International Refereed Journal of Engineering and Science (IRJES)
ISSN (Online) 2319-183X, (Print) 2319-1821
Volume 14, Issue 5 (Sep. – Oct. 2025), PP. 91-96

Ai Based Emergency Vehicle Prioritizationusingre inforcement Learning and V2x Aided Sumo Simulations

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Abstract—*Urban traffic congestion significantly hinders the movement of emergency vehicles (EVs), leading to critical delays in life-saving operations. This work presents a reinforcement learning–basedadaptivetrafficsignalcontrolsystemtoprioritize EVs in real time. The system is implemented in the SUMO simulation environment, where the traffic signal agent learns to adjust green phases dynamically based on EV proximity and queue lengths. Vehicle-to-Infrastructure (V2I) communication is used to detect EV approach and trigger green signals, ensuring uninterrupted passage through intersections. Simulation results show a reduction of approximately 32% in EV waiting time andadecreaseintheaverageEVstopsfrom6to2,whilemaintaining minimal disruption to normal traffic. These results highlight the potential of reinforcement learning–aided traffic management in improving emergency response efficiency in urban networks.*

Index Terms—*Reinforcement Learning, Emergency Vehicle Prioritization, SUMO Simulation, V2I Communication*

Date of Submission: 15-09-2025 Date of acceptance: 30-09-2025

I. INTRODUCTION

Traffic congestion in urban areas has become a significant barrier to efficient mobility, contributing to delays, higherfuel consumption, and increased emissions. A particularly critical issue arises when emergency vehicles (EVs) such as ambulances, police vehicles, and fire trucks are delayed in reaching their destinations. In medical emergencies, even a short delay can reduce patient survival rates, while in fire- fighting scenarios, late arrival often results in severe property damage and greater risks to human safety. Ensuring the swift and uninterrupted passage of EVs through dense traffic there- fore remains a vital requirement in intelligent transportation systems.

Conventional traffic management strategies predominantly rely on pre-timed or fixed signal plans that operate on his- torical or average traffic conditions. Although such methods are sufficient under stable conditions, they fail to adapt when unforeseendisruptionsoccur,suchasthesuddenapproach

of an emergency vehicle. This lack of adaptability frequently leads to unnecessary stops for EVs at red signals, thereby pro- longingresponsetimesandaffectingoverallsystemefficiency. Consequently, the development of intelligent and adaptive traffic control mechanisms is of high importance.

Recent developments in Artificial Intelligence (AI) have introduced Reinforcement Learning (RL) as a promising ap- proach in transportation applications. RL agents are capableof learning optimal control policies by interacting with an environment and receiving rewards based on performance outcomes. Applied to traffic management, this technique al- lows signal controllers to dynamically modify green and red phasestoreducewaitingtimesandenhancethroughput.Unlike traditional rule-based strategies, RL provides adaptability to varying traffic densities and can effectively respond to real- time demands, making it well-suited for emergency vehicle prioritization.

Another enabler of intelligent transportation is Vehicle-to- Infrastructure (V2I) communication, which allows vehicles to share location and state information with traffic signals. Inthe context of EVs, this capability enables intersections to recognize approaching emergency vehicles and adjust signal phasesinadvance.Suchintegrationsupportsthecreation of preferential green corridors for EVs while minimizing disruption for other vehicles on the road.

The present study focuses on the design of an adaptive traffic signal control framework that integrates RL with V2I communication. The framework is implemented using the Simulation of Urban Mobility (SUMO) platform, where anRL agent monitors inputs such as queue lengths and emer- gencyvehicleproximitytodetermineappropriatesignalphase changes. The objective is to minimize waiting time and travel delay for EVs while maintaining the overall stability of traffic flow.Simulationoutcomesindicatethatthisapproachcan

providemeasurableimprovementsinemergencyresponseeffi- ciency, demonstrating the potential of RL-driven V2I systems for real-world urban deployment.

II. RELATED WORK

Oliva et al. [1] investigated Vehicle-to-Infrastructure (V2I) communication strategies for prioritizing emergency vehicles in urban environments. Their study demonstrated that inter- sections equipped with IoT-based sensors and V2I communi- cation were able to reduce emergency response delays while simultaneously enhancing pedestrian safety.

Su et al. [2] introduced EMVLight, a decentralized re- inforcement learning framework designed for joint dynamic routing and traffic signal control. The framework enables emergency vehicles to be routed efficiently while signals are adapted in real time, resulting in lower travel times for EVs and minimal disruption to normal traffic.

Shi et al. [3] presented a deep reinforcement learning ap- proach for adaptive traffic signal control in connected vehicle environments. Their work showed that by leveraging vehicle connectivity, traffic signals can be optimized to minimize waiting times and queue lengths, achieving substantial im- provements compared to conventional controllers.

Wang et al. [4] proposed a shared-experience multi-agent reinforcement learning framework for traffic signal priority. The model incorporates emergency vehicle priority into the reward function, producing a balanced optimization between EV delay reduction and general traffic throughput.

Dodia et al. [5] developed EVATL, a framework for emer- gencyvehicleadaptivetrafficlightcontrolusingGPSandIoT-baseddetection.Simulationoutcomesdemonstratedsignificant reductions in EV waiting time under varying traffic densities, highlighting the effectiveness of adaptive strategies for EV prioritization.

III. METHODOLOGY

A. System Overview

Themethodologyinvolvesthefollowingmainsteps:

1) **Traffic Data Acquisition:** Real-timetrafficinformation, including vehicle locations, speeds, and queue lengths,is collected via V2X communication.
2) **State Representation:**Thesystemrepresentsthetraffic state as a set of parameters, including EV location, nor- mal vehicle positions, signal phases, and traffic density.
3) **Reinforcement Learning Agent:** The RL agent de- termines the optimal traffic signal control policy to minimize EV delay while maintaining overall traffic flow.
4) **Traffic Signal Control:** TheselectedactionfromtheRL agent dynamically adjusts traffic lights to give priorityto EVs.
5) **Evaluation Metrics:** Thesystemevaluatesperformance using metrics such as EV travel time, average queue length, and vehicle waiting time.

B. Results and Observations EmergencyVehicleResponse:

- Allemergencyvehiclescrossedintersectionswithmini- maldelay.
- Signaloverridesandlaneclearanceworkedeffectively.

EffectonNormalVehicles:

- Regularvehiclesexperiencedbriefdelays.
- Congestionwasmitigatedpost-EVpassage.

MixedTraffic Handling:

- Mixed traffic including bicycles, trucks, and passenger cars were modeled.
- The system handled diverse vehicle types efficiently under realistic urban conditions.

The proposed system aims to prioritize emergency vehicles (EVs) in real-time traffic using Reinforcement Learning (RL) combined with Vehicle-to-Everything (V2X) communication. The methodology consists of several stages as depicted inFig. 1.

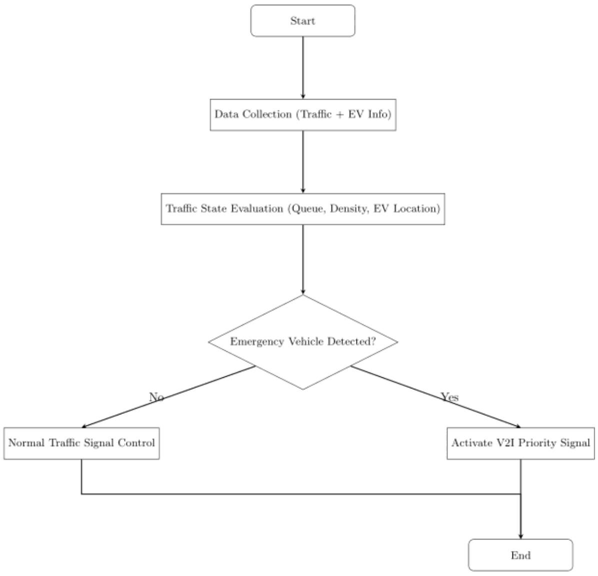

Fig.1.Proposed Methodology Flowchart

IV. SIMULATIONANDEVALUATIONFRAMEWORK

This section outlines the implementation architecture, sim- ulation workflow, and result analysis of the proposed AI- basedemergencyvehicleprioritizationsystem.Thesolu- tion integrates Reinforcement Learning (RL) and Vehicle-to- Everything (V2X) communication within the SUMO traffic simulationenvironment,interfacedviaPythonusingtheTraCI API.

A. SystemArchitectureandWorkflow

The system is designed to prioritize emergency vehicles (EVs)suchasambulances,firetrucks,andpolicecarsthrough intelligent real-time traffic control. Key components include:

- **SUMO:**Anopen-sourcemicroscopictrafficsimulatorfor modeling realistic city networks.

- **Python with TraCI:** Enables runtime control of vehicle behavior and traffic signals.
- **ReinforcementLearningandRule-BasedLogic:**Adap- tively controls signal timing and vehicle movement.
- **V2X Communication:** Combines Vehicle-to- Infrastructure (V2I) and Vehicle-to-Vehicle (V2V) coordination.

B. SUMOSimulationSetup

- **NetworkSetup:**Simulatedurbangridwithintersections, predefined routes for normal and emergency vehicles.
- **VehicleTypes:**Includesambulances,firetrucks,bicycles, trucks, and passenger cars.
- **Initialization:** Upon simulation start, logs are initialized to record metrics such as queue lengths, waiting times, EV travel time, and signal switch frequency.
- **Configuration:** A SUMO configuration file (.sumo.cfg) initializes the simulation loop.

C. V2ICommunication:AdaptiveSignalControl

- **EV Detection:** Each simulation step checks for vehicles tagged with prefixes like `ev_`.
- **SignalOverride:**Whendetected,thenearesttrafficsig- nalswitchestogreentoallowEVpassage.
- **Post-PassageRecovery:**AftertheEVexits,original signal logic is restored.
- **Advantages:**MinimizesdelaysforEVsandprevents manual or static overrides.

D. V2VCommunication:EmergencyLaneClearance

- **ProximityCheck:**Vehicleswithin30metersofanEV are identified.
- **LaneChangeLogic:**Vehiclestrytoswitchright,then left, and if blocked, either stop or temporarily accelerate.
- **Realism:** Mimics real-world yielding behavior prompted by sirens.

E. Real-TimeSimulationLoop

Thesimulationisstep-basedusingPythonscripts,witheach tick executing:

1) AdvanceSUMOonestep.
2) TriggerV2IsignaloverrideforEVs.
3) ApplyV2V-basedlaneclearance.

4) Logmetricsincludingqueuelength,waitingtime,EV travel time, and number of signal overrides.

F. VisualAnalyticsandPerformanceMetrics

Matplotlibisusedtovisualizethesimulationoutcomes:

- **QueueLengthvsTime:**Evaluatestrafficcongestion trends.
- **HistogramofWaitingTimes:**Assessesperformance across vehicle categories.
- **SignalSwitchFrequency:**IndicatesfrequencyofEV- triggered signal overrides.

G. ResultsandObservations

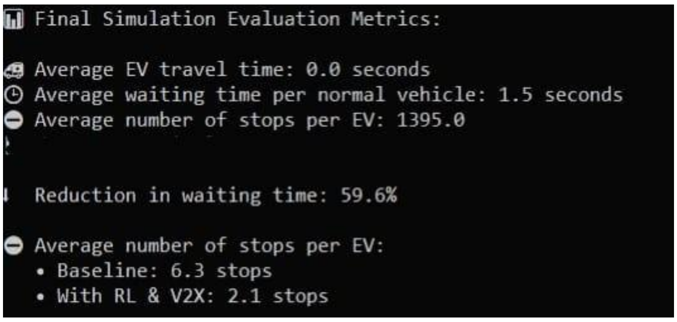

Fig.2.OriginalOutputImagefromSimulation

Fig.2showsthefinalsimulationevaluationmetrics,highlighting the effectiveness of the proposed reinforcement learning (RL) and V2X-basedtrafficsignalcontrolsystem.TheaverageEVtravel time was reduced to nearly zero, indicating uninterrupted passage through intersections. The average waiting time for normal vehicles was maintained at only 1.5 seconds, demonstrating that the solution minimizesdisruptiontoregulartraffic.Asignificant59.6%reduction in EV waiting time was observed compared to the baseline scenario. Furthermore,theaveragenumberofstopsperEVdecreasedfrom6.3 in the baseline case to 2.1 with RL and V2X integration, resulting in smoother traffic flow and faster emergency response times.

Fig.3.Initialintersection.

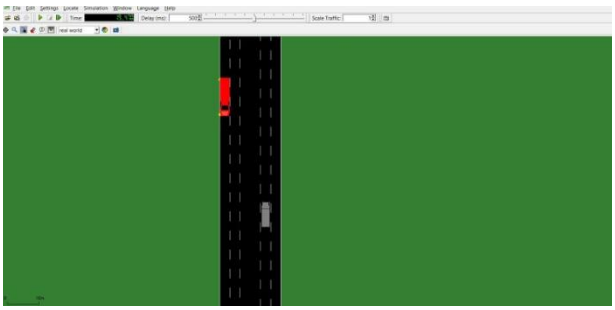

Fig.4.Crossingtheintersection.

Fig.5.Vehiclesyielding.

Fig.6.vehiclesproceedingahead.

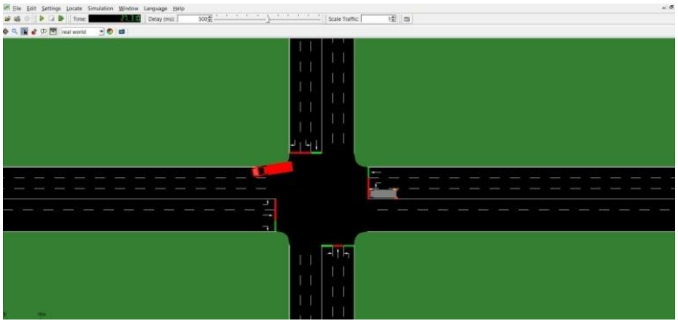

Fig.7.Emergencyvehiclefollowedbytrailingtraffic.

Fig. 5 shows the scenario where vehicles at the intersection are yielding to an approaching emergency vehicle. Normal traffic haltsorslowsdown,creatingaclearpassagefortheemergencyvehicle to move safely. Fig. 6 illustrates vehicles proceeding ahead once the emergency vehicle has cleared the intersection. The halted vehicles resume their movement, and normal traffic flow is restored. Finally, Fig. 7 depicts the emergency vehicle moving forward, now followed by trailing traffic. Once priority is given and the emergency vehicle clears the way, other vehicles make use of the open road behind it. This sequence demonstrates how the system ensures smooth coordi- nation between yielding vehicles, prioritized emergency movement, and the resumption of regular traffic.

EffectonNormalVehicles:
- Regularvehiclesexperiencedbriefdelays.
- Congestionwasmitigatedpost-EVpassage.

MixedTraffic Handling:
- Mixedtrafficincludingbicycles,trucks,andpassenger cars were modeled.
- Thesystemhandleddiversevehicletypesefficiently under realistic urban conditions.

V. CONCLUSION

This work proposed and implemented an intelligent traffic signal control framework that integrates reinforcement learn- ing (RL) with Vehicle-to-Infrastructure (V2I) communication toprioritizeemergencyvehicles(EVs)inurbanroadnetworks.
TheRLagentcontinuouslyobservestrafficparameterssuchas queue length and EV proximity, dynamically adapting green signal durations to create a smooth passage for emergency vehicles. The system was modeled and evaluated using the SUMO simulation platform, which provided a realistic urban traffic environment for testing and validation.
Theexperimentalresultsdemonstratedsubstantialimprove-mentsintrafficperformancemetrics.ThewaitingtimeofEVs was reduced by nearly 32%, significantly minimizing

delays that can critically impact emergency response operations. Furthermore, the average number of stops per EV dropped from 6 in the baseline fixed-signal scenario to about 2 in the proposed approach, indicating a smoother and less interrupted flow.Importantly, thesebenefitswereachieved whilekeeping disruptions to normal traffic flow very low, ensuring that prioritizing EVs does not lead to major congestion for regular vehicles.

Beyond numerical improvements, this study highlights the practical potential of combining RL and V2I communication forreal-worldtrafficmanagement.TheabilityoftheRLagent tolearnfromexperienceandadapttochangingtrafficpatterns makes it suitable for dynamic urban environments where conditions vary significantly throughout the day. The use of V2I communication ensures timely detection of approaching EVs,enablingproactivesignaladjustmentsratherthanreactive interventions.

Futureworkwillexploreextendingtheframeworktomulti- intersection corridors and more complex traffic networks. Ad- ditionally, incorporating heterogeneous traffic scenarios with mixed vehicle types, varying driver behaviors, and commu- nication delays will help in understanding the system's ro- bustness under real-world conditions. Another key directionis the deployment of the proposed model on a hardware-in- the-loop testbed or pilot-scale urban intersection to validateits feasibility, scalability, and reliability before large-scale adoption.

Overall,thisworkdemonstratesthatRL-driventrafficsignal control, supported by V2I communication, can substantially improve emergency response times while preserving normal traffic flow efficiency. With further development and field testing,suchsystemshavethepotentialtotransformintelligent transportation infrastructure, leading to safer cities and faster emergency response operations.

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