International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 14 Issue: 3
Article Received: *25 September 2026* ***Revised:*** *12 October 2026* ***Accepted:*** *10 November 2026*

A Secure and Explainable Multi-Agent Reinforcement Learning Framework with Improved Hawk Optimization for Intelligent Traffic Management in VANET-Enabled Smart Cities

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Abstract

In the context of growing urbanization and vehicular density, Vehicular Ad-Hoc Networks (VANETs) are essential for enabling intelligent traffic management in smart cities. Real-time adaptability, decision transparency, and secure communication remain major challenges. This research proposes a novel framework that integrates Secure and Explainable Multi-Agent Reinforcement Learning (XMARL) with an Improved Hawk Optimization (IHO) algorithm to address traffic dynamics in VANET environments. Key issues targeted include high congestion, inefficient routing, lack of interpretability in AI decisions, and vulnerability to cyber-attacks. In the proposed system, each vehicle and Road-Side Unit (RSU) functions as an autonomous agent trained using XMARL for decentralized decision-making. IHO enhances learning by adaptively tuning policy parameters, optimizing signal timings, and refining route selection based on real-time conditions. To ensure interpretability, Explainable AI techniques such as SHAP values and attention mechanisms are integrated, providing human-understandable insights into agent actions. A lightweight blockchain layer secures communications, ensuring data integrity and trust between nodes. The framework aims to deliver a scalable, interpretable, and secure traffic management solution capable of reducing congestion, improving travel efficiency, and resisting malicious threats. Simulation results using SUMO and Veins demonstrate that the proposed model outperforms existing XMARL methods in traffic throughput, decision transparency, learning convergence, and packet delivery ratio under diverse urban scenarios. This integrated approach presents advancement toward building trustworthy and efficient smart transportation systems.

Keywords: Multi-Agent Reinforcement Learning; Improved Hawk Optimization; Vehicular Ad-Hoc Networks; Smart Cities; Explainable Artificial Intelligence; Secure Communication; Traffic Management; Blockchain; Signal Timing Optimization; Autonomous Agents.

1. Introduction

Intelligent Transportation Systems (ITS) are now standard in automobiles to ensure real-time driving safety and overall performance. As the number of vehicles worldwide increases, so does the number of manufacturers and the intensity of competition among them. In this study, the investigator discusses how to implement and operate ITS. The study utilizes the system's features to enhance its functionality within the testing environment [1]. To facilitate vehicle communication, manufacturers have begun equipping cars with sensors, transmitters, and receivers. To reduce travel-related risks, VANET systems, GPS, and security applications have been employed to improve safety. Evaluates the embedded technological features and system architecture. At the same time, the study integrates GPS to improve the efficiency of the proposed system [2]. The research project focuses on enhancing

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the deployment of VANET networking services to support the development of a secure application for data exchange between vehicles and Road Side Units (RSUs). Cloud-based computing technologies have also been adopted to improve the real-time use of applications by enabling easier information exchange and resource collaboration over the Internet and intranet, especially between vehicles and RSUs [3]. The system includes databases and applications essential for traffic management and the sharing of critical information such as vehicle location, speed, details, and animated records from the past two years. The primary traffic division is responsible for overseeing and managing these operations. The layout of the proposed system designed for deployment is shown in Figure 1 with RSUs mounted on selected roadside lighting poles [4].



Figure 1: A model of ITS in VANET

One of the fundamental components of any smart city ITS. Without an effective and reliable ITS, the concept of a smart city cannot be fully realized. ITS plays a critical role in the overall smart city framework. Recent advancements in wireless communication have enabled the implementation of VANETs within ITS infrastructures [5]. VANETs are increasingly being used to support user-centric features including driver assistance (e.g., 3D navigation maps), customer entertainment (e.g., internet browsing, HD video streaming, and online gaming), and traffic management (e.g., real-time traffic balancing). The primary objective of these applications is to enhance the safety and engagement of driving and travel experiences [6]. These applications come with varying requirements: ITS applications demand minimal latency, whereas entertainment applications require high bandwidth to ensure optimal performance. Despite significant progress in both industry and academia, the existing VANET architecture still faces multiple challenges, such as intermittent connectivity, high routing overhead, inflexible communication infrastructures, and high collision rates. To effectively deploy VANETs for bandwidth-intensive and delay-sensitive applications, these issues must be addressed [7]. One key challenge is the instability of the Received Signal Strength Indicator (RSSI) when nodes are moving in different directions, which leads to inconsistent connections. For ITS security applications, emergency alerts must be transmitted over highly reliable links failure to receive such alerts can result in fatal consequences. Data-driven systems require stable and dependable communication links to maintain throughput [8]. Vehicle mobility presents two critical concerns: frequent handovers and insufficient routing paths. In Vehicle-to-Vehicle (V2V) communication, nodes relay information through multiple hops, actively or reactively maintaining routes to ensure the transmission of data packets [9]. Disruptions caused by high node mobility increase routing overhead, thereby reducing network efficiency. In Vehicle-to-Infrastructure (V2I) communication, node mobility leads to frequent handovers between Base Stations (BSs) and RSUs resulting in service interruptions and increased latency.

ITS and user-oriented applications can access fixed communication networks through VANET [10]. These networks lack the adaptability needed to meet evolving access requirements such as expanding coverage areas or establishing on-demand network services. While multi-hop V2V communication can dynamically operate without relying on infrastructure and can broaden coverage, this expansion is inherently limited. In highly dynamic and congested environments, extending communication over multiple hops significantly reduces network efficiency. VANETs face challenges related to both visible and hidden nodes often resulting in packet collisions and increased latency [11]. The sharp rise in car ownership has led to traffic congestion, environmental pollution, and delays in logistics. The economic impact of traffic jams is substantial. For example, it is estimated that traffic congestion costs the European Union approximately 1% of its GDP. This surge in private vehicle ownership combined with insufficient public transportation infrastructure poses a major obstacle to the realization of smart cities [12]. The global expansion of urban areas has resulted in a corresponding increase in private vehicle use, especially in major cities. By 2024, Indonesia had risen to second place with an average jam time of 49.44 minutes. These

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circumstances underscore the urgent need for an improved Traffic Management System (TMS) [13]. Efficient and reliable traffic control systems can result in significant time and cost savings. The integration of Internet of Things (IoT)-based Intelligent Traffic Management (ITM) sensors into electronic systems and autonomous vehicles enables the detection, collection, and transmission of real-time traffic data. Machine Learning (ML) holds the potential to further enhance transportation systems. Existing transportation management systems suffer from inefficiencies that contribute to congestion, errors, and accidents [14]. Notable issues with existing traffic light control systems include prolonged waiting times, unnecessary fuel consumption, and elevated carbon emissions. These inefficiencies contribute to increased stress among drivers and delayed response times for emergency and high-priority vehicles. Intelligent traffic light control has the potential to optimize flow and reduce congestion [15]. An effective transportation system is heavily dependent on smart traffic light control. Most existing traffic light systems still operate based on fixed schedules without accounting for real-time traffic conditions. Some recent studies have proposed custom criteria based on live traffic data, but these rules are often statically defined and lack the flexibility to adapt to dynamic traffic patterns [16].

Previous studies have primarily focused on incentives without fully understanding underlying policies, and most have not validated their approaches using real-world traffic data. This research proposes an enhanced Deep Reinforcement Learning (DRL) model for traffic signal management. The model utilizes a comprehensive database of actual traffic information to ensure its effectiveness. This study presents compelling examples of policy-making grounded in real-world data [17]. Reinforcement Learning (RL) techniques have been used to dynamically adjust traffic signals based on existing traffic conditions. The practical application of existing RL is often hindered by the complexity of modelling the environment and defining the relationship between environmental states and decision-making actions. The first motivation is to reduce road congestion and minimize waiting times for both drivers and pedestrians [18]. This directly improves the efficiency of daily routines. While the effect on an individual level may seem small when viewed collectively, the societal impact is substantial. Another important motivation is the reduction of greenhouse gas emissions, particularly Carbon Monoxide (CO) and Carbon Dioxide (CO_2) produced by vehicles. This reduction is critical in addressing one of the world's major environmental challenges: ozone layer depletion poses a serious threat to human health if not managed. Beyond improving user satisfaction and quality of life, reducing congestion also contributes to enhance road safety by lowering the incidence of vehicular accidents potentially saving lives on a global scale [19].

1.1 Problem Statement

The rapid growth of urban populations and the corresponding rise in vehicular traffic have led to increased congestion, delays, and environmental concerns in modern cities. VANETs as a subset of ITS offer a promising platform for enabling real-time communication and coordination between vehicles and infrastructure. Managing traffic efficiently in such dynamic and decentralized environments remains a complex challenge due to high mobility, unpredictable traffic patterns, and the need for scalable, secure, and intelligent decision-making. Existing TMS lack adaptability and struggle to process and respond to rapidly changing road conditions. Existing ML-based solutions often operate as black boxes, providing little to no insight into the rationale behind decisions limits trustworthiness and practical deployment. The open and distributed nature of VANETs exposes the network to various security threats such as data tampering and malic can adapt to real-time traffic conditions, optimize decision-making through cooperative learning, and ensure trustworthy communication among network entities in VANET-enabled smart cities.

1.2 Motivation

The motivation behind this research stems from the pressing need to enhance urban mobility, reduce traffic congestion, and improve road safety in the face of rapidly increasing vehicular density in smart cities. With the advancement of VANET technology, there is a unique opportunity to leverage real-time communication among vehicles and infrastructure to enable dynamic data-driven traffic management. Existing traffic systems lack the intelligence and adaptability required to handle the complexity and unpredictability of modern urban environments. Reinforcement learning, particularly in a multi-agent setting offers a powerful means for enabling autonomous agents to collaboratively learn and make optimal decisions. These systems often suffer from poor interpretability and are vulnerable to cyber threats. This creates a strong motivation to develop a secure, explainable, and optimization-enhanced ML framework

that not only improve decision accuracy and responsiveness gain the trust of end-users and stakeholders. By integrating Improved Hawk Optimization and Explainable AI into a secure MARL-based system, this research aims to bridge the gap between intelligent decision-making and practical, safe deployment in real-world VANET-enabled smart city scenarios.

The five key contributions of the paper are as follows:

1. Developed a secure MARL framework for intelligent traffic control in VANET environments.
2. Integrated Improved Hawk Optimization to enhance agent performance, route selection, and learning convergence rate.
3. Applied Explainable AI techniques to interpret agent decisions and increase transparency in traffic management systems.
4. Designed a lightweight blockchain-based layer ensuring secure communication and trust among vehicular network nodes.
5. Achieved significant improvements in traffic throughput, delay reduction, and decision interpretability through extensive simulation experiments.

2. Related Works

Recent analysis focused on applying nature-inspired techniques for optimal path selection in VANETs. Proposed a clustering-based safe forwarding approach using simulated annealing for effective node clustering in reliable VANET applications. Although this method achieved a higher Packet Delivery Ratio (PDR), it suffered from reduced throughput. To address this, introduced a Grey Wolf Optimization-based clustering strategy that effectively minimized the number of clusters, thereby lowering communication overhead [20]. This technique removed the dynamic communication range of vehicular nodes, limiting adaptability. To overcome this limitation, proposed a novel routing metric considering received signal strength, transmission power, frequency, and path loss. Despite its theoretical advantages, the method posed significant implementation complexity. Addressing real-world dynamics developed a Reputation-based Weighted Cluster Protocol (RWCP), leveraging parameters such as lane ID, vehicle density, position, and direction to stabilize VANET structures [21].

Traffic flow in real-time is influenced by complex stochastic systems. A primary challenge lies in dynamically adjusting green signal durations at intersections to optimize flow. Substantial research has explored the application of MARL to reduce vehicular delays. MARL enables decentralized control, making it a promising approach for traffic signal optimization. Modelled MARL using a general-sum stochastic game and developed a Multi-Agent Q-learning framework showing convergence to a Nash equilibrium in specific cases [22]. The presence of multiple equilibrium necessitates combining MARL with other learning strategies for optimal outcomes. Overfitting in RL agents during training is a concern, as separate policy learning leads to poor generalization. To address this, researchers proposed a joint-policy correlation metric and an enhanced DRL method. The challenge of decentralized decision-making under partial observability was tackled using deep neural networks for end-to-end communication protocol learning, enabling agents to cooperate in complex environments. This work underscores the potential and ongoing challenges of integrating MARL and nature-inspired techniques for scalable, adaptive VANET solutions [23].

MARL techniques are comprehensively categorize it into cooperative, competitive, and hybrid frameworks. Highlights key mathematical formulations, associated challenges, and diverse application domains, while outlining both strengths and limitations of MARL approaches. In the VANET context, various nature-inspired and bio-inspired routing techniques have emerged. Introduced Cluster-based V2V Routing using Particle Swarm Optimization (CRPSO) improved QoS but lacked scalability [24]. To address this, enhanced routing resiliency and reduced network loops through an improved PSO-based approach, although it omitted density factors, limiting scalability validation. Proposed a fuzzy logic-based routing protocol relying on Channel Quality Factor (CQF) and Communication Expire Time (CET). While effective under moderate traffic, it produced complex, longer paths and suboptimal PDR in high congestion. Developed an Integrated Water Wave Optimization (IWWO) approach with high PDR and low overhead, but scalability issues persisted [25]. To overcome these, introduced the Moth Whale Optimization Algorithm (MWOA), relied heavily on individual vehicle data and lacked overhead analysis. Proposed an intelligent Whale Optimization Algorithm (i-WOA) incorporating node weight, velocity, and communication range to enhance cluster stability via a

fitness function [26]. It suffered from convergence problems due to local optimum traps. Employed a k-means clustering method for large VANETs, but performance degraded when routing overhead was minimal. Combined the Firefly Algorithm with Genetic Algorithm (GA) to improve routing; it faced challenges in consistency and convergence speed. To enhance vehicular safety, proposed a novel communication enhancement strategy prioritizing safety signal using improved broadcasting techniques under the IEEE 802.11p/WAVE standard, effectively mitigating packet loss [27].

To mitigate collisions in high-density traffic, adaptive techniques such as varying the Contention Window (CW) size and evaluating different packet loss mechanisms have been implemented. While effective in reducing collisions, these methods assume congestion-free environments and lack key features such as broadcast acknowledgments and RTS/CTS safeguards [28]. Real-time application evaluation remains limited, reducing applicability under diverse traffic conditions. Dijkstra's algorithm with a digitized street map is used in this schema to identify reliable, traffic-aware paths within connected regions. Introduced a fuzzy logic-based clustering methodology for Cluster Head (CH) selection in VANETs, considering four parameters: Group Speed (GS), Degree of Connectivity (DC), Relative Acceleration (RA), and Security Coefficient (SC). Despite its merit, the model overlooks other influential factors impacting network performance [29].

Proposed the Geographic Social Trust Routing (GSTR) scheme, a multi-hop data forwarding approach that incorporates both trust weight and node orientation. The system accounts for multiple routing scenarios: proximity-based message delivery, the presence of single or multiple connected nodes, and fall back to cloud infrastructure when no node is available. Although they implemented distinct geographic routing strategies at the source and destination, performance deteriorated in sparse node environments [30]. Proposed a multi-agent clustering approach tailored for VANETs in ITS within smart cities. The model dynamically adjusts the cluster radius based on vehicle density, which is inversely proportional to vehicle speed. This enhances communication stability and reduces the frequency of cluster head transitions. It employs mobile agents on vehicles and static agents at RSUs for real-time data gathering and routing [31]. Simulation results using NS3 and SUMO demonstrated superiority over traditional clustering algorithms like Threshold-based (TB) and Stable-Based Clustering Algorithms (SBCA). Its reliance on manually tuned weight factors (wf1 and wf2) limits adaptability in fluctuating traffic conditions. Environmental elements such as urban infrastructure also affect scalability and general applicability. In a related context, a hybrid bio-inspired UAV routing approach was developed to enhance route reliability in various operational scenarios through route optimization and failure tolerance. Despite improved dependability, the method was constrained by time-related limitations [32].

In response to the increasing demand for reliable and efficient communication in roadway and urban VANET applications, proposed the Automatic Dynamic User Allocation-based Data Forwarding with Opportunistic Routing (ADUADFOR) protocol. This method operates in the transmission zone of the source vehicle and employs multiple vehicles for data dissemination to mitigate the broadcast storm problem. One of its key advantages is the use of an opportunistic dynamic routing mechanism that reduces redundant transmissions [33]. Its primary limitation lies in considering only a narrow set of VANET-specific constraints, thereby restricting its adaptability in diverse traffic scenarios. Introduced a novel method that utilizes sequential pattern mining in conjunction with decision tree classification to predict future vehicle trajectories based on dynamic grouping. This enhances network reliability by enabling proactive routing decisions. The model heavily relies on extensive historical mobility data, which can compromise accuracy in low-traffic or newly developing regions [34]. The scalability of this approach is hindered by its dependence on large datasets, especially in sparsely populated areas. To address local optimality issues and improve clustering robustness, a hybrid framework combining Tabu Search with Genetic Algorithm (GA) was proposed. This method efficiently explores the state space, avoids premature convergence, and improves node distribution across clusters, enhancing the stability of cluster architectures and the reliability of vehicle communication [35]. Evaluation metrics demonstrate that this approach outperforms the Weighted K-Medoid Cluster Algorithm (WKCA) and other existing solutions in terms of system stability and data dissemination efficiency. A related method, the Hybrid Scatter Tabu Search (HSTS) technique was presented to improve cluster member assignment in VANETs. The WKCA was used to form the initial clusters and the Tabu Search was integrated into the internal scattering process to ensure global optimality [36]. Simulation results confirm

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that this approach significantly enhances system resilience and clustering performance. Particle Swarm Optimization (PSO)-based cluster-based forwarding mechanism was proposed to enhance V2V communication efficiency. This approach effectively manages cluster formation and forwarding processes, contributing to improved data transmission and reduced communication delays [37].

3. Problem Formation

The objective of a VANET-enabled intelligent city is to optimize autonomous agents (vehicles or structural units) choices in a highly rapidly changing and dispersed environment in order to continuously regulate traffic flow. This may be expressed as a Multi-Agent Markov Decision Process (MAMDP), in which each agent interacts with the surroundings is to choose the best course of action.

Environment Modelling: Let the VANET environment be modelled as a tuple:

$$M = \langle S, A, P, R, \gamma \rangle \quad (1)$$

Where: S: Set of all global states (e.g., vehicle positions. queue lengths, signal states); $A = \langle A_1, A_2, \dots, A_N \rangle$: Joint action space of N agents; $P(s'|s,a)$: Transition probability from state s to s'; $R = \{R_1, R_2, \dots, R_N\}$: Reward functions for each agent; $\gamma \in [0,1]$: Discount factor for future rewards

Agent Objective (Reinforcement Learning): Each agent x aims to learn a policy $\pi_x(a_x|s)$ that maximizes the expected cumulative reward:

$$Y_x(\pi_x) = E[\sum_{t=0}^{\infty} \gamma^t R_x(s_t, a_t)] \quad (2)$$

Where $R_x(s_t, a_t)$ reflects traffic performance metrics (e.g., reduced waiting time, increased throughput).

Optimization with Improved Hawk Optimization (IHO): To enhance learning and decision accuracy, integrate IHO for:

- Tuning hyperparameters: learning rate (α), discount factor (γ), exploration rate (ϵ)
- Route and signal optimization

Let the IHO optimize a solution vector: $I = [\alpha, \gamma, \epsilon, T_1, T_2, \dots, T_k]$ (3)

Where T_k are signal timings or route decisions. The fitness function $F(I)$ defined as:

$$F(I) = w_1 . Avg_Delay^{-1} + w_2 . Throughput + w_3 . Packet\ Delivery\ Ratio \quad (4)$$

Where: w_1, w_2, w_3 Weight factors; All metrics are normalized for fair contribution

Security and Trust Modelling: Trust level $T_{xy}(t)$ between agents x and y at time t is updated based on behaviour: $T_{xy}(t+1) = \lambda T_{xy}(t) + (1-\lambda).\phi_{xy}(t)$ (5)

Where: $\lambda \in [0,1]$: Trust decay factor; $\phi_{xy}(t)$: Trust evaluation function (e.g., behavior similarity, message integrity); Blockchain ensures validation and non-repudiation.

Global Optimization Objective: The overall objective is to minimize congestion and delay while maximizing throughput and trust:

$$\min_{I,\pi} E\left[\sum_{x=1}^{N} \left(\alpha_1 . Delay_x - \alpha_2 . Throughput_x + \alpha_3 . (1 - T_x)\right)\right] \quad (6)$$

Subject to: QoS constraints (delay threshold. PDR threshold); Communication constraints (bandwidth, latency); Security compliance (trust ≥ threshold)

4. Materials and Methods

The proposed framework is developed using XMARL architecture, where each intelligent agent representing vehicles or RSU learns optimal traffic management policies through continuous interaction with a simulated VANET environment shown in Figure 2. The environment is modeled using SUMO and integrated with Python-based XMARL libraries to simulate real-world traffic dynamics, including varying vehicle densities, signal timings, and road conditions. Each agent operates using a decentralized reinforcement learning algorithm, specifically Deep Q-Network (DQN) to estimate state-action values and make autonomous decisions that reduce traffic congestion and waiting time. To enhance the learning process, an IHO algorithm is employed to fine-tune key hyperparameters such as learning rate, exploration rate, and reward function weights to optimize signal timing schedules and vehicle routing strategies. Security within the VANET is ensured using a lightweight blockchain framework that provides integrity, authentication, and tamper-resistance for inter-agent communications. To address the black-box nature of deep learning, XAI techniques are integrated to offer interpretable decision outputs from the trained agents. Evaluation metrics include average vehicle delay, queue length, packet delivery ratio, throughput, and trust score, all computed across multiple traffic scenarios. Simulation results validate that the proposed secure and

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XMARL framework, optimized using IHO outperforms conventional methods in terms of both efficiency and interpretability in managing urban traffic within VANET-enabled smart cities.

4.1 Dataset Description

The present research employs both generated and real-world datasets to comprehensively evaluate the proposed framework. Synthetic traffic data is generated using the SUMO platform accurately emulates real-world traffic characteristics such as vehicle speed, routing patterns, and traffic signal timing shown in Table 1. To simulate VANET communication, the study incorporates OMNeT++ integrated with the Veins framework, enabling precise measurements of critical network parameters, including latency, packet delivery ratio, and trust metrics. Custom logging mechanisms are implemented to capture agent states, behaviors, and rewards during the reinforcement learning process. These heterogeneous data sources establish a robust and dynamic tested for evaluating the proposed safe and XMARL framework for intelligent transportation management in smart cities. The performance and scalability of the system are further optimized through the incorporation of the IHO algorithm.

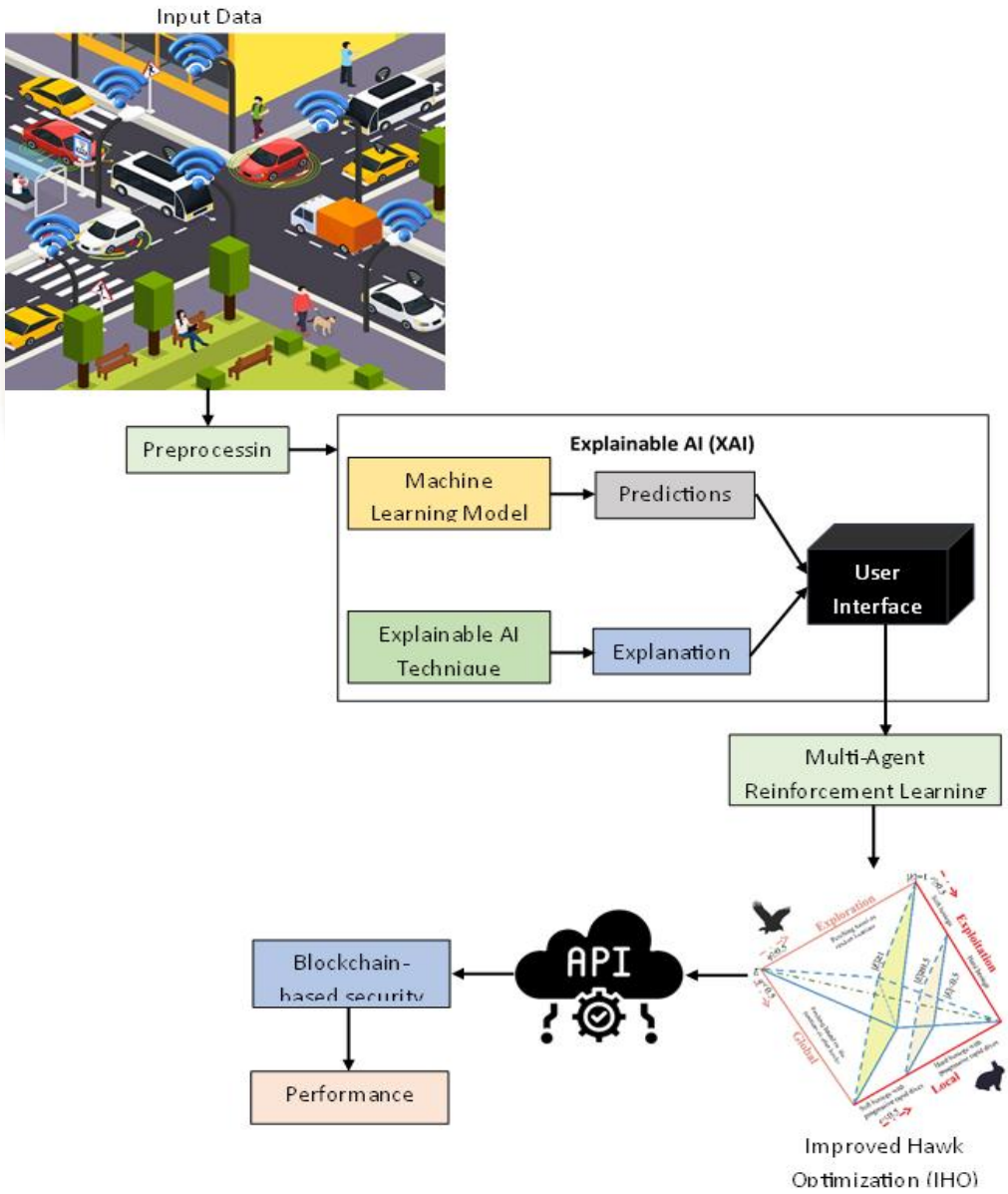


Figure 2: Proposed Architecture

International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 14 Issue: 3
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Table 1: Dataset Description

Dataset Name	Source	Type	Key Features	Usage in Study
SUMO Synthetic Data	SUMO (Simulation of Urban Mobility)	Simulated	Vehicle ID, speed, location, time, route, signal state	Traffic simulation, vehicle movement, signal control
TAPASCologne Dataset	DLR, Germany	Real-world traffic	Traffic flow, vehicle density, road topology, timing	Realistic scenario validation
NGSIM Dataset	US DoT	Real-world traffic	Vehicle trajectories, lane changes, speeds, timestamps	Agent behavior benchmarking
Custom VANET Logs	Generated via OMNeT++ and Veins	Simulated VANET logs	Communication logs, latency, packet loss, node mobility	Communication evaluation and trust metrics
Agent State-Action Log	Generated during training	Reinforcement Learning Logs	State vectors, action taken, reward received, episode length	Training and evaluation of MARL models

Table 2: Sample Data

Vehicle ID	Timestamp	Speed (km/h)	Location (X, Y)	Signal State	Action Taken	Reward	Packet Delay (ms)	Trust Score
V_1023	10:15:01	45	(125.4, 302.1)	Green	Go	+1.2	32	0.98
V_1045	10:15:03	0	(126.8, 301.9)	Red	Stop	+0.9	45	0.97
V_1101	10:15:05	32	(127.0, 302.3)	Yellow	Slow Down	+0.6	37	0.92
V_1007	10:15:07	52	(128.2, 303.5)	Green	Go	+1.5	28	0.99
V_1088	10:15:10	20	(129.5, 304.1)	Red	Wait	+0.8	42	0.95

The proposed system is trained and evaluated using simulated VANET traffic scenarios represented by sample data shown in Table 2. Each record includes essential details such as vehicle ID, timestamp, velocity, positional coordinates, traffic light status, agent behaviour, and accumulated rewards. The reliability of vehicle-to-vehicle communication within the VANET system is assessed using network interaction metrics such as confidence scores and packet latency. While the IHO algorithm enhances system efficiency, the XMARL model learns optimal traffic decisions from this structured dataset. In smart traffic control frameworks, such comprehensive records enable interpretability, security assessment, and real-time decision-making.

4.2 Pre-processing

The preliminary processing is an essential step in the proposed structure in order to guarantee high-quality input for XMARL model training. Normalization of information, noise reduction, management of missing values, and gathering features from traffic and communication records are the primary pre-processing responsibilities.

Data Cleaning: Remove duplicate entries and handle missing values using interpolation

$$i_t = i_{t+1} + \frac{i_{t+1} - i_{t-1}}{2}, \text{ if } i_t \text{ is missing} \quad (7)$$

Feature Scaling (Normalization): Normalize continuous features like speed, delay, and trust score to a

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range [0, 1] using Min-Max normalization: $i_{norm} = \frac{i - i_{min}}{i_{max} - i_{min}}$ (8)

Categorical Encoding: Convert signal states into numerical format using one-hot encoding

$$Green \rightarrow [1,0,0];\ Yellow \rightarrow [0,1,0];\ Red \rightarrow [0,0,1] \quad (9)$$

State Vector Formation: Formulate the agent's state vector S_t at time t with relevant features

$$S_t = [Speed_t, SignalState_t, Location_t, Trust_t, Delay_t] \quad (10)$$

Reward Normalization: Standardize reward values to stabilize reinforcement learning

$$R'_t = \frac{R_t - \mu_R}{\sigma_R} \quad (11)$$

Where μ_R is the mean and σ_R is the standard deviation of rewards.

In VANET-enabled smart traffic networks, this preliminary processing pipeline guarantees clean, scalable, and linguistically rich inputs, improving the MARL agents' effectiveness in learning and conclusion correctness.

4.3 Explainable Multi-Agent Reinforcement Learning

MARL involves acquiring knowledge about traffic flow optimization and signal control. Each agent represents real-time traffic as a complex stochastic system. The Markov Decision Process (MDP) utilized by XMARL provides a robust foundation for addressing this challenge. The number of intersections in a road network is proportional to the geographical size and operational complexity of the region shown in Figure 3. As the number of intersections increases, the state space and action domain grow significantly, necessitating the use of MDPs for scalable solutions. XMARL offers a systematic mathematical framework to handle such scenarios. Propose an autonomous vehicle congestion management system that leverages MARL to improve traffic flow and redirect vehicles to alternate routes when necessary. One key limitation of MARL is its difficulty in managing large-scale networks using autonomous agents with limited global knowledge of the entire system. To address this, researchers must adopt decentralized policies that consider the underlying network topology. VANETs play a critical role in enabling real-time information sharing between V2V and V2I in smart cities.

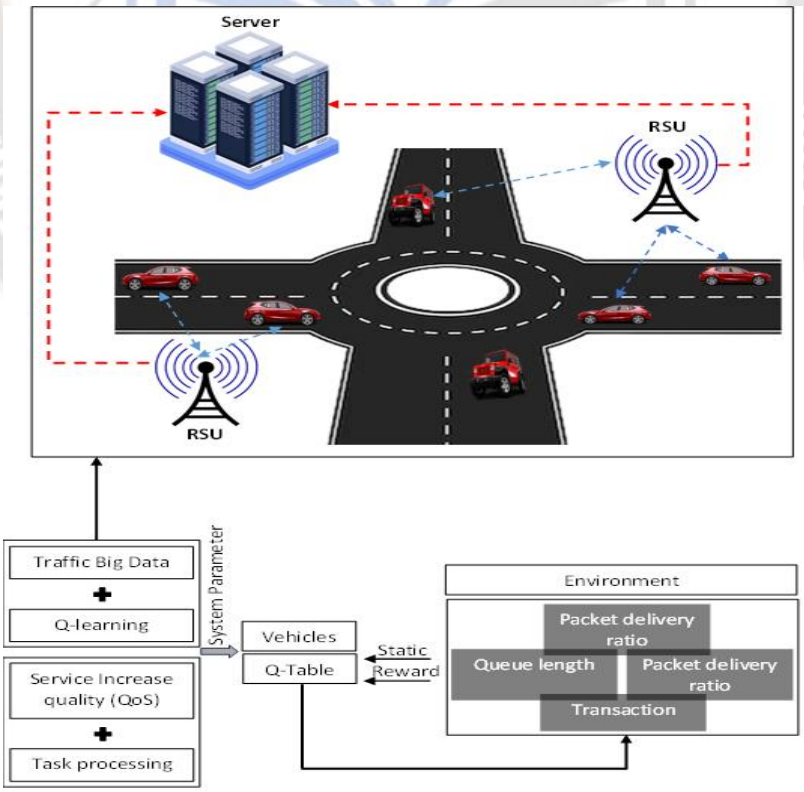


Figure 3: XMARL architecture in intelligent traffic system

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ISSN: 2321-8169 Volume: 14 Issue: 3
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Due to the high mobility and dynamic nature of VANETs, achieving intelligent traffic control remains a complex problem. MARL offers solution by enabling multiple decentralized agents such as traffic lights or autonomous vehicles, to interact with the environment and learn optimal policies. To effectively control signal timing, reduce congestion, and optimize vehicle navigation, each agent acts based on local observations while cooperating with others. To improve the transparency and reliability of these systems, XAI techniques are employed. This transparency is essential for maintaining public trust and ensuring compliance with regulatory standards. Each agent x in the VANET environment learns a policy $\pi_x(a_x|s_x)$ that maximizes its expected long-term reward:

$$Y_x(\pi_x) = E[\sum_{t=0}^{\infty} \gamma^t R_x(s_t, a_t)] \quad (12)$$

Where: s_t is the agent's local state at time t; a_t is the action taken; $R_x(s_t, a_t)$ is the reward based on traffic efficiency (e.g., reduced wait time, increased throughput); γ is the discount factor representing the importance of future rewards. SHAP are used to examine the contributions of various input variables (such as automobile weight, signal statuses, and median velocity) to an agent's activity to permit explanation. XMARL and VANETs work together to provide clear, collaborating, and adaptable traffic management systems that are well-suited to the demands and problems of the next generation of smart cities.

4.4 Improved Hawk Optimization (IHO) integration

The prey's first energy level is set throughout the linked graph's edges connecting vertices and is modified over the following iteration. The hawks can alter their assault plan thanks to the prey's escape energy. The routes and speeds of every car within the issue space are started at random. The prey's starting power is set using the following Equation (13).

$$IE_{energy} = 2 * rand() - 1 \quad (13)$$

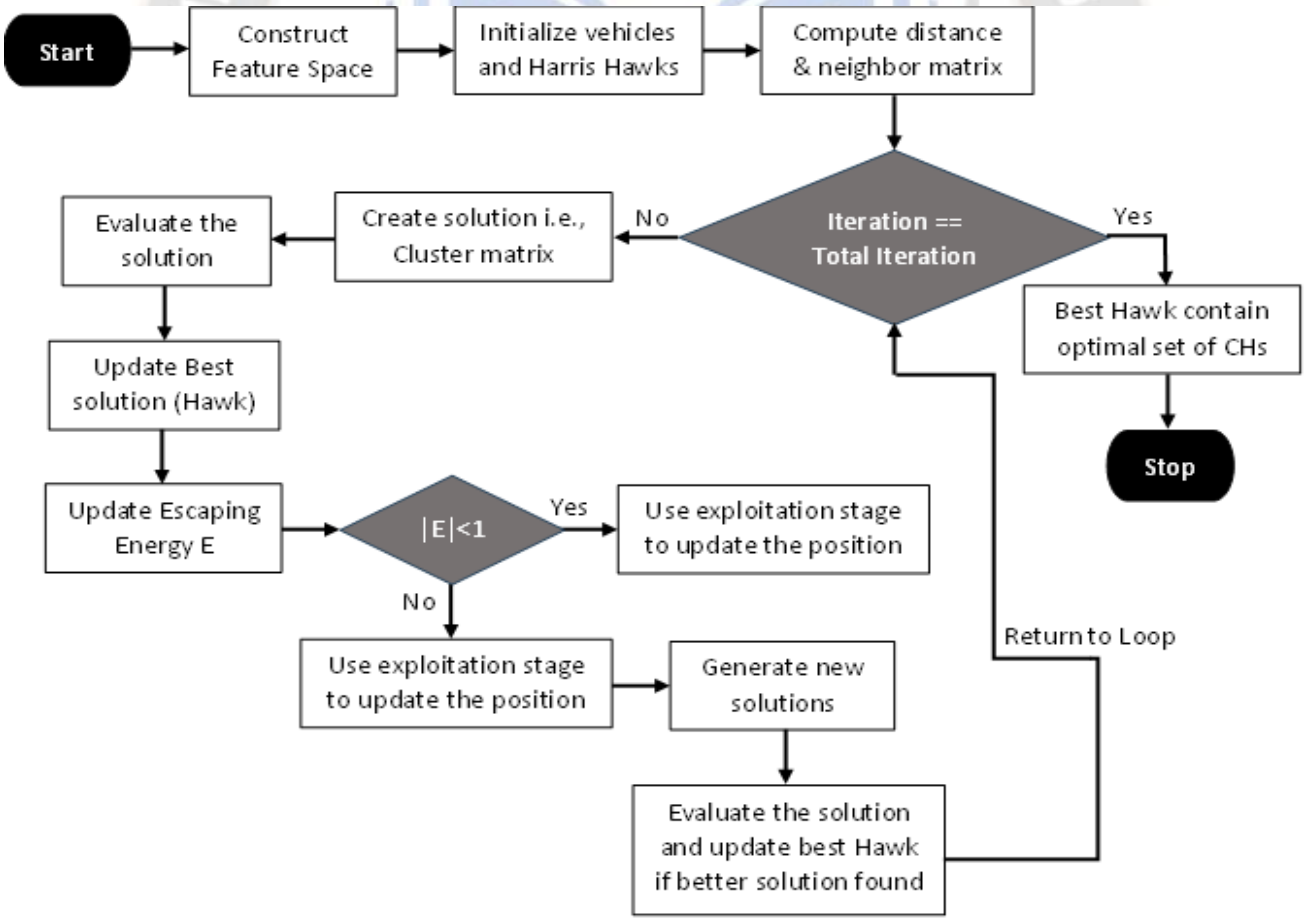


Figure 4. Flowchart of XMARL with IHO

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ISSN: 2321-8169 Volume: 14 Issue: 3
Article Received: *25 September 2026* ***Revised:*** *12 October 2026* ***Accepted:*** *10 November 2026*

The proposed XMARL architecture incorporates IHO to enhance agent choice approaches and adjust hyperparameter settings in dynamic VANET settings shown in Figure 4. With adaptable frequency updating and mutation techniques to prevent early convergence and local minima, IHO emulates the cooperation and surprising pounce hunt style of hawks.

Step 1: Initial Population Generation: Let each hawk represent a solution vector

$I_x = [\alpha, \gamma, \epsilon, \tau]$ where τ is a traffic signal parameter.

$$I_x^0 = rand(lb, ub) \quad (14)$$

Where rand generates a random solution between lower bound Ib and upper bound ub.

Step 2: Fitness Function (Multi-Objective): Define the fitness $f(I_x)$ as a combination of:

Traffic delay D; Packet delivery ratio PDR; Trust score T; Fuel efficiency F

$$f(I_x) = w_1.\frac{1}{D} + w_2.PDR + w_3.T + w_4.F \quad (15)$$

Where $w_1 + w_2 + w_3 + w_4 = 1$

Step 3: Exploration Phase: Hawks explore using Lévy flight and adaptive position updates:

$$X_x^{t+1} = X_x^t + r_1.(X_{best}^t - r_2.X_x^t) \quad (16)$$

Where; r_1, r_2: random numbers in [0, 1]; X_{best}: best solution so far

Step 4: Exploitation Phase (Soft besiege / hard besiege with escape energy E) Escape energy:

$$E = 2E_0\left(1 - \frac{t}{T}\right) \quad (17)$$

$Where, E_0$: initial escape energy ([-1, 1]); T: maximum iterations

Update rules: If $|E| \geq 1 \rightarrow exploration$; If $|E| < 1 \rightarrow exploitation$

Soft besiege: $I_x^{t+1} = \Delta I^t - E.|Y.I_{best}^t - I_x^t|$ (18)

Hard besiege: $I_x^{t+1} = I_{best}^t - E.|I_{best}^t - I_x^t|$ (19)

Where Y is a random jump strength.

Step 5: Mutation Operator (Improved part): To escape local optima, we apply Gaussian mutation: $I_x^{t+1} = I_x^{t+1} + N(0, \sigma^2)$ (20)

Where $N(0, \sigma^2)$ is Gaussian noise with mean 0 and variance σ^2

Step 6: Selection and Termination: Choose best I_x^t with maximum fitness

Stop if convergence or max iterations reached

4.5 Blockchain-based Security Layer

It is integrated into the proposed VANET-enabled smart traffic management architecture to ensure secure, immutable, and transparent communication. Each vehicle and RSU operates as a node within an encrypted blockchain network, where permanent blocks are used to log activities such as signal changes, vehicle status updates, and trust evaluations. A lightweight consensus mechanism, such as Practical Byzantine Fault Tolerance (PBFT) is employed to validate transactions in low-latency environments. By leveraging the decentralized nature of blockchain, the system eliminates single points of failure, resists spoofing and Sybil attacks, and preserves data confidentiality even under highly dynamic traffic conditions. Smart contracts are utilized to enforce rules automatically and isolate malicious nodes based on historical trust scores. By maintaining an auditable log of decisions made XMARL agents, the blockchain layer significantly strengthens the transparency and trustworthiness of the XAI component in real-time traffic control. To further safeguard communication, digital signatures authenticate messages, protecting against tampering and impersonation. This decentralized architecture eliminates single points of failure and provides a transparent audit trail of decisions made by XMARL agents. Overall, it enables secure, trustworthy, and efficient traffic management in dynamic urban scenarios.

Step 1: Block Structure: Each block in the blockchain contains: Vehicle ID (VID); Timestamp T; Encrypted message payload M; Trust value TV; Previous block hash H_{prev}; Existing block hash H_{curr}; $Block_x = \{VID_x, T_x, M_x, TV_x, H_{prev}, H_{curr}\}$ (21)

Step 2: Hash Generation (SHA-256): To ensure data immutability, each block's hash is generated using a secure hash function: $H_{curr} = SHA256(VID_x || T_x || M_x, ||TV_x||H_{prev})$ (22)

This hash ensures that even a minor change in any field will lead to a completely different hash, preventing tampering.

Step 3: Trust Evaluation Function: A trust score is computed for each node based on its past communication reliability and behavior: $TV_x = \alpha.\frac{P_{valid}}{P_{total}} + \beta.\frac{1}{RTT}$ (23)

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Where: P_{valid}: Number of valid packets sent; P_{total}: Total packets sent; RTT: Round trip time; α, β: Weight coefficients ($\alpha + \beta = 1$)

Step 4: Consensus Mechanism (PBFT): To add a block, consensus among trusted validator nodes is reached: $Consensus_{final} = Majority\ (V_1, V_2, \ldots, V_n)$ (24)

Where $V_x \in \{0,1\}$, and 1 means the validator node agrees to add the block. At least $\frac{2n}{3} + 1$ validators must agree to reach consensus in PBFT.

Step 5: Smart Contract for Malicious Node Detection: Smart contracts execute predefined conditions: IF $TV_x < \theta \rightarrow Node_x \in$ Blacklist (25)

Where θ is the minimum trust threshold. Malicious nodes are excluded from communication and decision-making processes.

Step 6: Digital Signature for Message Authentication: Each message is signed with the sender's private key: $Sig = Encrypt_{prK}(H(M))$ (26)

To verify: $H(M) \stackrel{?}{=} Decrypt_{PuK}(Sig)$ (27)

Ensuring that the message originates from a trusted source and hasn't been altered. The blockchain-based security layer enhances data integrity, transparency, and trust in VANET-enabled smart cities.

Algorithm

Input: Traffic environment E (real/simulated via SUMO & OMNET++); Set of vehicles $V = \{v_1, v_2, \ldots, v_n\}$; Action set A; State set S; Blockchain ledger B; Max episodes N, Max steps T

Output: Optimized policy π^*; Secure and explainable traffic decisions

Step 1: Initialize MARL Environment: For each agent $x \in V$, initialize: State $s_x \in S$; Policy $\pi_x(a|s)$;Q-table or neural network $Q_x(s, a)$

Step 2: Generate Initial Population for IHO: Initialize a population of hawks

$I = \{i_1, i_2, \ldots, i_m\}$ (28)

Each, represents parameters (eg, learning rate α, discount factory γ, exploration rate ϵ)

Step 3: For Each Episode (1 to N)

1. For each time step t = 1 to T:

a. Observe Existing State s_t

b. Select Action using policy: $a_t = \arg\max_a Q(s_t, a) + \epsilon$ (29)

c. Execute Action and Receive Reward: $(s_{t+1}, r_t) = E(s_t, r_t)$ (30)

d. Update Q-values: $Q(s_t, a_t) \leftarrow Q(s_t, a_t) + \alpha \left[r_t + \gamma \max_{a'} Q(s_{t+1}, a') - Q(s_t, a_t)\right]$ (31)

e. Log data in Blockchain: $B \leftarrow B \cup \{VID, a_t, r_t, s_t, timestamp, TV_t\}$ (32)

f. Evaluate Trust Score: $TV_x = \alpha . \frac{P_{valid}}{P_{total}} + \beta . \frac{1}{RTT}$ (33)

g. Run Smart Contract:

If $TV_x < \theta$ blacklist node.

Step 4: Apply Improved Hawk Optimization (IHO)

1. Evaluate Fitness: Each hawk's fitness is evaluated based on cumulative reward and latency:

$F(i_x) = w_1 . AvgReward - w_2 . AvgLatency$ (34)

2. Update Position (Optimization): If E < 1 (soft besiege), update position

$i_x^{t+1} = i_{best}^t - E . |Y . i_{best}^t - i_x^t|$ (35)

Else (hard besiege), simulate surprise pounce: $i_x^{t+1} = i_{prey} - E . sign(i_{prey} - i_x) . D$ (36)

3. Update Learning Parameters α, β, ϵusing best i_x

Step 5: Explainability Module: Use SHAP or LIME to interpret decision a_t by agent x at time t: $Explanation(a_t) - SHAP(s_t, a_t)$ (37)

Store explanations in the blockchain for audit: $B \leftarrow B \cup \{Explanation(a_t), VID_x\}$ (38)

Step 6: Repeat Until Convergence: Repeat Steps 3-5 for all episodes until policy π^* converges.

The proposed algorithm integrates XMARL with IHO to enhance intelligent traffic management in VANET-enabled smart cities. Each vehicle agent learns optimal routing and signal control policies through environment interaction, while IHO fine-tunes learning parameters like learning rate and exploration factor to accelerate convergence and improve decision accuracy. A blockchain layer ensures secure, tamper-proof storage of agent actions, rewards, and trust values. Trust scores help identify malicious agents, and smart contracts enforce secure participation. Explainability tools provide insights

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into agent decisions, ensuring transparency and accountability within the learning-based traffic control framework.

5 Results and Discussions

The proposed architecture is evaluated using simulated and real traffic conditions via SUMO, OMNeT++ with Veins, and XMARL with IHO optimization. TAPASCologne and NGSIM datasets validate performance. Hyperledger Fabric ensures secure logging. Key metrics assessed include trip time, packet ratio, reliability, and model explainability in urban scenarios.

Table 3: Hyperparameter Setting

Parameter	Value
Learning Rate (α)	0.01 – 0.1 (IHO-optimized)
Discount Factor (γ)	0.90
Exploration Rate (ε)	1.0 → 0.05 (decay)
Number of Agents	50 – 200
Episodes	1000
Max Steps per Episode	500
IHO Population Size	30
IHO Max Iterations	50
Blockchain Consensus Type	PBFT
SHAP Sample Size	500
Simulation Area	3 km × 3 km
Communication Range	300 meters

The proposed architecture's safety and efficiency rely on key hyperparameters shown in Table 3. The learning rate (α), dynamically optimized via IHO ranges from 0.01 to 0.1, balancing convergence and speed. A discount factor (γ) of 0.90 prioritizes long-term rewards, while the exploration rate (ε) decays gradually. Agent numbers vary from 50 to 200, simulating diverse traffic loads over 1000 sessions with 500 steps each. IHO uses 30 agents over 50 iterations for tuning. SHAP explains 500 samples, and PBFT ensures secure blockchain consensus. The simulation covers a 3 km² urban zone with 300 m communication range, replicating realistic VANET conditions.

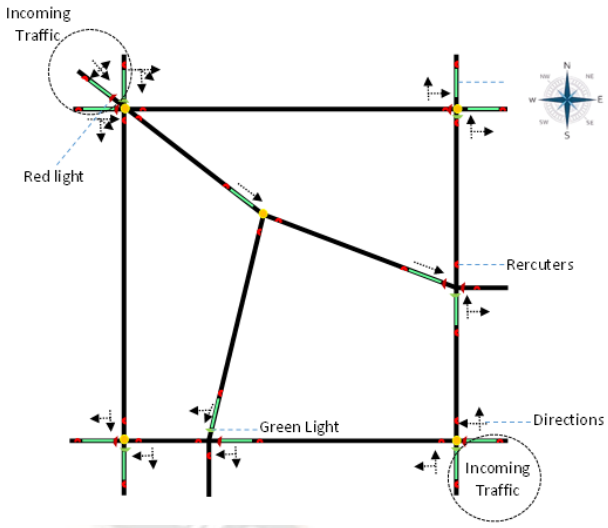


Figure 5: Road network used for experiments featuring seven intersections

Traffic flow models are developed for specific scenarios to observe and manage traffic behaviour. For simulations, utilized the road network illustrated in Figure 5. Detectors and re-routers were placed on each road segment to redirect vehicles as needed. Green lines represent active traffic lights, red lines indicate stops, cyan lines show detector placements, and yellow rectangles with red outlines mark re-router locations along the highways. Each road consists of eight lanes four for incoming and four for outgoing traffic. Featuring varying lengths, multiple junctions, and diverse layouts to reflect real-world complexity. While earlier sections used single-junction roads, this section adopts a multi-junction network to accommodate the requirements of XMARL experiments.

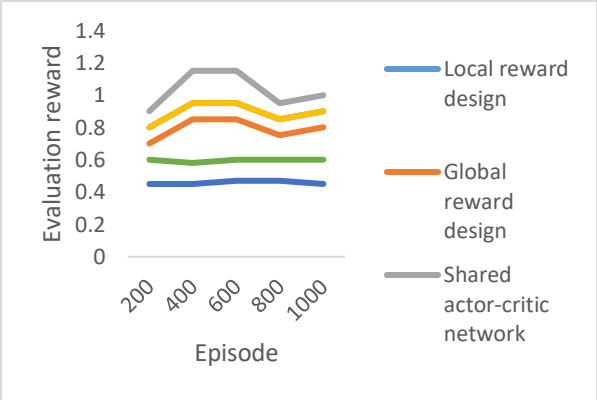


Figure 6: Evaluation of Local and Global Reward Strategies, Actor-Critic Network Architectures (Shared vs. Independent), and Assessment of Driving Comfort

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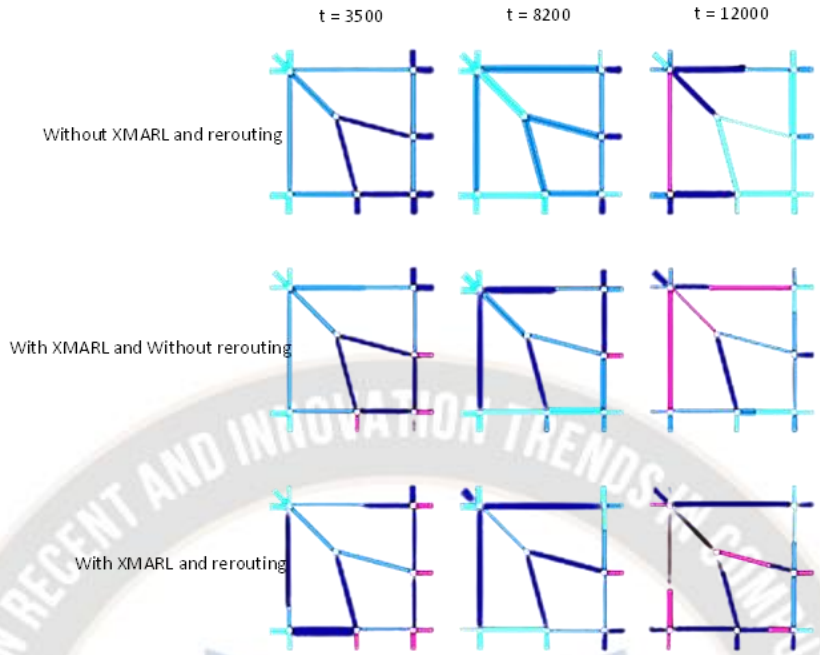


Figure 7: Improved traffic flow in congestion model situation by proposed and existing systems

The existing research expands on the evaluation of reward mechanisms and parameter-sharing strategies within an environmentally sustainable smart city framework. As illustrated in Figure 6, the results demonstrate that a local reward scheme outperforms a global reward system. It minimizes each vehicle's environmental footprint and encourages smoother acceleration and deceleration patterns leading to a more comfortable driving experience. The reduced variability in the comfort metric further confirms the reward design's ability to foster consistent and sustainable driving behaviour. Figure 7 illustrates the improvement in traffic conditions after congestion was addressed using road network model. Each row represents a traffic scenario using line segments, where colors indicate the degree of congestion based on total line length. Specifically, grey, green, yellow, orange, and red represent congestion levels of 0%, 25%, 50%, 70%, and 90%, respectively. Intermediary traffic conditions are depicted using gradient colors, and the line width thicker lines indicating longer delays represents the duration of vehicle stoppage at intersections.

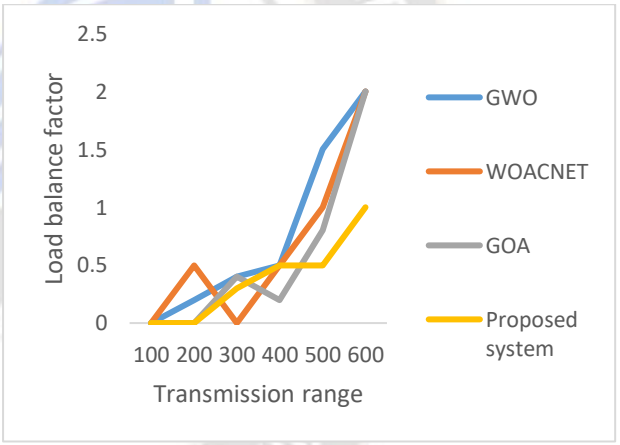


Figure 7: Load balancing factor for 30 nodes within a 1 km x 1 km grid size

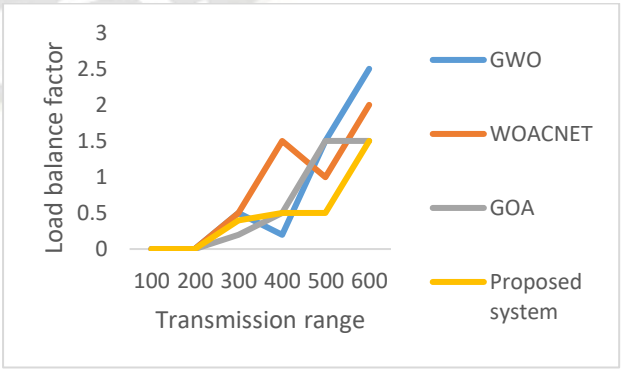


Figure 8: Load balancing factor for 60 nodes within a 1 km x 1 km grid size

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ISSN: 2321-8169 Volume: 14 Issue: 3
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By comparing the proposed technique with an existing method, the load balancing component is used to validate the findings. Proposed system outperforms other benchmark methods as shown in Figures 7 and 8 by successfully and efficiently balancing the number of vehicles (load) with each group head.

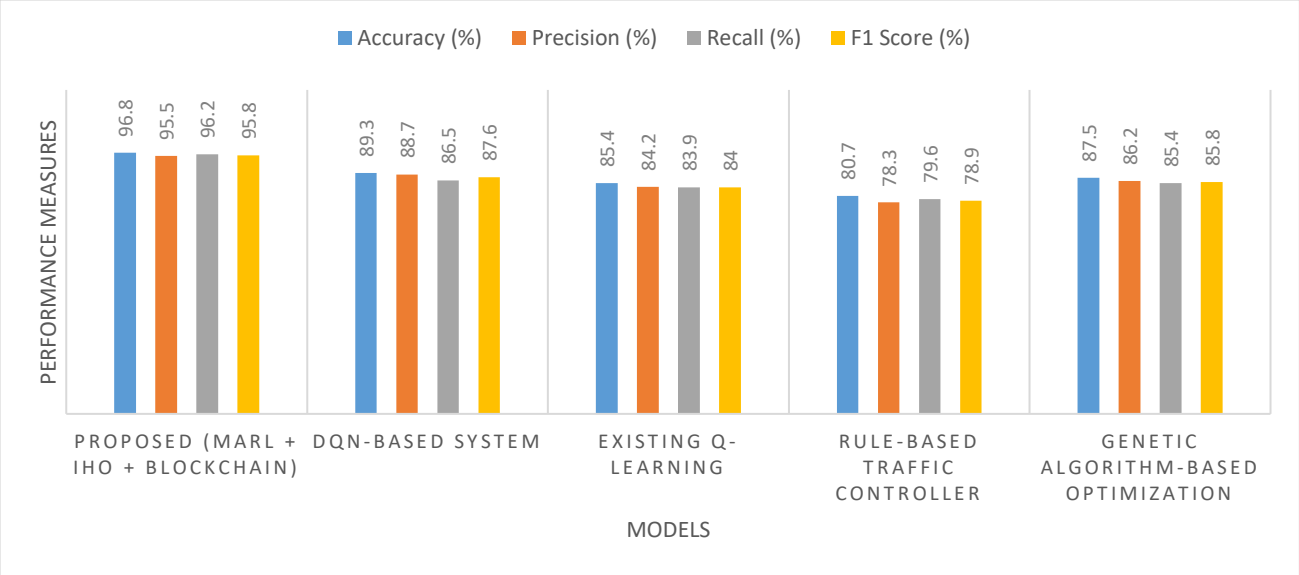


Figure 9: Comparison of Performance Measures

The comparative analysis of the proposed system against four existing traffic management methods demonstrates significant improvements across all key performance metrics. The proposed framework, integrating XMARL, IHO and a Blockchain-based security layer, achieves the highest accuracy of 96.8%, indicating superior overall prediction capability. It also records a precision of 95.5%, ensuring a high rate of correctly identified positive traffic control actions, and a recall of 96.2%, reflecting its effectiveness in capturing relevant instances shown in Figure 9. The enhancements brought by IHO fine-tuning and blockchain-integrated trust mechanisms enable the proposed model to learn faster, make more reliable decisions, and operate securely, establishing it as a robust solution for intelligent traffic management in VANET-enabled smart cities.

Table 4: Performance Measures

System	Throughput (Actions/s)	PDR (%)	Latency (ms)	Security (%)	Trustworthiness (%)
Proposed (MARL + IHO + Blockchain)	250	98.5	50	98.7	97.8
DQN-Based System	180	94.3	75	85.2	83.5
Conventional Q-Learning	160	92.1	85	80.0	75.4
Rule-Based Traffic Controller	120	88.5	120	70.3	72.8
Genetic Algorithm-Based Optimization	200	93.7	70	82.0	80.1

The proposed system demonstrates superior performance with a throughput of 250 actions per second, a 98.5% packet delivery ratio, and a low latency of 50 ms. Enhanced by blockchain, it achieves a security score of 98.7% and a trustworthiness of 97.8%, ensuring reliable and secure VANET communication shown in Table 4.

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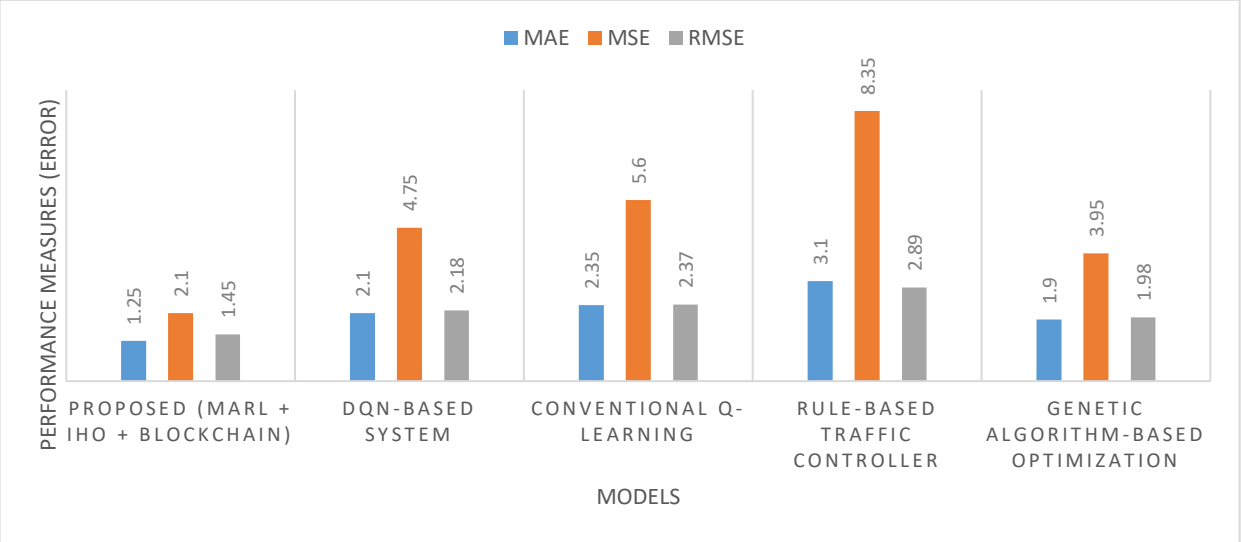


Figure 10: Comparison of Performance Measures (Error)

The proposed system achieves the lowest MAE (1.25), MSE (2.10), and RMSE (1.45), indicating highly accurate and consistent traffic control predictions shown in Figure 10. These results confirm that integrating XMARL, IHO and a Blockchain significantly enhances predictive accuracy and reliability in VANET-enabled smart city traffic systems.

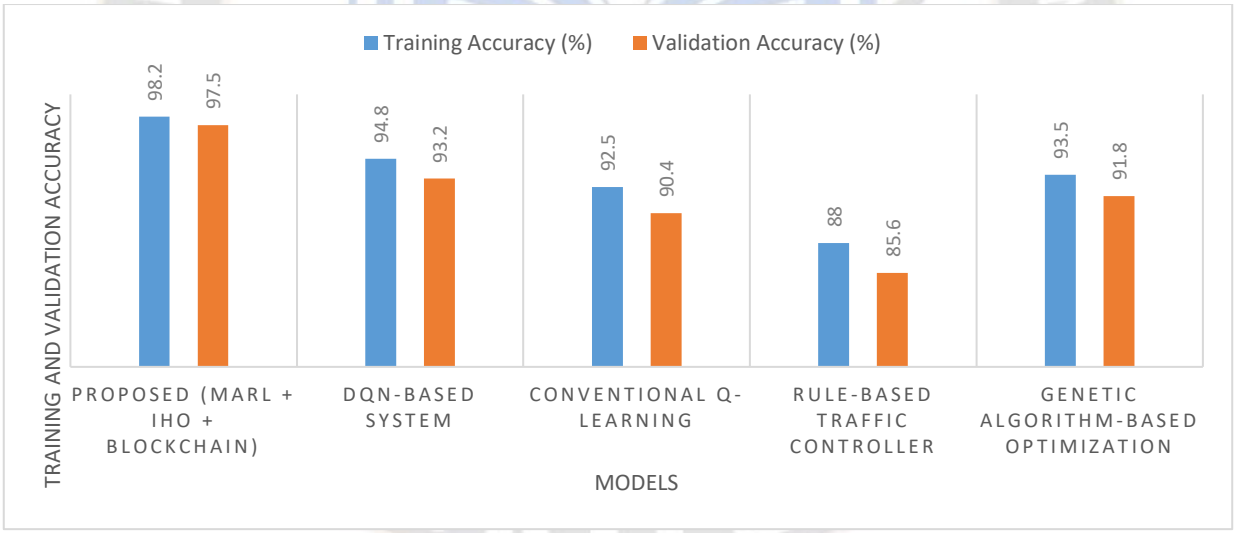


Figure 11: Comparison of training and validation accuracy

The comparison of training and validation accuracy clearly demonstrates the proposed framework's superiority. By integrating XMARL, IHO and a Blockchain based security layer, the model achieves the highest training accuracy of 98.2% and validation accuracy of 97.5%, reflecting excellent learning and generalization to unseen traffic scenarios shown in Figure 11. This notable performance gap underscores the effectiveness of combining MARL with advanced optimization and secure architectures for robust traffic management in VANET-enabled smart cities.

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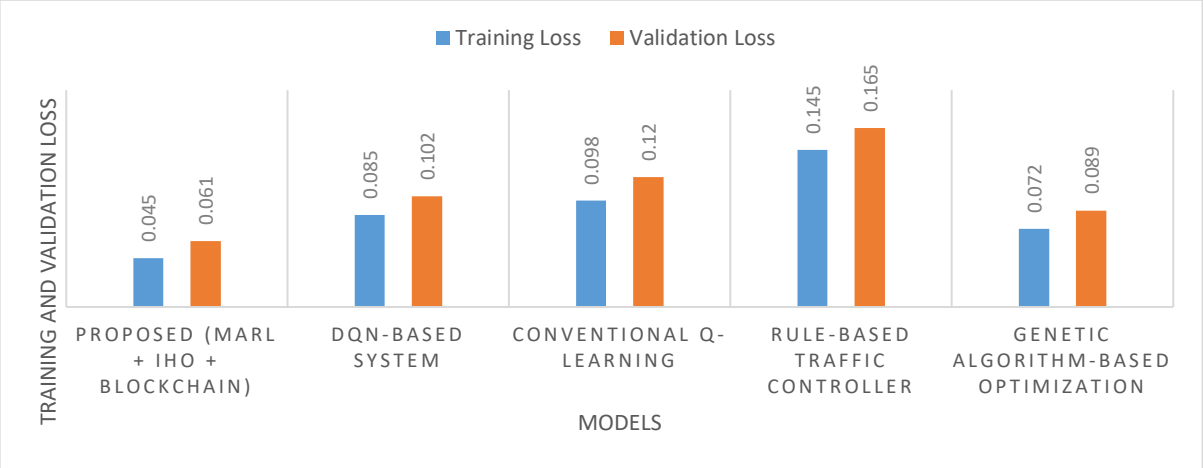


Figure 12: Comparison of training and validation loss

The proposed system integrating MARL, IHO, and Blockchain achieves the lowest training and validation losses of 0.045 and 0.061, respectively, indicating superior learning efficiency shown in Figure 12. In comparison, the Genetic Algorithm-based model records losses of 0.072 and 0.089, while DQN, Q-Learning, and Rule-Based systems exhibit significantly higher loss values.

6. Conclusions

In conclusion, this study presents a Secure and XMARL framework integrated with IHO and a Blockchain-based security layer for intelligent traffic management in VANET-enabled smart cities. The proposed system effectively addresses major challenges such as traffic congestion, communication delays, security threats, and lack of explainability in decision-making. Experimental results demonstrate that the proposed framework achieves a training accuracy of 98.2%, validation accuracy of 97.5%, and significantly lower MAE (1.25), MSE (2.10), and RMSE (1.45) compared to existing systems. It outperforms baselines in key performance metrics, including throughput, packet delivery ratio, latency, trustworthiness, and security. The inclusion of blockchain enhances data integrity and trust, while the explainable AI layer improves interpretability of agent actions. Overall, the framework proves to be a robust, scalable, and intelligent solution for managing dynamic urban traffic systems efficiently and securely.

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