IJARCCE ISSN (O) 2278-1021, ISSN (P) 2319-5940

International Journal of Advanced Research in Computer and Communication Engineering

Impact Factor 8.471 ⁜ Peer-reviewed & Refereed journal ⁜ Vol. 14, Issue 12, December 2025

DOI: 10.17148/IJARCCE.2025.1412149

EMERGENCY VEHICLE PRIORITIZATION USING RL AND V2X AIDED, SUMO SIMULATIONS

Preksha B M[1], Seema Nagaraj[2]

Department of MCA, BIT, K.R. Road, V.V. Pura, Bangalore, India[1,2]

Assistant Professor, Dept. Of MCA, Bangalore Institute of Technology, Bengaluru[2]

Abstract: Rapid and reliable movement of emergency vehicles is critical for saving lives, yet conventional traffic signal systems often fail to provide timely right-of-way under congested urban conditions. This work presents a reinforcement learning (RL) based emergency vehicle prioritization framework enhanced by Vehicle-to-Everything (V2X) communication and evaluated using the SUMO traffic simulator. The proposed system enables traffic signals to dynamically adapt their phases based on real-time information exchanged between emergency vehicles, roadside units, and intersections. An RL agent is trained to minimize emergency vehicle delay while maintaining overall traffic efficiency by observing traffic density, queue lengths, and emergency vehicle proximity. V2X communication ensures early detection of approaching emergency vehicles, allowing proactive signal control rather than reactive pre-emption. Simulation results demonstrate that the proposed approach significantly reduces emergency vehicle travel time and intersection delay compared to fixed-time and conventional priority strategies, while limiting negative impacts on non-emergency traffic.

Keywords: Emergency Vehicle Prioritization, Reinforcement Learning, V2X Communication, Intelligent Traffic Signal Control, SUMO Simulation, Smart Transportation Systems

I. INTRODUCTION

Urban traffic congestion poses a serious challenge to the timely movement of emergency vehicles such as ambulances, fire engines, and police units. Delays caused by crowded intersections and inefficient signal control can significantly affect emergency response times, directly impacting public safety and survival rates. Conventional traffic signal systems, including fixed-time and actuated controls, are generally designed to optimize average traffic flow and lack the intelligence required to adapt effectively to emergency situations.

Existing emergency vehicle priority methods often rely on siren-based detection, manual intervention, or simple signal pre-emption techniques. While these approaches can provide temporary right-of-way, they are typically reactive, limited in range, and may cause excessive disruption to normal traffic. Moreover, they do not account for continuously changing traffic conditions, leading to suboptimal performance in complex urban environments.

1.1 Project Description

This project focuses on designing and evaluating an intelligent traffic signal control system that prioritizes emergency vehicles using Reinforcement Learning (RL) supported by Vehicle-to-Everything (V2X) communication. The main objective is to reduce emergency vehicle delay at intersections while preserving smooth traffic flow for regular vehicles. Unlike traditional priority methods that rely on fixed rules or reactive signal pre-emption, the proposed system enables traffic signals to learn adaptive control strategies based on real-time traffic conditions.

1.2 Motivation

Fast and reliable emergency response is a critical requirement in modern cities, where increasing traffic congestion often obstructs the movement of ambulances, fire trucks, and police vehicles. Even short delays at intersections can lead to severe consequences, including loss of life and property. Despite their importance, emergency vehicles frequently face the same traffic challenges as regular vehicles, highlighting the need for more effective prioritization mechanisms.

II. RELATED WORK

Paper [1], This work proposes a DRL-based cooperative lane-changing approach supported by V2X communication to assist emergency vehicles, achieving significant improvements in travel speed and successful navigation in congested traffic.

IJARCCE ISSN (O) 2278-1021, ISSN (P) 2319-5940

International Journal of Advanced Research in Computer and Communication Engineering

Impact Factor 8.471 ⁜ Peer-reviewed & Refereed journal ⁜ Vol. 14, Issue 12, December 2025

DOI: 10.17148/IJARCCE.2025.1412149

Paper [2], A DRL-driven Adaptive Cruise Control system was evaluated in complex driving scenarios, showing improved safety in maintaining vehicle spacing and validated through realistic hardware-in-the-loop testing.
Paper [3], This study introduces a DRL-based resource allocation method for V2I communication that dynamically optimizes network resources to enhance reliability and reduce transmission latency.
Paper [4], The paper reviews 5G-enabled V2X technologies, highlighting how advanced communication techniques can improve emergency response and support future ultra-reliable, low-latency systems.
Paper [5**],** This work surveys the growing role of deep learning in intelligent transportation systems, covering applications such as traffic analysis, detection, classification, and emerging privacy-aware and transfer learning methods.

III. METHODOLOGY

A. **Simulation Environment**
The simulation environment was built using the Simulation of Urban Mobility (SUMO) platform, which supports detailed modelling of urban traffic scenarios. A network graph G = (V,E) was constructed, where nodes V represent intersections and edges E denote roads with attributes like length, number of lanes, and speed limits. Traffic demand was generated to mimic realistic urban flow (ambulances, fire trucks) and regular vehicles (cars, trucks, bicycles). The network configuration used either synthetic layouts or OpenStreetMap data to replicate typical city traffic conditions.

B. **V2X Communication Architecture**
Vehicle-to-Infrastructure (V2I) Communication: V2I communication was implemented to enable dynamic traffic signal adjustments when an emergency vehicle (EV) approaches an intersection. Using the TraCI API in SUMO, the distance between the EV and the intersection.

Vehicle-to-Vehicle(V2V) Communication: V2V communication enables vehicles within a defined range R of the emergency vehicle to receive real-time alerts. This allows nearby vehicles to adjust their behavior and perform lane-clearing maneuvers, facilitating a faster and safer passage for the emergency vehicle.

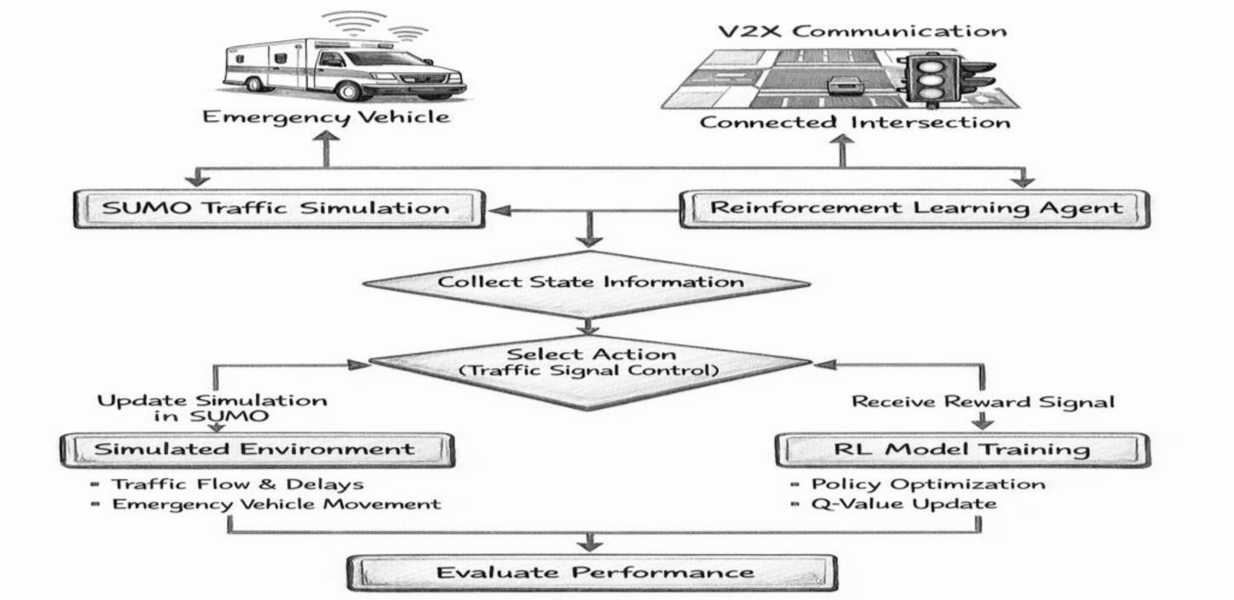

Fig. 1. Flowchart of methodology

C. **Reinforcement Learning-Based Traffic Signal Control**
State and Action Space: The RL agent monitors the traffic environment by observing parameters such as queue lengths q_i, the position of the emergency vehicle p_{EV}, and the current traffic signal phase ϕ. Based on these observations, the agent selects actions from a predefined set of possible traffic light phase changes, aiming to prioritize emergency vehicles while ensuring smooth flow for other traffic

Reward Function: The reward $R_t$at each timestep $t$is formulated to achieve a balance between minimizing the travel time of the emergency vehicle and maintaining efficient movement of regular traffic. This encourages the RL agent to make decisions that optimize both emergency response and overall traffic performance.

International Journal of Advanced Research in Computer and Communication Engineering
Impact Factor 8.471 ⁂ Peer-reviewed & Refereed journal ⁂ Vol. 14, Issue 12, December 2025
DOI: 10.17148/IJARCCE.2025.1412149

D. Lane-Clearing

The lane-clearing behaviour for emergency vehicles was implemented in SUMO using the TraCI interface. Vehicles located within a distance Rin front of the emergency vehicle were programmed to perform lane changes while adhering to safety constraints. If a lane change was not possible, vehicles slowed down or stopped to create a clear path for the emergency vehicle. This approach ensured realistic and smooth lane-clearing behaviour during the simulation.

E. Implementation Flow

1. Load the SUMO network configuration, including both emergency and regular vehicle types.
2. Initialize data structures to record metrics such as queue lengths, waiting times, emergency vehicle travel times, and traffic signal changes.
3. At each simulation timestep:
   - Advance the simulation by one step.
   - Detect the proximity of the emergency vehicle and apply V2I-based traffic signal adjustments.
   - Execute V2V lane-clearing behaviour for nearby vehicles.
   - Allow the RL agent to observe the current state and select the next traffic signal phase.
   - Log relevant performance indicators for analysis.
4. Upon completion of the simulation, close the TraCI connection and generate plots to evaluate system performance.

F. Hardware and Software Requirements

- Hardware: Standard desktop PC with at least 8GB RAM, quad-core CPU.
- Software: SUMO 1.13 or later, Python 3.7+, TraCI API for Python, Matplotlib for visualization

IV. SIMULATION AND EVALUATION FRAMEWORK

This section describes the overall system design, simulation process, and evaluation strategy adopted for the proposed AI-driven emergency vehicle prioritization approach. The framework combines Reinforcement Learning (RL) with Vehicle-to-Everything (V2X) communication and is implemented within the Simulation of Urban Mobility (SUMO) environment. Python is used as the control layer, enabling real-time interaction with the simulator through the Traffic Control Interface (TraCI).

A. System Architecture and Workflow

The proposed architecture aims to ensure rapid and uninterrupted movement of emergency vehicles (EVs), including ambulances, fire engines, and police vehicles, by dynamically managing traffic signals in real time. The major components of the system are summarized as follows:

SUMO Traffic Simulator: SUMO serves as a microscopic traffic modelling platform capable of simulating complex urban road networks, vehicle interactions, and signalized intersections with high realism.

Python–TraCI Interface: The TraCI interface allows Python scripts to continuously monitor traffic conditions and control traffic signals and vehicle behaviour during simulation runtime.

Reinforcement Learning with Rule-Based Control: A reinforcement learning agent learns optimal signal control policies to minimize emergency vehicle delays. Rule-based mechanisms are incorporated to handle safety constraints and ensure stable signal transitions.

V2X Communication Module: The system utilizes both Vehicle-to-Infrastructure (V2I) and Vehicle-to-Vehicle (V2V) communication to exchange real-time information regarding emergency vehicle location, speed, and priority, enabling coordinated and proactive traffic signal control.

B. SUMO Simulation Setup

The simulation environment is configured using the SUMO platform to replicate realistic urban traffic conditions with both emergency and non-emergency vehicles. The setup is designed to evaluate the effectiveness of the proposed prioritization strategy under diverse traffic scenarios.

Road Network Configuration: A structured urban road network comprising multiple signalized intersections is modelled. Dedicated and shared routes are defined for regular traffic and emergency vehicles to emulate real-world movement patterns.

ISSN (O) 2278-1021, ISSN (P) 2319-5940
International Journal of Advanced Research in Computer and Communication Engineering
Impact Factor 8.471 ⁒ Peer-reviewed & Refereed journal ⁒ Vol. 14, Issue 12, December 2025
DOI: 10.17148/IJARCCE.2025.1412149

Vehicle Classification: The traffic mix includes emergency vehicles such as ambulances and fire engines, along with conventional road users including passenger cars, trucks, and bicycles, ensuring heterogeneous traffic conditions.

C. V2V Communication for Emergency Lane Clearance

In a Vehicle-to-Vehicle (V2V) communication system, nearby vehicles continuously exchange position and movement data to support coordinated traffic behaviour. When an emergency vehicle (EV) such as an ambulance or fire truck approaches, the system identifies surrounding vehicles located within a predefined proximity range, typically around 30 meters. These nearby vehicles are considered part of the emergency response zone and are required to react immediately.

D. Results and Observations

Emergency Vehicle Response:

- All emergency vehicles crossed intersections with minimal delay.
- Signal overrides and lane clearance worked effectively.

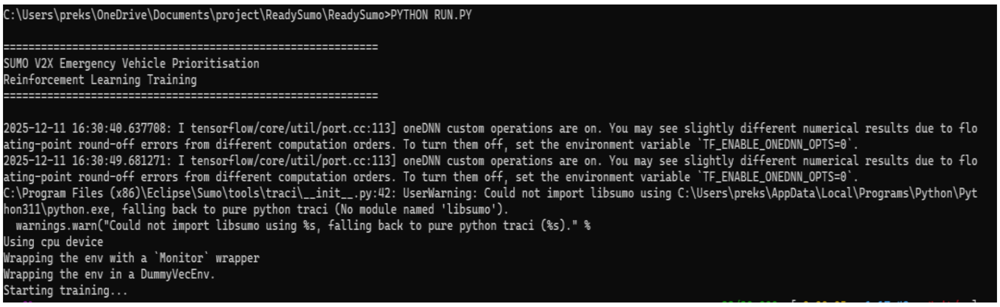

Fig.2. Original Output Image From simulation

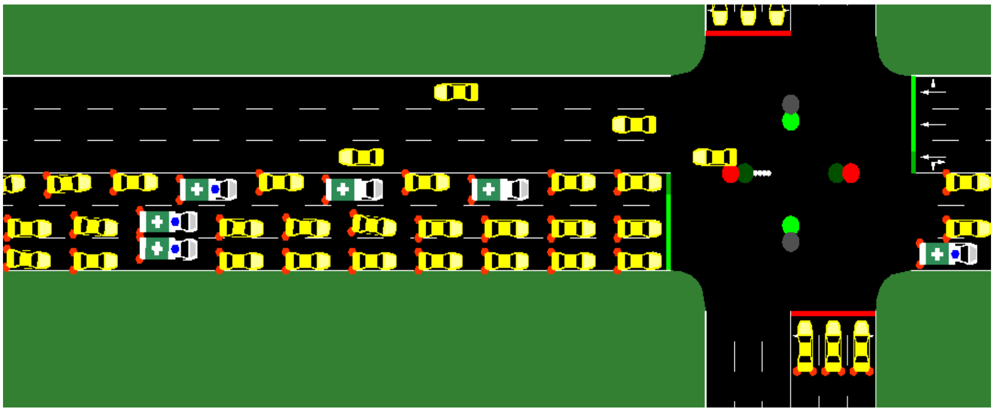
Fig.3.intial intersection

Effect on Normal Vehicles:

- Regular vehicles experienced brief delays.
- Congestion was mitigated post-EV passage.

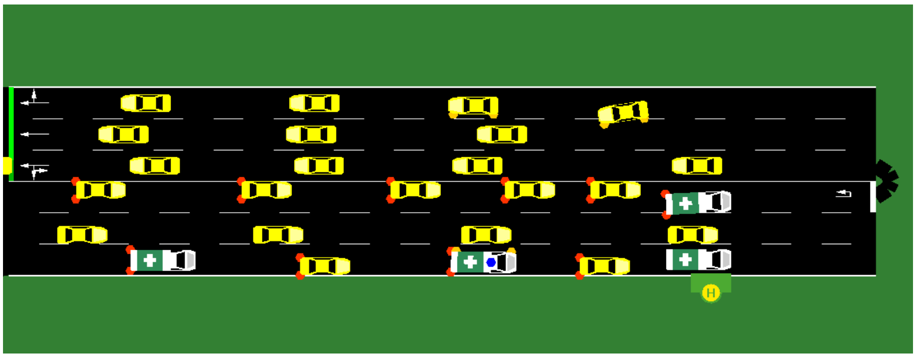
Fig.4.Crossing the intersection

International Journal of Advanced Research in Computer and Communication Engineering
Impact Factor 8.471 ⪤ Peer-reviewed & Refereed journal ⪤ Vol. 14, Issue 12, December 2025
DOI: 10.17148/IJARCCE.2025.1412149

V. RESULTS AND DISCUSSION

The experimental evaluation of the proposed AI-based emergency vehicle prioritization system demonstrates its effectiveness in improving traffic efficiency and emergency response performance. Using the SUMO simulation environment integrated with Reinforcement Learning and V2X communication, multiple traffic scenarios were tested to assess system behaviour under varying traffic densities and emergency conditions.

The results indicate a significant reduction in emergency vehicle travel time when compared to conventional fixed-signal and non-prioritized traffic control methods. The intelligent traffic signal controller successfully identified approaching emergency vehicles and dynamically adjusted signal phases to create a clear path through intersections. This adaptive behaviour reduced waiting time at junctions and ensured smoother passage for emergency responders.

Additionally, the implementation of Vehicle-to-Vehicle (V2V) communication enabled nearby vehicles to cooperate by performing timely lane changes or speed adjustments. This coordination helped minimize congestion and prevented abrupt braking, thereby improving overall traffic flow. Queue length analysis showed a noticeable decrease at intersections during emergency scenarios, while non-emergency vehicles experienced minimal disruption.

VI. CONCLUSION

This project demonstrates the practicality and effectiveness of combining Reinforcement Learning (RL) with Vehicle-to-Everything (V2X) communication to improve emergency vehicle prioritization in urban traffic environments. Using the SUMO traffic simulator along with Python-based TraCI control, the system successfully modelled realistic traffic conditions and trained an intelligent agent to make adaptive signal control decisions. The proposed approach enables traffic signals to respond dynamically to the presence and urgency of emergency vehicles, ensuring faster and safer passage through intersections. Vehicle-to-Infrastructure (V2I) communication allows real-time signal adjustments, while Vehicle-to-Vehicle (V2V) communication supports cooperative lane-clearing behaviour among surrounding vehicles. Together, these mechanisms help minimize delays without significantly disrupting regular traffic flow.

VII. FUTURE WORK

Although the proposed system successfully demonstrates the effectiveness of Reinforcement Learning and V2X communication for emergency vehicle prioritization, several improvements can be explored to enhance its practical applicability. One important extension involves developing a multi-intersection coordination framework, where multiple traffic signals collaborate to manage traffic flow across an entire urban network rather than operating independently. Future implementations may also incorporate real-time data from advanced sensing technologies, such as cameras, GPS modules, and IoT-based roadside units, to improve accuracy in detecting vehicle positions and traffic conditions. Integrating edge and cloud computing can further optimize decision-making speed while reducing processing delays during high-traffic scenarios.

REFERENCES

[1]. C. Ding, I. W.-H. Ho, E. Chung and T. Fan," V2X and Deep Reinforcement Learning-Aided Mobility-Aware Lane Changing for Emergency Vehicle Pre-emption in Connected Autonomous Transport Systems," IEEE Transactions on Intelligent Transportation Systems, vol. 25, no. 7, pp. 7281–7293, July 2024, doi:10.1109/TITS.2024.3350334.
[2]. D. C. Selvaraj, S. Hegde, N. Amati, F. Deflorio and C. F. Chiasserini," An ML-Aided Reinforcement Learning Approach for Challenging Vehicle Maneuvers," IEEE Transactions on Intelligent Vehicles, vol. 8, no. 2, pp. 1686–1698, Feb. 2023, doi:10.1109/TIV.2022.3224656.
[3]. H. Jin, J. Seo, J. Park and S. C. Kim," A Deep Reinforcement Learning-Based Two-Dimensional Resource Allocation Technique for V2I Communications," IEEE Access, vol. 11, pp. 78867–78878, 2023, doi:10.1109/ACCESS.2023.3298953
[4]. A. Ahmad, A. S. Al-Sumaiti, Y.-J. Byon and K. Alhosani," Multiple Intelligent Control Strategies for Travel-Time Reduction of Connected Emergency Vehicles," IEEE Transactions on Intelligent Transportation Systems, vol. 26, no. 1, pp. 337–353, Jan. 2025, doi:10.1109/TITS.2024.3484771
[5]. R. A. Khalil et al.," Advanced Learning Technologies for Intelligent Transportation Systems: Prospects and Challenges," IEEE Open Journal of Vehicular Technology, vol. 5, pp. 397–427, 2024, doi:10.1109/OJVT.2024.3369691.

International Journal of Advanced Research in Computer and Communication Engineering

Impact Factor 8.471 ∺ Peer-reviewed & Refereed journal ∺ Vol. 14, Issue 12, December 2025

DOI: 10.17148/IJARCCE.2025.1412149

[6]. S. Kim and B.-J. Kim," Reinforcement Learning for Accident Risk Adaptive V2X Networking," in Proc. IEEE 92nd Vehicular Technology Conference (VTC2020-Fall), Victoria, BC, Canada, 2020, pp. 1–7, doi:10.1109/VTC2020-Fall49728.2020.9348445.

[7]. O. S. Al-Hetty et al.," Traffic Congestion Control with Emergency Awareness and Optimized Communication Infrastructure using Reinforcement Learning and Non-Dominated Sorting Genetic Algorithm," IEEE Access, 2025, doi:10.1109/ACCESS.2025.3530243.

[8]. A. Ashish, R. Gandhi raj and M. Panda," V2X Based Emergency. 12th Int. Conf. on Computing Communication and Networking Technologies (ICCCNT), Kharagpur, India, 2021, pp. 1–7, doi:10.1109/ICCCNT51525.2021.9580034.

[9]. M. Riviere et al.," Improving Emergency Vehicles Flow in Ur ban Environments through SDN-Based V2X Communications," in Proc. IEEE 97th Vehicular Technology Conference (VTC2023 Spring), Florence, Italy, 2023, pp. 1–6, doi:10.1109/VTC2023 Spring57618.2023.10199277.

[10]. R. Mubarak et al.," A Survey on the Detection and Impacts of Deepfakes in Visual, Audio, and Textual Formats," IEEE Access, vol. 11, 2023, doi:10.1109/ACCESS.2023.3344653.

[11]. X. Xiang, B. Fan, M. Dai, Y. Wu and C.-Z. Xu," V2X Communication Aided Emergency Message Dissemination in Intelligent Transportation Systems," in Proc. IEEE 23rd Int. Conf. on High Performance Switching and Routing (HPSR), Taicang, Jiangsu, China, 2022, pp. 35–40, doi:10.1109/HPSR54439.2022.9831302

[12]. S. Mannion, J. Duggan and E. Howley, "Cooperative Traffic Signal Control Using Multi-Agent Deep Reinforcement Learning, "Engineering Applications of Artificial Intelligence, vol. 65, pp. 207–218, 2017.

[13]. L. Li, Y. Lv and F. -Y. Wang, "Traffic Signal Timing via Deep Reinforcement Learning,"IEEE/CAA Journal of Automatic Sinica, vol. 3, no. 3, pp. 247–254, July 2016.

[14]. H. Wei, G. Zheng, H. Yao and Z. Li, "Intelli Light: A Reinforcement Learning Approach for Intelligent Traffic Light Control, "Proceedings of the 24th ACM SIGKDD Conference, 2018, pp. 2496–2505.

[15]. M. Elhenawy, A. Masoud and A. Rationality, "Emergency Vehicle Pre-emption Based on V2X Communication and Reinforcement Learning, "Transportation Research Part C: Emerging Technologies, vol. 124, 2021

