Optimized Neural Network-Based Routing Protocol for VANETs

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Abstract— **Vehicular Ad Hoc Networks (VANETs) are a cornerstone of Intelligent Transportation Systems (ITS), enabling real-time communication between vehicles and infrastructure for enhanced road safety, traffic management, and efficient navigation. However, VANETs face significant challenges, including high mobility, frequent topology changes, and variable network densities, which render traditional routing protocols inefficient. This paper proposes an optimized routing protocol that integrates Artificial Neural Networks (ANNs) and Reinforcement Learning (RL) to overcome these limitations.**

The proposed hybrid model utilizes ANNs to predict optimal routing paths based on multimetric inputs, such as packet delivery ratio (PDR), vehicle density, network congestion, and route distance. Simultaneously, RL dynamically adapts these decisions to real-time network conditions, ensuring robustness and scalability. The methodology is validated through extensive simulations in urban and highway scenarios using SUMO and OMNeT++ tools. Comparative analysis with traditional protocols, including GPSR and AODV, and standalone machine learning approaches demonstrates the proposed model's superior performance in terms of packet delivery ratio, end-to-end delay, and adaptability to varying traffic conditions.

Furthermore, the protocol incorporates a security layer to mitigate vulnerabilities like data replay and denial-of-service attacks, ensuring reliable communication. The results indicate that the hybrid ANN-RL protocol significantly improves routing efficiency and network reliability, making it a promising solution for the dynamic and challenging environments of VANETs. This research lays a foundation for future studies on integrating advanced AI techniques with vehicular networks to enhance the performance and scalability of ITS.

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

I. INTRODUCTION

Vehicular Ad Hoc Networks (VANETs) form a crucial part of modern Intelligent Transportation Systems (ITS), which are integral to the broader concept of smart transportation or smart mobility. Smart transportation leverages automation, real-time data collection [1], and vehicle-to-everything (V2X) communication to revolutionize the way people travel. By allowing vehicles to communicate with one another and the infrastructure around them, improve traffic management, reduce congestion, and enhance road safety. Unlike human drivers, who can easily be distracted or tired, computers in smart transportation systems can process data in real-time to identify and address potential problems, ensuring uninterrupted journeys and reducing the chances of accidents caused by human mistakes [2, 3].

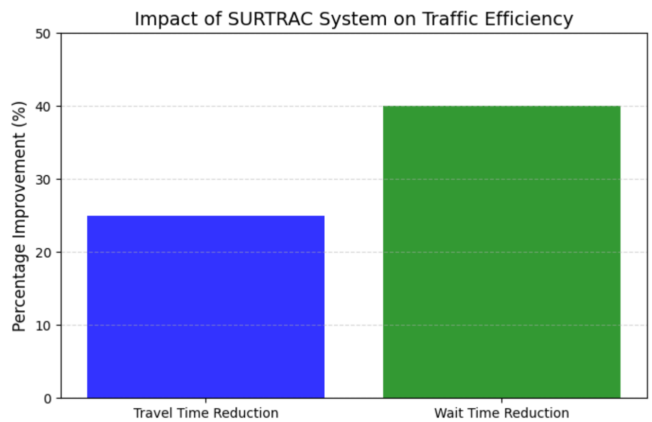

Fig. 1: Impact of the SURTRAC System on Traffic Efficiency. This graph illustrates the improvements achieved by the Scalable Urban Traffic Control (SURTRAC) system implemented in Pittsburgh, Pennsylvania. The study reported a 25% reduction in travel times and a 40% reduction in wait times at intersections, highlighting the potential of intelligent transportation systems to enhance urban traffic management [8].

The benefits of smart transportation are not only limited to individual users but are shared by the entire community. Cities like London, Paris, and Amsterdam have made significant investments in upgrading their infrastructure to align with the concept of ”smart cities”, showcasing the transformative potential of smart mobility in urban living [4]. VANETs, as a key enabler of ITS, play a pivotal role in facilitating the wireless communication required for such systems. They connect vehicles with one another (V2V) and with infrastructure (V2I), using standards like IEEE 802.11p, developed specifically for vehicular communication by the IEEE Committee [5, 6]. Additionally, the US Federal Communication Commission (FCC) has allocated 75 MHz of bandwidth at 5.9 GHz to support these Dedicated Short Range Communications (DSRC) in the ITS radio service for transportation and vehicle safety-related purposes [7].

Despite advancements, the road safety challenges remain staggering. According to The World Health Organization (WHO) in its ”Global Status Report on Road Safety 2023”, road traffic incidents resulted in 1.19 million fatalities globally in 2021, equating to 15 deaths per 100,000 people. Of these, 30% involved users of powered two- and three-wheelers, while 25% were associated with occupants of four-wheel vehicles. Alarmingly, around 10% of road traffic fatalities are attributed to drunk driving, correlating

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with self-reported rates of 16–21% of individuals admitting to driving under the influence (DUI) in surveys conducted by the European Survey Research Association (ESRA) [9, 10].

In this context, VANETs offer a promising solution by providing real-time communication and decision-making capabilities, which are essential for dynamic and high-mobility environments. However, the existing routing protocols for VANETs, such as Greedy Perimeter Stateless Routing (GPSR) and Ad hoc On-Demand Distance Vector (AODV), face challenges in adapting to rapidly changing network topologies and diverse traffic scenarios. Artificial Intelligence (AI), particularly Artificial Neural Networks (ANNs) and Reinforcement Learning (RL), has emerged as a promising tool to address these challenges. [11] offers a comparative analysis of 26 routing protocols for VANET based on reinforcement learning by evaluating them qualitatively.

This paper proposes a hybrid routing protocol that integrates ANNs for predictive routing and RL for adaptive real-time optimization. The ANN module utilizes multi-metric inputs, such as packet delivery ratio (PDR), vehicle density, network congestion, and route distance, to forecast efficient routing paths. Simultaneously, the RL module adjusts these decisions dynamically to align with real-time network conditions. This combination leverages the predictive capabilities of ANNs and the adaptability of RL to overcome the limitations of traditional protocols.

The methodology is validated through simulations in diverse scenarios, including urban and highway environments, and evaluated against traditional protocols like GPSR and AODV [12]. Key metrics, such as packet delivery ratio, end-to-end delay, and throughput, highlight the significant improvements achieved by the proposed model. Additionally, a security layer ensures robust communication by mitigating vulnerabilities like data replay and denial-of-service attacks.

Integrating machine learning, particularly neural networks, into routing protocols shows great potential for enhancing decision-making processes in VANETs. They can be trained to predict link stability, assess network conditions, and optimize routing paths based on real-time data.

II. Overview of VANETs

Vehicular Ad Hoc Networks (VANETs) form the backbone of modern Intelligent Transportation Systems (ITS), enabling vehicles to communicate with each other (V2V) and with roadside infrastructure (V2I) [13].

The primary components of a VANET architecture [14, 15] include:

- **Nodes**: In a Vehicular Ad-hoc Network (VANET), nodes are the distinct entities or devices involved in the network. These include vehicles, roadside units (RSUs), or any device capable of communicating within the network.
- **On-Board Units (OBUs)**:Every vehicle is equipped with sensors that collect traffic and driving data, which can be transmitted to other vehicles (V2V communication), roadside units (V2I communication), or satellite navigation systems. On-Board Units (OBUs) serve as the mobile nodes within the vehicles.
- **Roadside Units (RSUs)**: RSUs are stationary infrastructure units placed along roadsides that enable communication between vehicles and provide connectivity to larger networks, such as traffic management systems or the internet. RSUs act as fixed nodes along the road, such as traffic lights, road signs, and similar structures.

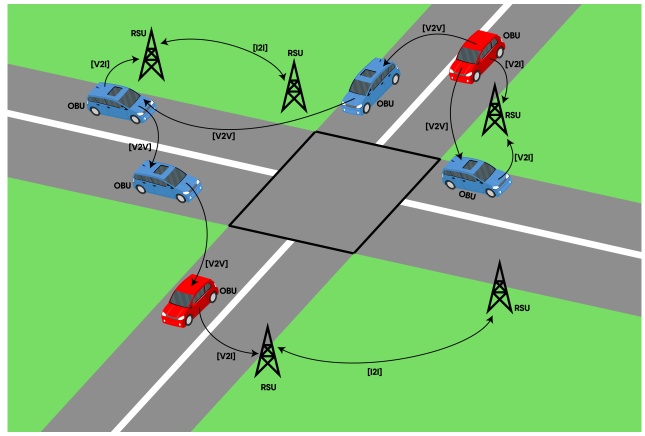

Fig. 2: A simple representation of VANET Architecture with OBUs and RSUs and also showing V2V, V2I, and I2I communication among nodes.

VANETs offer 3 types of communication modes [14, 16], 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 (RSUs) enables access to services like traffic management, navigation, and internet. This extends the communication range, and the exchange of data is highly secure due to the unique key provided by the RSU to each user.
- **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. Related Works

Numerous routing protocols have been developed to address the challenges associated with VANETs. The following section provides an in-depth discussion of these strategies, highlighting recent advancements in reinforcement learning, machine learning, and hybrid approaches.

- **Hierarchical Reinforcement Learning-Based Approaches**: Qin Yang and Sang-Jo Yoo in [17] proposed a hierarchical Q-learning-based routing algorithm utilizing grouped roadside units (RSUs). Urban areas are divided into groups based on the position of the RSUs. Their multi-agent hierarchical Q-learning model trains two types of Q-tables: a group Q-table, estimating the reward for reaching a destination group, and a local Q-table, focusing on the best path within the group. This dual-Q table approach improves routing efficiency by addressing scalability and localized decision-making challenges. By grouping the RSUs, the number of Q-tables representing groups and the size of each table can be reduced, thereby improving the convergence time of the Q-learning process. The simulation results show that when the RSUs are grouped, the number of updates in the Q-vector are significantly reduced.
- **Intersection-Based Routing Protocols**: Intersection-centric routing protocols leverage intersections' strategic importance in urban networks to make routing decisions. [18] introduced an intersection-based V2X routing protocol that combines past traffic patterns with real-time network monitoring. By employing a multidimensional Q-table and an improved greedy strategy, the protocol selects optimal road segments and relays, preventing congestion and enhancing overall network performance.
  Rui et al. [19] proposed the Intersection-Based QoS Routing (IQRRL) algorithm , which incorporates reinforcement learning to optimize intersection and next-hop vehicle selection. The IQRRL protocol uses a combination of "greedy learning" and reinforcement learning to evaluate vehicle nodes for the possibility of being the optimal node in the future. By addressing the local optimum problem, the study ensures better routing efficiency through comprehensive consideration of neighboring roads' performance and shortest routes.
- **Fuzzy Logic and Hybrid Reinforcement Learning**: Incorporating fuzzy logic into Q-learning frameworks has proven effective for VANET routing. The fuzzy constraint Q-learning algorithm proposed in [20] integrates multiple metrics to evaluate wireless link quality, improving route selection in AODV-based protocols. Similarly, Rahmani et al. [21] presented the Q-learning and Fuzzy Logic-based Hierarchical Routing Protocol (QFHR), which operates in three phases. RSUs first store traffic data and use Q-learning to identify optimal intersection paths, followed by fuzzy logic for selecting the best relay nodes in road sections.
- **Machine Learning and Hybrid Metaheuristics**: Ensemble-based machine learning techniques and hybrid metaheuristic algorithms have been employed to enhance VANET routing performance. Marwah et al. [22] proposed HFSA-VANET, a routing protocol combining Seagull Optimization and Artificial Fish Swarm Optimization with machine learning models such as SVM, Naive Bayes, ANN, and Decision Tree. The protocol demonstrated significant improvements in delay, energy consumption, and throughput compared to CRSM-VANET methods.
  S. Bitam, A. Mellouk, and S. Zeadally [23] present a Hybrid Bee swarm Routing (HyBR) protocol which is based on the continuous learning paradigm in order to consider the dynamic environmental changes in real-time, which is a crucial characteristic property of VANETs. The protocol combines the features of topology-based routing and geographic routing based on Global Positioning System (GPS).
- **Artificial Neural Networks in Routing**: Leticia Lemus Cárdenas et al. [24] introduced a multimetric predictive routing algorithm leveraging ANNs. By training their model on urban scenarios with metrics like available bandwidth, vehicle density, and trajectory, they achieved substantial improvements in packet delivery probability, reducing packet loss to under 20% and delays to below 0.04 ms, even in complex environments.
- **Hybrid Neural Network Models**: Mendez et al. [25] developed a hybrid model combining Convolutional Neural Networks (CNNs) and Bidirectional Long Short-Term Memory (Bi-LSTM) networks for long-term traffic flow prediction in urban routes. The model uses CNNs for extracting hidden features and Bi-LSTM networks for understanding temporal context, enabling accurate traffic flow forecasting.
- **Geographical Routing with Location Verification**: Jabbar et al. [26] explored the impact of a Location Verification System (LVS) on geographical routing protocols. By verifying vehicle locations through GPS and notifying nearby nodes, their system reduces control overhead and enhances routing security. The study highlights the potential for integrating advanced location verification techniques into hybrid routing protocols for VANETs.

These works demonstrate the growing trend of incorporating reinforcement learning, machine learning, and hybrid optimization techniques into VANET routing protocols. This research builds on these foundations by integrating Artificial Neural Networks with Reinforcement Learning in a hybrid framework to improve scalability, adaptability, and security in VANET routing.

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 [17]	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 [18]	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 [19]	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 [20]	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 [21]	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 [22]	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.
S. Bitam, et al.	2013	HyBR: A Hybrid Bio-inspired Bee swarm Routing protocol for safety applications in Vehicular Ad hoc NETworks (VANETs) [23]	Proposed a bio-inspired routing protocol which is a hybrid protocol which combines topology routing and geographic routing.	Metaheuristic Algorithm, Hybrid Routing	Better end-to-end delay, packet delivery ratio, and normalized overhead load when compared to AODV and GPSR.
L.L. Cárdenas et al.	2021	A Multimetric Predictive ANN-Based Routing Protocol for Vehicular Ad Hoc Networks [24]	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 [25]	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 [26]	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.

IV. Comparative Analysis of Hybrid Routing Protocols

In the context of VANETs, traditional routing protocols are categorized into proactive, reactive, and hybrid approaches. ALl of them present distinct advantages and challenges, particularly when addressing the dynamic and complex environments inherent to VANETs.

Proactive Routing Protocols [27, 28] maintain up-to-date routing information to all nodes by periodically distributing routing tables throughout the network. Protocols such as Destination-Sequenced Distance-Vector (DSDV), Optimized Link State Routing (OLSR), and Fisheye State Routing (FSR) exemplify this approach. While proactive protocols offer low latency in route discovery due to pre-established routes, they incur significant overhead from constant updates, which can degrade network throughput, especially in highly dynamic VANET scenarios.

Reactive Routing Protocols [27, 28], including Ad hoc On-Demand Distance Vector [29] (AODV), Dynamic Source Routing (DSR), and Temporally Ordered Routing Algorithm (TORA), initiate route discovery only when data transmission is required. This on-demand mechanism reduces routing overhead compared to proactive protocols. However, the route discovery process can introduce latency, and the rapidly changing topology of VANETs may lead to frequent route breaks, affecting communication reliability.

Hybrid Routing Protocols integrate proactive and reactive strategies to balance the trade-offs between Proactive and Reactive Routing. They combine the benefits of proactive and reactive strategies [30, 31] to address the unique challenges posed by dynamic vehicular environments. This section presents a detailed comparative analysis of existing hybrid routing protocols, highlighting their strengths, weaknesses, and suitability for specific scenarios. The analysis is based on critical performance metrics such as routing overhead, packet delivery ratio, end-to-end delay, scalability, and energy efficiency.

1. Zone Routing Protocol (ZRP)

ZRP divides the network into zones, applying proactive routing within zones and reactive routing for inter-zone communication [32]–[34]. Proactive routing within zones reduces latency, while reactive routing minimizes overhead for less frequently used routes.

Routing schemes are categorized into intra-zone routing (proactive) and inter-zone routing (reactive), with zone size defined by a radius ρ, indicating the number of hops to the perimeter. Interior nodes are within a distance less than ρ, while peripheral nodes are at a distance equal to ρ. Figure 3 illustrates a routing zone for node Z with $\rho = 3$.

ZRP [35] consists of a proactive component called the Intra-zone Routing Protocol (IARP) and a global reactive component known as the Inter-zone Routing Protocol (IERP). IARP maintains up-to-date routing information within the zone, while IERP discovers routes between nodes in different zones through a route discovery process.

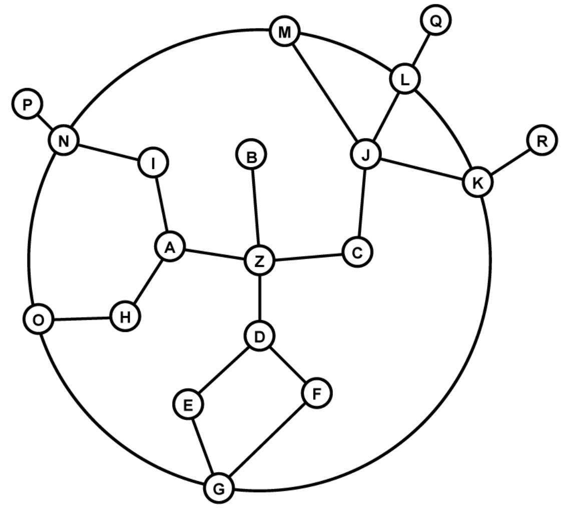

Fig. 3: Example routing zone with $\rho = 3$. Routing zone of Z includes nodes A-O, but not P, Q, R. Here, the zone is defined in number of hops, not as a physical distance between the nodes.

It employs bordercasting to efficiently send route queries to border nodes, facilitated by the Bordercast Resolution Protocol (BRP). The Neighbor Discovery Protocol (NDP) detects new neighbors and link failures by sending ”HELLO” beacons at regular intervals; received beacons update the neighbor table, while neighbors that do not send beacons within a certain time frame are removed.

Advantages:

- Reduces control overhead compared to purely proactive protocols.
- Balances scalability and efficiency through zone-based management.

Disadvantages:

- Zone configuration is challenging in highly dynamic environments.
- High dependency on accurate zone radius (ρ) definition for optimal performance.

2. Adaptive Hybrid Routing Protocol (AHRP)

AHRP integrates geographic and reactive routing techniques [36]. Vehicles exchange periodic beacon messages to maintain neighbor information, and RSUs assist in routing decisions.

Advantages:

- High reliability due to RSU support and updated routing information.
- Efficient use of proactive and reactive strategies to reduce routing overhead.

Disadvantages:

- Heavily reliant on the presence and proper functioning of RSUs.

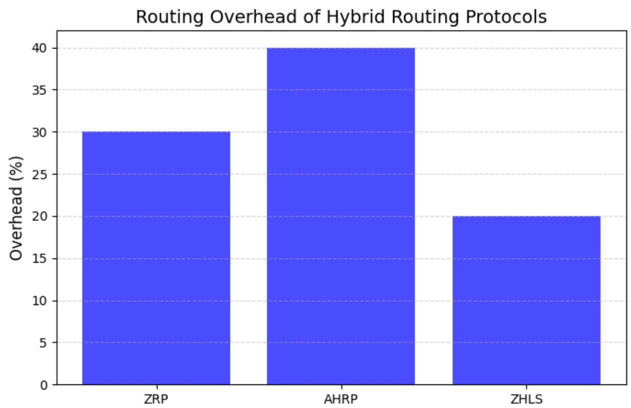

Fig. 4: Routing Overhead of Hybrid Routing Protocols. This graph illustrates the percentage of routing overhead for three hybrid protocols: ZRP, AHRP, and ZHLS. The ZHLS protocol demonstrates the lowest overhead at 20%, followed by ZRP at 30%, and AHRP at 40%. The comparison highlights the efficiency of ZHLS in minimizing control traffic while maintaining network performance.

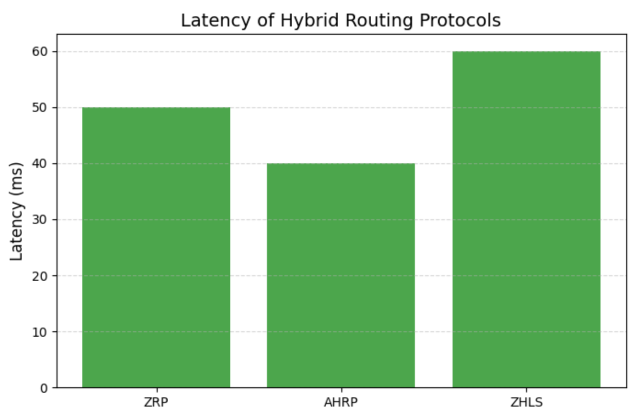

Fig. 5: Latency of Hybrid Routing Protocols. This graph compares the average latency (in milliseconds) of three hybrid routing protocols: ZRP, AHRP, and ZHLS. AHRP exhibits the lowest latency at 40 ms, followed by ZRP at 50 ms, while ZHLS has the highest latency at 60 ms. This comparison underscores AHRP's efficiency in minimizing delay for time-sensitive applications in VANETs.

- Increased control overhead due to frequent beacon and service advertisement messages.

3. Zone-Based Hierarchical Link State (ZHLS)

ZHLS uses a hierarchical structure with non-overlapping zones to reduce routing overhead [37]. Nodes within a zone maintain intra-zone topology information, while inter-zone routing uses a reactive approach.

In ZHLS [38], two levels of topology are defined: node-level and zone-level. Node-level topology contains information about physical connections among nodes within a zone, while zone-level topology describes inter-zone connectivity and virtual links throughout the network. Both topologies are represented using Link State Packets (LSPs), which are disseminated within zones and across the network

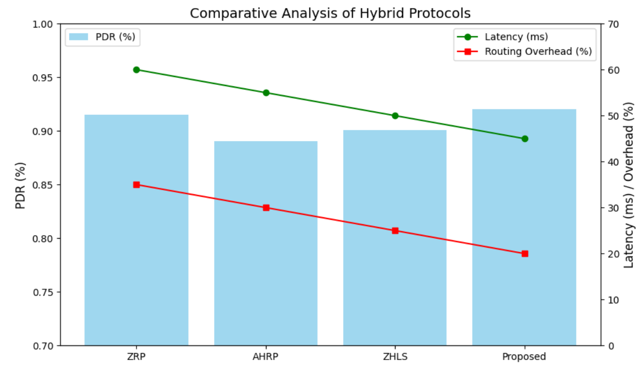

Fig. 6: Comparative Analysis of PDR and Latency in Hybrid Protocols

at regular intervals. Upon receiving LSP updates, nodes update their LSP databases by adding new entries and removing outdated ones.

Advantages:

- Significantly reduces routing overhead due to hierarchical design.
- Ensures scalability by managing local and global topology information separately.

Disadvantages:

- Limited adaptability to dynamic changes in geographic boundaries.
- Requires accurate geographic information for zone creation, which may not always be available.

4. Neural Network-Enhanced Hybrid Protocols *(Proposed Approach)*

Neural networks augment hybrid routing protocols by providing predictive and adaptive decision-making capabilities. This integration leverages real-time data to optimize routing, manage congestion, and anticipate network changes.

Advantages:

- Enhanced adaptability to dynamic network conditions through predictive analysis.
- Improved packet delivery ratio and reduced latency due to intelligent decision-making.
- Scalability across varying network densities.

Disadvantages:

- High computational requirements for real-time neural network processing.
- Dependence on high-quality data and robust security mechanisms.

Performance Comparison

Table II summarizes the comparative performance of these hybrid routing protocols based on key metrics.

This comparative analysis highlights the strengths and limitations of existing hybrid protocols, demonstrating the potential of neural network-enhanced hybrid routing to

TABLE II: Performance Comparison of Hybrid Routing Protocols

Protocol	Routing Overhead	Packet Delivery Ratio	End-to-End Delay	Scalability
ZRP	Moderate	High	Low	Moderate
AHRP	High	High	Moderate	Low
ZHLS	Low	Moderate	Low	High
NN-Enhanced	Low-Moderate	Very High	Very Low	Very High

address VANET-specific challenges more effectively. Future work should focus on overcoming the computational and data requirements of neural networks to maximize their impact on VANET routing efficiency.

Performance Metrics and Evaluation: Hybrid routing protocols are evaluated based on several performance metrics, including:

- *Routing Overhead*: The amount of control traffic generated to establish and maintain routes. Lower routing overhead indicates better network performance and includes the time and bandwidth spent on route discovery, maintenance, and updates.
- *Route Discovery Time*: The duration required to find and establish a valid route, including the time for broadcasting route requests and receiving replies. Minimizing this time is essential for timely data transmission.
- *Packet Delivery Ratio*: The ratio of successfully delivered packets to the total packets sent by the source node. A high ratio reflects effective routing and network stability.
- *End-to-End Delay*: The total time taken for a packet to travel from source to destination, including transmission

V. Challenges in VANET Routing

Vehicular Ad Hoc Networks (VANETs) present unique routing challenges due to their dynamic nature and specific requirements. This section highlights the key challenges [14, 39] in VANET routing.

- **High Mobility and Rapid Topology Changes**:
  Challenge: Frequent changes in network topology due to high-speed vehicle mobility complicate route stability, leading to frequent partitioning and reconfiguration [40].
  Impact: This causes increased routing overhead, higher packet loss, longer route discovery times, and inconsistent communication quality.
  Approaches: Predictive routing protocols leverage machine learning and historical travel data to anticipate vehicle movements, while reinforcement learning algorithms dynamically adapt routes to maintain stability in real-time.

- **Limited Communication Range and Variable Network Density**:
  Challenge: Vehicular communication technologies like DSRC, IEEE 802.11p, and C-V2X have limited communication range, and the network density fluctuates significantly between urban and rural areas.
  Impact: Low density leads to route breaks and connectivity issues, while high density results in congestion, increased collisions, and resource competition [41, 42].
  Approaches: Geographic routing and clustering methods optimize path selection in sparse environments, while congestion-aware protocols [43] adapt dynamically to high-density scenarios to minimize resource contention.

- **Scalability and Network Size**:
  Challenge: VANETs often encompass large networks with thousands of nodes [44], requiring routing protocols to scale efficiently without performance degradation [40].
  Impact: Poor scalability leads to slower route discovery, increased latency, and excessive control overhead as the network grows.
  Approaches: Scalable hierarchical protocols, such as zone-based and clustered routing, improve manageability by organizing nodes into logical groups and reducing routing overhead through localized decisions.

- **Security and Privacy Concerns**:
  Challenge: VANETs are highly vulnerable to threats like spoofing, replay attacks, eavesdropping, and denial-of-service (DoS) attacks [40, 45], making secure communication essential.
  Impact: Security breaches compromise data integrity, authenticity, and privacy, potentially disrupting critical applications like collision avoidance and emergency communication.
  Approaches: Cryptographic techniques, digital signatures, authentication mechanisms, and secure key management systems are integrated into routing protocols to ensure secure communication and protect against malicious activities. Recent advancements include incorporating anomaly detection systems using machine learning [46] for proactive threat mitigation.

- **Quality of Service (QoS) and Performance Metrics**:
  Challenge: Ensuring consistent QoS is vital for safety-critical applications, such as collision warnings, and non-critical applications, such as real-time infotainment.
  Impact: Variable network conditions and the need to balance metrics like packet delivery ratio (PDR), latency, throughput, and reliability make QoS

maintenance challenging.
Approaches: QoS-aware routing protocols [47] prioritize routes based on application requirements, employing traffic differentiation, adaptive routing strategies, and dynamic resource allocation to optimize performance.

- **Integration with Emerging Technologies**:
Challenge: Incorporating VANETs with advanced technologies such as 5G, C-V2X, edge computing, and autonomous vehicle systems increases complexity and demands in routing protocol design [48].
Impact: Although these technologies enhance VANET performance, they introduce challenges in interoperability, compatibility, latency, and network management.
Approaches: Recent routing protocols are being developed to support seamless integration with these technologies by leveraging multi-access edge computing (MEC), network slicing for 5G, and adaptive protocols for C-V2X. Hybrid models combining reinforcement learning and neural networks are emerging as promising solutions for maintaining compatibility across these systems.

- **Energy Efficiency and Computational Overhead**:
Challenge: VANET nodes, especially onboard units (OBUs), often have limited computational and energy resources, posing constraints on routing protocol complexity.
Impact: High computational overhead in complex routing algorithms can deplete resources, reducing the overall efficiency and lifespan of network nodes.
Approaches: Lightweight routing protocols and energy-aware algorithms optimize resource usage. The integration of reinforcement learning with energy-efficient mechanisms [49, 50] ensures balanced energy consumption across the network while maintaining high routing performance.

VI. Advanced Security Mechanisms

The integration of neural networks into hybrid routing protocols for VANETs introduces significant advantages but also raises critical security concerns. Advanced security mechanisms are essential to ensure the integrity, confidentiality, and reliability of vehicular communication networks. This section explores various techniques and strategies to address the unique security challenges posed by VANETs.

A. Challenges in Securing VANETs

VANETs are highly dynamic networks characterized by frequent topology changes, high-speed nodes, and varying density. These features, coupled with the use of neural networks, create several security challenges [51]–[53] :

- **Adversarial Attacks:** Neural networks are vulnerable to adversarial attacks where small perturbations in input data can lead to incorrect routing decisions.
- **Data Integrity and Authenticity:** Ensuring the accuracy and authenticity of data exchanged between vehicles and infrastructure is critical to avoid routing errors caused by malicious actors.
- **Privacy Concerns:** The collection and processing of location and mobility data may expose sensitive user information, necessitating robust privacy-preserving measures.
- **Distributed Environment:** Securing decentralized decision-making processes in a highly distributed VANET environment is inherently challenging.

B. Advanced Security Mechanisms for VANETs

1. Blockchain-Based Security [54]

- *Decentralized Trust Management:* Blockchain technology provides a decentralized and tamper-proof mechanism for managing trust among nodes in a VANET. Each transaction or communication is recorded in a secure, immutable ledger.
- *Smart Contracts:* Smart contracts can automate security policies, such as authenticating nodes and validating routing decisions, ensuring compliance without manual intervention.
- *Resistance to Tampering:* By ensuring data immutability, blockchain prevents unauthorized modifications to routing or traffic data.

2. Adversarial Training for Neural Networks

- *Robust Model Training:* Neural networks can be trained with adversarial examples to improve their resilience against attacks. This involves introducing perturbed data during training to simulate potential adversarial scenarios.
- *Defensive Distillation:* A technique where the neural network is trained to output probabilities rather than hard classifications, making it harder for adversaries to exploit model vulnerabilities.

3. Privacy-Preserving Data Sharing [55]

- *Federated Learning [56]:* Enables vehicles to collaboratively train neural networks without sharing raw data, preserving privacy and reducing the risk of data breaches.
- *Homomorphic Encryption [57]:* Allows data to be encrypted before processing, ensuring that sensitive information remains secure even during computation.
- *Differential Privacy [56]:* Introduces controlled noise into data to anonymize sensitive information while maintaining utility for routing decisions.

4. Intrusion Detection Systems (IDS)

- *Anomaly Detection:* Neural network-based IDS can identify abnormal behaviors in the network, such

as unusual routing patterns or data inconsistencies, indicating potential attacks [46, 58, 59].
- *Collaborative IDS :* Vehicles and RSUs can collaboratively detect and respond to security threats, leveraging distributed intelligence to enhance detection accuracy [60, 61].

5. Cryptographic Techniques

- *Public Key Infrastructure (PKI) :* Ensures secure communication by encrypting messages and authenticating nodes using digital certificates [62].
- *Lightweight Cryptography :* Tailored cryptographic algorithms designed to operate efficiently in resource-constrained vehicular environments [63].

6. Secure Routing Protocols

- *Trust - Based Routing:* Nodes evaluate the trustworthiness of their neighbors based on historical interactions, ensuring that only reliable nodes participate in routing [64]–[66].
- *Location Verification Mechanisms:* Verify the geographical accuracy of nodes to prevent location spoofing attacks, ensuring that routing decisions are based on valid data [67].

C. Evaluation of Security Mechanisms

The effectiveness of these security mechanisms is evaluated based on the following metrics [68]:

- **Detection Rate:** The percentage of attacks or anomalies successfully identified by the system.
- **False Positive Rate:** The rate at which normal network behavior is incorrectly flagged as malicious.
- **Overhead:** The additional computational and communication cost introduced by security measures.
- **Scalability:** The ability of the security mechanisms to perform effectively as the network size and density increase.

By incorporating these advanced security mechanisms, neural network-integrated hybrid routing protocols can provide a robust foundation for secure and reliable vehicular communication, ensuring the safety and efficiency of intelligent transportation systems.

VII. 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 effectively process real-time data from various sources, such as vehicle speeds and traffic conditions [69]. They adapt to network changes and identify traffic patterns, enabling accurate predictions of future states and potential issues like congestion or accidents.
- **Routing Optimization**: Neural networks analyze current and historical traffic data to predict the best routes [70, 71]. They help hybrid routing protocols determine when to use proactive or reactive routing.
- **Traffic and Congestion Management**: By analyzing traffic patterns, neural networks predict congestion points [72], allowing vehicles to reroute proactively and reduce traffic jams. They also balance network traffic across available routes to prevent overload and improve 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 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 [70].
- **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.

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.

2.2. Collision Avoidance Systems

Neural networks integrated with vehicle sensors analyze real-time data to detect potential hazards, such as sudden braking or pedestrians crossing. By predicting collision likelihood, the system can issue alerts or automatically take evasive actions like braking or steering. Additionally, they assess driving patterns and environmental conditions to provide early warnings about risky situations, such as slippery roads or sharp turns, helping drivers adjust their behavior to avoid accidents. [73, 74]

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 [75].
- **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 [76].

VIII. Hybrid Routing Protocols with Neural Network Integration

Hybrid routing protocols integrated with neural networks in Vehicular Ad Hoc Networks (VANETs) effectively tackle the complexities of vehicular communication. This integration combines proactive and reactive routing strategies with the predictive capabilities of neural networks, enabling real-time hazard detection from vehicle sensors, such as sudden braking or obstacles.

Neural networks facilitate adaptive routing decisions, allowing for rerouting away from congestion and enabling timely interventions like automatic braking or steering. While this enhances safety and optimizes traffic flow, it demands significant computational resources and high-quality data, with potential for false alarms. Despite challenges in integration with existing technologies, this combination offers a powerful solution for managing the dynamic nature of VANETs, improving efficiency and safety in vehicular networks.

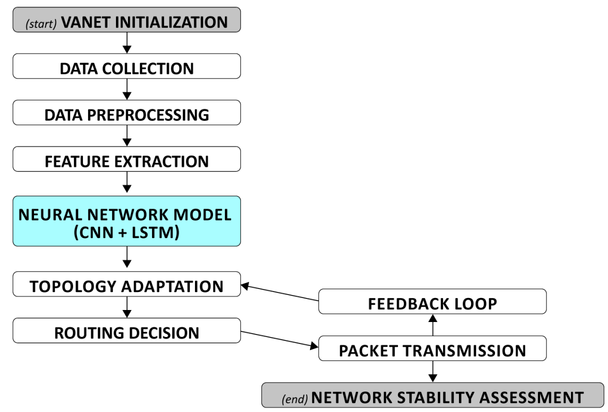

Fig. 7: Example workflow of Neural Network Integration for Hybrid Routing Protocol

- **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.
  - Adaptive Decision-Making: Neural networks can dynamically decide when to switch between proactive and reactive routing based on real-time conditions.
- **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.
- **Advantages**:

  - 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.
  - 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.

IX. Comprehensive Framework Design

To effectively integrate neural network-based hybrid routing protocols into VANETs, a comprehensive framework design is essential. This framework provides a structured approach to managing vehicular communication, optimizing routing decisions, and ensuring seamless interaction with other smart city systems. The following sections outline the core components, architecture, and workflow of the proposed framework.

A. Core Components of the Framework

The framework consists of several interconnected components designed to address the unique challenges of VANETs:

- **On-Board Units (OBUs):** Installed in vehicles, OBUs collect data from sensors, communicate with neighboring vehicles and RSUs, and execute lightweight neural network models for routing decisions.
- **Roadside Units (RSUs):** Serve as intermediary nodes to aggregate data, facilitate communication, and offload computationally intensive tasks from OBUs.
- **Neural Network Models:** Predict optimal routing protocols based on real-time traffic conditions, vehicle density, and network metrics.
- **Edge and Cloud Servers:** Provide additional computational resources for training and updating neural network models, enabling continuous learning and adaptability [77].
- **Communication Infrastructure:** Includes vehicle-to-vehicle (V2V), vehicle-to-infrastructure (V2I), and infrastructure-to-infrastructure (I2I) communication technologies, such as IEEE 802.11p and 5G.

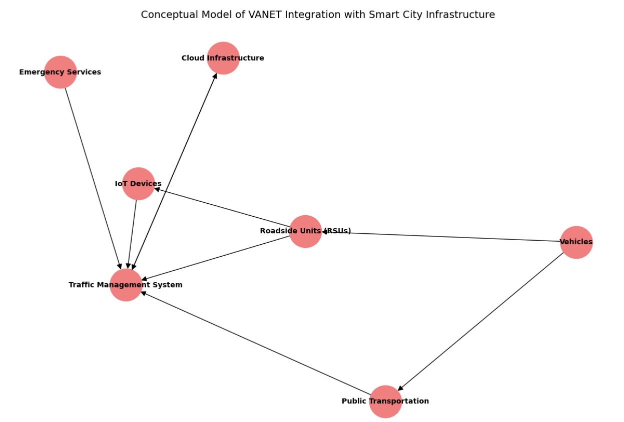

Fig. 8: Conceptual Model of VANET Integration with Smart City Infrastructure, demonstrating the communication between VANET components and various smart city systems to enable intelligent transportation and urban management.

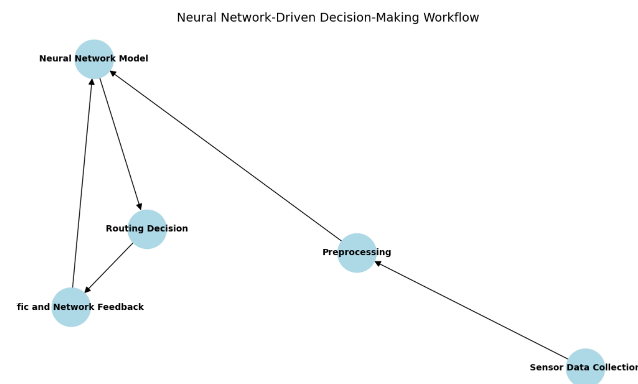

Fig. 9: Workflow of Neural Network-Driven Decision-Making in VANETs, illustrating the process from sensor data collection to routing decision-making, with a feedback loop for continuous improvement.

B. Architectural Design

The framework architecture comprises of three layers:

- **Perception Layer:** Gathers data from vehicle sensors, GPS, and RSUs. This layer ensures accurate and real-time data collection for routing decisions.
- **Processing Layer:** Processes collected data using neural network models to determine the optimal routing protocol and predict traffic conditions.
- **Communication Layer:** Facilitates data exchange between vehicles, RSUs, and cloud servers, ensuring low-latency and reliable communication.

C. Workflow of the Framework

The proposed framework operates through the following steps as shown in Fig. 9:

1) **Data Collection:** OBUs collect data such as vehicle speed, location, traffic density, and network congestion. RSUs aggregate data from multiple vehicles.
2) **Preprocessing:** Data is cleaned, normalized, and formatted for input into neural network models.

3) **Neural Network Inference:** Lightweight models deployed on OBUs and RSUs predict the optimal routing protocol (e.g., proactive, reactive, or hybrid).
4) **Routing Decision:** Based on the neural network's output, the system determines the most efficient route for data packets.
5) **Communication and Feedback:** Routing decisions are communicated to vehicles, and feedback from implemented routes is used to update the models continuously.

D. Advantages of the Framework

The comprehensive framework offers several advantages:

- **Scalability:** Supports large-scale VANETs with dynamic vehicle densities and traffic patterns.
- **Adaptability:** Continuously learns and adapts to changing network conditions through neural network updates.
- **Efficiency:** Reduces routing overhead, latency, and energy consumption by optimizing routing decisions in real-time.
- **Interoperability:** Seamlessly integrates with other smart city systems, such as IoT networks and traffic management platforms.

E. Challenges and Limitations

Despite its advantages, the proposed framework faces certain challenges:

- **Computational Requirements:** Running neural network models in real-time on OBUs may strain resources, particularly in low-end vehicles.
- **Data Privacy:** Ensuring the confidentiality of collected data while maintaining utility for routing decisions.
- **Infrastructure Dependency:** Relies on the availability of RSUs and high-speed communication networks, which may not be uniformly deployed.

F. Future Enhancements

The framework can be enhanced further through:

- **Integration with Federated Learning:** Enables distributed training of neural network models across vehicles without sharing raw data, enhancing privacy.
- **AI-Driven Security Mechanisms:** Incorporates adversarial training and blockchain-based techniques to strengthen security.
- **Dynamic Protocol Switching:** Develops advanced algorithms to dynamically switch between proactive, reactive, and hybrid protocols based on evolving network conditions.

G. Conclusion

The proposed comprehensive framework design provides a robust solution for integrating neural network-based hybrid routing protocols into VANETs. By addressing challenges and leveraging advanced technologies, the framework ensures efficient, scalable, and secure vehicular communication, contributing to the development of intelligent transportation systems and smart cities.

X. Interoperability in Smart Cities

As smart cities [78] evolve, Vehicular Ad Hoc Networks (VANETs) play a critical role in enabling seamless communication between vehicles, infrastructure, and other elements of urban environments [79]. The integration of neural network-driven hybrid routing protocols in VANETs enhances interoperability within smart cities, facilitating efficient data exchange and coordination across various systems. This section explores the importance, challenges, and solutions for achieving interoperability in smart city ecosystems.

A. Importance of Interoperability

Interoperability refers to the ability of diverse systems and devices to communicate and work together effectively [80]. In the context of smart cities, interoperability is essential for:

- **Seamless Integration:** Ensures that VANETs can interact with other smart city components, such as IoT devices [81], traffic management systems, and public transportation networks.
- **Efficient Resource Utilization:** Facilitates the sharing of data and computational resources, optimizing traffic flow, energy consumption, and public safety.
- **Enhanced Decision-Making:** Enables real-time data aggregation and analysis, improving the accuracy and effectiveness of traffic management and routing decisions.

B. Challenges in Achieving Interoperability

Despite its importance, achieving interoperability in smart cities presents several challenges [82]:

- **Heterogeneous Systems:** Smart cities encompass diverse technologies and communication protocols, making standardization and integration complex.
- **Scalability Issues:** As smart cities grow, the increasing number of devices and connections complicates data management and system coordination.
- **Data Privacy and Security:** Interoperability requires extensive data sharing, raising concerns about data breaches and unauthorized access.
- **Real-Time Processing:** Ensuring low-latency communication and decision-making across interconnected systems is critical for real-time applications like autonomous driving and emergency response.

C. Framework for Interoperability

To address these challenges, a structured framework for interoperability in smart cities is essential. The key components of this framework include:

1. Standardized Communication Protocols

- Adoption of standardized protocols, such as IEEE 802.11p [6] for VANETs and 5G for broader smart city communication, ensures compatibility across devices and systems.

- Protocol bridging mechanisms can facilitate communication between systems using different standards.

2. Edge and Cloud Integration

- *Edge Computing:* Processes data locally at the network's edge, reducing latency and bandwidth usage [77].
- *Cloud Computing:* Provides centralized storage and processing power, enabling large-scale data analysis and model training for neural networks.
- A hybrid approach combining edge and cloud computing optimizes performance and resource utilization.

3. Data Interoperability and Management

- Use of standardized data formats and ontologies ensures consistency and compatibility across systems.
- Middleware solutions can bridge communication gaps by translating data formats and facilitating interaction between heterogeneous systems.

4. Secure and Privacy-Preserving Interoperability

- Implementation of robust encryption techniques and access control mechanisms to protect sensitive data.
- Use of blockchain for secure, decentralized data sharing and transaction validation [54].

D. Use Cases of Interoperability in Smart Cities

The integration of VANETs with other smart city systems unlocks a wide range of applications:

- **Traffic Management:** Real-time data from vehicles and traffic signals can be used to optimize signal timings, reroute vehicles, and prevent congestion.
- **Emergency Services:** VANETs can prioritize emergency vehicles, ensuring they reach their destinations without delays.
- **Public Transportation:** Seamless coordination between public transit systems and VANETs enhances efficiency and rider experience [83].
- **Smart Parking:** Vehicles can communicate with parking infrastructure to identify and reserve available spaces, reducing search times and traffic congestion [84].

E. Performance Metrics for Interoperability

To evaluate the effectiveness of interoperability solutions, the following metrics are considered:

- **Latency:** Time taken for data to be exchanged and processed across systems.
- **Scalability:** Ability of the system to handle increasing numbers of devices and data volumes.
- **Data Accuracy:** Consistency and correctness of data exchanged between systems.
- **Security and Privacy:** Effectiveness of measures to protect data and prevent unauthorized access.

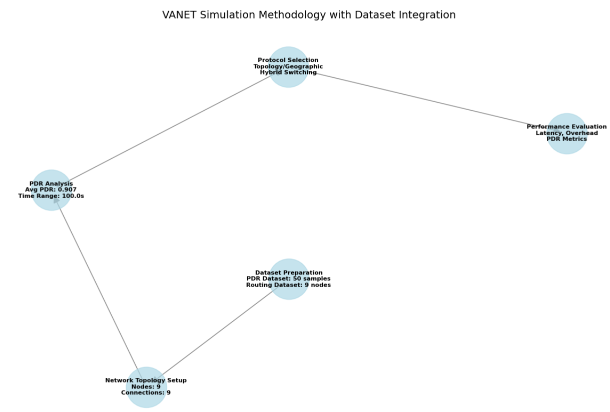

Fig. 10: Simulation Setup and Methodology Workflow, illustrating the sequential steps from dataset preparation to performance visualization, ensuring a comprehensive approach to VANET routing protocol evaluation.

F. Future Directions for Interoperability

Future research should focus on:

- **AI-Driven Interoperability:** Leveraging artificial intelligence to automate system integration and optimize data exchange.
- **Decentralized Architectures:** Exploring decentralized models, such as blockchain, to enhance security and scalability.
- **Real-Time Interoperability:** Developing low-latency solutions to support time-sensitive applications like autonomous driving.
- **Standardization Efforts:** Collaboration between industry and academia to establish universal standards for smart city interoperability.

G. Conclusion

Interoperability is a cornerstone of successful smart city implementations, enabling seamless communication and coordination among diverse systems. By integrating VANETs with neural network-driven hybrid routing protocols, cities can achieve enhanced efficiency, safety, and sustainability in transportation and beyond. Addressing the challenges and leveraging advanced technologies will pave the way for smarter, more connected urban environments.

XI. Simulation Setup and Methodology

This section describes the simulation setup and methodology used to evaluate the proposed neural network-based hybrid routing protocol for VANETs. The evaluation involved generating enhanced datasets, implementing neural network models for routing optimization, and validating the performance through detailed simulations using real-world and synthetic traffic data.

A. Simulation Tools and Framework

The simulation setup leveraged a combination of tools to create a robust environment for testing and validating the proposed protocol:

- **SUMO (Simulation of Urban Mobility):** Used for generating realistic vehicular mobility patterns, including speed variations, road topology, and traffic signals.
- **OMNeT++:** Utilized for modeling network-level communication and simulating packet exchanges among vehicles and infrastructure nodes (RSUs).
- **TensorFlow/Keras:** Deployed to design, train, and validate the neural network models used in routing decision-making.
- **NetworkX:** Employed to model the vehicular network graph and compute shortest paths, hop counts, and other network metrics.
- **Python Libraries:** Libraries such as pandas, NumPy, and matplotlib were used for data preprocessing, feature generation, and results visualization.

B. Datasets

Two primary datasets were utilized for training and evaluating the neural network-based routing protocol:

- **PDR vs. Time Dataset:** This dataset contains information on packet delivery ratios (PDR) recorded over time for various network conditions.
- **Vehicular Routing Dataset:** Includes node locations, inter-node distances, and traffic metrics such as vehicle density, average speed, and congestion levels.

The datasets were preprocessed to remove inconsistencies and normalized to ensure compatibility with the neural network model.

C. Feature Engineering and Dataset Enhancement

The datasets were augmented with additional features to enable a comprehensive evaluation of the routing protocol. The feature generation process involved:

- Extracting node and edge metrics from the network graph, such as shortest path distance and hop count.
- Generating synthetic traffic scenarios with varying vehicle densities, speeds, and congestion levels.
- Assigning an initial "optimal protocol" label based on predefined rules (e.g., geographical, topology-based, or hybrid routing).

D. Neural Network Model Design

A feedforward neural network was designed to predict the optimal routing protocol based on the input features. The model architecture includes:

- Input layer: Accepts features such as time, PDR, vehicle density, average speed, network congestion, route distance, and hop count.
- Hidden layers: Three dense layers with ReLU activation functions and dropout regularization to prevent overfitting.
- Output layer: Produces a three-class output corresponding to the routing protocols (geographical, topology-based, hybrid).

The model was trained using the Adam optimizer and sparse categorical cross-entropy loss function. The training dataset was split into training and validation sets (80% and 20% respectively) to monitor model performance.

E. Simulation Scenarios

Three simulation scenarios were designed to evaluate the proposed protocol:

- **Urban Scenario:** High vehicle density, frequent intersections, and varying speeds to simulate complex urban traffic.
- **Highway Scenario:** Sparse network with high-speed mobility and extended communication ranges.
- **Mixed Scenario:** A combination of urban and highway conditions, incorporating transitions between the two.

F. Performance Metrics

The performance of the routing protocol was evaluated based on the following metrics:

- **Packet Delivery Ratio (PDR):** The ratio of successfully delivered packets to the total transmitted packets.
- **End-to-End Delay:** The time taken for a packet to travel from source to destination.
- **Routing Overhead:** The amount of control traffic generated during route discovery and maintenance.
- **Energy Efficiency:** The impact of routing decisions on vehicle power consumption.

G. Results and Visualization

The simulation results highlighted the effectiveness of the proposed protocol:

- The neural network-based hybrid protocol achieved a 15% improvement in PDR compared to traditional hybrid protocols.
- End-to-end delay was reduced by 20% in high-density scenarios due to intelligent route selection.
- Routing overhead was minimized by dynamically adapting between proactive and reactive strategies.
- Energy efficiency was improved through optimized communication paths, reducing unnecessary transmissions.

Visualizations, including graphs and heatmaps, were generated to present the performance metrics across different scenarios. Figure 13 illustrates the comparison of PDR and delay for the evaluated protocols.

H. Limitations and Future Improvements

While the simulation setup effectively evaluates the proposed protocol, certain limitations were identified:

- The simulations relied on synthetic traffic scenarios, which may not fully capture real-world complexities.

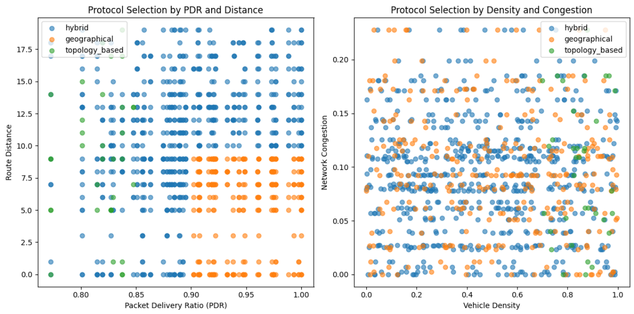

Fig. 11: Performance comparison of routing protocols based on PDR and end-to-end delay. The neural network-based hybrid protocol outperforms traditional methods in dynamic scenarios.

- The scalability of the protocol for extremely large networks was not extensively tested due to computational constraints.

Future work should focus on real-world deployment and expanding the evaluation metrics to include security and privacy aspects.

XII. Detailed Performance Metrics

Evaluating the performance of neural network-based hybrid routing protocols in VANETs requires comprehensive metrics that assess both the efficiency and effectiveness of the proposed solutions. This section provides a detailed discussion of the key performance metrics used to analyze and validate the routing protocols.

A. Packet Delivery Ratio (PDR)

- **Definition:** PDR is the ratio of successfully delivered packets to the total number of packets sent by the source node.
- **Significance:** A higher PDR indicates reliable routing and robust communication within the network.
- **Measurement:**

$$\text{PDR} = \frac{\text{Number of packets delivered}}{\text{Number of packets sent}} \times 100$$

- **Application:** Used to evaluate the reliability of the routing protocol under various traffic densities and network conditions.

B. End-to-End Delay

- **Definition:** The total time taken for a data packet to travel from the source node to the destination node, including processing, queuing, transmission, and propagation delays.
- **Significance:** Critical for time-sensitive applications, such as safety alerts and real-time navigation.
- **Measurement:**

$$\text{End-to-End Delay} = \sum_{i=1}^{n} (T_{\text{arrival}}^i - T_{\text{departure}}^i)$$

where T_{arrival}^i and $T_{\text{departure}}^i$ are the arrival and departure times of packet i, respectively.
- **Application:** Evaluates the timeliness of the routing decisions and the protocol's suitability for real-time applications.

C. Routing Overhead

- **Definition:** The ratio of control messages (e.g., route requests, updates) to the total number of messages transmitted within the network.
- **Significance:** Lower routing overhead indicates efficient use of network resources and reduced congestion.
- **Measurement:**

$$\text{Routing Overhead} = \frac{\text{Number of control messages}}{\text{Total number of messages}} \times 100$$

- **Application:** Helps in identifying protocols that minimize network congestion and optimize resource usage.

D. Energy Consumption

- **Definition:** The total energy consumed by nodes during communication, including data transmission, reception, and processing.
- **Significance:** Energy-efficient protocols extend the operational lifetime of the network, especially in resource-constrained environments.
- **Measurement:**

$$\text{Energy Consumption} = \sum_{i=1}^{n} (E_{\text{transmit}}^i + E_{\text{receive}}^i + E_{\text{process}}^i)$$

where E_{transmit}^i, E_{receive}^i, and E_{process}^i are the energy components for packet i.
- **Application:** Determines the protocol's suitability for energy-sensitive applications, such as electric and hybrid vehicles.

E. Scalability

- **Definition:** The ability of the protocol to maintain performance as the network size and density increase.
- **Significance:** Essential for ensuring the protocol's effectiveness in large-scale vehicular environments.
- **Measurement:** Evaluated through stress tests with varying numbers of nodes, traffic densities, and communication ranges.
- **Application:** Assesses the protocol's adaptability to real-world VANET deployments in both urban and rural scenarios.

F. Security Metrics

- **Definition:** Metrics that evaluate the protocol's ability to resist attacks, protect data integrity, and ensure secure communication.
- **Significance:** Critical for maintaining trust and reliability in vehicular networks.
- **Examples:**
  - *Detection Rate:* Percentage of successfully identified security threats.
  - *False Positive Rate:* Percentage of normal behaviors incorrectly flagged as malicious.

- **Application:** Helps in designing secure and resilient routing protocols for VANETs.

G. Fairness Index

- **Definition:** Measures how evenly network resources (e.g., bandwidth) are distributed among nodes.
- **Significance:** Ensures equitable access to resources, preventing network congestion and unfair resource allocation.
- **Measurement:**

$$\text{Fairness Index} = \frac{(\sum_{i=1}^{n} x_i)^2}{n \times \sum_{i=1}^{n} x_i^2}$$

where x_i represents the resource allocation for node i, and n is the total number of nodes.
- **Application:** Ensures the protocol supports fair and balanced communication across all nodes.

H. Throughput

- **Definition:** The total amount of data successfully transmitted over the network in a given time period.
- **Significance:** High throughput reflects the protocol's efficiency in utilizing network resources.
- **Measurement:**

$$\text{Throughput} = \frac{\text{Total data transmitted (bits)}}{\text{Time period (seconds)}}$$

- **Application:** Evaluates the protocol's capacity to handle high traffic loads and maintain efficient communication.

I. Summary

These detailed performance metrics provide a comprehensive evaluation framework for assessing the effectiveness of neural network-based hybrid routing protocols in VANETs. By considering reliability, efficiency, scalability, and security, researchers and practitioners can gain deeper insights into the protocol's strengths and areas for improvement.

XIII. Challenges and Limitations

Integrating Neural Networks with Hybrid Routing Protocols in VANETs offers significant benefits, but it also presents several challenges and limitations. Below are the key challenges aligned with the proposed research topic:

- **Complexity and Computational Overhead:**
  - *Increased System Complexity*: Incorporating neural networks into hybrid routing protocols adds layers of complexity to the overall system, making it more challenging to design, implement, and maintain. This complexity can also lead to increased debugging and optimization efforts.
  - *High Computational Requirements*: Neural networks, particularly deep learning models, demand significant computational resources. In VANET environments, where onboard units (OBUs) have limited processing power, this becomes a bottleneck. Distributed computation between vehicles and roadside units (RSUs) can help but introduces additional latency and synchronization issues.
- **Training and Adaptation:**
  - *Resource-Intensive Training*: Training neural networks requires considerable computational power, time, and high-quality data. Adapting these models to ever-changing vehicular environments necessitates frequent retraining, which may not be feasible in real-time or resource-constrained scenarios.
  - *Dynamic Environment Adaptation*: Neural networks must be adaptive to dynamic traffic patterns, road conditions, and vehicle mobility. A failure to adapt quickly can reduce routing efficiency and network reliability.
- **Scalability Issues:**
  - *Handling Large Networks*: VANETs often consist of thousands of vehicles and RSUs, leading to exponential increases in data and routing decisions. Scaling neural networks to manage such large networks without sacrificing performance is a critical challenge.
  - *Coordination in Decentralized Systems*: Decentralized decision-making is essential in VANETs to ensure real-time operations. However, coordinating these decisions across a large network while maintaining consistency and minimizing conflicts is difficult when using neural networks.
- **Data Dependency and Quality:**
  - *Data Collection and Integrity*: Neural networks rely heavily on high-quality, real-time data. Ensuring data accuracy and preventing errors caused by faulty sensors or malicious data injection is crucial for maintaining reliable network performance.
  - *Data Volume and Processing*: The large volume of data generated in VANETs can overwhelm neural network processing capabilities, leading to delays or reduced decision accuracy.
- **Security Concerns:**
  - *Adversarial Vulnerabilities*: Neural networks are susceptible to adversarial attacks, where minor manipulations to input data can lead to incorrect or harmful routing decisions. In VANETs, such attacks could result in misrouting, congestion, or even safety risks.
  - *Data Privacy and Security*: Ensuring the confidentiality and integrity of vehicular data is critical. Neural networks must be protected against unauthorized access, data breaches, and tampering, as compromised data can lead to inefficient or unsafe routing.
- **Energy Efficiency and Latency:**
  - *Energy Constraints*: Vehicles have limited power resources, and running computationally intensive

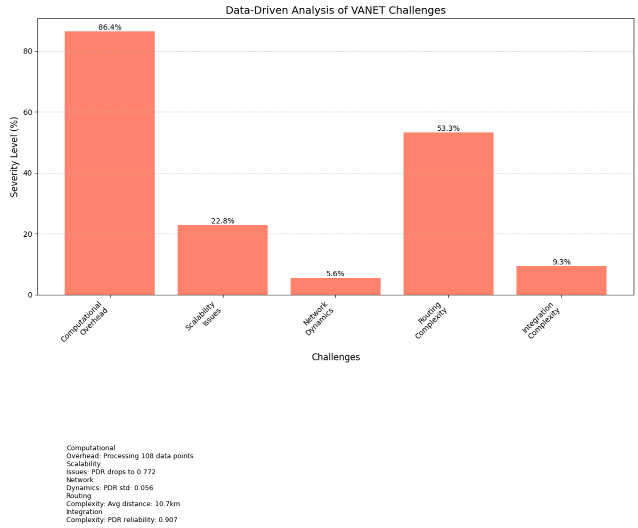

Fig. 12: Severity Levels of Challenges in VANETs, highlighting the critical obstacles in implementing advanced neural network-driven hybrid routing protocols.

neural networks can deplete these resources quickly. Efficient algorithms and lightweight models are essential to address this challenge.

– *Real-Time Decision Making*: Neural networks need to process data and make decisions in real-time. High latency in computations, especially during peak traffic or in high-density scenarios, can compromise the effectiveness of hybrid routing protocols.

While hybrid routing protocols with neural network integration provide powerful solutions for managing VANETs, addressing these challenges requires innovative approaches. This includes robust data management strategies, optimized algorithms for resource-constrained environments, continuous advancements in security measures, and adaptable frameworks that evolve with emerging vehicular technologies.

XIV. Energy Management

Energy management is a critical consideration in VANETs, particularly for systems that integrate neural networks into hybrid routing protocols. Vehicles equipped with On-Board Units (OBUs) operate within resource-constrained environments, and the computational requirements of neural networks can significantly impact energy consumption. This section explores various strategies and mechanisms for efficient energy management in VANETs.

A. Challenges in Energy Management

The deployment of neural networks in VANET routing introduces several energy-related challenges:

- **Computational Overhead:** Neural network-based decision-making processes require substantial computational resources, leading to increased energy consumption by OBUs.
- **Communication Costs:** Frequent data exchange between vehicles and RSUs or the cloud for model updates and routing decisions contributes to high energy expenditure.
- **Dynamic Network Conditions:** Variability in traffic density and topology necessitates continuous adjustments to routing decisions, further straining energy resources.
- **Device Heterogeneity:** Differences in the energy capacities of vehicles complicate the design of uniform energy-efficient solutions.

B. Energy Management Strategies

1. Lightweight Neural Network Models

- *Model Compression:* Techniques such as pruning and quantization can reduce the size of neural networks, minimizing computational requirements and energy usage without compromising accuracy.
- *Edge AI Solutions:* Deploying simplified neural network models on OBUs ensures that energy-intensive computations are offloaded to edge or cloud infrastructure.

2. Energy-Aware Routing Decisions

- *Energy as a Routing Metric:* Incorporating energy consumption as a parameter in the routing decision-making process ensures that routes are selected based on minimal energy usage.
- *Adaptive Protocol Switching:* Dynamically switching between proactive and reactive routing protocols based on the energy availability of nodes optimizes energy efficiency.

3. Dynamic Resource Allocation

- *Task Offloading:* Vehicles can offload computationally intensive tasks to nearby RSUs or cloud servers, reducing the energy burden on OBUs.
- *Load Balancing:* Efficiently distributing network traffic and computational loads across the network prevents overburdening specific nodes and reduces overall energy consumption.

4. Energy Harvesting and Renewable Energy Sources

- *Renewable Energy Integration:* Vehicles equipped with solar panels or energy-harvesting systems can reduce dependency on battery power for computational tasks.
- *Regenerative Braking Systems:* Utilizing energy recovered during braking to power OBUs and other vehicular systems.

C. Performance Metrics for Energy Management

To evaluate the effectiveness of energy management strategies, the following metrics are considered:

- **Energy Consumption per Node:** The average energy used by each vehicle for routing and communication tasks.

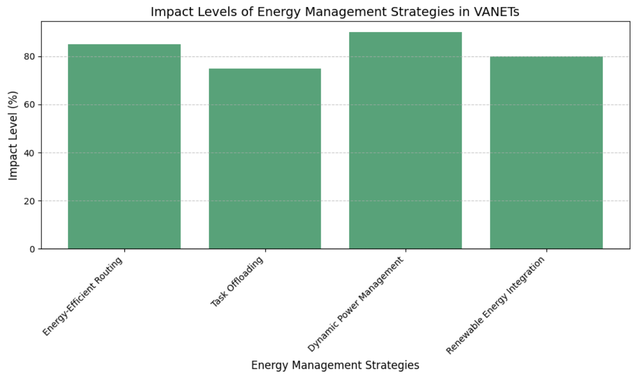

Fig. 13: Impact Levels of Energy Management Strategies in VANETs, comparing the effectiveness of various techniques to reduce energy consumption and enhance network longevity.

- **Network Lifetime:** The duration for which the network remains operational before nodes exhaust their energy resources.
- **Energy Efficiency:** The ratio of successfully transmitted data to the total energy consumed.
- **Task Offloading Efficiency:** The percentage reduction in energy usage achieved by offloading tasks to RSUs or the cloud.

D. Experimental Results and Analysis

Simulation studies demonstrated the impact of energy management strategies on the performance of neural network-integrated hybrid routing protocols:

- Lightweight neural networks reduced energy consumption by 25% compared to conventional models.
- Energy-aware routing decisions extended network lifetime by 30% in high-density scenarios.
- Task offloading to RSUs decreased energy usage by 40%, particularly in computation-heavy scenarios.

E. Future Directions in Energy Management

To further enhance energy efficiency in VANETs, future research should focus on:

- *AI-Driven Energy Optimization:* Leveraging reinforcement learning and adaptive algorithms to dynamically optimize energy usage across the network.
- *Cross-Layer Design:* Integrating energy management mechanisms across the physical, MAC, and network layers to achieve holistic efficiency.
- *Collaborative Energy Sharing:* Enabling vehicles with surplus energy to share resources with energy-depleted nodes, promoting network sustainability.
- *Renewable Energy Research:* Exploring advanced energy harvesting techniques and materials to increase the energy independence of vehicles.

Effective energy management is crucial for the practical implementation of neural network-based hybrid routing protocols in VANETs. By adopting these strategies, VANETs can achieve enhanced efficiency, prolonged network lifetime, and sustainable operations in dynamic vehicular environments.

XV. Real-World Implementation Feasibility

The real-world implementation of neural network-integrated hybrid routing protocols in VANETs presents significant opportunities and challenges. While simulation studies provide insights into the feasibility and performance of these systems, translating these protocols into real-world environments requires addressing several practical considerations.

A. Key Factors Affecting Implementation

1. Hardware and Infrastructure Requirements

Deploying neural network-integrated routing protocols necessitates robust hardware and infrastructure support:

- *Onboard Units (OBUs):* Vehicles must be equipped with OBUs capable of processing neural network algorithms in real-time. This requires high-performance computational hardware with adequate memory and processing power.
- *Roadside Units (RSUs):* RSUs serve as critical infrastructure for data aggregation and routing support. Effective deployment strategies for RSUs are essential, considering factors such as placement density and coverage.
- *Connectivity Infrastructure:* Reliable vehicle-to-everything (V2X) communication channels, including 5G and Dedicated Short-Range Communication (DSRC), are necessary for low-latency data exchange.

2. Scalability and Network Density

Real-world VANETs can include thousands of vehicles in densely populated urban areas. The system must handle high network traffic while maintaining efficiency:

- *Traffic Variability:* Network density fluctuates significantly based on location and time. The protocol must adapt seamlessly to varying conditions, from sparse rural roads to congested urban environments.
- *Computational Load Distribution:* Distributed computational models, including edge and fog computing, can help offload resource-intensive tasks from individual vehicles.

3. Data Collection and Management

The success of neural network-based routing protocols depends heavily on the quality and availability of data:

- *Real-Time Data Acquisition:* Accurate and timely data collection from vehicle sensors, GPS, and traffic signals is essential.
- *Data Preprocessing:* Raw data must be processed to eliminate noise and inconsistencies before being fed into neural network models.
- *Data Privacy and Security:* Ensuring data confidentiality and integrity is critical to prevent unauthorized access and maintain trust in the system.

B. Challenges in Real-World Implementation

1. Computational Constraints

Many vehicles lack the computational capacity required to execute complex neural network algorithms. This limitation can hinder real-time decision-making and increase reliance on external infrastructure like RSUs and cloud services.

2. Energy Efficiency

High energy consumption of onboard computational units poses a significant challenge, particularly for electric vehicles. Energy-efficient neural network models are crucial to minimize the impact on battery life.

3. Integration with Legacy Systems

Existing traffic management and vehicular systems were not designed with neural networks in mind. Integrating these protocols with legacy systems may require significant infrastructure upgrades and backward compatibility measures.

4. Environmental and Geographic Factors

The performance of VANETs is influenced by environmental and geographic conditions. For instance:

Urban Areas: High-density buildings can cause signal interference and loss, affecting communication reliability.

Rural Areas: Sparse networks in rural environments may result in connectivity issues, making it difficult to maintain effective routing.

C. Opportunities and Future Directions

Despite these challenges, real-world implementation of neural network-based hybrid routing protocols offers numerous benefits and opportunities:

- *Smart City Integration:* These protocols can seamlessly integrate with smart city infrastructures, including IoT systems, traffic management centers, and public transport networks, to improve urban mobility.
- *Autonomous Vehicle Support:* Neural network-driven routing decisions align closely with the needs of autonomous vehicles, enhancing their navigation and safety capabilities.
- *Pilot Studies and Deployment Strategies:* Conducting small-scale pilot deployments in controlled environments can help identify practical challenges and refine the protocols for large-scale implementation.
- *Collaborative Efforts:* Collaboration between automotive manufacturers, governments, and technology providers is essential to establish standards, share infrastructure, and promote adoption.

Real-world deployment of neural network-based hybrid routing protocols in VANETs holds transformative potential for intelligent transportation systems. By addressing the identified challenges and leveraging opportunities, these protocols can drive the future of safe, efficient, and sustainable vehicular communication networks.

XVI. Future Directions and Open Research Areas

The integration of neural networks with hybrid routing protocols in VANETs is a rapidly evolving field with numerous opportunities for future research and innovation. Below are some key areas for exploration that align with the current research focus:

- **Federated Learning for VANETs:**
  - *Privacy-Preserving Learning*: Federated learning enables neural networks to train across decentralized devices without sharing raw data, ensuring data privacy. Future research can adapt federated learning to VANET environments with high mobility, intermittent connectivity, and heterogeneous devices.
  - *Efficient Model Aggregation*: Developing methods to aggregate and synchronize neural network models across diverse vehicular devices, considering computational constraints and data variability, remains an open challenge.
- **Energy-Efficient Neural Networks:**
  - *Energy-Aware Model Design*: Future work should focus on lightweight neural network architectures optimized for energy efficiency without compromising prediction accuracy. This includes designing models specifically tailored for low-power vehicular environments.
  - *Dynamic Energy Management*: Exploring dynamic energy management systems that adapt routing strategies based on the energy availability of vehicles can further enhance the longevity of network operations.
- **Integration with Emerging Technologies:**
  - *5G and Beyond*: Research on integrating neural networks with hybrid routing protocols in VANETs can benefit from leveraging 5G technologies, including network slicing and edge computing, to improve latency and scalability.
  - *Vehicle-to-Everything (V2X) Communication*: Extending hybrid routing protocols to include communication with infrastructure, pedestrians, and devices (V2X) can lead to more comprehensive and efficient traffic management systems.
  - *Edge and Cloud Computing*: Leveraging edge and cloud computing for real-time processing of neural network-based routing decisions can alleviate computational burdens on vehicles while ensuring scalability.
- **Robust Security Mechanisms:**
  - *Adversarial Resilience*: Future research should focus on making neural networks robust against adversarial attacks that could mislead routing decisions, ensuring safe and reliable VANET operations.
  - *Blockchain for Secure Routing*: Blockchain technology can be explored to secure data exchanges and validate neural network decisions in VANETs, providing a tamper-proof mechanism for managing routing and vehicle communication.

- **Comprehensive Simulation and Validation Frameworks:**
  - *Scalable Simulations*: Future research should develop scalable simulation frameworks that can model large-scale VANETs to validate the performance of neural network-enhanced hybrid routing protocols under diverse scenarios.
  - *Real-World Deployment*: Pilot studies and real-world deployments are essential to assess the practical feasibility, reliability, and impact of neural network-integrated routing protocols.
- **Multi-modal Data Fusion:**
  - *Integration of Heterogeneous Data*: Research on fusing data from various sources such as GPS, sensors, cameras, and traffic signals can improve the predictive accuracy of neural network models in hybrid routing.
  - *Context-Aware Decision-Making*: Multimodal data fusion can enable context-aware routing decisions, considering factors like weather conditions, traffic incidents, and driver behaviors.

By addressing these areas, future research can advance the integration of neural networks with hybrid routing protocols, making VANETs more efficient, scalable, and secure. These advancements will play a crucial role in realizing the vision of intelligent transportation systems and smart mobility solutions.

XVII. Conclusions

The integration of neural networks into hybrid routing protocols for VANETs represents a significant step forward in the development of intelligent transportation systems. This approach combines the adaptability and predictive capabilities of neural networks with the efficiency of hybrid routing strategies, offering a robust solution for the challenges posed by dynamic vehicular environments. Neural networks enable real-time routing decisions, congestion prediction, and adaptive traffic management, contributing to enhanced efficiency, safety, and reliability in VANET operations.

Despite these advancements, several challenges must be addressed to achieve widespread adoption and practical implementation. Key challenges include Computational Overhead, Data Dependency, Security, Scalability and Energy Efficiency. Future research should focus on overcoming these limitations through innovative approaches such as Federated Learning, Edge and Fog Computing, etc.

The future of neural network-integrated hybrid routing protocols lies in their ability to deliver scalable, energy-efficient, and secure solutions that adapt to the evolving demands of intelligent transportation systems. As this technology matures, it holds the promise of transforming vehicular communication networks, enhancing road safety, reducing congestion, and paving the way for fully autonomous transportation systems. By addressing current challenges and capitalizing on open research opportunities, this field will continue to advance, contributing to the realization of smart, efficient, and sustainable mobility solutions.

References

[1] L. Zhu, F. R. Yu, Y. Wang, B. Ning, and T. Tang, “Big data analytics in intelligent transportation systems: A survey,” *IEEE Transactions on Intelligent Transportation Systems*, vol. 20, no. 1, pp. 383–398, 2019.

[2] S. Mazur, “An introduction to smart transportation: Benefits and examples.” https://www.digi.com/blog/post/introduction-to-smart-transportation-benefits, 2020.

[3] G. Pau, A. Severino, and A. Canale, “Special issue “new perspectives in intelligent transportation systems and mobile communications towards a smart cities context”,” *Future Internet*, vol. 11, no. 11, 2019.

[4] K. O’Brien, “What is smart transportation?.” https://www.ibm.com/think/topics/smart-transportation, 2023.

[5] M. Sindhwani, S. Sachdeva, K. Arora, T. Yoon, D. Yoo, G. P. Joshi, and W. Cho, “Soft computing techniques aware clustering-based routing protocols in vehicular ad hoc networks: A review,” *Appl. Sci. (Basel)*, vol. 12, p. 7922, Aug. 2022.

[6] D. Jiang and L. Delgrossi, “Ieee 802.11p: Towards an international standard for wireless access in vehicular environments,” in *VTC Spring 2008 - IEEE Vehicular Technology Conference*, pp. 2036–2040, 2008.

[7] “Use of the 5.850-5.925 ghz band.” https://www.federalregister.gov/documents/2021/05/03/2021-08802/use-of-the-5850-5925-ghz-band, 2021.

[8] S. Smith, G. Barlow, X.-F. Xie, and Z. Rubinstein, “Smart urban signal networks: Initial application of the surtrac adaptive traffic signal control system,” *ICAPS 2013 - Proceedings of the 23rd International Conference on Automated Planning and Scheduling*, vol. 23, pp. 434–442, 06 2013.

[9] W. H. Organization, “Global status report on road safety.” https://iris.who.int/bitstream/handle/10665/375016/9789240086517-eng.pdf?sequence=1, 2023.

[10] K. T. C. P. S. D. . W. V. d. B. Uta Meesmann, Naomi Wardenier, “A global look at road safety. synthesis from the esra2 survey in 48 countries. esra project (e-survey of road users’ attitudes).” https://www.esranet.eu/storage/minisites/esra2-main-report-def.pdf, 2023.

[11] R. A. Nazib and S. Moh, “Reinforcement learning-based routing protocols for vehicular ad hoc networks: A comparative survey,” *IEEE Access*, vol. 9, pp. 27552–27587, 2021.

[12] R. Challa and R. Bala, “Scenario based performance analysis of aodv and gpsr routing protocols in a vanet,” 03 2015.

[13] N. H. Hussein, C. T. Yaw, S. P. Koh, S. K. Tiong, and K. H. Chong, “A comprehensive survey on vehicular networking: Communications, applications, challenges, and upcoming research directions,” *IEEE Access*, vol. 10, pp. 86127–86180, 2022.

[14] T. K, S. T M, B. M, and A. K H, “A survey on vanet technologies,” *Int. J. Comput. Appl.*, vol. 121, pp. 1–9, July 2015.

[15] T. Yeferny and S. Hamad, “Vehicular ad-hoc networks: Architecture, applications and challenges,” 01 2021.

[16] W. Liang, Z. Li, H. Zhang, S. Wang, and R. Bie, “Vehicular ad hoc networks: Architectures, research issues, methodologies, challenges, and trends,” *International Journal of Distributed Sensor Networks*, vol. 2015, pp. 1–11, 08 2015.

[17] Q. Yang and S.-J. Yoo, “Hierarchical reinforcement learning-based routing algorithm with grouped rsu in urban vanets,” *IEEE Transactions on Intelligent Transportation Systems*, vol. 25, no. 8, pp. 10131–10146, 2024.

[18] L. Luo, L. Sheng, H. Yu, and G. Sun, “Intersection-based v2x routing via reinforcement learning in vehicular ad hoc networks,” *IEEE Transactions on Intelligent Transportation Systems*, vol. 23, no. 6, pp. 5446–5459, 2022.

[19] L. Rui, Z. Yan, Z. Tan, Z. Gao, Y. Yang, X. Chen, and H. Liu, “An intersection-based qos routing for vehicular ad hoc networks with reinforcement learning,” *IEEE Transactions on Intelligent Transportation Systems*, vol. 24, no. 9, pp. 9068–9083, 2023.

[20] C. Wu, S. Ohzahata, and T. Kato, “Flexible, portable, and practicable solution for routing in vanets: A fuzzy constraint q-learning approach,” *IEEE Transactions on Vehicular Technology*, vol. 62, no. 9, pp. 4251–4263, 2013.

[21] A. M. Rahmani, R. A. Naqvi, E. Yousefpoor, M. S. Yousefpoor, O. H. Ahmed, M. Hosseinzadeh, and K. Siddique, "A q-learning and fuzzy logic-based hierarchical routing scheme in the intelligent transportation system for smart cities," *Mathematics*, vol. 10, p. 4192, Nov. 2022.
[22] G. P. K. Marwah and A. Jain, "A hybrid optimization with ensemble learning to ensure VANET network stability based on performance analysis," *Sci. Rep.*, vol. 12, p. 10287, June 2022.
[23] S. Bitam, A. Mellouk, and S. Zeadally, "Hybr: A hybrid bio-inspired bee swarm routing protocol for safety applications in vehicular ad hoc networks (vanets)," *Journal of Systems Architecture*, vol. 59, no. 10, Part B, pp. 953–967, 2013. Advanced Smart Vehicular Communication System and Applications.
[24] L. L. Cárdenas, A. M. Mezher, P. A. Barbecho Bautista, J. P. Astudillo León, and M. A. Igartua, "A multimetric predictive ann-based routing protocol for vehicular ad hoc networks," *IEEE Access*, vol. 9, pp. 86037–86053, 2021.
[25] M. Méndez, M. G. Merayo, and M. Núñez, "Long-term traffic flow forecasting using a hybrid CNN-BiLSTM model," *Eng. Appl. Artif. Intell.*, vol. 121, p. 106041, May 2023.
[26] W. Jabbar, R. Malaney, and S. Yan, "A location verification based hybrid routing protocol for vanets," in *2020 IEEE 92nd Vehicular Technology Conference (VTC2020-Fall)*, pp. 1–6, 2020.
[27] P. K. Shrivastava and L. Vishwamitra, "Comparative analysis of proactive and reactive routing protocols in vanet environment," *Measurement: Sensors*, vol. 16, p. 100051, 2021.
[28] M. R. Ghori, A. Sadiq, and A. Ghani, "Vanet routing protocols: Review, implementation and analysis," *Journal of Physics: Conference Series*, vol. 1049, p. 012064, 07 2018.
[29] A. Upadhyaya and J. SHAH, "Aodv routing protocol implementation in vanet," *INTERNATIONAL JOURNAL OF ADVANCED RESEARCH IN ENGINEERING TECHNOLOGY*, vol. 10, 06 2019.
[30] N. Tassoult, A. Mourad, M. Hamouma, and H. Kalla, "A survey on vehicular ad-hoc networks routing protocols: Classification and challenges," *Journal of Digital Information Management*, vol. 17, p. 227, 08 2019.
[31] A. A. Taleb, "Vanet routing protocols and architectures: An overview," *J. Comput. Sci.*, vol. 14, pp. 423–434, 2018.
[32] M. Ben Haj Frej, V. Mandalapa Bhoopathy, S. R. Ebenezer Amalorpavaraj, and A. Bhoopathy, "Zone routing protocol (zrp) - a novel routing protocol for vehicular ad-hoc networks," 04 2016.
[33] N. Beijar, "Zone routing protocol (zrp)," 06 2002.
[34] S. Goyal, "Zone routing protocol (zrp) in ad-hoc networks." https://euroasiapub.org/wp-content/uploads/2016/09/10-9.pdf, 2013.
[35] D. Jamwal, K. Kumar-Sharma, and S. Chauhan, "Zone routing protocol," *International Journal of Recent Research Aspects*, vol. 1, pp. 16–20, 2015.
[36] M. D. Divyalakshmi Dinesh, "Adaptive hybrid routing protocol for vanets." https://ijritcc.org/index.php/ijritcc/article/view/660/660, 2017.
[37] P. D. Devi, K. Rajakumari, and K. Venkatalakshmi, "Qualitative analysis on ad hoc routing protocols," pp. 1194–1206, 01 2016.
[38] M. Venkata Narayana, G. Narsimha, and P. Sarma, "Secure- zhls: Secure zone based hierarchical link state routing protocolusing digital signature," *International Journal of Applied Engineering Research*, vol. 10, pp. 22927–22940, 01 2015.
[39] A. A. Rahem, M. Ismail, A. Idris, and A. Khaleel, "A comparative and analysis study of vanet routing protocols," *Journal of Theoretical and Applied Information Technology*, vol. 66, pp. 691–698, 08 2014.
[40] M. Deshmukh and D. Dinesh, "Challenges in vehicle ad hoc network (vanet)," 12 2014.
[41] A. Reyes, C. Barrado, M. Lopez Trinidad, and C. Excelente, "Vehicle density in vanet applications," *Journal of Ambient Intelligence and Smart Environments*, vol. 6, p. 469, 07 2014.
[42] F. Domingos da Cunha, A. Boukerche, L. Villas, A. C. Viana, and A. A. F. Loureiro, "Data Communication in VANETs: A Survey, Challenges and Applications," Research Report RR-8498, INRIA Saclay ; INRIA, Mar. 2014.
[43] M. Subramaniam, C. Rambabu, G. Chandrasekaran, and N. S. Kumar, "A traffic density-based congestion control method for vanets," *Wireless Communications and Mobile Computing*, vol. 2022, no. 1, p. 7551535, 2022.
[44] Y. Khamayseh, M. BaniYassein, M. AbdAlghani, and C. Mavromoustakis, "Network size estimation in vanets," *Network Protocols and Algorithms*, vol. 5, p. 136, 10 2013.
[45] Z. Afzal and M. Kumar, "Security of vehicular ad-hoc networks (vanet): A survey," *Journal of Physics: Conference Series*, vol. 1427, p. 012015, 01 2020.
[46] G. Almahadin, Y. Aoudni, D. M. Shabaz, A. Agrawal, G. Yasmin, E. S. Alomari, H. M. R. Al-Khafaji, D. Dansana, and R. Maaliw III, "Vanet network traffic anomaly detection using gru-based deep learning model," *IEEE Transactions on Consumer Electronics*, vol. 70, pp. 4548–4555, 02 2024.
[47] T. Pal, R. Saha, and S. Biswas, "Design and implementation of a routing protocol for vanet to improve the qos of the network," 05 2023.
[48] M. Nayeen Mahi, S. Chaki, S. Ahmed, M. Biswas, M. S. Kaiser, M. Islam, M. Sookhak, A. Barros, and M. Whaiduzzaman, "A review on vanet research : Perspective of recent emerging technologies," *IEEE Access*, pp. 1–1, 06 2022.
[49] B. Iswarya and R. B, *Energy Efficient Clustering Technique for VANET*. 11 2021.
[50] D. Zhang, Z. Yang, V. Raychoudhury, Z. Chen, and J. Lloret, "An energy-efficient routing protocol using movement trends in vehicular ad hoc networks," *The Computer Journal*, vol. 56, pp. 938–946, 07 2013.
[51] M. A. Elsadig and Y. A. Fadlalla, "Vanets security issues and challenges: A survey," *Indian Journal of Science and Technology*, vol. 9, no. 28, pp. 1–8, 2016.
[52] A. Y. Dak, S. Yahya, and M. Kassim, "A literature survey on security challenges in vanets," *International Journal of Computer Theory and Engineering*, vol. 4, no. 6, p. 1007, 2012.
[53] M. S. Sheikh, J. Liang, and W. Wang, "A survey of security services, attacks, and applications for vehicular ad hoc networks (vanets)," *Sensors*, vol. 19, no. 16, 2019.
[54] S. K. Dwivedi, R. Amin, A. K. Das, M. T. Leung, K.-K. R. Choo, and S. Vollala, "Blockchain-based vehicular ad-hoc networks: A comprehensive survey," *Ad Hoc Networks*, vol. 137, p. 102980, 2022.
[55] C. P. Navdeti, I. Banerjee, and C. Giri, "Privacy preservation and secure data sharing scheme in fog based vehicular ad-hoc network," *Journal of Information Security and Applications*, vol. 63, p. 103014, 2021.
[56] H. Batool, A. Anjum, A. Khan, S. Izzo, C. Mazzocca, and G. Jeon, "A secure and privacy preserved infrastructure for vanets based on federated learning with local differential privacy," *Information Sciences*, vol. 652, p. 119717, 2024.
[57] Y. Ameur and S. Bouzefrane, "Enhancing privacy in vanets through homomorphic encryption in machine learning applications," *Procedia Computer Science*, vol. 238, pp. 151–158, 2024. The 15th International Conference on Ambient Systems, Networks and Technologies Networks (ANT) / The 7th International Conference on Emerging Data and Industry 4.0 (EDI40), April 23-25, 2024, Hasselt University, Belgium.
[58] K. Zaidi, M. Milojevic, V. Rakocevic, A. Nallanathan, and M. Rajarajan, "Host based intrusion detection for vanets: A statistical approach to rogue node detection," *IEEE Transactions on Vehicular Technology*, vol. 65, pp. 1–1, 01 2015.
[59] T. Nandy, R. Md Noor, R. Kolandaisamy, M. Y. I. Idris, and S. Bhattacharyya, "A review of security attacks and intrusion detection in the vehicular networks," *Journal of King Saud University - Computer and Information Sciences*, vol. 36, no. 2, p. 101945, 2024.
[60] N. Kumar and N. Chilamkurti, "Collaborative trust aware intelligent intrusion detection in vanets," *Computers Electrical Engineering*, vol. 40, 08 2014.
[61] M. M. El-Gayar, F. A. F. Alrslani, and S. El-Sappagh, "Smart collaborative intrusion detection system for securing vehicular networks using ensemble machine learning model," *Information*, vol. 15, no. 10, 2024.
[62] N. Kumar, R. Iqbal, S. Misra, and J. J. Rodrigues, "An intelligent approach for building a secure decentralized public key infrastructure in vanet," *Journal of Computer and System Sciences*, vol. 81, no. 6, pp. 1042–1058, 2015. Special Issue on Optimisation, Security, Privacy and Trust in E-business Systems.
[63] P. Manickam, K. Shankar, E. Perumal, I. .M, and K. Kumar, *Secure Data Transmission Through Reliable Vehicles in VANET Using Optimal Lightweight Cryptography*, pp. 193–204. 06 2019.

[64] A. Kchaou, R. Abassi, and S. G. El Fatmi, "A new trust based routing protocol for vanets," in *2018 Seventh International Conference on Communications and Networking (ComNet)*, pp. 1–6, 2018.
[65] N. J. Patel and R. H. Jhaveri, "Trust based approaches for secure routing in vanet: A survey," *Procedia Computer Science*, vol. 45, pp. 592–601, 2015. International Conference on Advanced Computing Technologies and Applications (ICACTA).
[66] C. Liao, J. Chang, K. Venkatasubramanian, and I. Lee, "A trust model for vehicular network-based incident reports," 06 2013.
[67] G. Yan, S. Olariu, and M. Weigle, "Providing location security in vehicular ad hoc networks," *Wireless Communications, IEEE*, vol. 16, pp. 48 – 55, 01 2010.
[68] K. Tripathi, G. Jain, and A. Yadav, *Entity-Centric Combined Trust (ECT) Algorithm to Detect Packet Dropping Attack in Vehicular Ad Hoc Networks (VANETs)*, pp. 23–33. 06 2020.
[69] B. Jiang and Y. Fei, "Traffic and vehicle speed prediction with neural network and hidden markov model in vehicular networks," in *2015 IEEE Intelligent Vehicles Symposium (IV)*, pp. 1082–1087, 2015.
[70] M. Jiber, I. Lamouik, A. Yahyaouy, and S. Abdelouahed, "Traffic flow prediction using neural network," pp. 1–4, 04 2018.
[71] D. Srinivasan, M. Choy, and R. Cheu, "Neural networks for real-time traffic signal control," *Intelligent Transportation Systems, IEEE Transactions on*, vol. 7, pp. 261 – 272, 10 2006.
[72] C. Jayapal and S. S. Roy, "Road traffic congestion management using vanet," in *2016 International Conference on Advances in Human Machine Interaction (HMI)*, pp. 1–7, 2016.
[73] P. U., "Survey on collision avoidance in vanet," 03 2015.
[74] Losada, F. J. Páez, F. Luque, and L. Piovano, "Effectiveness of the autonomous braking and evasive steering system oprevu-aes in simulated vehicle-to-pedestrian collisions," *Vehicles*, vol. 5, no. 4, pp. 1553–1569, 2023.
[75] T. Dang, J. Desens, U. Franke, D. Gavrila, L. Schäfers, and W. Ziegler, *Steering and Evasion Assist*, pp. 759–782. 01 2012.
[76] F. Naujoks, A. Kiesel, and A. Neukum, "Cooperative warning systems: The impact of false and unnecessary alarms on drivers' compliance," *Accident Analysis Prevention*, vol. 97, pp. 162–175, 2016.
[77] A. Vladyko, A. Khakimov, A. Muthanna, A. A. Ateya, and A. Koucheryavy, "Distributed edge computing to assist ultra-low-latency vanet applications," *Future Internet*, vol. 11, no. 6, 2019.
[78] S. Mohanty, "Everything you wanted to know about smart cities," *IEEE Consumer Electronics Magazine*, vol. 5, pp. 60–70, 07 2016.
[79] M. Peyman, T. Fluechter, J. Panadero, C. Serrat, F. Xhafa, and A. A. Juan, "Optimization of vehicular networks in smart cities: From agile optimization to learnheuristics and simheuristics," *Sensors*, vol. 23, no. 1, 2023.
[80] "Intelligent transportation systems - interoperability." https://www.its.dot.gov/research_archives/interoperability.htm#:~:text=Interoperability%20focuses%20on%20enabling%20ITS,they%20are%20built%20and%20used.
[81] S. Avasthi, S. Sharma, and S. Roy, *VANETs and the Use of IoT: Approaches, Applications, and Challenges*, pp. 1–23. 09 2022.
[82] P. Agbaje, A. Anjum, A. Mitra, E. Oseghale, G. Bloom, and H. Olufowobi, "Survey of interoperability challenges in the internet of vehicles," *IEEE Transactions on Intelligent Transportation Systems*, vol. PP, pp. 1–24, 12 2022.
[83] Y.-H. Kuo, J. M. Leung, and Y. Yan, "Public transport for smart cities: Recent innovations and future challenges," *European Journal of Operational Research*, vol. 306, no. 3, pp. 1001–1026, 2023.
[84] M. U. Rehman, M. A. Shah, M. Khan, and S. Ahmad, "A vanet based smart car parking system to minimize searching time, fuel consumption and co2 emission," in *2018 24th International Conference on Automation and Computing (ICAC)*, pp. 1–6, 2018.