by the RSU to each connected user.

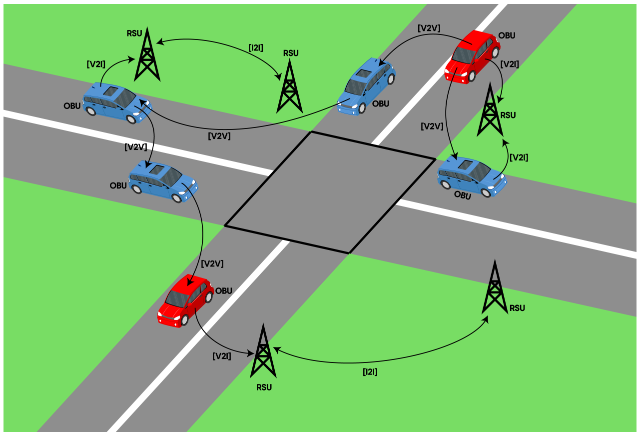

Fig. 3: A simple representation of VANET Architecture with OBUs and RSUs and also showing V2V, V2I, and I2I communication among nodes.

- **Infrastructure to Infrastructure (I2I)**: RSUs can connect to internet and communicate among themselves to provide a wider range through seamless exchange of data between various roadside units like traffic signals, road signs, etc.

III. Challenges in VANET Routing

Vehicular Ad Hoc Networks (VANETs) pose unique routing challenges due to their dynamic nature and specific requirements. Routing protocols in VANETs must effectively address critical issues to ensure reliable and efficient communication. This section discusses the primary challenges [6, 7] associated with routing in VANETs.

- **High Mobility and Rapid Topology Changes Challenge**: The high mobility of vehicles results in frequent changes in network topology, which complicates the maintenance of stable routes. Vehicles continuously enters and leaves the communication range, leading to frequent network partitioning and reconfiguration.
  Impact: The dynamic nature of VANETs can lead to increased routing overhead, higher packet loss rates, and longer delays in route discovery.
  Approaches: Some routing protocols employ predictive models to anticipate vehicle movements based on historic travel data and hence maintain route stability.

- **Limited Communication Range and Variable Network Density** Challenge: The communication range of vehicular communication technologies, such as DSRC or C-V2X, is limited, and the density of vehicles can vary significantly.
  Impact: Limited communication range can lead to frequent route breaks and decreased network connectivity, especially in low-density scenarios. High-density scenarios, on the other hand, can often cause network congestion and increased competition for communication resources.
  Approaches: Protocols designed to handle variable network density include geographic routing methods that use location information to select optimal paths and clustering approaches that group vehicles to manage communication more effectively.

- **Scalability and Network Size Challenge**: With increasing number of vehicles, routing protocols must scale to handle larger network sizes with increased number of nodes without degrading performance in order to be deployable in real-world scenarios.
  Impact: Protocols that don't scale well can suffer from slower route discovery and higher overhead and latency with increase in number of nodes.
  Approaches: Scalable routing protocols often use hierarchical structures, zone-based routing, or efficient indexing mechanisms to manage routing information and reduce overhead.

- **Security and Privacy Concerns Challenge**: VANETs are susceptible to various threats, including spoofing, eavesdropping, and denial-of-service attacks which makes it highly crucial to ensure security and privacy of communication.
  Impact: Security vulnerabilities can compromise data integrity, authenticity, and privacy, leading to potential misuse of information and disruption of network operations.
  Approaches: Security mechanisms in VANET routing include cryptographic techniques, authentication protocols, and secure key management systems. Some protocols integrate security features directly into the routing process to protect data and prevent attacks.

- **Quality of Service (QoS) and Performance Metrics Challenge**: Providing consistent Quality of Service (QoS) is important for applications that require guaranteed performance, such as safety-related communications and real-time infotainment services.
  Impact: QoS requirements can be challenging to meet due to the variable network conditions and the need to balance multiple performance metrics.
  Approaches: QoS-aware routing protocols prioritize routes based on performance metrics and adapt to changing network conditions to meet specific requirements. Techniques such as adaptive routing, traffic differentiation, and resource allocation are employed to enhance Quality of Service.

- **Integration with Emerging Technologies Challenge**: The integration of VANETs with emerging technologies, such as 5G, C-V2X, and advanced driver assistance systems (ADAS), introduces new complexities and necessities for routing protocols.
  Impact: Emerging technologies offer new opportunities

for enhancing VANET performance but also introduce additional challenges related to interoperability, compatibility, and network management.

Approaches: Routing protocols are being developed to leverage new technologies and standards, incorporating features that support seamless integration and interoperability.

IV. Related Works

Numerous routing protocols currently exist in VANET. The following section provides an in-depth discussion of these existing routing strategies.

The authors, Qin Yang and Sang-Jo Yoo, in [8] proposed a hierarchical Q-learning-based routing algorithm with grouped roadside units. Two types of Q-tables are trained using multi-agent hierarchical Q-learning algorithm, group Q-table and local Q-table. The group Q-table estimates the reward for reaching the destination group, whereas the local Q-table focuses on reaching the destination RSU inside that group.

RSU-centric routing protocols have been proposed to address the challenges associated with intersections. They rely on vehicles or infrastructure elements placed at intersections to determine the routing direction by selecting a sequence of intersections. [9] propose an intersection-based V2X routing protocol that includes a routing strategy based on past traffic patterns using Q-learning and real-time network status monitoring. The hierarchical routing protocol consists of a multidimensional Q-table, which is established to select the optimal road segments for forwarding packets at the intersections; and an improved greedy strategy, which is employed to choose the optimal relays of paths. The monitoring models can detect network load and adjust routing decisions promptly to prevent network congestion. Intersection-based routing is known to enhance the performance of the geographic routing protocol. Rui et al. (2023) [10] proposed an Intersection-Based QoS Routing (IQRRL) algorithm for VANETs, which integrates reinforcement learning to optimize intersection selection and next-hop vehicle decisions. The study also addresses the problem of local optimum in the selection of the intersection and the study considers the performance of neighbouring roads and shortest routes among the remaining roads to minimize this problem. The studies discussed above use Reinforcement Learning, particularly Q-learning. The final output result is obtained after a series of decision-making processes to deduce information about the external environment. The nodes in VANET (OBUs and RSUs) are defined as states of the agent and the possible next hops of the agent as the set of actions for the Q-learning algorithm. Each node maintains a Q-table and chooses a node from the neighbor node with the largest Q-value as the best next hop.

[11] employs a fuzzy constraint Q-learning algorithm based on ad hoc on-demand distance vector (AODV) routing to determine the optimal route. The protocol uses fuzzy logic to determine quality of a wireless link by considering multiple metrics. The authors of [12] have also put forward a Q-learning and fuzzy logic-based hierarchical routing protocol (QFHR). QFHR consists of three phases. In the first phase, each roadside unit (RSU) stores a traffic table containing traffic information about the road sections connected to the intersection. Subsequently, the RSUs use a Q-learning-based routing method to determine the best path between different intersections. Finally, vehicles in each road section use a fuzzy logic-based routing technique to choose the best relay node for the next hop.

The research [13] focuses on improving the performance of Vehicular Ad Hoc Networks (VANETs) through the use of ensemble-based machine learning techniques and hybrid metaheuristic algorithms for routing. The study employs methods such as Seagull optimization and Artificial Fish Swarm Optimization, along with machine learning algorithms including SVM, Naive Bayes, ANN, and Decision Tree. Comparative analysis between the proposed HFSA-VANET method and the CRSM-VANET method shows significant improvements in delay, energy consumption, and throughput.

Leticia Lemus Cárdenas et al. [14] introduce a machine learning-based approach to enhance routing protocols in VANETs, specifically focusing on a multimetric predictive algorithm that utilizes artificial neural networks (ANNs) to optimize the selection of next-hop vehicles for packet forwarding. The authors developed a dataset from simulated urban scenarios, capturing critical metrics such as available bandwidth, vehicle density, and trajectory, and used it to train the model. The results demonstrated significant improvements in packet delivery probability, achieving less than 20% packet loss and average delays below 0.04 ms, even in complex environments.

[15] presents a hybrid model, combining a Convolutional Neural Network and a Bidirectional Long–Short-Term Memory (Bi-LSTM) network, and apply it to long-term traffic flow prediction in urban routes. This model uses CNN to extract importent hidden features from the input model and BiLSTM to understand the temporal context.

The study by W. Jabbar et al. [16] explores the impact of a Location Verification System (LVS) on the control overhead of a geographical routing protocol for vehicular networks. The proposed system verifies vehicle locations using GPS and notifies all vehicles in the transmission range of the decisions, resulting in a more secure routing protocol. The research proves that advanced location verification techniques can be seamlessly integrated into hybrid routing protocols in vehicular networks.

TABLE I: Comprehensive Overview of Related Works

Author(s)	Year	Title	Proposed Work	Technique Used	Results
Qin Yang and Sang-Jo Yoo	2024	Hierarchical Reinforcement Learning-Based Routing Algorithm With Grouped RSU in Urban VANETs [8]	Multi-agent Hierarchical Q-learning-based routing algorithm with grouped roadside units. Two types of Q-tables are trained, group Q-table and local Q-table.	Q-Learning	Reduced broadcasting overhead, prolong path lifetime, a high packet delivery ratio and low average end-to-end delay.
L. Luo et al.	2022	Intersection-Based V2X Routing via Reinforcement Learning in Vehicular Ad Hoc Networks [9]	A multidimensional Q-table is established to select the optimal road segments for packet forwarding at intersections; and an improved greedy strategy, which is employed to choose the optimal relays on paths.	Q-Learning	Better performance than three benchmark algorithms in terms of communication overhead and latency, reliable transmission of packets (better packet delivery ratio).
L. Rui et al.	2023	An Intersection-Based QoS Routing for Vehicular Ad Hoc Networks With Reinforcement Learning [10]	Aimed at solving local optimization problem of intersection-based routing through two steps: next intersection selection (considers communication quality) and next hop vehicle selection (adopts multi-hop evaluation technology and greedy decision making).	Q-Learning and Greedy Decision Making	Improves the packet delivery ratio, reduce the average end-to-end delay.
C. Wu et al.	2013	Flexible, Portable, and Practicable Solution for Routing in VANETs: A Fuzzy Constraint Q-Learning Approach [11]	Propose PFQ-AODV, protocol that learns the optimal route by employing a fuzzy constraint Q-learning algorithm based on AODV routing.	Q-Learning and Fuzzy Logic	Independent of lower layers, flexible, portable, and practicable.
A.M. Rahmani et al.	2022	A Q-Learning and Fuzzy Logic-Based Hierarchical Routing Scheme in the Intelligent Transportation System for Smart Cities [12]	Proposed QFHR protocol which consists of three phases - identifying traffic conditions, routing algorithm at the intersection level, and routing algorithm at the road level.	Q-Learning and Fuzzy Logic	Gets better packet delivery rate, decreased delay and lower number of hops but increased overhead.
G.P.K. Marwah and A. Jain	2022	A hybrid optimization with ensemble learning to ensure VANET network stability based on performance analysis [13]	Proposed method, HFSA-VANET combines hybrid metaheuristic algorithm with ensemble learning to reduce latency.	Metaheuristic Algorithms, Ensemble Learning	Lower delay, decrease in energy consumption and increase in throughput as compared with the CRSM-VANET.
L.L. Cárdenas et al.	2021	A Multimetric Predictive ANN-Based Routing Protocol for Vehicular Ad Hoc Networks [14]	Machine learning-based approach focusing on multimetric predictive algorithm that utilizes ANN to optimize the selection of next-hop vehicles for packet forwarding.	Artificial Neural Networks (ANNs)	Significant improvement in packet delivery probability and lesser average delays.
M. Méndez, M.G. Merayo and M. Núñez	2023	Long-term traffic flow forecasting using a hybrid CNN-BiLSTM model [15]	Proposes a hybrid model combining a CNN and a Bi-LSTM network to apply it to long-term traffic flow prediction in urban routes.	Convolutional Neural Network (CNN) and a Bidirectional Long–Short-Term Memory (Bi-LSTM) Network	The hybrid model outperformed the baseline models with respect to mean absolute error, root mean squared error and accuracy.
W. Jabbar, R. Malaney, and S. Yan	2020	A Location Verification Based Hybrid Routing Protocol for VANETs [16]	The proposed method verifies vehicle locations using GPS and informs all other vehicles in the transmission range about the decisions and hence resulting in a more secure routing protocol.	Location Verification System (LVS)	Likelihood of a vehicle being malicious is significantly reduced.

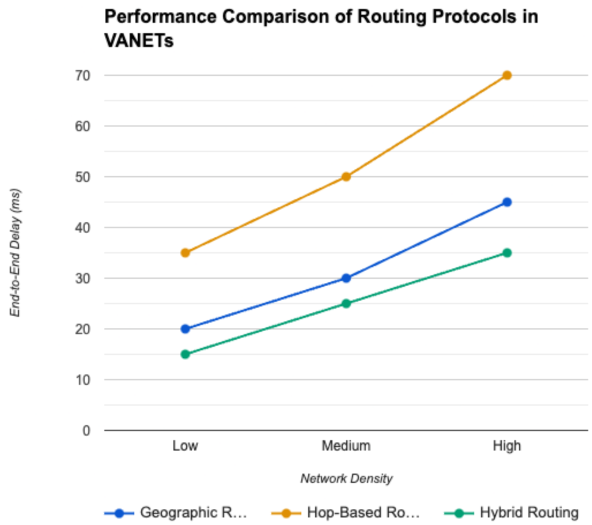

Fig. 4: Comparison of end-to-end delay for Geographical, Hop-based, and Hybrid routing protocols for different network densities.

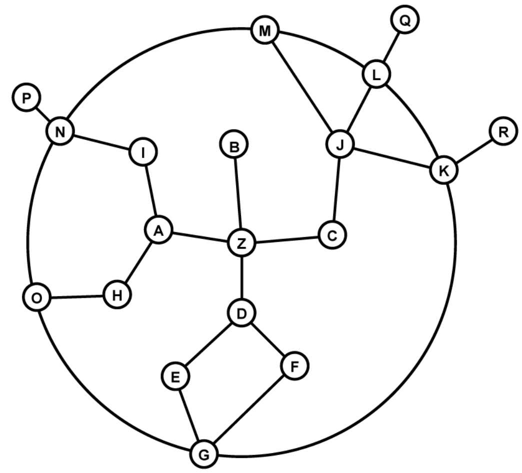

Fig. 5: Example routing zone with $\rho = 3$. Routing zone of Z include includes nodes A-O, but not P,Q,R. Here the zone is defined in number of hops, not as a physical distance between the nodes.

V. Hybrid Routing Protocols in VANETs

In proactive routing protocols [17]–[19], routing information for each node (OBUs or RSUs) is maintained in a routing table. Since the nodes are highly mobile in a VANET, regularly updating the nodes joining or leaving the network, as well as for broken or established links is necessary. This leads to an increased overhead and an impact on network throughput. Notable proactive protocols include DSDV, OLSR, and FSR.

Reactive Routing Protocols [17]–[19], on the other hand, aim at finding a route between the source and the destination when needed. When a mobile node needs to send a packet to a specific destination, these protocols use route discovery techniques to find a suitable route. Examples of protocols in this category include AODV, AODV + PGB, DSR, and TORA.

Hybrid routing protocols in Vehicular Ad Hoc Networks (VANETs) combine elements of both proactive and reactive routing approaches to address the unique challenges of vehicular communication. These protocols aim to balance the trade-offs between route discovery latency (because of reactive protocols) and routing overhead (because of proactive protocols), providing a more versatile solution for dynamic and variable network conditions.

1. Overview of Hybrid Routing Protocols

Hybrid routing protocols leverage the strengths of both proactive and reactive methods to optimize performance in VANETs. Proactive protocols maintain up-to-date routing information at all times, while reactive protocols discover routes on-demand. Hybrid protocols seek to combine these approaches to achieve a balance between maintaining route information and minimizing overhead while speeding up the packet delivery to destination [].

Key Features:

- **Combination of Strategies**: Hybrid protocols integrate proactive and reactive mechanisms to enhance routing efficiency and adaptability.
- **Adaptive Behavior**: They adjust their routing strategy based on network conditions, such as vehicle density and mobility patterns.
- **Optimized Performance**: By combining proactive and reactive elements, hybrid protocols aim to reduce routing overhead while ensuring timely route discovery.

2. Examples of Hybrid Routing Protocols

2.1. Zone-Based Routing Protocol (ZRP)

The Zone-Based Routing Protocol (ZRP) [17, 20] divides the network into multiple zones, with proactive routing used within each zone (in a node's neighborhood) and reactive routing for inter-zone communication(between neighborhoods). This approach minimizes the overhead associated with maintaining global routing information while ensuring efficient communication between different zones. This protocol encompasses various elements such as power transmission, signal strength, speed, and mobility [21]. There are two categories of routing schemes: inner zone routing employs proactive protocols, while outer zone routing utilizes reactive protocols. The size of a zone [22] is not determined by its geographical size but is represented by a radius of length ρ, where ρ is the number of hops to the perimeter of the zone. Fig. 5 shows an example of routing zone of node Z with $\rho = 3$. There are two types of nodes - interior nodes and peripheral nodes. Interior nodes are those who have minimum distance less than the zone radius ρ,

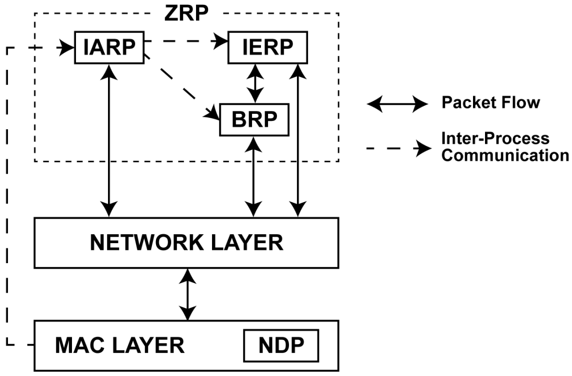

Fig. 6: Architecture of Zone Routing Protocol

whereas peripheral nodes have minimum distance equal to ρ.

ZRP includes a proactive part within the local area known as IntrA-zone Routing Protocol and a global reactive part called IntEr-zone Routing Protocol. IARP maintains up-to-date routing information within the zone whereas IERP is responsible for finding routes between nodes that are outside each other's zones using a route discovery process. Bordercasting is used to efficiently send route queries to nodes at the border of the zone using topology information provided by the IARP. Bordercast Resolution Protocol (BRP) provides the bordercast packet delivery service. ZRP detects new neighbour nodes and link failures using the Neighbour Discovery Protocol (NDP) provided by the Media Access Control (MAC) layer. The NDP sends out "HELLO" beacons at consistent intervals. When a beacon is received, the neighbour table gets updated. Neighbours, for which no beacon is received within a set time, are eliminated from the table. Fig. 6 illustrates the relationship between these components. [19, 23, 24]

Advantages:

- *Scalability*: The protocol is easily and effectively scalable for large networks, as it restricts the scope of proactive updates to the zones, preventing unnecessary global route updates.
- *Efficient Route Discovery*: Localized routing within zones minimizes the necessity for frequent route discovery, improving the protocol's efficiency in stable regions.

Disadvantages:

- *Complexity*: The division into zones and the coordination between proactive and reactive components tends to add complexity.
- *Sub-optimal Zones*: Defining and managing zone boundaries can be challenging, especially in highly dynamic environments. The performance of ZRP highly depends on the optimal size of the zone, and finding the right balance can be challenging.

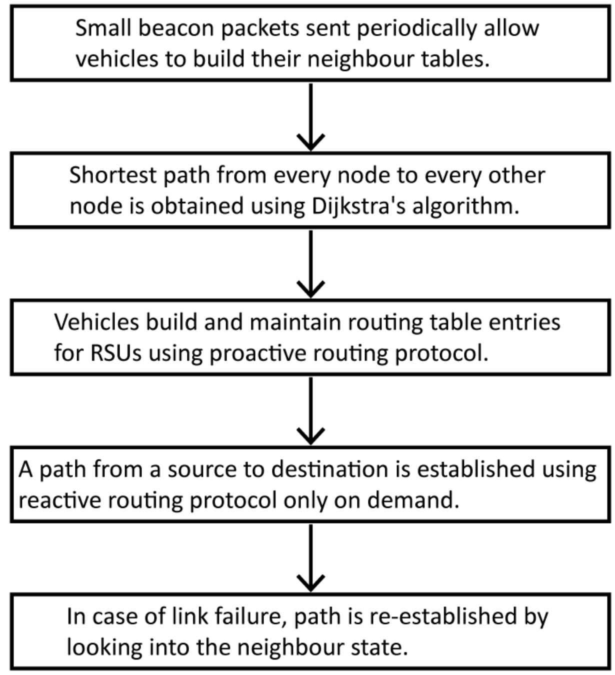

Fig. 7: Flow of Adaptive Hybrid Routing Protocol [25]

2.2. Adaptive Hybrid Routing Protocol (AHRP)

In the Adaptive Hybrid Routing Protocol, vehicles intermittently broadcast small beacon packets locally, containing their ID and current location coordinates to build neighbor information tables. The system uses a geographic routing protocol, and each RSU has an exclusive ID and is connected to others through a wired/wireless network. Each RSU transfers a beacon message periodically called a service advertisement message to gather the routing information. Vehicles establish fresh routes to RSUs upon accepting advertisements and keep their location informed to corresponding RSUs for new robust routes. Fig. 7 shows overview of the Adaptive Hybrid Routing Protocol. These static units store the list of all the registered vehicles and their entire route, while vehicles build a table of the routes between adjoining RSUs. If the source vehicle has no route to the destination vehicle, it initiates on-demand route discovery using the reactive routing protocol AODV and geographic routing protocol (GSR). [25]

Advantages:

- *Improved Communication Reliability*: Continuous updates from RSUs ensure that vehicles maintain robust and reliable routes.
- *Efficient Route Discovery*: AHRP combines geographic and reactive routing, reducing overhead by only initiating route discovery when necessary.

Disadvantages:

- *High Dependency on RSUs*: The performance of AHRP heavily relies on the presence and proper functioning of RSUs, which may not always be available.

- *Increased Control Overhead*: The use of periodic beacon messages and service advertisements can lead to network congestion, especially in dense environments leading to increased overhead.
- *Complex Implementation*: Integrating both proactive and reactive routing mechanisms adds complexity to the protocol design and deployment.

2.3. Zone-based Heirarchical Link State (ZHLS)

The Zone-Based Hierarchical Link State (ZHLS) Routing Protocol [26] is a hybrid hierarchical routing protocol that uses location details to create non-overlapping zones. Each node in the zone maintains information about the internal topology, while outside the zone, only regional connectivity data is stored. ZHLS employs a hierarchical addressing system for inter-zone routing packet forwarding and it is aided by the hierarchical address comprising zone routing. Packet forwarding beyond the zone is done using a reactive approach. It identifies a destination node's current location using the zone ID it belongs to and a route search mechanism. The inter-zone routing table is updated using a shortest path algorithm on the zone's node-level topology, obtained through an intra-zone clustering mechanism that operates similar to link state updates on nodes within the zone. Each node establishes a one-hop topology through a link request and link response mechanism.

In the ZHLS protocol, two levels of topology are defined namely node-level topology and zone-level topology. A node-level topology has information about the physical connections among nodes within a zone. The zone-level topology explains how the zones are interconnected and contains details about the virtual links that exist within the entire network. Zone and node-level topologies are represented using Link State Packets (LSPs) and disseminated within the zones and the network, respectively, at regular intervals. Upon receiving an LSP update, nodes update their LSP database by adding new LSPs and removing outdated ones. [27]

Advantages:

- *Reduced Overhead*: Since ZHLS uses the hierarchical approach, it reduces the storage requirements and also the overhead created by communication between the nodes.
- *Zone Creation*: The zones created don't overlap with each other.

Disadvantages:

- *Dynamic Geographical Boundary*: The geographical location is needed to create a zone level topology but the geographical information is not always available. ZHLS does not work well in dynamic geographic boundary conditions.

3. Performance Metrics and Evaluation

Hybrid routing protocols are evaluated based on several performance metrics, including:

- Routing Overhead: The amount of control traffic (control messages) generated to establish and maintain routes. A lower routing overhead indicates better network performance. It includes the time and bandwidth spent on route discovery, maintenance, and updates.
- Route Discovery Time: The time required to discover and establish a valid route. This involves finding and selecting a path that meets the communication needs, including the time taken for broadcasting route requests and receiving route replies. Minimizing route discovery time is crucial for timely data transmission.
- Packet Delivery Ratio: The ratio of successfully delivered packets to the total number of packets sent by the source node. A high packet delivery ratio signifies effective routing and network stability.
- End-to-End Delay: The time taken for a packet to travel from the source to the destination. This delay includes transmission time, propagation time, queuing time, and any other delays encountered along the route. Lower end-to-end delay is essential for real-time applications and effective communication in VANETs.

A useful graph to illustrate the performance of hybrid routing protocols would be a performance comparison chart showing key metrics for different hybrid protocols. Fig. **??** provides a visual summary of how different hybrid routing protocols perform across various metrics, highlighting their strengths and weaknesses in the context of VANETs.

VI. Neural Networks Driven decision making in VANETs

Neural Network-Driven Decision-Making in Vehicular Ad Hoc Networks (VANETs) leverages the power of machine learning, specifically neural networks, to optimize various aspects of network performance.

1. Overview of Neural Networks Driven Decision Making

Neural networks significantly enhance decision-making in VANETs by providing adaptive, predictive, and real-time capabilities that traditional routing algorithms may lack. They optimize routing, manage traffic, and ensure efficient communication in highly dynamic vehicular networks.

Key Features:

- **Dynamic Environment Handling**: Neural networks excel at processing real-time data from multiple sources, such as vehicle speeds, traffic density, and road conditions. They not only adapt to changes in the network environment but also identify patterns in traffic flow, vehicle movement, and network topology. This dual capability allows neural networks to make more

accurate and responsive decisions by predicting future states of the network and anticipating issues like congestion or accidents.
- **Routing Optimization**:Neural networks predict the best routes by analyzing current and historical traffic data. They also assist hybrid routing protocols by determining when to employ proactive (preemptive) routing or reactive (on-demand) routing based on real-time network conditions, enhancing overall routing efficiency.
- **Traffic and Congestion Management**:Neural networks analyze traffic patterns to predict potential congestion points, enabling vehicles to reroute preemptively and reduce traffic jams. Simultaneously, they balance network traffic by distributing it evenly across available routes, preventing overloading of any single path and improving overall network performance.

2. Examples of Neural Network Based Decision Making

2.1. Intelligent Traffic Management

Neural networks analyze real-time traffic data from various vehicles to predict congestion at specific road segments and optimize the timing of traffic signals. By forecasting traffic flow through intersections and identifying potential congestion points, the system can dynamically adjust signal timings and suggest alternative routes to vehicles. This dual approach reduces overall traffic congestion, minimizes wait times at intersections, and improves the overall flow of traffic.

Advantages:

- **Enhanced Traffic Flow**: By predicting and avoiding congestion and making dynamic adjustments in traffic signals, neural networks can suggest alternative routes and minimize wait time at intersections, which helps in better regulation of traffic.
- **Real-Time Adaptability**: Neural networks can adapt quickly to real-time traffic conditions, making immediate adjustments to routing and signal timings as traffic patterns change throughout the day.
- **Improved Efficiency**: By optimizing traffic signals and routing, neural networks can decrease travel times for drivers which in-turn leads to smoother traffic flow, leading to more efficient use of roadways and thereby helps to decrease fuel consumption and emissions.

Disadvantages:

- **Data and Computational Requirements**: Neural networks for traffic management require large volumes of real-time data and significant computational resources. Collecting and processing this data continuously can be challenging and costly, demanding advanced hardware and substantial computational power.
- **System Complexity**: Integrating neural networks with existing traffic management systems is complex and requires significant infrastructure modifications. Additionally, maintaining and tuning these models is essential to keep them effective as traffic patterns and conditions change.
- **Latency and Reliability Issues**: Ensuring real-time responses from neural networks can be challenging, especially in high-traffic scenarios. The effectiveness of these systems also heavily relies on the quality and accuracy of the input data, as inaccurate or incomplete data can cause poorer decisions and reduced performance.

2.2. Collision Avoidance Systems

Neural networks integrated with vehicle sensors analyze real-time data to detect potential hazards, such as sudden braking by vehicles ahead or pedestrians crossing the road. By predicting the likelihood of a collision, the system can issue alerts or automatically take evasive actions, like braking or steering. Additionally, neural networks assess driving patterns and environmental conditions to provide early warnings about risky situations, such as slippery roads or sharp turns, helping drivers to adjust their behavior and avoid accidents.

Advantages:

- **Enhanced Safety**: Neural networks detect potential hazards and provide early warnings, enabling timely driver alerts and proactive adjustments to reduce collision risk and enhance safety.
- **Automatic Evasive Actions**: Automatic interventions, such as braking or steering adjustments, can occur faster than human reactions, helping to avoid collisions that might occur too quickly for manual responses.
- **Adaptive Learning**: Neural networks can continuously learn from new data, improving their ability to predict and respond to hazards over time, adapting to different driving conditions and environments.

Disadvantages:

- **Dependence on Sensor Data**: The effectiveness of the hazard detection system relies heavily on the accuracy and reliability of sensor data. Faulty or inaccurate sensors can lead to incorrect hazard predictions and missed alerts.
- **Computational Load**: Real-time analysis of sensor data and the execution of predictive algorithms require significant computational resources, which may impact system performance or increase costs.
- **False Alarms**: The system might sometimes generate incorrect alerts because it misinterprets sensor data or environmental conditions, which could result in drivers feeling frustrated or becoming less responsive to alerts.

VII. Hybrid routing protocols with neural network integration

Hybrid routing protocols with neural network integration in Vehicular Ad Hoc Networks (VANETs) offer a

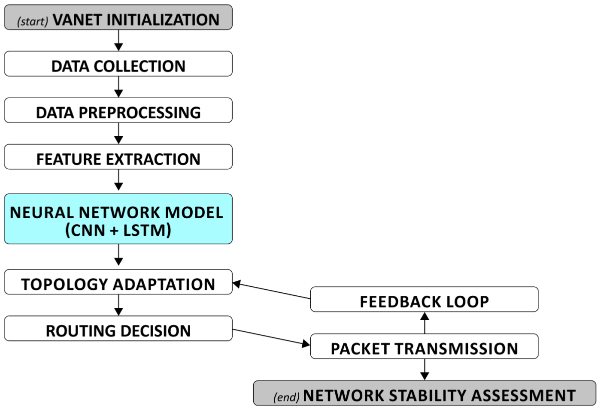

Fig. 8: Example workflow of Neural Network Integration for Hybrid Routing Protocol

sophisticated solution to the complexities of vehicular communication. This integration combines the best aspects of hybrid routing—where proactive and reactive strategies are used to manage data packets efficiently—with the advanced predictive and decision-making capabilities of neural networks. Neural networks enhance hybrid routing by processing real-time data from vehicle sensors to detect immediate hazards, such as sudden braking or road obstacles, and by predicting future traffic conditions based on historical and environmental data.

This allows for more adaptive routing decisions, such as rerouting vehicles to avoid congestion or hazardous conditions, and for timely automatic interventions like braking or steering adjustments. While this integration improves safety and optimizes traffic flow, it also requires substantial computational resources and high-quality data for accurate predictions. Additionally, the system can sometimes produce false alarms and presents challenges in integration with existing vehicular technologies. Nonetheless, the combination of hybrid routing and neural networks provides a powerful approach to managing the dynamic nature of VANETs, enhancing both the efficiency and safety of vehicular communication networks.

- **Hybrid Routing Protocols**:
  - Proactive Component: Proactively maintains routes within certain zones or areas, ensuring that frequently used routes are readily available without the need for constant re-discovery.
  - Reactive Component: On-demand route discovery for routes outside the proactively maintained zones, reducing overhead when routes are not frequently used.

- **Role of Neural Networks**:
  - Predictive Analysis: Neural networks can predict changes in the network topology based on vehicle movement patterns, traffic conditions, and environmental factors. This allows the routing protocol to anticipate disruptions and adjust routes proactively.
  - Adaptive Decision-Making: Neural networks can dynamically decide when to switch between proactive and reactive routing based on real-time conditions such as vehicle density, speed variations, and road network changes.
  - Optimization: Neural networks can continuously optimize routing paths by learning from historical data and current network states, improving the overall efficiency and reliability of the network.

- **How Integration Works**:
  - Data Collection: Data is accumulated from various sources, including GPS information, speed sensors, traffic signals, and vehicle-to-vehicle (V2V) communication. This data serves as input to the neural network.
  - Training and Learning: The neural network is trained on this data to identify trends that indicate optimal routing paths, potential network congestion, or areas where proactive routing should be prioritized.
  - Real-Time Decision-Making: During network operation, the neural network processes real-time data and feeds its predictions and decisions into the hybrid routing protocol. For example:- route stability prediction, congestion detection, dynamic zone adjustment, etc.

- **Advantages**:
  - Improved Scalability: Neural networks help hybrid routing protocols scale better in large and dense networks by making intelligent decisions that reduce unnecessary overhead.
  - Increased Efficiency: By predicting and reacting to network changes in real-time, the integration leads to more efficient routing, reducing latency, packet loss, and overall network congestion.
  - Better Adaptability: The combined system is more adaptable to sudden changes in network topology, such as accidents or road closures, thanks to the predictive capabilities of the neural network.

- **Use cases**:
  - Urban Traffic Management: In densely populated urban areas with complex road networks, neural networks can help optimize traffic flow by predicting congested routes and adjusting the routing strategy accordingly.
  - Highway Communication: On highways, where vehicles move at high speeds and network topology changes rapidly, the system can ensure stable communication by predicting the most reliable

routes in advance.
  - Emergency Situations: In scenarios like natural disasters or accidents, the integrated system can quickly adapt to new conditions, ensuring that emergency vehicles or messages reach their destinations promptly.

VIII. Challenges and Limitations

Integrating Neural Networks with Hybrid Routing Protocols in VANETs offers significant benefits, but it also presents several challenges and limitations. Here's an overview of the challenges that are faced while integrating Neural Networks with Hybrid Routing Protocols:

- **Complexity and Computational Overhead:**
  - Increased System Complexity: The integration of neural networks adds layers of complexity to the routing protocol. This complexity can make the system harder to design, implement, and maintain.
  - High Computational Requirements: Neural networks, especially deep learning models, require significant computational power. In a VANET, where resources may be limited and distributed across numerous vehicles, this can be a bottleneck.
  - Real-Time Processing Demands: In order to be efficient, the neural network needs to analyze data and make decisions instantaneously. This demands rapid processing capabilities, which may not always be achievable in environments with limited resources.
- **Training and Adaptation:**
  - Training Time and Resources: Training neural networks, especially deep models, requires significant time and computational resources. In a rapidly changing environment like VANETs, the model needs to be frequently updated, which can be resource-intensive.
  - Adaptation to New Scenarios: The neural network must continuously adapt to new traffic patterns, road conditions, and vehicle behaviors.
- **Scalability Issues:**
  - Network Size and Density: The system must be able to scale to handle more data, more complex routing decisions, and higher network traffic.
  - Distributed Decision-Making: In a large VANET, decisions might be needed to be made in a decentralized way across numerous vehicles. Coordinating these decisions while maintaining consistency and efficiency is difficult, especially when integrating neural networks.
- **Security Concerns**:
  - Vulnerability to Attacks: Neural networks can be vulnerable to adversarial attacks, where small, intentional perturbations to the input data cause the model to make incorrect decisions. In a VANET, such attacks could have serious consequences, such as misrouting vehicles or causing congestion.
  - Data Integrity: Ensuring that the data used by the neural network is accurate and has not been tampered with is critical. Malicious data could lead to poor routing decisions and compromised network performance.
- **Energy Efficiency:**
  - Battery and Power Consumption: Vehicles in VANETs have limited power resources. Running computationally intensive neural networks can drain these resources quickly, especially if the vehicle relies on battery power for its operations.
  - Energy Trade-Offs: The system needs to find a balance between making precise, real-time decisions and conserving energy. This trade-off can be challenging, particularly in electric vehicles where preserving battery life is a crucial consideration.
- **Cost and Deployment:**
  - High Deployment Costs: Incorporating neural networks into VANETs necessitates advanced hardware, software, and infrastructure, resulting in substantial deployment expenses.
  - Maintenance and Upgrades: Ongoing maintenance, updates, and upgrades to the neural network models are necessary to keep the system functioning optimally.

While hybrid routing protocols with neural network integration offer powerful solutions for managing VANETs, they come with significant challenges and limitations. Addressing these challenges requires careful design, robust data management, efficient computational strategies, and ongoing adaptation to new technologies and conditions.

IX. Future Directions and Open research areas

The integration of neural networks with hybrid routing protocols in VANETs is an area of rapid development with plentiful prospects for future research and advancement. Some of the areas for future directions and open rrsearch are as follows:

- **Edge and Fog Computing Integration:**
  - Distributed Processing: Moving the neural network computations closer to the data source using edge or fog computing can significantly reduce latency and improve real-time decision-making in VANETs.
  - Collaborative Decision-Making: Investigating how multiple edge nodes can collaborate to make more informed routing decisions in real-time is an open research area. This includes exploring the balance between local and global network information in decision-making processes.

- **Federated Learning for VANETs:**
  - Privacy-Preserving Learning: Federated learning enables neural networks to be trained across various decentralized devices without exchanging raw data, thus upholding privacy. Research can focus on adapting federated learning techniques to solve the unique challenges of VANETs, such as high mobility and intermittent connectivity.
  - Model Aggregation and Synchronization: Developing efficient methods for aggregating and synchronizing neural network models across vehicles in a VANET is an open challenge. This includes addressing issues related to heterogeneous data and varying computational capabilities of vehicles.
- **Adaptive and Self-Learning Systems:**
  - Continuous Learning: Exploring ways for neural networks to continuously learn and adapt to new traffic patterns, environmental conditions, and network topologies is a promising research direction. This includes developing methods for online learning and model updating without requiring frequent retraining from scratch.
  - Context-Aware Routing: Researching how to incorporate contextual information (e.g., weather conditions, time of day, or event-driven traffic) into routing decisions using neural networks can lead to more intelligent and adaptive VANETs.
- **Energy-Efficient Neural Networks:**
  - Energy-Aware Routing Decisions: Developing neural network models that can make routing decisions while minimizing energy consumption is a key area of research. This includes exploring trade-offs between computational complexity and decision accuracy.
- **Scalability and Performance Optimization:**
  - Scalable Neural Network Models: As VANETs grow in size and complexity, research is needed to ensure that neural network models can scale effectively. This includes exploring distributed and parallel processing techniques to handle large-scale networks.
  - Performance Metrics and Benchmarking: Developing standardized metrics and benchmarks to evaluate the performance of neural network-driven hybrid routing protocols in VANETs is an open research area.
- **Integration with Advanced Vehicular Technologies:**
  - Autonomous Vehicles and VANETs: As autonomous vehicles become more prevalent, integrating neural network-driven VANET routing protocols with autonomous driving systems is an open research area. This includes ensuring seamless communication and coordination between autonomous vehicles and the broader vehicular network.
  - V2X Communication: Researching how neural networks can optimize vehicle-to-everything (V2X) communication, including interactions with infrastructure, pedestrians, and other road users, is a key area of interest.

X. Conclusions

The application of neural networks within hybrid routing protocols in VANETs offers a significant step forward in enhancing intelligent transportation systems. This approach leverages the strengths of both hybrid routing strategies and neural network-driven decision-making, enabling more adaptive, efficient, and scalable communication in highly dynamic vehicular environments.

However, this integration also brings significant challenges, including the need for robust data collection, high computational power, and real-time processing capabilities. Issues related to model interpretability, security, scalability, and energy efficiency must be carefully addressed to ensure the practical viability of these systems.

Future research directions, such as the use of edge and fog computing, federated learning, adaptive and self-learning, and energy-efficient neural networks, offer pathways to overcoming these challenges. The development of resilient, adaptive, and privacy-preserving models will be crucial for the widespread adoption of this technology in VANETs.

As neural network-based hybrid routing protocols advance, they hold the promise of greatly improving the efficiency and reliability of VANETs, ultimately resulting in safer and more effective and reliable transportation networks. By addressing and exploring the current limitations and exploring open research areas, we can help and contribute towards the field of research and help in realizing the full potential of intelligent vehicular networks.

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