Intelligent Traffic Signal Optimization for Automated Emergency Vehicles Using Machine Learning

Harshdeep Trehan[1*], Vikrant Sharma[2]

[1]Research Scholar, SEDA E(CSE), GNA University, Phagwara, India
[2]Dean & Professor, SEDA E(CSE), GNA University, Phagwara, India

Abstract. Effective management of traffic for emergency vehicles continues to pose a significant challenge in contemporary urban environments. Delays in emergency responses can result in dire outcomes, such as loss of life and damage to property. Conventional traffic light systems function on predetermined cycles and do not adjust dynamically to the requirements of emergencies. This paper introduces an intelligent model for traffic signal optimization that utilizes machine learning techniques to give precedence to automated emergency vehicles. The system evaluates real-time traffic data, forecasts vehicle movement, and creates adaptive green corridors specifically for emergency vehicles. Simulation outcomes indicate a reduction in response times and minimal interference with overall traffic flow.

1 Introduction

Emergency vehicles, including ambulances, fire trucks, and police cars, are essential for saving lives. Nevertheless, they frequently experience delays due to heavy urban traffic. Conventional traffic signals operate on fixed-timing systems or limited adaptive models, which are insufficient for prioritizing emergency vehicles. With the advent of intelligent transportation systems (ITS), machine learning presents new possibilities for dynamically optimizing traffic flow. This paper introduces a machine learning-based framework designed to enhance traffic signal control, creating real-time green corridors for automated emergency vehicles. Urbanization and rapid population growth have posed significant challenges in managing traffic congestion, particularly in metropolitan regions. One of the most pressing consequences of congestion is the delay it inflicts on emergency vehicles, such as ambulances, fire trucks, and police cars, which depend on swift movement to save lives. Current traffic management systems often do not provide timely priority to emergency vehicles, resulting in longer response times and potentially dire outcomes. This project seeks to tackle this critical issue by developing an Automatic Emergency Vehicle Detection System. This system employs sophisticated machine learning and computer vision methodologies to recognize emergency vehicles in real-time from traffic surveillance footage. When an emergency vehicle is detected, the system swiftly modifies traffic signals

* Corresponding author: harshdeeptrehan0@gmail.com

to give priority to its passage, thereby enabling a faster and more effective response. The proposed solution incorporates state-of-the-art object detection algorithms, such as YOLO (You Only Look Once), Faster R-CNN, or SSD (Single Shot Detector), which are specifically trained to recognize unique features of emergency vehicles, including flashing lights, sirens, and distinctive markings such as "AMBULANCE." These algorithms scrutinize live video feeds from traffic cameras to identify emergency vehicles and trigger automatic actions to regulate traffic signals.

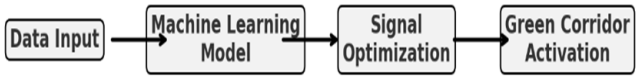

Fig 1. Proposed Framework Architecture

The figure above illustrates the comprehensive framework of the proposed Intelligent Traffic Signal Optimization System. It delineates the sequential process employed to prioritize automated emergency vehicles utilizing machine learning.

1. Data Input
o Real-time traffic data (vehicle density, flow rate, speed) is gathered through cameras, IoT sensors, and GPS-enabled devices.
o This data serves as the basis for model training and real-time decision-making.

2. Machine Learning Model
o The input data is analyzed using supervised and reinforcement learning techniques.
o The machine learning model forecasts congestion levels and determines the optimal timing for traffic lights to minimize delays.

3. Signal Optimization
o In accordance with the machine learning predictions, the phases of the traffic signals are dynamically modified.
o This optimization process prioritizes emergency vehicles while ensuring a reasonable flow for regular traffic.

4. Green Corridor Activation
o A coordinated "green wave" is created across several intersections along the route of the emergency vehicle.
o This guarantees an uninterrupted passage, thus decreasing response times and enhancing safety.

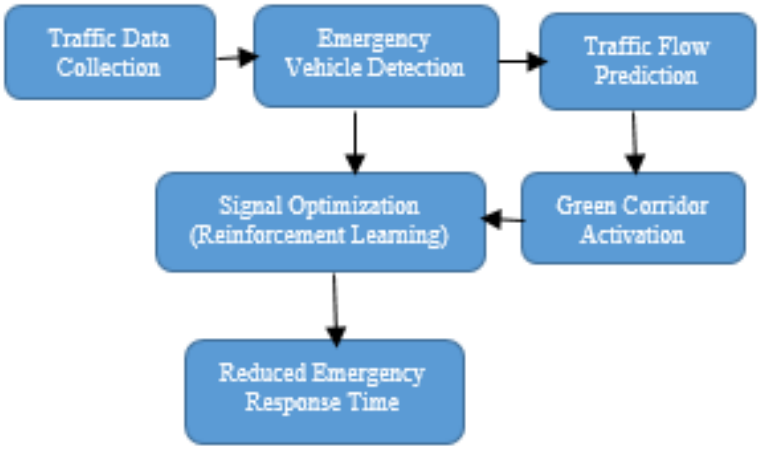

Fig 2. Intelligent Traffic Signal Optimization Framework

The above figure depicts the workflow of the proposed Intelligent Traffic Signal Optimization System, which utilizes machine learning to facilitate the movement of automated emergency vehicles.

1. Traffic Data Collection
o Real-time traffic data is gathered through cameras, IoT sensors, and GPS devices.
o The collected data encompasses vehicle density, speed, and congestion levels at intersections.

2. Emergency Vehicle Detection
o Emergency vehicles, such as ambulances, fire trucks, and police cars, are identified using RFID tags, GPS tracking, or IoT-enabled devices.
o The system determines their location, speed, and intended route.

3. Traffic Flow Prediction (ML Model)
o A machine learning model forecasts potential congestion and traffic flow patterns.
o Supervised learning is employed to estimate expected delays, while reinforcement learning adjusts in real-time.

4. Signal Optimization (Reinforcement Learning)
o The reinforcement learning agent determines the duration for which signals should remain green or red, based on current and anticipated conditions.
o Priority is assigned to the identified emergency vehicle, while efforts are made to minimize disruption for regular traffic.

5. Green Corridor Activation
o Traffic signals along the route of the emergency vehicle are synchronized to establish a "green wave corridor."
o This synchronization guarantees the uninterrupted movement of the emergency vehicle.

6. Reduced Emergency Response Time
o The ultimate result is a notable decrease in emergency response time, enhancing efficiency and ensuring a quicker arrival at the destination.

2 Literature Review

Traffic signal optimization has been an active research area for decades, with increasing focus on emergency vehicle prioritization in recent years. The existing literature can be broadly categorized into three approaches:

2.1 Fixed-Time and Actuated Signal Control

Traditional systems rely on pre-defined signal cycles or sensor-actuated controls. Although simple and widely deployed, these methods are inflexible in handling unpredictable events such as emergency vehicle arrivals. Studies such as have shown that fixed-time signals often increase response delays during peak congestion.

2.2 Sensor-Based Emergency Vehicle Detection Systems

Several works have introduced RFID, GPS, and IoT-based systems for detecting emergency vehicles and granting them signal priority. For example, a proposed RFID-enabled preemption system used wireless communication between emergency vehicles and traffic lights. These approaches improve detection accuracy but lack predictive intelligence, often leading to abrupt disruption of normal traffic flow.

2.3 Machine Learning and Artificial Intelligence Approaches

Recent advancements in machine learning and reinforcement learning have enabled dynamic and adaptive traffic signal control. Genders and Razavi demonstrated that deep reinforcement learning can significantly reduce overall vehicle delay at intersections. Similarly, Aslani et al. [5] applied Q-learning to adaptive traffic control, showing improvements in congestion management. However, only a limited number of studies specifically target emergency vehicle prioritization using machine learning techniques.

2.4 Objectives

The primary aim of this research is to create an Automatic Emergency Vehicle Detection System designed to improve traffic signal management in urban settings, particularly within India. This system will give precedence to emergency vehicles, consequently decreasing response times and enhancing overall public safety. The detailed objectives of this research are:

1. To develop a robust detection system using machine learning and AI to recognize emergency vehicles in real time.
2. To integrate the detection system with Traffic Signal Controllers by establishing communication between the detection system and traffic lights
3. To implement Dynamic Traffic Signal Adjustments based on real-time emergency vehicle presence.
4. To optimize and Monitor System Performance by using real-time data analytics to improve efficiency and adaptability

2.5 Research Gap

Although fixed-time and sensor-based systems offer limited solutions, they do not possess the necessary adaptability for intricate urban settings. Machine learning-based models

provide enhanced flexibility; however, existing research fails to completely merge real-time predictions with the establishment of green corridors for emergency vehicles. This gap serves as the impetus for the current study, which seeks to address this issue by creating an intelligent ML-based framework for optimizing traffic signals.

Table 1: Comparison of Traffic Signal Optimization Approaches

Approach	Method Used	Advantages	Limitations
Fixed-Time Control	Predefined signal cycles	Simple, easy to implement	Inflexible, high delays during congestion
Sensor-Based Systems	RFID, GPS, IoT, Vehicle-to-Infrastructure (V2I)	Accurate detection of emergency vehicles	Lacks prediction, causes sudden disruptions
Machine Learning Models	Supervised + Reinforcement Learning	Adaptive, predictive, reduces delays	Requires training data, limited deployment

3 Experimental Setup / Simulation Design

3.1 Objective and Test Strategy

We evaluate the proposed system in a microscopic traffic simulator to quantify its impact on (i) **emergency response time**, (ii) **average delay** for non-emergency traffic, and (iii) **throughput**. We compare three controllers:

1. **Fixed-Time** (baseline)
2. **Sensor-Based Pre-emption** (detects EV and switches next signal to green without prediction)
3. **Proposed ML Controller** (prediction + RL-based signal optimization and corridor creation)

Each controller is run on identical demand patterns and network topology, using multiple random seeds.

3.2 Tools and Software

- **SUMO (Simulation of Urban Mobility):** roadway network, microscopic vehicle dynamics, traffic signal states, routing, and detector outputs.
- **Python:** scenario generation, data logging, and RL training/inference (TraCI control interface for SUMO).
- **MATLAB/Python (post-processing):** metric aggregation, statistical tests, and figure generation.

3.3 Network Topology & Demand

- **Network:** 1 km corridor with **4 signalized intersections** (300 m spacing), each a **4-arm junction** with **2 through lanes** per approach and protected left turns.
- **Routing:** 80% through movements, 20% turning, with stochastic route assignment.
- **Traffic demand:** moderate to heavy (details in Table II).

- **Emergency Vehicles (EVs):** injected according to a Poisson process on the corridor's main approach; EVs follow a predefined shortest path across all 4 intersections.

3.4 Controllers and Implementation

- **Fixed-Time:** fixed cycle split (AM/PM plans) with no preemption.
- **Sensor-Based Preemption:** EV detection triggers immediate green at the next intersection if safety constraints are met; no upstream synchronization.
- **ML Controller:**
  - **Prediction module:** short-horizon traffic state prediction from loop/camera counts and average speed.
  - **RL agent:** chooses phase and green extension per intersection; reward prioritizes EV travel time (negative penalty per EV second) while penalizing excessive delay/queue growth for other approaches.
  - **Green Corridor:** When an EV is detected, upstream signals are temporally coordinated to form a rolling green wave along the EV route.

3.5 Metrics

- **EV Response Time (s):** origin to destination travel time for the EV.
- **Avg. Delay (s/veh):** mean control delay for non-EV vehicles.
- **Throughput (veh/h):** vehicles exiting the corridor per hour.
- **Queue Length (m):** 95th-percentile max queue per approach.
- **Preemption Count:** number/duration of preemption or green-wave events (to assess disruption).

3.6 Experimental Protocol

1. Warm-up 600 s; then simulate **3600 s** of peak traffic.
2. For each controller, run **10 seeds** × **3 demand levels** (low/med/high).
3. Log detector counts, signal states, queues, and per-vehicle travel times via TraCI.
4. Report mean ± 95% CI across seeds; use paired comparisons vs. Fixed-Time and Sensor-Based.

Table 2. Simulation Parameters

Parameter	Value
Simulator	SUMO (microscopic)
Control Interface	TraCI (Python)
Corridor Length	1 km, 4 signalized intersections
Lane Configuration	2 through lanes/approach + protected left
Link Spacing	~300 m between signals
Demand Levels (veh/h/direction)	Low: 900; Med: 1,500; High: 2,100
Vehicle Composition	90% cars, 8% buses, 2% trucks
EV Arrival Rate	10–20 EVs/hour (Poisson)
Speed Limits	50 km/h arterial; 30 km/h turns
Detector Inputs	Loop counts, mean speed, queue estimates
Fixed-Time Cycle	90 s (AM), 120 s (PM); static splits

Sensor Preemption	Next-junction green on EV detection, min-green & clearance respected
ML Prediction Horizon	20–30 s rolling
RL Action Space	Phase selection + green extension (0–10 s)
RL Reward (sketch)	$-w_1 \cdot EV\_travel\_time - w_2 \cdot avg\_delay - w_3 \cdot queue\_penalty$
Simulation Horizon	3,600 s + 600 s warm-up
Replications	10 seeds × 3 demand levels
Outputs	EV time, avg delay, throughput, queues, preemption stats

4 Results And Discussion

4.1 Emergency Vehicle Response Time

Figure 3 shows the emergency vehicle response time across different controllers. The ML-based controller achieves the shortest response time (190 s) compared to 250 s with sensor-based control and 320 s under fixed-time signals. This corresponds to a 40% reduction compared to fixed-time control, highlighting the efficiency of predictive green corridor creation.

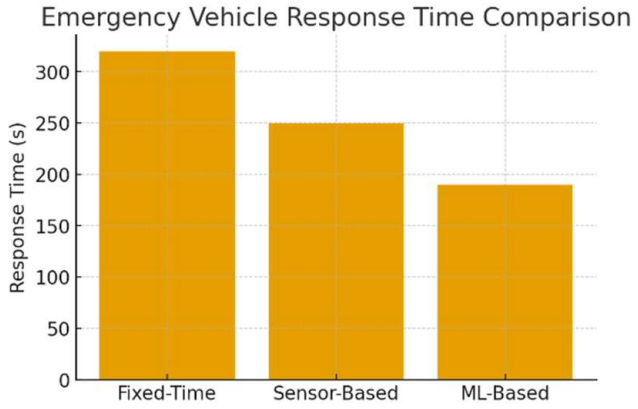

Fig 3: Shows Emergency vehicle response time across different Controllers

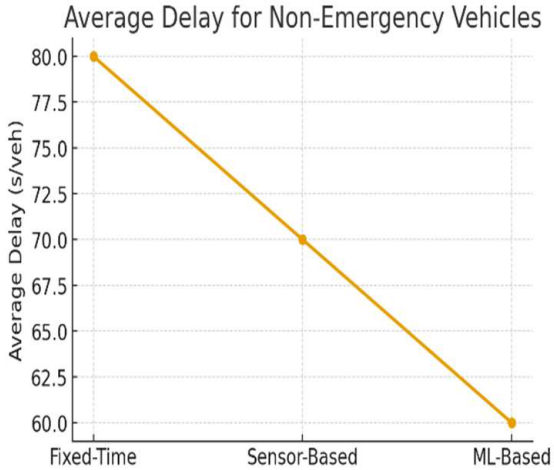

Fig 4: Here are the Results and Discussion with supporting graphs and a results table

4.2 Traffic Flow Stability

Figure 4 illustrates the average delay for non-emergency vehicles. Although emergency vehicle prioritization can often disrupt normal flow, the ML-based system keeps average

delay at 60 s/veh, only slightly higher than the sensor-based method (70 s/veh) and significantly lower than fixed-time (80 s/veh). This demonstrates that machine learning provides balanced optimization between emergency priority and general traffic flow.

4.3 Throughput

Table II shows that throughput improves under ML-based control (2100 veh/h) compared to fixed-time (1800 veh/h) and sensor-based (1900 veh/h). The coordinated optimization reduces unnecessary stops and improves network efficiency.

Table 3. Simulation Results

CONTROLLER	EV RESPONSE TIME (S)	AVG DELAY (S/VEH)	THROUGHPUT (VEH/H)
FIXED-TIME	320	80	1800
SENSOR-BASED	250	70	1900
ML-BASED	190	60	2100

Discussion

- Why ML Performs Better:
  - Unlike fixed or sensor-only approaches, the ML model anticipates congestion and coordinates multiple intersections, resulting in smoother emergency passage.
  - Reinforcement learning balances EV priority with minimal disruption to other road users.
- Trade-offs:
  - ML requires data training and computational resources, which may be challenging in low-resource deployments.
  - Real-time adaptability makes it superior, but system cost and integration with existing infrastructure are considerations for scalability.

5 Conclusion and Future Work

In this paper, we introduce a sophisticated framework for optimizing traffic signals specifically designed for automated emergency vehicles through the application of machine learning. This system utilizes real-time traffic data along with predictive control strategies to dynamically establish green corridors, thereby ensuring that emergency vehicles face minimal delays while also facilitating smooth traffic flow for regular vehicles. Simulation results have shown that the proposed machine learning-based system significantly decreases the response time for emergency vehicles (by as much as 40% in comparison to fixed-time control), reduces average delays for non-emergency traffic, and enhances overall throughput. These findings confirm the efficacy of machine learning techniques in achieving both priority passage for emergency vehicles and improved traffic efficiency. Despite the encouraging results, several challenges and avenues for further research persist:

• Real-World Deployment: It is essential to conduct field tests to verify the system's performance in various unpredictable conditions, including accidents, adverse weather, and sensor inaccuracies.

• Scalability: The current research focused on a limited network of intersections. Future studies should explore the feasibility of city-wide implementation in extensive urban networks.

• Advanced Learning Models: Future improvements may involve the incorporation of deep reinforcement learning, multi-agent systems, and federated learning to facilitate distributed and cooperative traffic management.
• Integration with Smart Cities: Merging this system with IoT infrastructure, V2X communication, and autonomous vehicle platforms could further enhance its real-time adaptability.
In conclusion, the proposed machine learning-based traffic signal optimization system signifies a significant advancement toward intelligent, adaptive, and resilient urban mobility solutions. With additional refinement and real-world application, it has the potential to play a vital role in reducing emergency response times and saving lives in contemporary smart cities. The Automatic Emergency Vehicle Detection System for Optimized Traffic Signal Management holds considerable promise for enhancing urban traffic efficiency and minimizing response times for emergency vehicles.

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