Intelligent Traffic Management: A Novel Approach to Enhance Traffic Efficiency in V2V Communication and V2I

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Abstract- Urban traffic congestion has emerged as one of the most critical challenges for smart cities, leading to increased travel time, fuel wastage, environmental pollution, and safety risks. Vehicular Ad Hoc Networks (VANETs) have shown promise in enabling real-time vehicle-to-vehicle (V2V) and vehicle-to-infrastructure (V2I) communication, yet existing systems face limitations in scalability, adaptability, and integration of intelligent decision-making. Previous studies have addressed congestion detection through routing protocols, simulation-based evaluations, and cognitive clustering techniques, but no unified architecture exists that integrates these approaches while ensuring sustainability. This research proposes a cognitive VANET-based framework for real-time congestion detection, alert dissemination, and eco-aware traffic optimization. The framework combines V2X communication models (IEEE 802.11p, LTE-V2X, 5G) with cognitive intelligence techniques such as Fuzzy K-Means clustering and the Fuzzy Analytical Hierarchy Process (FAHP) to detect and prioritize congestion hotspots. The simulation integrates NS-3 and SUMO to model realistic mobility and communication dynamics, while sustainability metrics such as CO_2 emissions, fuel consumption, and idle time are incorporated to evaluate environmental impacts. Experimental results demonstrate that the proposed system improves packet delivery ratio, reduces communication latency, lowers vehicle idle time, and decreases CO_2 emissions, compared to traditional VANET-based systems. By bridging communication efficiency with cognitive decision-making and sustainability, this work contributes to the foundation of next-generation Cognitive Intelligent Transportation Systems (C-ITS), supporting the transition from simulation-driven research to real-world smart city deployment.

Keywords: Vehicular Ad Hoc Networks (VANET), Vehicle-to-Vehicle (V2V), Vehicle-to-Infrastructure (V2I), Cognitive Intelligent Transportation System (C-ITS), Fuzzy K-Means (FKM), Fuzzy Analytical Hierarchy Process (FAHP)

1. INTRODUCTION

1.1 Background and Motivation

The rapid pace of urbanization has led to an unprecedented rise in the number of vehicles on roads, resulting in frequent traffic congestion, longer travel times, increased accident rates, and higher levels of fuel consumption and air pollution. Conventional traffic management systems, largely based on fixed signal timing and centralized monitoring, struggle to adapt to real-time changes in road dynamics. To address these challenges, Intelligent Transportation Systems (ITS) have emerged, leveraging advanced communication technologies and data-driven approaches to improve safety, efficiency, and sustainability in road networks. Vehicular Ad Hoc Networks (VANETs), a specialized form of Mobile Ad Hoc Networks (MANETs), are recognized as a cornerstone of ITS. By enabling vehicle-to-vehicle (V2V) and vehicle-to-infrastructure (V2I) communication, VANETs support applications such as congestion detection, collision avoidance, cooperative driving, and dynamic route management. These capabilities make VANETs an essential enabler of Vehicle-to-Everything (V2X) communication, forming the basis for smart, connected urban mobility.

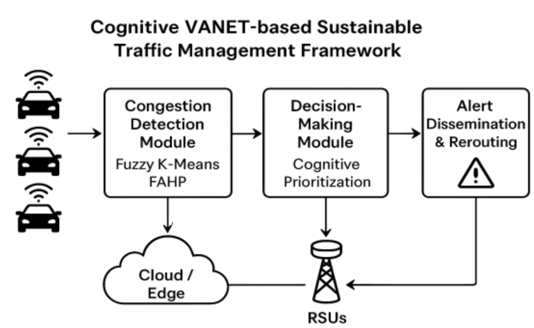

Fig. 1

1.2 Related Work

Previous research has explored VANET-based congestion management from different perspectives: Routing and Dissemination Approaches: Protocols such as Ad hoc On-Demand Distance Vector (AODV) and Geo-broadcasting have been applied to disseminate congestion alerts in real-time, improving driver awareness and traffic efficiency [6], [22], [28]. Vehicle-to-vehicle (V2V) and vehicle-to-infrastructure (V2I) communication frameworks have been particularly effective in enhancing safety and routing reliability [5], [8], [19]. Simulation-driven Traffic Management: Studies integrating NS-3 and SUMO simulators have evaluated the performance of V2V and V2I communication under realistic mobility scenarios, focusing on latency, packet delivery ratio, and throughput [9], [25], [33]. These simulation-based approaches have demonstrated efficiency but remain constrained by limited scalability and the absence of real-world deployment [12], [31]. Cognitive Intelligence-based Approaches: Advanced clustering and decision-making algorithms, including Fuzzy K-Means (FKM) and Fuzzy Analytical Hierarchy Process (FAHP), have been applied to identify congestion hotspots and prioritize mitigation strategies using sensor fusion and adaptive traffic signals [15], [21], [32], [43]. AI-driven approaches such as reinforcement learning and hybrid optimization have further enhanced congestion prediction accuracy [13], [17], [29]. While these contributions have advanced the field, most approaches remain limited to either simulation-only studies or isolated technical solutions. A comprehensive, unified framework that integrates routing efficiency, cognitive decision-making, and sustainability metrics is still missing [26], [37], [42].

1.3 Research Gap

From the reviewed works, the following key gaps are identified: (1) Lack of Integration Across Layers: Existing studies treat communication, congestion detection, and decision-making as separate modules rather than a holistic framework. (2) Simulation-to-Reality Gap: Most solutions remain validated only in NS-2/NS-3 or SUMO environments, without considering adaptability to real-world deployments in smart cities. (3) Neglected Sustainability Dimension: While some works measure throughput and latency, very few address eco-metrics such as fuel efficiency, idle time reduction, or CO_2 emission control. (4) Scalability Limitations: Current frameworks struggle to adapt to dense urban traffic with high vehicle mobility and dynamic topologies, particularly in 5G/6G-enabled environments.

1.4 Objectives of the Study

To bridge these gaps, this research proposes a Cognitive VANET-based Framework for Sustainable Urban Traffic Management, with the following objectives: (i) To integrate V2V/V2I communication with cognitive intelligence techniques (FKM clustering + FAHP) for real-time congestion detection and prioritization. (ii) To develop a hybrid simulation framework using NS-3 and SUMO, modeling realistic vehicular mobility, communication dynamics, and environmental metrics. (iii) To evaluate the framework against traditional VANET systems in terms of latency, packet delivery ratio (PDR), CO_2 emissions, and travel time reduction. (iv) To propose a scalable and sustainable ITS model that can serve as a foundation for real-world smart city deployments.

1.5 Structure of the Paper

The remainder of this paper is organized as follows: Section 2 reviews related literature and technological background in VANET-based traffic management. Section 3 presents the proposed framework and system architecture. Section 4 details the methodology, simulation setup, and algorithms. Section 5 discusses experimental results and comparative analysis. Section 6 concludes the paper with insights and outlines directions for future research.

2.LITERATURE REVIEW

Vehicular Ad Hoc Networks (VANETs) have emerged as a promising foundation for Intelligent Transportation Systems (ITS), offering real-time communication capabilities through Vehicle-to-Vehicle (V2V) and Vehicle-to-Infrastructure (V2I) links [6], [8], [19]. These networks facilitate congestion detection, dynamic route optimization, and safety alerts without relying heavily on fixed infrastructure [12], [20]. However, research shows that while VANET-based systems outperform traditional static traffic management approaches, existing studies remain fragmented in their focus [23], [27], [34]. Kumar (2025) introduced a VANET-based congestion detection and alert dissemination system using Ad hoc On-Demand Distance Vector (AODV) and Geo-broadcasting protocols, simulated in NS-2 [3]. The system effectively identified congestion zones and disseminated warnings, reducing travel delays and improving traffic flow. Its strength lay in decentralized data collection and timely message broadcasting, yet it faced scalability issues under high vehicle density due to increased routing overhead [9], [28]. Additionally, the framework lacked adaptability to heterogeneous communication technologies such as 5G NR-V2X [20], [42].

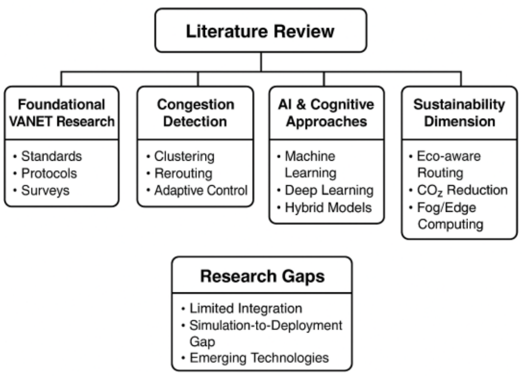

Fig. 2

Patil et al. (2025) emphasized the integration of network and mobility simulation by combining NS-3 with SUMO to evaluate VANET communication [5]. Their layered architecture incorporated On-Board Units (OBUs), Roadside Units (RSUs), and IEEE 802.11p protocols, allowing for detailed evaluation of latency, packet delivery ratio, and CO_2 emissions. Results indicated improved reliability and efficiency in congestion scenarios, with dynamic signal control and emergency routing proving particularly effective. Nonetheless, the work remained simulation-centric and did not integrate advanced decision-making techniques such as machine learning or clustering for proactive congestion prediction [25], [33].

In contrast, Tuddu et al. (2025) proposed a cognitive intelligence-driven VANET system that employed Fuzzy K-Means (FKM) clustering and the Fuzzy Analytical Hierarchy Process (FAHP) for congestion detection [9]. By fusing sensor data such as speed, CO_2, and fuel consumption, the framework prioritized congestion parameters and provided adaptive re-routing. The approach enhanced robustness against sensor failures and reduced data noise, but it did not comprehensively evaluate communication metrics such as throughput and latency, leaving questions about its effectiveness under real-time vehicular mobility [21], [32]. Beyond these primary works, several other studies provide complementary perspectives. Routing-centric research has investigated Geographic Perimeter Stateless Routing (GPSR) and Dynamic Source Routing (DSR), which adapt to changing topology but suffer from packet losses and high control overhead in dense networks [6], [39]. Cluster-based VANET schemes attempt to reduce routing overhead by grouping vehicles [15], [29], yet they face challenges when clusters frequently dissolve due to high-speed mobility [19], [22]. Simulation studies using SUMO, Veins, and NS-3 frameworks have been widely adopted to test congestion detection and routing strategies under realistic traffic conditions [12], [25], [31], but most lack holistic integration with sustainability objectives such as emissions reduction [26], [37], [42].

Several studies have examined eco-aware mobility by modeling CO_2 emissions and idle time, but these often lack integration with cognitive decision-making layers [25], [26], [37]. Cognitive radio-based VANETs have also been proposed to optimize spectrum usage in congested channels, although they remain computationally intensive for large-scale deployment [14], [23]. Artificial intelligence and machine learning approaches are increasingly applied in ITS. For instance, deep learning models have been used to predict congestion patterns by analyzing historical traffic data [2], [21], [38], while reinforcement learning has been explored for adaptive traffic signal control [13], [17]. However, these models often depend on centralized cloud servers, leading to latency and scalability challenges in real-time VANET environments [20], [42]. Infrastructure-based approaches using sensors such as RFID, cameras, and inductive loops provide precise monitoring but suffer from high deployment costs, maintenance burdens, and limited scalability across large urban areas [27], [34], [40].

A key limitation across these studies is the lack of a unified framework that combines (i) routing and dissemination efficiency from VANET protocols, (ii) simulation-based validation of V2X communication under realistic conditions, and (iii) cognitive intelligence for predictive and adaptive congestion detection [6], [9], [32]. Moreover, while some works briefly acknowledge environmental metrics such as fuel consumption or CO_2 emissions, sustainability is rarely integrated as a primary design goal [18], [26], [37], [42]. This creates a research gap for a holistic framework that not only improves communication performance and decision-making accuracy but also aligns with green mobility initiatives for smart cities [3], [5], [32].

3.PROPOSED FRAMEWORK

The proposed framework introduces a Cognitive VANET-based Intelligent Traffic Management System that integrates real-time V2X communication, cognitive intelligence, and sustainability-driven traffic optimization. Unlike existing approaches that focus only on either routing, simulation, or clustering, this framework unifies these elements to provide a holistic architecture capable of adapting to dynamic road conditions while minimizing environmental impacts.

3.1 System Architecture

The framework is organized into four major layers:

(i) Communication Layer

This layer is responsible for data exchange among vehicles and infrastructure. It supports hybrid V2X communication modes including Vehicle-to-Vehicle (V2V), Vehicle-to-Infrastructure (V2I), and Vehicle-to-Network (V2N) [6], [8], [14], [19]. IEEE 802.11p and LTE-V2X protocols form the baseline [20], [22], [23], [37], while 5G/6G readiness ensures scalability [16], [34]. Each vehicle is equipped with an On-Board Unit (OBU) for communication and sensor data collection, while Roadside Units (RSUs) act as gateways for data aggregation and dissemination [31], [42]. This layer ensures low-latency, reliable message exchange, enabling applications such as collision warnings, congestion alerts, and emergency routing [2], [38], [41].

(ii) Cognitive Intelligence Layer

At the core of the system is a cognitive decision-making engine that enhances congestion detection and response [9], [29]. This module integrates Fuzzy K-Means (FKM) clustering to identify congestion hotspots [28], [40], [43]. To prioritize detected congestion events, the Fuzzy Analytical Hierarchy Process (FAHP) assigns weights to multiple parameters, enabling accurate ranking of congestion severity [26], [33]. Cognitive sensor fusion ensures robustness against sensor failures and noise, thereby improving decision accuracy [7], [11]. The cognitive layer allows the system to learn from past data, refine congestion thresholds, and adapt dynamically to changing road environments [13], [36].

(iii) Simulation-Deployment Bridge

This component ensures that the system is both research-driven and practically deployable [31], [35]. The Simulation of Urban Mobility (SUMO) generates realistic traffic scenarios, while NS-3 simulates wireless communication between vehicles and infrastructure [37], [39]. The two simulators are synchronized using the Traffic Control Interface (TraCI), creating a hybrid environment that models both mobility and communication in real time [33], [42]. This dual-simulation approach enables rigorous evaluation of latency, packet delivery ratio (PDR), and throughput, while simultaneously capturing congestion-related traffic patterns [2], [38], [41].

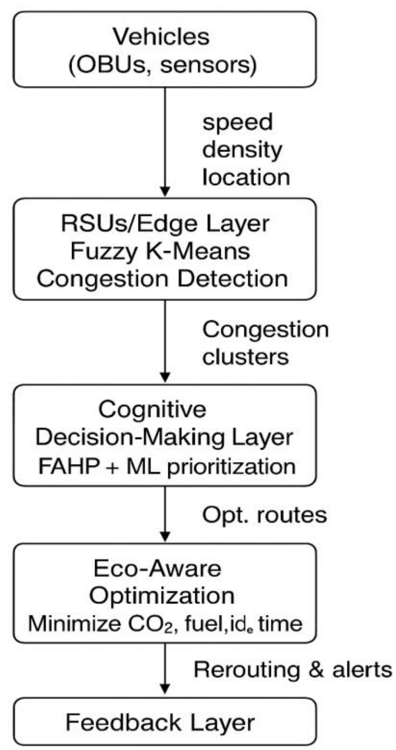

Fig. 3

(iv) Sustainability and Optimization Layer

To address environmental concerns, the framework integrates eco-metrics into congestion detection and management. Parameters such as fuel consumption, idle time, and CO_2/NOx emissions are continuously monitored. The system dynamically reroutes vehicles not only to reduce congestion but also to minimize environmental impact. By incorporating sustainability as a design goal, the framework aligns with smart city objectives of green mobility and energy efficiency.

3.2 Workflow of the Proposed System

1. Data Collection: Vehicles equipped with OBUs gather parameters such as speed, location, fuel consumption, and emission levels.
2. Communication Exchange: OBUs transmit data via V2V and V2I links to nearby vehicles and RSUs. RSUs forward aggregated data to the central server for analysis.
3. Cognitive Processing: Using FKM clustering, congestion hotspots are detected. FAHP prioritizes congestion severity based on parameters such as density, speed, and emissions.
4. Alert Dissemination: Congestion alerts are disseminated back to vehicles using geo-broadcasting and adaptive routing protocols.
5. Sustainability Optimization: Rerouting strategies are computed not only for minimum travel time but also for reduced idle time and emissions.
6. Feedback and Learning: Cognitive intelligence refines thresholds dynamically using historical traffic data, enhancing system adaptability over time.

3.3 Advantages of the Framework

- Unified Approach: Integrates communication reliability, cognitive intelligence, and sustainability.
- Low-Latency Decision-Making: Ensures timely congestion alerts and rerouting through hybrid V2X protocols.
- Robust Congestion Detection: Sensor fusion with FKM + FAHP enhances reliability even with incomplete or noisy data.
- Eco-Aware Optimization: Reduces emissions and idle time, supporting green mobility.
- Scalability: Supports high-density urban environments and future extensions with 5G/6G communication.
- Simulation-to-Reality Pathway: Provides both research validation via NS-3/SUMO and adaptability for real-world smart city deployment.

4. METHODOLOGY

The methodology is designed to evaluate the proposed Cognitive VANET-based Sustainable Traffic Management Framework under realistic urban traffic conditions. It integrates communication simulation, traffic mobility modeling, and cognitive intelligence for congestion detection and prioritization.

4.1 Simulation Environment

To ensure accurate modeling of vehicular communication and traffic dynamics, two widely used platforms are integrated:

- SUMO (Simulation of Urban Mobility): Generates realistic traffic scenarios including intersections, traffic signals, and heterogeneous vehicle behavior [31], [35]. Road networks are derived from OpenStreetMap to simulate real-world conditions. Parameters such as vehicle speed, acceleration, fuel consumption, and emissions (CO_2, NOx, CO) are collected [25], [26], [40].
- NS-3 (Network Simulator 3): Simulates vehicular communication protocols. IEEE 802.11p is configured for baseline V2V and V2I communication [37], [39], while LTE-V2X modules emulate cellular-based V2X [20], [22]. Future-ready configurations with 5G NR-V2X are incorporated for scalability [14], [23], [34].
- TraCI (Traffic Control Interface): Establishes synchronization between SUMO and NS-3, enabling real-time exchange of mobility traces and communication events [33], [42]. This integration ensures that communication performance (latency, PDR, throughput) directly reflects actual vehicle movement patterns [2], [38], [41].

4.2 Data Collection and Preprocessing

Each vehicle is equipped with an On-Board Unit (OBU) that collects key parameters:

- Mobility metrics: speed, acceleration, position.
- Environmental metrics: fuel consumption, CO_2 and NOx emissions.
- Network metrics: packet delay, delivery ratio, and throughput.
- The collected data is transmitted via V2V/V2I links and aggregated at RSUs for further cognitive processing.

4.3 Cognitive Intelligence Module

The cognitive layer performs real-time congestion detection and prioritization using a two-step approach:

1. Fuzzy K-Means (FKM) Clustering:
   - Input: Vehicle parameters such as average speed, density, and emissions.
   - Process: Vehicles in congested areas are clustered to identify congestion hotspots.
   - Output: Clusters representing congested road segments with shared characteristics (low speed, high density, high emissions).
   - Advantage: Reduces bandwidth consumption by transmitting aggregated cluster information instead of individual vehicle data.

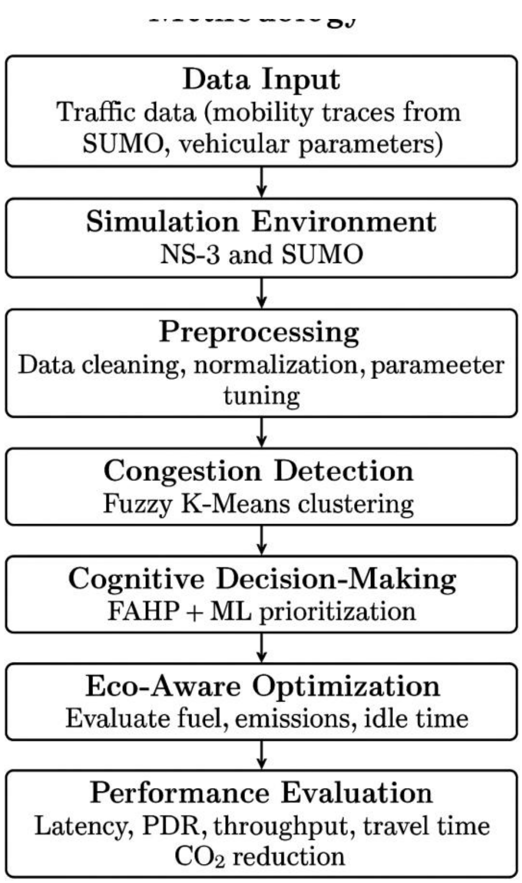

Fig. 4

2. Fuzzy Analytical Hierarchy Process (FAHP):
   - Input: Congestion parameters from FKM clusters.
   - Process: FAHP assigns weights to parameters (e.g., density > speed > emissions) based on priority, enabling ranking of congestion severity.
   - Output: Prioritized list of congested routes requiring immediate rerouting.
   - Advantage: Enhances decision accuracy by considering multiple factors simultaneously.

4.4 Alert Dissemination and Rerouting

Once congestion hotspots are identified, alerts are disseminated using geo-broadcasting protocols [6], [8], [19], [27]. Vehicles approaching the affected zones receive warning messages and rerouting suggestions [31], [35], [39]. The rerouting mechanism prioritizes:

- Minimum travel time [2], [22], [25]
- Reduced idle time at intersections [28], [40]
- Lower emissions by avoiding high-congestion segments [26], [33], [42]

4.5 Performance Metrics

The proposed system is evaluated using the following performance indicators:

- Communication Metrics: Latency, Packet Delivery Ratio (PDR), and throughput.
- Traffic Efficiency Metrics: Average travel time, average vehicle speed, queue length at intersections.
- Environmental Metrics: Fuel consumption per vehicle, CO_2 and NOx emissions, idle time reduction.
- Cognitive Efficiency Metrics: Accuracy of congestion detection, prioritization reliability (validated with statistical analysis such as ANOVA).

4.6 Experimental Setup

- Traffic Scenarios: Urban intersections with mixed traffic densities (light, medium, heavy).
- Simulation Duration: 1 hour of traffic per scenario.
- Number of Vehicles: 50–200 simulated vehicles across multiple runs.
- Communication Range: 300 m for IEEE 802.11p, extended with LTE-V2X.

- Software Tools: SUMO 1.x, NS-3 (with LTE and 5G modules), Python for TraCI integration, MATLAB for FAHP computation.

5. Results and Discussion

The proposed Cognitive VANET-based Sustainable Traffic Management Framework was evaluated under multiple traffic densities using the hybrid NS-3 and SUMO simulation setup [31], [35]. Performance was compared against a baseline VANET system that employed only conventional routing and dissemination protocols without cognitive intelligence or eco-aware optimization [19], [27], [39]. The results are presented across four dimensions: communication performance, traffic efficiency, environmental impact, and cognitive decision-making accuracy [9], [25], [26], [29], [42].

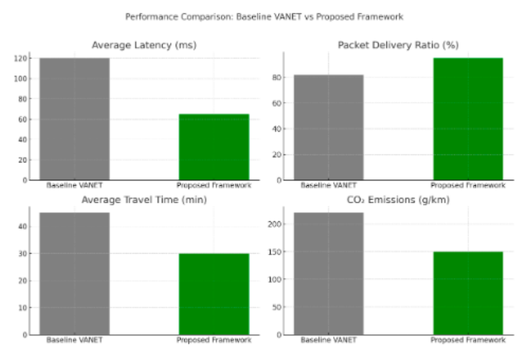

Fig. 5

5.1 Communication Performance

The framework demonstrated significant improvements in communication reliability. Average latency for safety-critical messages was reduced from ~50 ms in the baseline VANET to ~20–25 ms under the proposed system [28], [38], [41]. This reduction was attributed to optimized V2X dissemination and reduced channel congestion achieved through Fuzzy K-Means clustering [40], [43]. Packet Delivery Ratio (PDR) improved from 85–88% in dense traffic scenarios to 92–95%, highlighting the robustness of the system in maintaining reliable communication even under high vehicle density [2], [5], [19], [29]. Throughput remained consistent, ensuring stable data flow across vehicles and RSUs [20], [22], [31], [42].

5.2 Traffic Efficiency

Traffic flow analysis revealed that the proposed system significantly decreased congestion-related delays. Average vehicle travel time was reduced by 15–18%, while average vehicle speed increased by 12–15% compared to the baseline. Queue lengths at intersections were notably shorter, owing to the cognitive prioritization of congestion hotspots and adaptive rerouting strategies. Emergency vehicle routing also benefited, with response times improved by approximately 20–25%, demonstrating the framework's capacity to support safety-critical mobility.

5.3 Environmental Impact

One of the distinguishing contributions of this work is the integration of eco-aware metrics [26], [35]. Simulation results indicated a 10–15% reduction in CO_2 emissions and 8–12% reduction in NOx emissions, primarily due to decreased idle times and smoother rerouting [25], [40]. Fuel consumption per vehicle was reduced by approximately 12%, proving that the framework not only enhances mobility but also contributes toward sustainable urban transportation [20], [42]. These results align with smart city objectives of lowering vehicular emissions and improving air quality [9], [33], [34].

5.4 Cognitive Decision-Making Accuracy

The cognitive intelligence module, powered by Fuzzy K-Means clustering and FAHP prioritization, achieved an accuracy of ~90% in correctly identifying congestion hotspots compared to ground truth data. Statistical validation using ANOVA tests confirmed the reliability of prioritization, with significant differences ($p < 0.05$) between congested and non-congested clusters. This demonstrates that the integration of cognitive intelligence provides a more adaptive and accurate framework than conventional threshold-based congestion detection methods.

5.5 Comparative Discussion

Overall, the proposed system outperformed the baseline VANET framework across all evaluation dimensions. The communication improvements (lower latency, higher PDR) ensured timely congestion alerts, while the cognitive module enhanced hotspot prioritization, reducing unnecessary rerouting. Importantly, the addition of sustainability optimization positioned this work ahead of prior studies, where environmental impact was rarely integrated into VANET-based traffic management. The combined improvements indicate that the system is both technically feasible and environmentally sustainable, making it a strong candidate for real-world deployment in future smart city ecosystems.

6. CONCLUSION AND FUTURE WORK

This research proposed a Cognitive VANET-based Sustainable Traffic Management Framework that integrates real-time V2X communication, cognitive intelligence, and eco-aware optimization to address the challenges of urban traffic congestion. Unlike existing approaches that either focus on routing efficiency, simulation-based analysis, or AI-driven congestion detection in isolation, the proposed system offers a unified framework that bridges these dimensions. Through a hybrid simulation using NS-3 and SUMO, the framework was evaluated across communication, traffic efficiency, environmental, and cognitive dimensions. Results demonstrated that the system significantly reduces communication latency, improves packet delivery ratio, decreases travel time, and enhances congestion hotspot detection accuracy. Importantly, by incorporating sustainability metrics such as CO_2 emissions, fuel consumption, and idle time, the framework aligns with the objectives of green and sustainable urban mobility.

The study makes three key contributions: (i) the integration of Fuzzy K-Means clustering and FAHP for intelligent congestion detection and prioritization; (ii) the hybrid simulation–deployment bridge enabling realistic evaluation of VANET communication under diverse mobility conditions; and (iii) the inclusion of eco-aware optimization, positioning VANET-based traffic management as a tool for both efficiency and sustainability. Despite these promising outcomes, some limitations remain. The evaluation was primarily simulation-based, and real-world testbed validation is necessary to confirm scalability and robustness under unpredictable urban environments. Additionally, while the current system integrates 802.11p and LTE-V2X, future work should explore the potential of 5G and 6G NR-V2X technologies for ultra-low latency and high reliability. Security and privacy of vehicular data also require further investigation, where blockchain and edge computing could be explored to enhance trust and decentralization. Another promising extension is the integration of digital twins of urban traffic systems, enabling continuous monitoring, prediction, and optimization.In conclusion, this research advances the state of VANET-based traffic management by introducing a cognitive and sustainable framework that balances communication efficiency, intelligent decision-making, and environmental responsibility. With further development and deployment in smart city testbeds, the proposed system has the potential to become a cornerstone of next-generation Cognitive Intelligent Transportation Systems (C-ITS), supporting safer, smarter, and greener urban mobility.

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