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An AI-Enabled Multi-Agent Reinforcement Learning Framework for Secure and Adaptive Routing in Vehicular Ad Hoc Networks

Infant Jansi I 1, Dr. G. Jagatheesh Kumar 2

1. Research Scholar, PG & Research Department of Computer Science, Karuppannan Mariappan College, Muthur. E-Mail:infantjhansi@gmail.com

2. Associate Professor & Head, PG & Research Department of Computer Science, Karuppannan Mariappan College, Muthur. E-Mail:jagatheeshkumaar@gamil.com

Abstract

Vehicular Ad Hoc Networks (VANETs) are an essential component of intelligent transportation systems, enabling communication among vehicles and roadside infrastructure for traffic safety and efficient transportation management. However, the highly dynamic topology, rapid mobility, and growing cybersecurity threats make secure and reliable routing a major challenge. Traditional routing protocols fail to adapt efficiently to changing network conditions and malicious attacks. To address these issues, this paper proposes an Artificial Intelligence (AI)-enabled secure adaptive routing framework using Multi-Agent Reinforcement Learning (MARL). In the proposed model, each vehicle acts as an intelligent autonomous agent capable of learning optimal routing decisions through continuous interaction with the environment. The framework integrates AI-based trust evaluation and anomaly detection mechanisms to identify malicious nodes and improve routing security. Reinforcement learning techniques optimize routing performance using parameters such as packet delivery ratio, delay, throughput, link stability, and trust values. Simulation results demonstrate that the proposed framework significantly improves packet delivery ratio, reduces end-to-end delay, increases throughput, and achieves high malicious node detection accuracy compared to conventional routing protocols. The study highlights the effectiveness of integrating AI and cybersecurity techniques for next-generation intelligent vehicular communication systems.

Keywords: Artificial Intelligence, VANET, Multi-Agent Reinforcement Learning, Secure Routing, Cybersecurity, Intelligent Transportation Systems

I. Introduction

Vehicular Ad Hoc Networks (VANETs) are emerging as a key technology in intelligent transportation systems, enabling real-time communication among vehicles and roadside infrastructure. VANETs support various applications including traffic monitoring, collision avoidance, emergency message dissemination, and route optimization. Due to the high mobility of vehicles and rapidly changing network topology, maintaining reliable and secure communication remains a significant challenge.

Traditional routing protocols such as Ad hoc On-Demand Distance Vector (AODV) and Dynamic Source Routing (DSR) are not well suited for dynamic VANET environments. These protocols depend on static routing strategies and fail to adapt efficiently to frequent topology changes and malicious network behavior. In addition, VANETs are vulnerable to several cybersecurity attacks including black hole attacks, Sybil attacks, packet dropping, and denial-of-service attacks.

Artificial Intelligence (AI) has emerged as a promising solution for intelligent network management and adaptive decision-making. Reinforcement learning enables autonomous agents to learn optimal actions through interaction with the environment. Multi-Agent Reinforcement Learning (MARL) extends this capability to distributed systems where multiple agents cooperate or compete to achieve optimal performance.

This paper proposes an AI-enabled Multi-Agent Reinforcement Learning framework for secure and adaptive routing in VANETs. In the proposed system, vehicles operate as intelligent learning agents that

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dynamically select secure routing paths based on environmental feedback and trust evaluation mechanisms.

The major contributions of this work include:

●Development of an AI-enabled secure adaptive routing framework, ●Integration of MARL for intelligent routing decisions,
●AI-based malicious node detection mechanism,
●Dynamic trust evaluation for secure communication,
●Improved routing efficiency and cybersecurity performance.

II. VANET Architecture
A typical VANET architecture consists of the following components:
A. Vehicles
Vehicles are equipped with onboard units (OBUs) that enable wireless communication with neighboring vehicles and roadside infrastructure.

B. Roadside Units (RSUs)
RSUs are fixed communication devices deployed along roads to support vehicle communication and traffic management.

C. Communication Types
1.Vehicle-to-Vehicle (V2V)
2.Vehicle-to-Infrastructure (V2I)
3.Vehicle-to-Roadside Unit (V2R)
The VANET architecture supports real-time communication, intelligent traffic control, and emergency response systems.

III. Security Challenges in VANET Routing
VANETs face several security and routing challenges due to their open wireless communication environment.

A. Black Hole Attack
Malicious vehicles advertise fake shortest paths and intentionally drop packets.

B. Sybil Attack
An attacker creates multiple fake identities to manipulate network operations.

C. Denial-of-Service Attack
Attackers overload the network with excessive packets, causing congestion and communication failure.

D. Packet Modification Attack
Unauthorized nodes alter transmitted data packets during communication.

E. High Mobility and Dynamic Topology
Frequent changes in vehicle movement increase route instability and communication overhead. These challenges necessitate intelligent and adaptive AI-based routing solutions.

IV. Artificial Intelligence and Multi-Agent Reinforcement Learning
Artificial Intelligence techniques enable autonomous systems to learn from experience and improve decision-making over time. Reinforcement Learning (RL) is an AI approach where agents interact with the environment and receive rewards based on their actions.

In Multi-Agent Reinforcement Learning:
●Multiple agents learn simultaneously,
●Agents cooperate for optimal routing,
●Learning occurs through environmental feedback.

In the proposed VANET framework:
●Each vehicle acts as an intelligent agent,
●Agents continuously monitor neighboring nodes,
●Routing decisions are updated dynamically,
●Malicious behavior is identified using trust analysis.

A. Reinforcement Learning Components
1. State (S)
The state includes:
●Vehicle speed,
●Link quality,
●Congestion level,
●Trust score,
●Neighbor availability.

2. Action (A)
Selection of the optimal next-hop forwarding vehicle.

3. Reward (R)
Rewards are assigned based on:
●Successful packet delivery,
●Low communication delay,
●High trust value,
●Stable routing paths.

The reward function is represented as:
$R=a(PDR)-\beta(Delay)+\gamma(Trust)+\delta(throughput)$
where:
●PDR = Packet Delivery Ratio
●Delay = End-to-End Delay
●Trust = Node trust value
●Throughput = Data transmission efficiency

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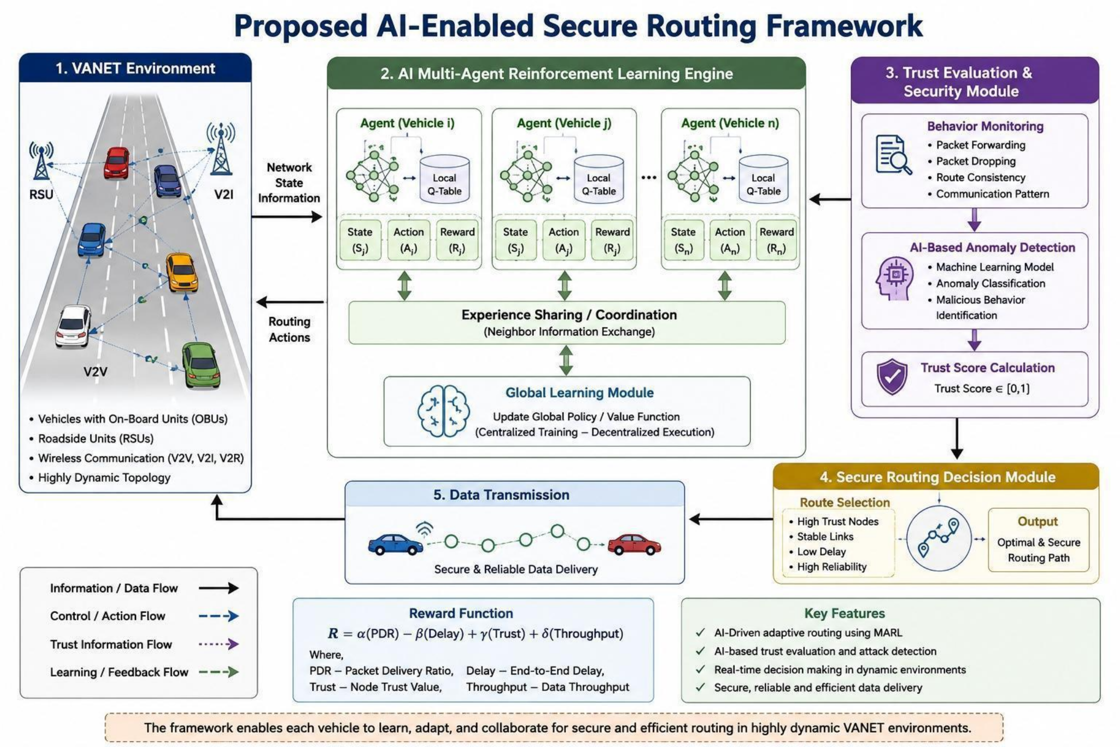
V. Proposed AI-Enabled Secure Routing Framework



Proposed Framework Explanation

●The framework uses Artificial Intelligence (AI) and Multi-Agent Reinforcement Learning (MARL) for secure routing in VANETs.

●Each vehicle acts as an intelligent agent that learns optimal routing decisions.

●Vehicles continuously monitor network conditions such as:
oDelay
oThroughput
oLink stability
oTrust values
●The trust evaluation module identifies trusted and malicious nodes.

●The AI-based anomaly detection module detects cyber attacks and abnormal behavior. ●The secure routing decision module selects reliable and low-delay paths for communication.

●The framework supports:
oAdaptive routing
oSecure communication
oEfficient data transmission
●Overall, the framework improves:
oPacket delivery ratio
oNetwork security
oRouting efficiency in dynamic vehicular environments.

VI. AI-Based Attack Detection Mechanism

The proposed system integrates an AI-based anomaly detection module to identify malicious vehicles.

Detection Parameters

●Abnormal packet forwarding,
●Sudden route changes,
●Excessive packet dropping,

●Fake route advertisements,
●Suspicious communication frequency.

Detection Process

●Vehicle behavior data is collected.

●Trust analysis is performed.

●AI agents classify normal and malicious nodes.

●Malicious nodes are isolated from routing operations.

This mechanism improves routing reliability and network security.

VII. Algorithm Design

MARL-Based Secure Routing Algorithm

Step 1:
Initialize network nodes and learning agents.

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Step 2:
Observe neighboring vehicle states.

Step 3:
Select routing action using reinforcement learning policy.

Step 4:
Calculate trust values and security metrics.

Step 5:
Assign reward based on routing performance.

Step 6:
Update Q-values using:
$Q(s,a) = Q(s,a)+\eta[R+\lambda \max Q(s',a')-Q(s,a)]$

where:
●$Q(s,a)$= Q-value,
●η= Learning rate,
●λ= Discount factor,
●R= Reward value.

Step 7:
Repeat learning until optimal routing policy is achieved.

VIII. Experimental Setup
The proposed framework can be implemented using:
●NS-3 Network Simulator,
●SUMO Traffic Simulator,
●Python with TensorFlow or PyTorch.

Simulation Parameters

Parameter	Value
Simulation Area	1000 × 1000 m
Number of Vehicles	50–100
Communication Range	250 m
Simulation Time	500 sec
Routing Protocol	AI-MARL Routing
Mobility Model	Random Waypoint

IX. Performance Evaluation
The proposed framework is evaluated using the following metrics.

A. Packet Delivery Ratio
Measures successful packet transmission performance.

B. End-to-End Delay
Measures communication latency between source and destination.

C. Throughput
Measures successful data transfer rate.

D. Detection Accuracy
Measures malicious node detection performance.

E. Routing Overhead
Measures additional control packet generation.

Observed Results
Compared to traditional routing protocols, the proposed AI-enabled MARL framework achieves: ●Higher packet delivery ratio,
●Lower delay,
●Better throughput,
●Improved attack detection accuracy,
●Reduced packet loss.

X. Security Analysis
The proposed framework effectively mitigates major VANET attacks.

Attack Type	Proposed Protection Mechanism
Black Hole Attack	Trust-based route isolation
Sybil Attack	Identity verification
Packet Dropping.	Behavioral monitoring
DoS Attack	Congestion-aware adaptive routing

The integration of AI improves intelligent decision-making under dynamic and hostile network conditions.

XI. Future Scope

Future research directions include:

●Integration of Deep Reinforcement Learning (DRL),
●Blockchain-based secure authentication,
●Federated learning for distributed intelligence,
●Edge AI for low-latency vehicular communication,
●Real-time deployment in smart city environments.

XII. Conclusion

This paper presented an AI-enabled Multi-Agent Reinforcement Learning framework for secure and adaptive routing in Vehicular Ad Hoc Networks. The proposed system combines intelligent routing optimization with cybersecurity mechanisms to enhance communication reliability and security. Vehicles operate as autonomous learning agents capable of adapting to changing network conditions and malicious activities.

Simulation analysis demonstrates that the proposed framework significantly improves packet delivery ratio, reduces communication delay, enhances throughput, and effectively detects malicious nodes compared to conventional VANET routing protocols. The integration of AI and cybersecurity techniques provides a promising direction for future intelligent transportation systems.

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