



Reinforcement Learning-Based Dynamic Traffic Control System with Emergency Vehicle Preemption Using Real-Time Traffic Dataset

**Presented By,
Shahriar Khan (2507023)
Data Science, UWTSD**

**Presented To,
Dr Seena Joseph
Lecturer, UWTSD**



Contents



Context or
Background



Problem or
Literature Gap



Aim and
Objective



Related Work or
Literature Gap



System Design
or Methodology



Planning and
Resources



Impact and
Limitations



Reference

Introduction

Traffic congestion is a major threat to big cities or developed countries.





There are several categories of traffic control systems, such as:

- ***Manual Traffic Control System***
 - A traffic police controls the regular traffic flows.
- ***Fixed Traffic Control System***
 - Based on predetermined rates (historical data)

No consider dynamically changing traffic environment.



Statistics



Bangladesh is also one of the worst traffic,



For Traffic in USA,



Around 19 million working hours are being lost daily



3-billion gallons fuel wasted



6 to 10 percent of the country's GDP is lost every year



7-billion extra hours consumed, 42h per traveler.



In Dhaka, daily loss of Tk 1.53 billion.



Extremely Growing air-pollution.

Intelligent Transportation System (ITS)



Monitoring the flow of traffic and Making appropriate decisions on real-time.



Decrease the AWT (Average Waiting Time) of vehicles and regulates traffic flow.



Connected Cloud Computing service to process data for making the decision.



For optimal decision, data from adjacent intersections is needed.



TABLE 2. VARIOUS METHODS FOR TRAFFIC LIGHT CONTROLLER

Method	Description	Pros and cons
Traffic Management System (TMS)	This technique is a top-down management perspective that integrates with technology in order to improve the traffic flow and safety. In this situation the task is divided into smaller systems put in various place. Real time traffic data is gathered from cameras and speed detectors are transmitted into Transportation Management Center (TMC) for improving traffic flow.	Pros: 1. Increased road user satisfaction for saving precious time of commuters. 2. Reduce possibilities of traffic jams. Cons: 1. Excessive delay may be caused due to TMS malfunction and downtime. 2. Unnecessary delays result in significant fuel waste and higher motorist time.
Green wave system	In this technique whenever the vehicle is crossing the intersections, an incoming emergency vehicle enables the traffic light to change to green. Image processing can be used for detecting the location of emergency vehicles more accurately. As a result, an emergency vehicle will receive all green signals along its route and will not be affected by any stops while on its way to its target destination	Pros: 1. Can allow emergency vehicle to pass through intersections safely and rapidly. 2. Useful for detecting the stolen vehicles that pass through intersections. Cons: 1. Weak performance in severe weather conditions. 2. If it does not work correctly, it can cause a heavy traffic jam
RFID tags	This technique overcomes the severe weather problem in Green Wave System as Radio Frequency is not affected by the weather. RFID uses tags assembled in the dashboard of the ambulance and RFID readers are installed at the 200 meters from junctions. The RFID reader will read all the data from tags in order to detect the ambulance as it approaches traffic light systems.	Pros: 1. The RFID tags can store a lot of information, and follow instructions 2. It is not affected by severe weather conditions. 3. These RFID tags are usually smaller than thumb tack and they can be embedded into dashboards. Cons: 1. Active RFID can be expensive because of power sources such as battery. 2. RFID may be easily intercepted, even if it is Encrypted.
Wireless Sensor Network (WSN)	This technique utilizes a set of magnetic sensors to improve the accuracy of vehicle detection. As a vehicle approaches a magnetic detector, there is a partial distortion of the local magnetic field that is generated by the detector. Whenever the vehicle is in the middle and the last portion of the magnetic field generated by the detector, the total local magnetic field is distorted. After that these data can be transmitted to a controller.	Pros: 1. WSN can be applied in large scale and in various fields as it avoids wiring. 2. It performs well at high speed and is flexible to go through a centralized monitor. Cons: 1. If Signal-to-Noise Ratio (S/N) is too low, it can potentially cause adverse effects in sending false alarm. 2. Easy for hackers to hack the system because the propagation of waves cannot be controlled.
Global System for Mobile Communication (GSM)	In this technique, embedded controller is used to produce data pattern as an input for microcontroller. The C program language, then is converted in HEX code and transfer into receiver of microcontroller. Then transmitter of microcontroller will send these data to GSM. The GSM can active messaging service with the 3G connection of SIM alert a specialist with message.	Pros: 1. Very useful in saving time because it can send a message to medical doctors about patient's situation before arrival of the ambulance. 2. It can show video display by using 3G connection in ambulance. As a result, the doctor can analyze the condition of patient and recommend some first aid steps. Cons: Concerns about losing control of their network and the data. Also, losing battery of mobile can disconnect the connection.
Infrared Sensor (IR)	Most of the traffic light systems have IR sensors which consists of IR transmitter and receiver. Whenever the vehicle passes between sensors, the IR sensors can be activated. The collected information can be analyzed to change the traffic light to green.	Pros: Reportedly stolen vehicles or vehicles of criminal suspects can be tracked, and the time and direction of travel can be traced. Cons: 1. Initial setup cost is high 2. An emergency cannot be automated and normally requires human intervention.

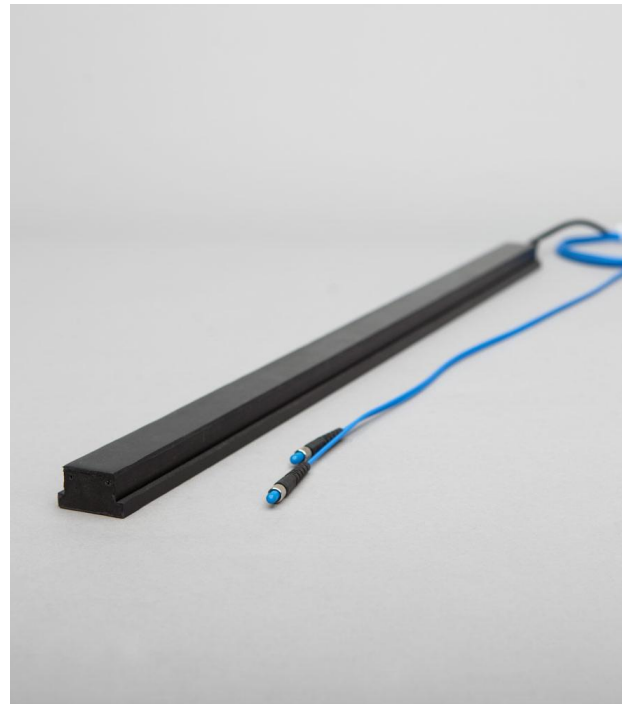
Wireless Sensor Network (using Fiber Optic Sensor)



Fiber optic sensors are becoming key tools in building more robust and accurate traffic monitoring systems.

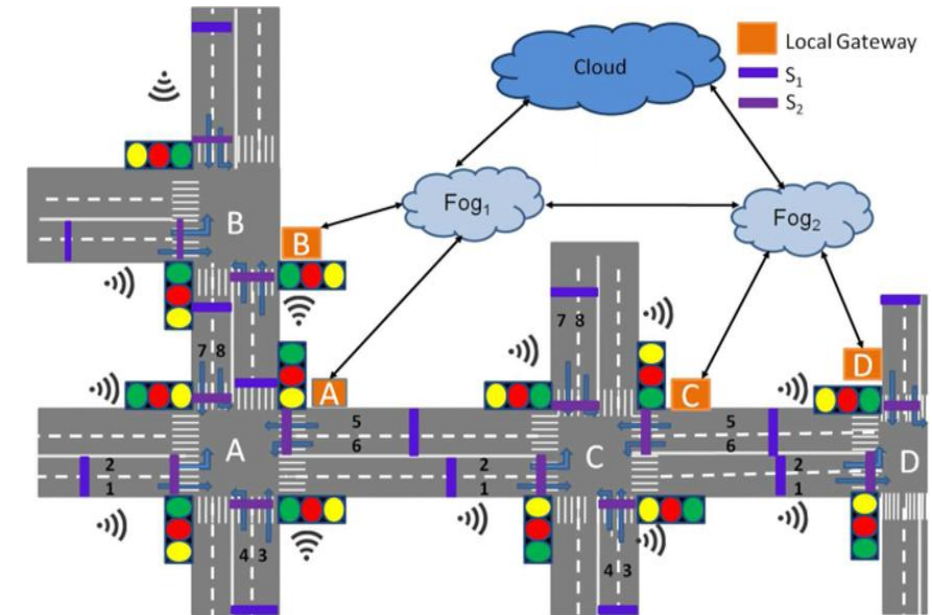


Implementations of fiber optic sensors as real-time traffic monitoring systems.



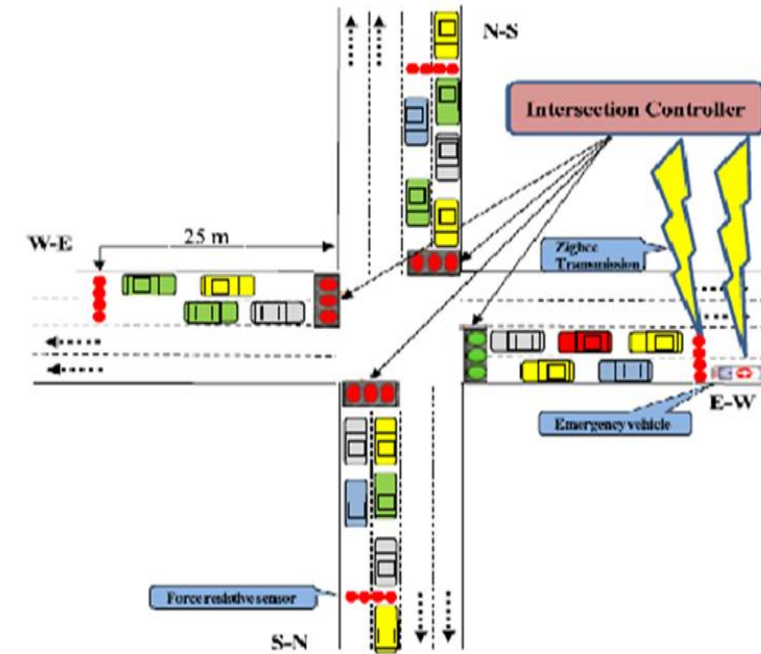
Fog based Architecture [1]

- For a dynamic traffic light control system for ITS
- Local gateway collects real time data using WSN
- Efficient Dynamic Traffic Light Control Algorithm for multiple(EDTLCM) optimizes green light based on
 - 1.reducing average waiting time
 - 2.minimizing the fuel consumption
 - 3.maximizing the throughput



In [2]

- Increases response time of **Emergency vehicles** .
- **Force Resistive sensors** are used to count the number of vehicles approaching to the intersection.
- Data will be transferred via Zigbee Protocol.
- **Intersection Controller** manages the arrival of emergency and non-emergency vehicles.
- Traditional traffic light controlling system do not consider dynamically changing traffic environments.

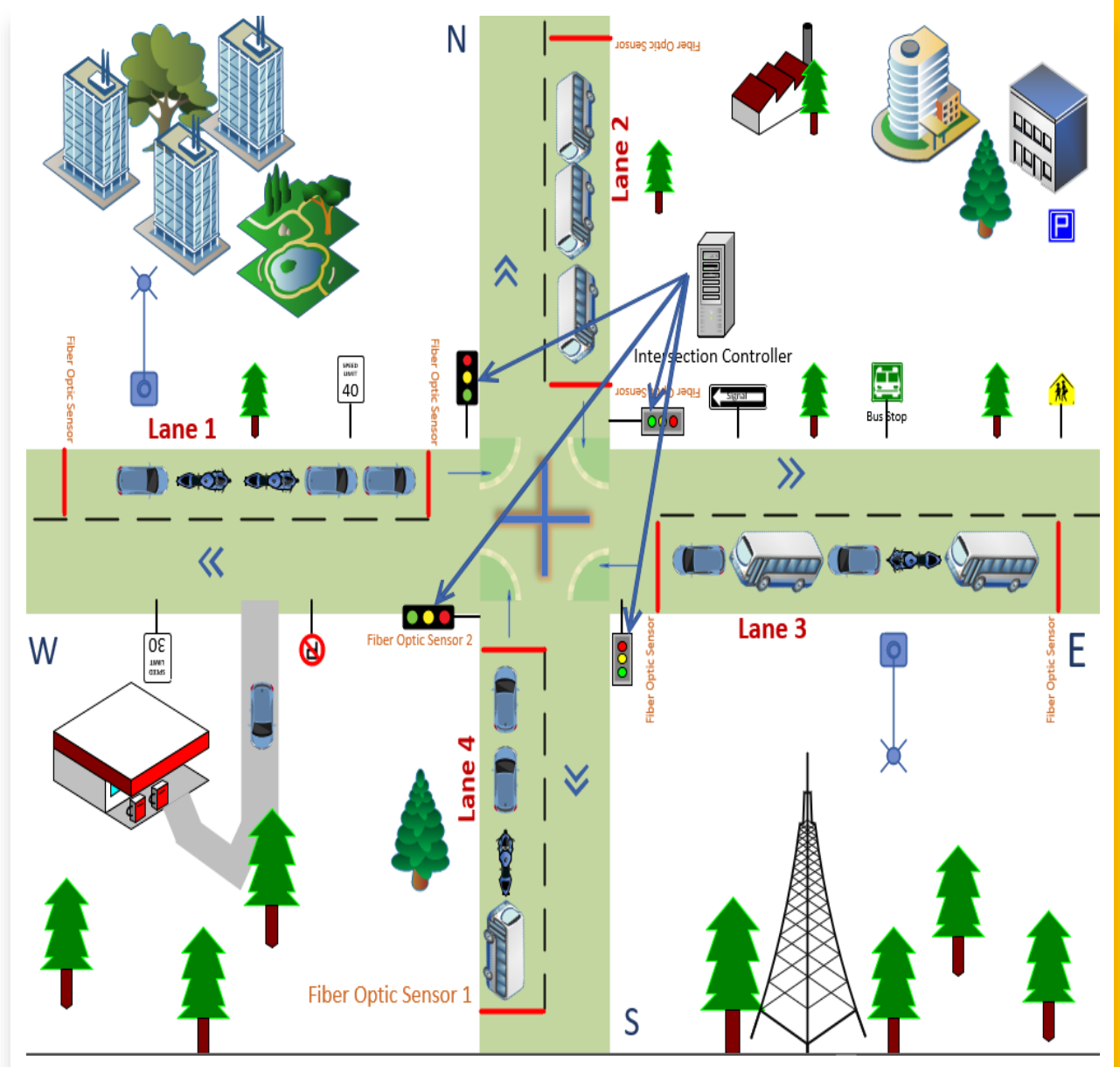


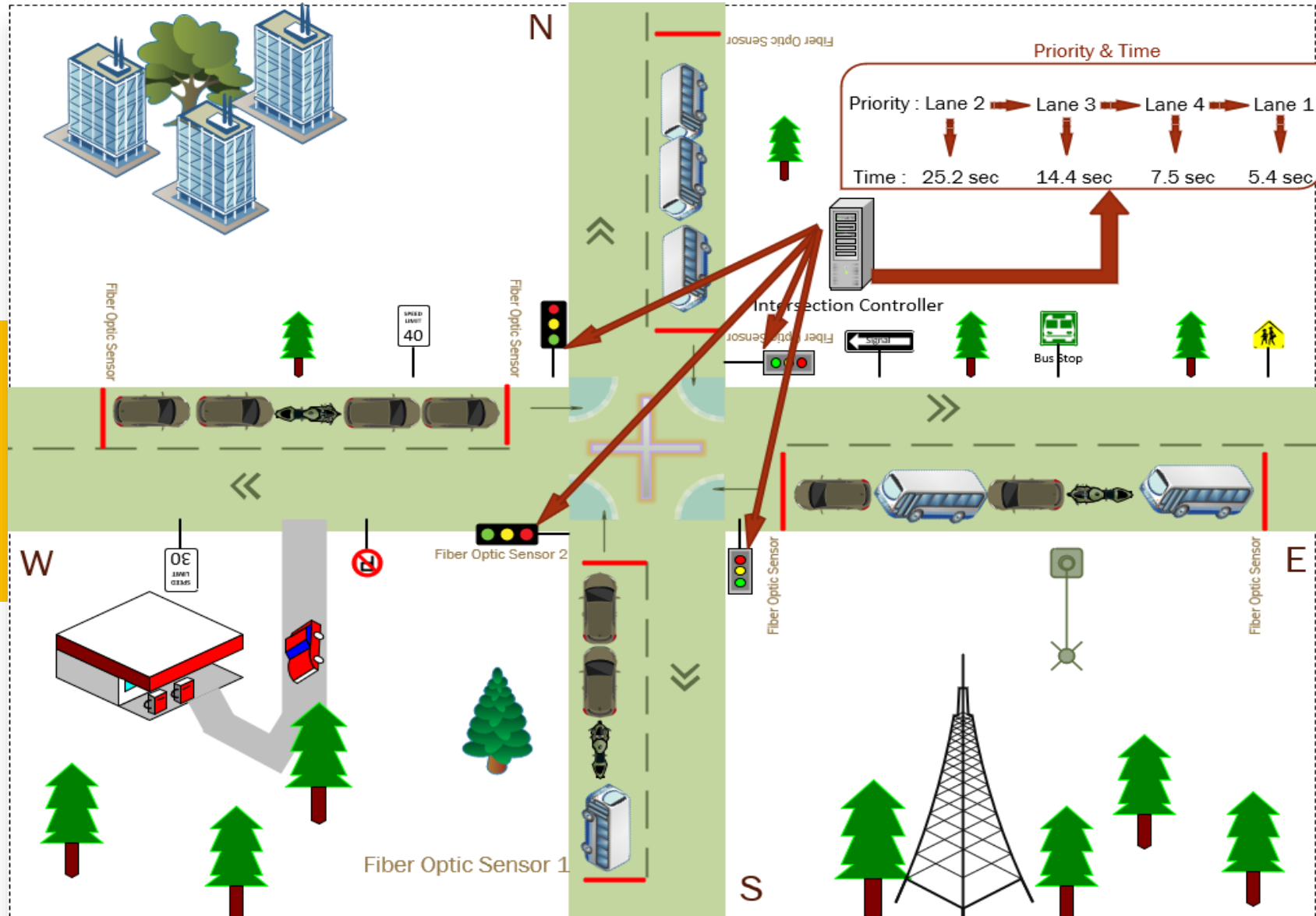
[2] A. Khan, F. Ullah, Z. Kaleem, S. Ur Rahman, H. Anwar and Y. -Z. Cho, "EVP-STC: Emergency Vehicle Priority and Self-Organising Traffic Control at Intersections Using Internet-of-Things Platform," in *IEEE Access*, vol. 6, pp. 68242–68254, 2018.

Name of the paper	Journal/ Conference	Key Idea	Observation
A Novel Real-Time Traffic Signal Control Strategy for Emergency Vehicles(EVs).	IEEE Access (February 7, 2022)	- A “green wave” signal control strategy for EVs. - Ensure that EVs can quickly pass through Intersections - Provides green signal guidance for EVs. - The impact of EV priority on the whole traffic flow is reduced by re-planning the signal cycle.	- Promote the shortening of the travel time of EVs. - Better for EVs but not briefly describe about ordinary vehicles flow.
EVP-STC: Emergency Vehicle Priority and Self-Organising Traffic Control at Intersections Using Internet-of-Things Platform	IEEE Access (November 5, 2018)	- Message is received from an emergency vehicle, the normal operation of the traffic lights is interrupted. - Priority is granted to the approach from which the arrival of emergency the vehicle is expected.	Based on emergency priority request(EPR) messages the intersection controller control the flows.
Fog-based dynamic traffic light control system for improving public transport.	Public Transp 12 (25 March 2020)	Local gateway at an intersection exchanges the traffic information with the adjacent intersection via fog nodes.	Solution for multiple intersections without considering any communication architecture. Using fog for low latency but EV can’t consider.
Adaptive Traffic Light Control with Wireless Sensor Networks.	2007 4th IEEE Conference (02 June 2014)	The traffic information collected from the wireless sensor network to achieve a real time adaptive traffic control.	Improve the localized flow model and coordination among the neighbour but don’t discuss about EVs.
A Collaborative Road Traffic Regulation Approach Using a Wireless Sensor Network.	IJSSMET (21 December 2021)	Simulations for demonstrate the efficiency and practicality approach to reduce AWT and queue lengths.	Proposed a coordinated traffic light control approach based wireless sensor network.

Previous work

- A dynamic traffic signal controller (DTLCS) using WSN
- Calculates priority using formulas (vehicle weight, length, queue length)
- Uses predefined equations for green time
- Simulation environment (PTV VISSIM)
- Makes decisions explicitly designed by me
- Performance evaluation metrics

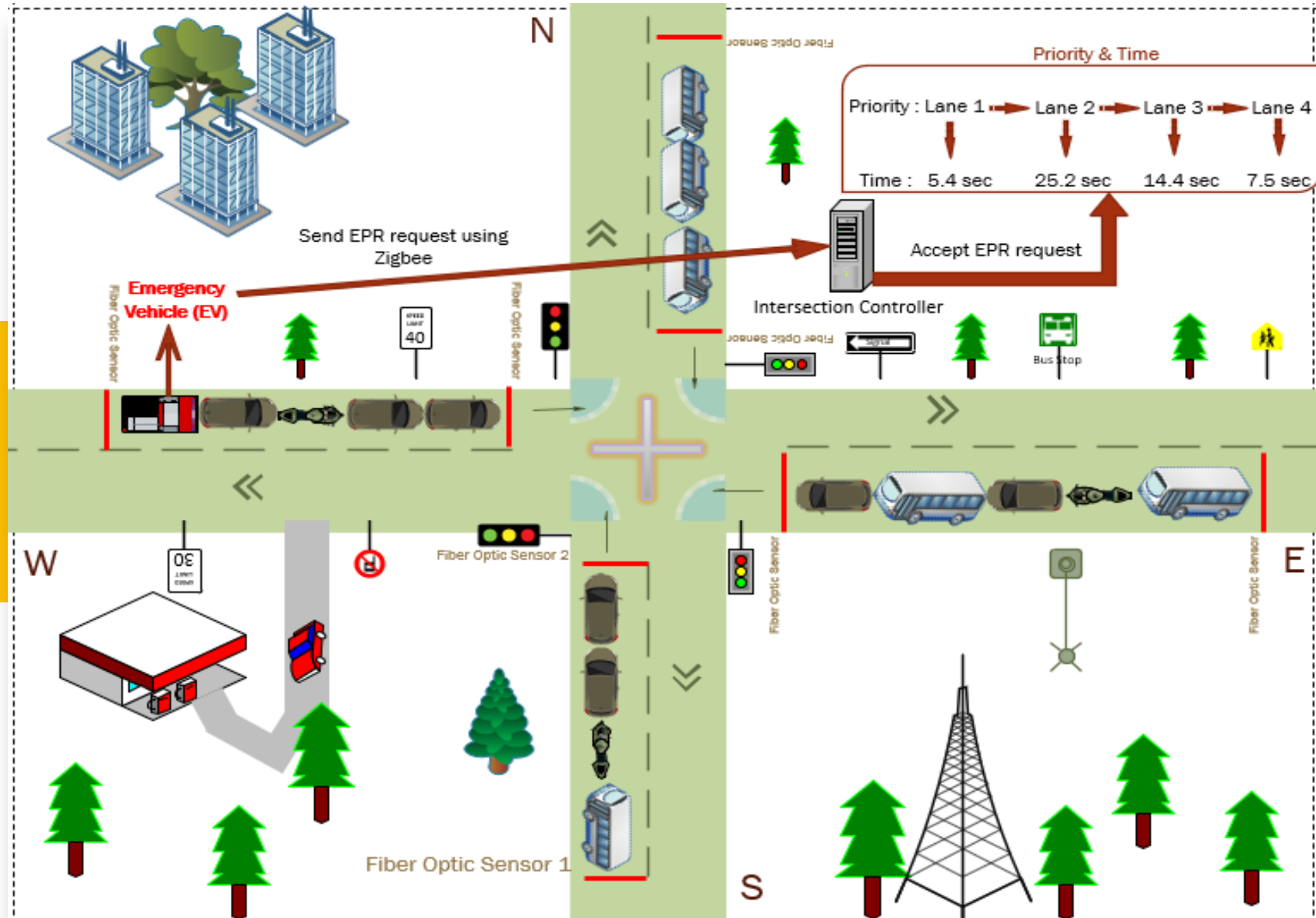




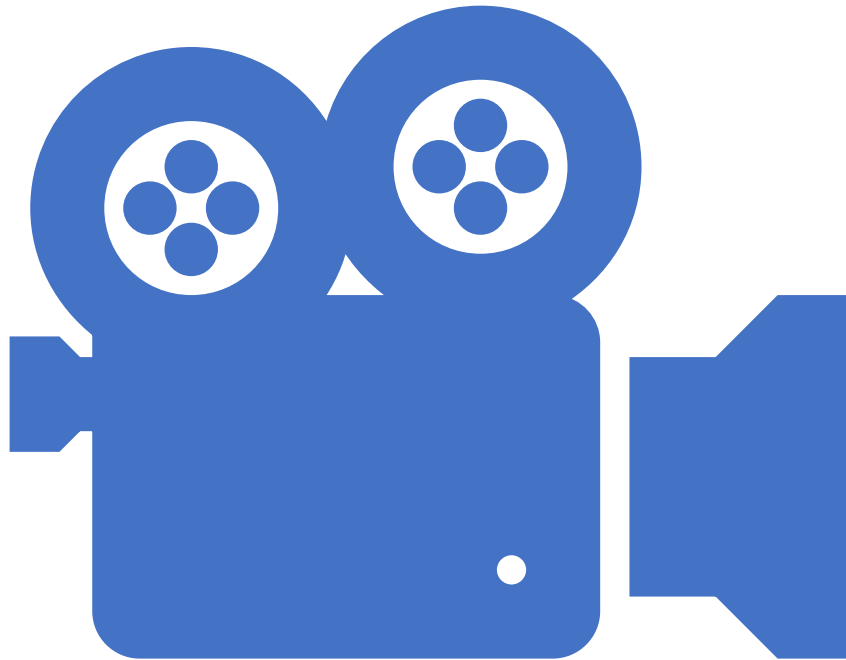
The Intersection Controller sets the priority and signal time for each lane

Previous lane priorities were : Lane 2 -> Lane 3 -> Lane 4 -> Lane 1

15



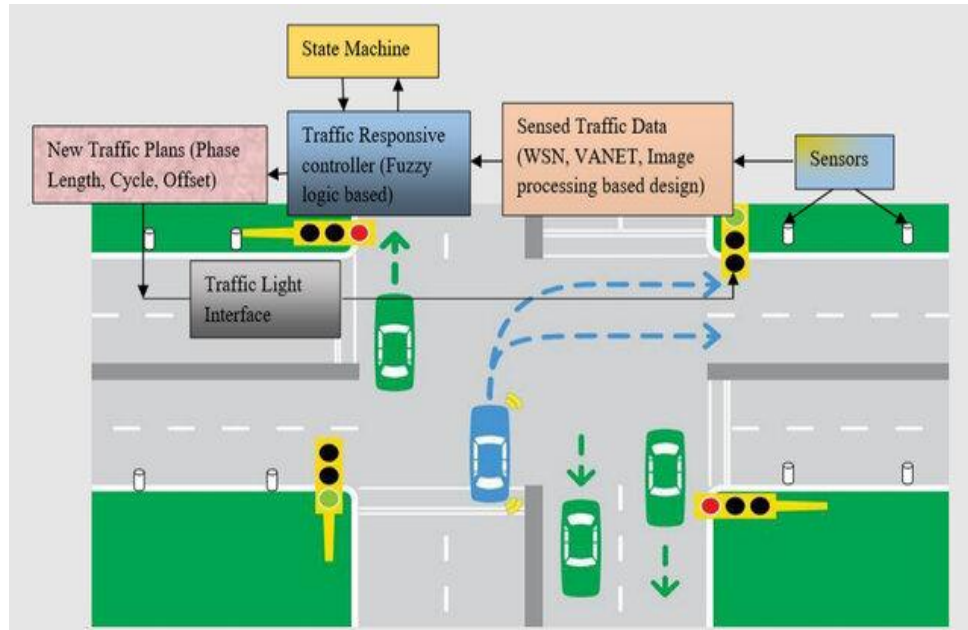
For
Emergency
Vehicle



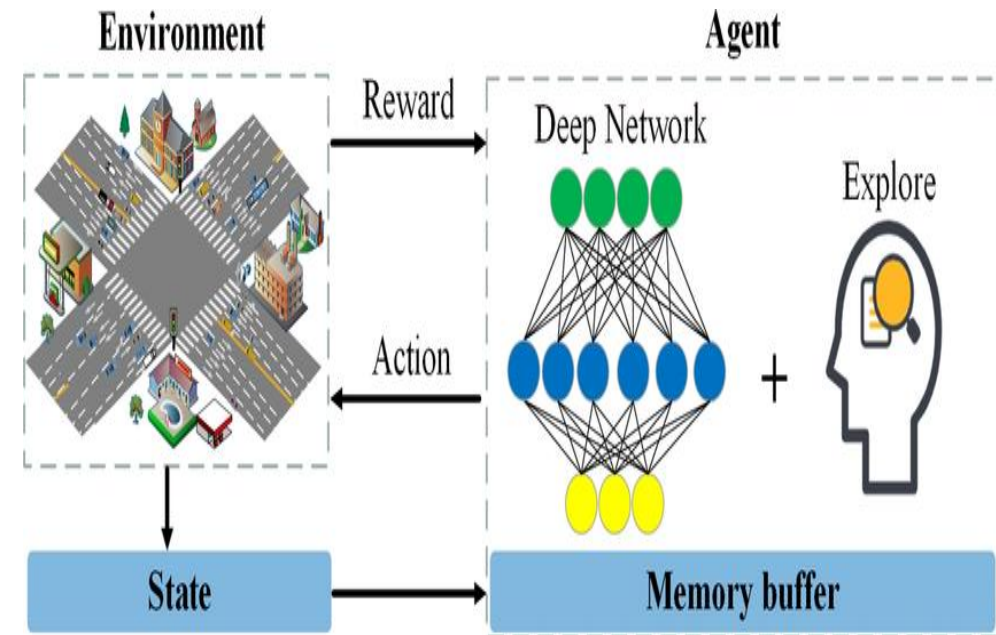
**Video for previous work simulation
(PTV VISSIM):**

<https://drive.google.com/file/d/1-ccdmvdshEFrHRskC3VFoAGOGibrE6Jz/view?usp=sharing>

Rule-based System



Learning-based decision making



Overview



Intelligent Traffic Control

Use Reinforcement learning for dynamically adjusts traffic signals to reduce delays and improve traffic flow efficiency.

Real-Time Vehicle Detection

Use YOLO-based models for enable accurate real-time detection of vehicles and emergency vehicles for informed control decisions.

Traffic Simulation Environment

SUMO simulates urban traffic scenarios to test and evaluate reinforcement learning controllers virtually.

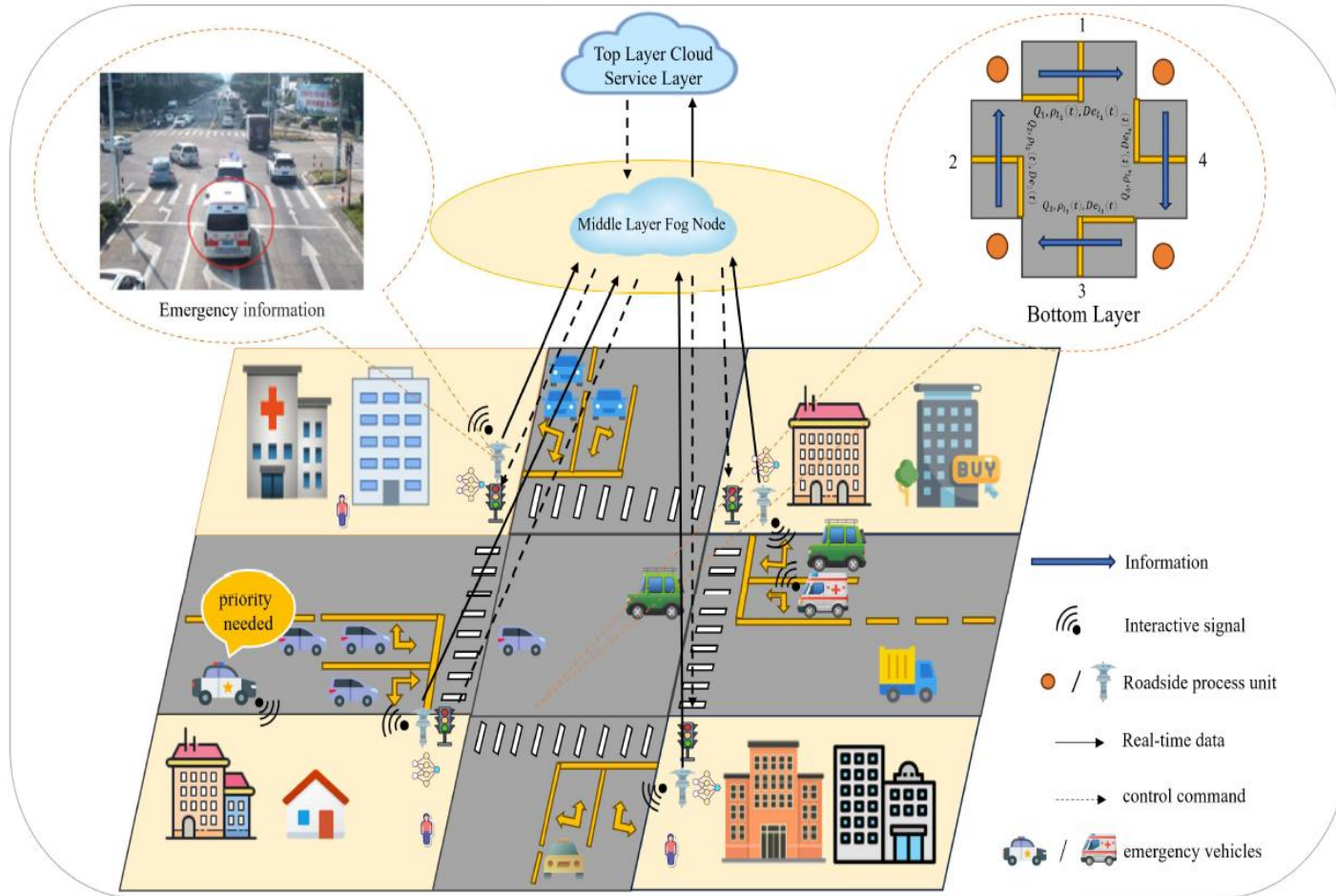
Smart City Impact

The system promotes urban mobility, emergency vehicle clearance, and smart city innovations for safety and efficiency.

Related Work



In [1]

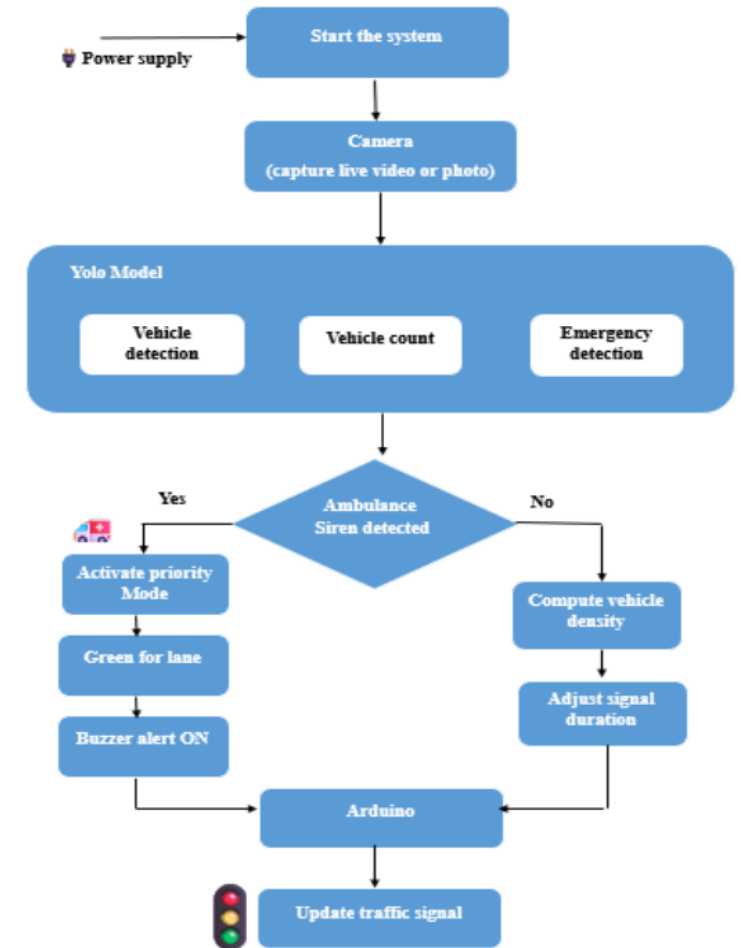


- Proposes DNLight, a DRL-based traffic signal control strategy for emergency vehicle priority.
- Uses a three-layer fog computing architecture to reduce latency and improve real-time decision-making.
- Employs advanced DRL for stable and efficient learning.
- Introduces a dynamic reward function balancing EV priority and fairness for normal vehicles.
- Achieves 40%+ improvement in emergency vehicle efficiency in SUMO simulations.
- Reduces negative impact on regular traffic by up to 50% using adaptive weighting.

F. Li, P. Dong, J. Wu, N. Tong, and T. Qiu, "Deep reinforcement learning-driven traffic signal control strategy for emergency vehicle scenarios in fog computing framework," IEEE Internet of Things Journal, vol. 12, no. 24, pp. 54133–54149, Dec. 2025.

In [2]

- YOLO-based real-time vehicle detection & counting.
- Dynamic green-time adjustment based on lane density.
- Acoustic siren detection for EV identification (98% accuracy).
- Instant green signal for ambulance lane (pre-clearing).
- Reduces congestion & emergency response delay significantly.
- YOLO model achieves >90% accuracy in real-time detection.



P. K. V., D. D. T. B., V. Bhumikasri, and R. Lathikha, "Real-Time Smart Traffic Signal Controller Using YOLO-Based Deep Learning for Emergency Vehicle Prioritization," *Proc. 10th IEEE Int. Conf. Smart Structures and Systems (ICSSS)*, 2025, pp. 1–6.

DOI: 10.1109/ICSSS66939.2025.11346224.

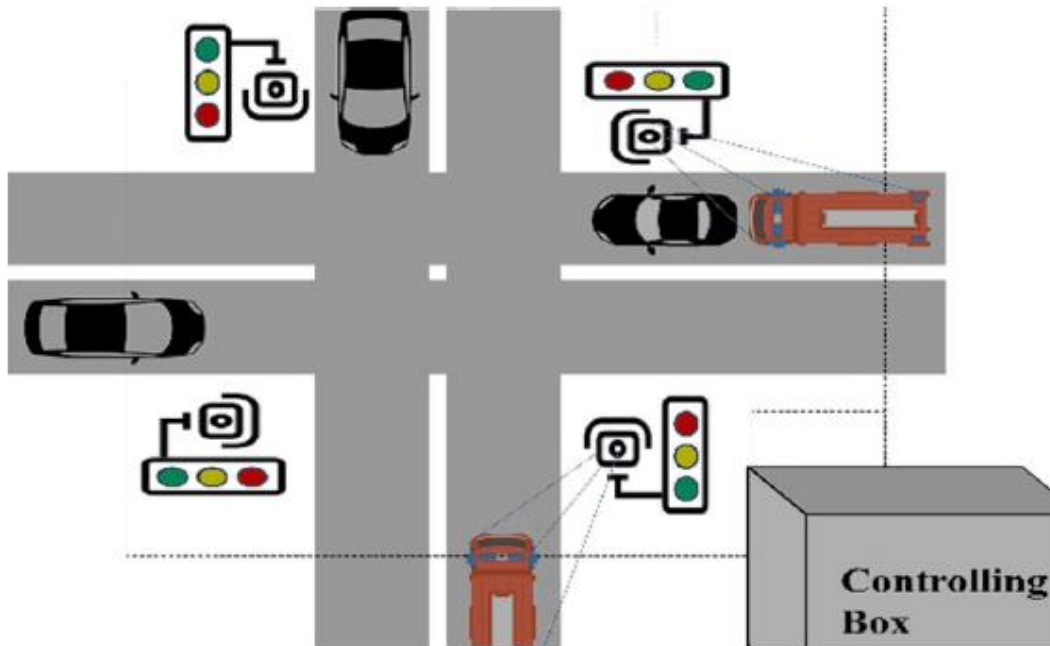
In [3]

- Modified SUMO-RL to support custom reward & observation functions.
- Enables multi-agent RL for smarter, coordinated traffic signal control.
- Tested on Žilina city map for realistic traffic simulation.
- RL methods showed lower trip time, delay, waiting time, and queue length vs fixed-time control.
- Provides improved tools for future adaptive traffic control research.

In [4]

- Compares fixed-cycle vs. adaptive (reactive & DQN) traffic light control using SUMO.
- Adaptive agents significantly reduce waiting time & stopped vehicles.
- Reactive agent outperforms DQN due to traffic complexity and RL learning difficulty.
- Shows strong potential of multi-agent adaptive TLS for improving traffic flow.

S. Phon-Amnuaisuk, S.-J. Tan, Y.-H. Yap, P. Vejjanugraha, K.-C. Khor, F. C.-M. Choong, and K.-H. Ng, "Multi-agent Traffic Light Controls with SUMO," in Proc. 2023 8th Int. Conf. on Business and Industrial Research (ICBIR), Bangkok, Thailand, May 2023, pp. 824–830, doi: 10.1109/ICBIR57571.2023.10147743.



In [5]

- Uses YOLOv8 for real-time emergency vehicle (EV) detection across multiple traffic paths.
- Dynamically adjusts traffic lights to give instant priority to EVs.
- Introduces collision-risk assessment to avoid EV crashes at intersections.
- YOLOv8 achieves high accuracy (Precision 0.962, mAP50 0.955).
- Supports multi-EV scenarios, improving safety and reducing traffic delays.

Thesis Section	Best Papers
YOLO detection	Paper 2, 5
RL (PPO/DQN)	Paper 1, 3, 4, 5
SUMO simulation	Paper 4
Emergency Vehicle Priority	Paper 1 , 5

1	2	3	4	5	6	7	8
Title & Year	Authors	Topic / Area of Study	Research Focus / Aim	Methodology	Key Findings	Limitations	Relevance to Your Research
Deep Reinforcement Learning-Driven Traffic Signal Control (2025)	Fengqi Li, Peng Dong, Jianting Wu, Ning Tong, Tie Qiu	RL-based adaptive traffic signal control with mention of EV priority issues	Improve traffic signal efficiency using Deep RL; highlight difficulty in guaranteeing EV priority	DRL models tested for traffic optimization	RL can improve control performance; fixed-time systems fail to guarantee emergency priority	Does not integrate YOLO or real-time EV detection; no computer-vision component	Supports your RL component and identifies EV priority as an unsolved gap your work addresses
Real-Time Smart Traffic Signal Controller Using YOLO (2025)	Priyadharshini K. V, Dhivya Dharani T. B, Bhumikasri V, Lathikha R	YOLO-based real-time traffic density detection & adaptive signaling	Remove inefficiency of fixed-time signals via YOLO-based adaptive control	YOLO used to detect flow → adaptive green-time	Reduces delays vs fixed-time signals; real-time detection effective	No RL optimization; no emergency vehicle preemption	Supports your YOLO detection module; your RL + EVP integration goes beyond this
Reinforcement Learning Approach to Adaptive Traffic Signal Control (2024)	Aleš Janota Filip, Kalus Rastislav, Pirník Júlia Kafková, Pavol Kuchár Michal, Skuba Peter Holečko	RL for adaptive traffic signal control in dynamic city networks	Use RL to optimize signal phases and reduce congestion	RL algorithms (likely PPO/DQN) evaluated using simulation	RL outperforms traditional signal plans	No vision input; no emergency vehicle support	Strong support for your RL (PPO/DQN) methodology, but you extend with YOLO + EVP
Multi-Agent Traffic Light Controls with SUMO (2023)	Somnuk Phon-Amnuaisuk, Soon-Jiann Tan, Yok-Hoe Yap, Pikul Vejjanugraha, Kok-Chin Khor, Florence Chiao-Mei Choong Keng-Hoong Ng	Multi-agent adaptive traffic light control using SUMO	Compare adaptive agent-based TLS with fixed-time cycles	Multi-agent RL tested using SUMO	Adaptive agents outperform fixed cycles	No emergency vehicle logic; no real-time perception	Supports your SUMO-RL environment; you expand by adding computer vision & EVP
A Novel Multi-Agent Deep RL Approach for Traffic Signal Control (2023)	Wang Shijie Wang, Shangbo	Multi-agent Deep RL for complex intersections	Improve control efficiency at multi-intersections using MARL	Deep multi-agent RL training and evaluation	MARL improves throughput and control stability	No YOLO, no emergency detection, no EVP	Backs your argument that RL works, but none integrate YOLO or emergency logic like yours

Fixed-time traffic signal systems cannot adapt to real-time traffic flow.

Sudden changes in traffic density are not detected by traditional controllers

Existing systems cannot automatically identify or prioritize emergency vehicles.

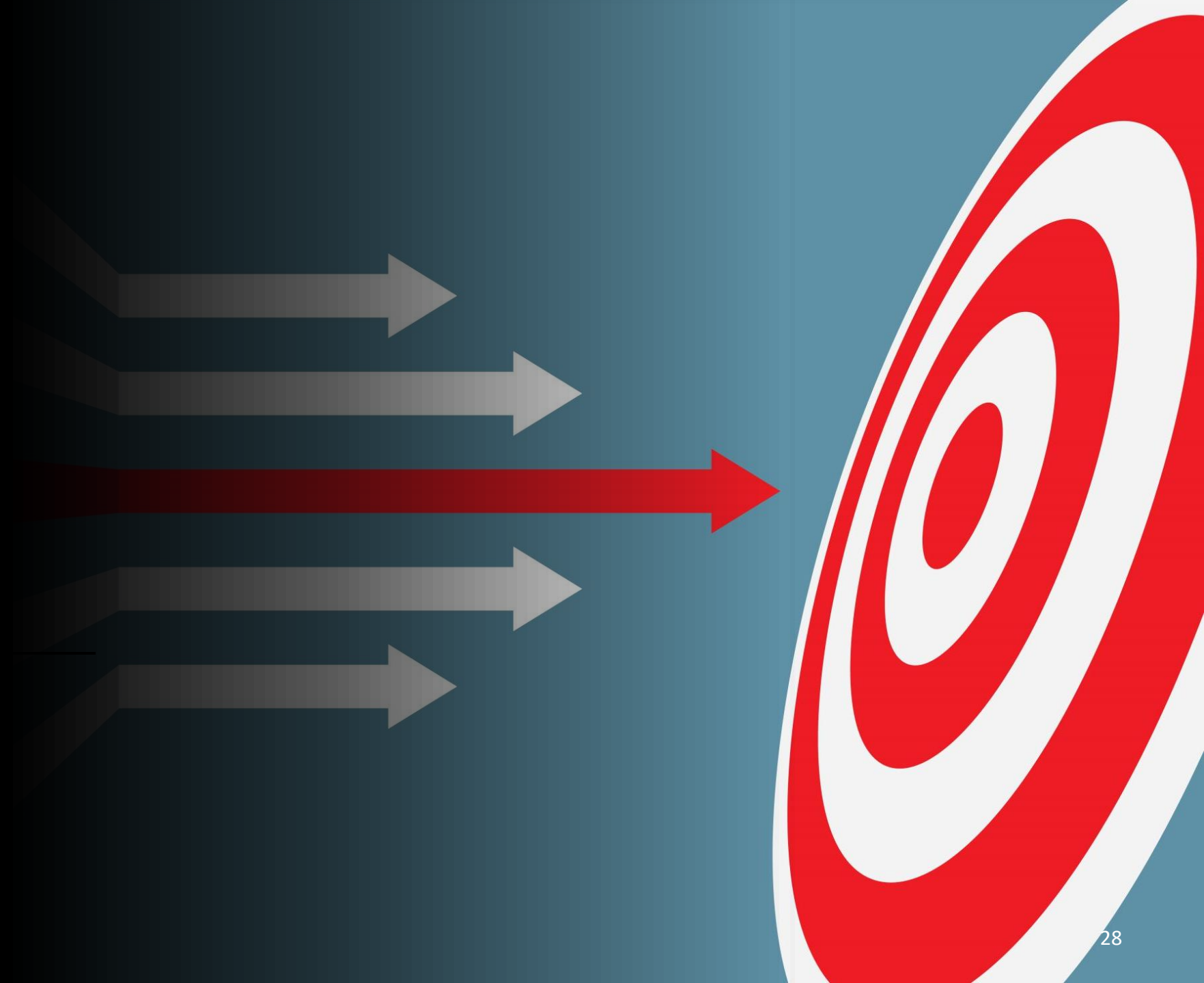
YOLO-based detection systems lack decision-making intelligence, while RL models lack real-time perception—an integrated solution is missing.

There is no unified framework combining YOLO for perception and RL for adaptive control with emergency vehicle priority, creating a major research and deployment gap in smart traffic systems.





Aim and Objectives



Objectives

- To adjust signal timings in real-time based on current traffic conditions, demand, and system capacity.
- To detect vehicles & EVs with YOLOv8, fix the priorities and signal timings for each lane at the intersection.
- To implement emergency vehicles pre-emption and give higher priority to the emergency lane.
- To maximize intersection throughput and minimize the average waiting time.



Current Approach (Reinforcement Learning)

- The traffic controller becomes an **agent**
- It learns signal timing automatically through interaction
- No fixed equations are required for decision making
- Priorities Emergency Vehicles (Ambulance, Police Car etc.)
- The agent learns policies like:
“When queue length = high **AND** emergency vehicle detected → give green immediately.”

Aim: To create an adaptive traffic signal system using YOLOv8 + RL (PPO/DQN) + EVP to minimize delay and prioritize emergency vehicles in real time.



Research Gap

Observations



Current adaptive systems rely on physical **sensors** (loops, radars), not real-time computer vision



Emergency vehicle priority is poorly addressed in existing literature



YOLO-based traffic systems exist but do not include RL



No unified architecture combining **YOLO (perception)** + **RL (decision-making)** + **EVP (priority routing)**



RL-based traffic control studies rarely integrate **camera-based** perception

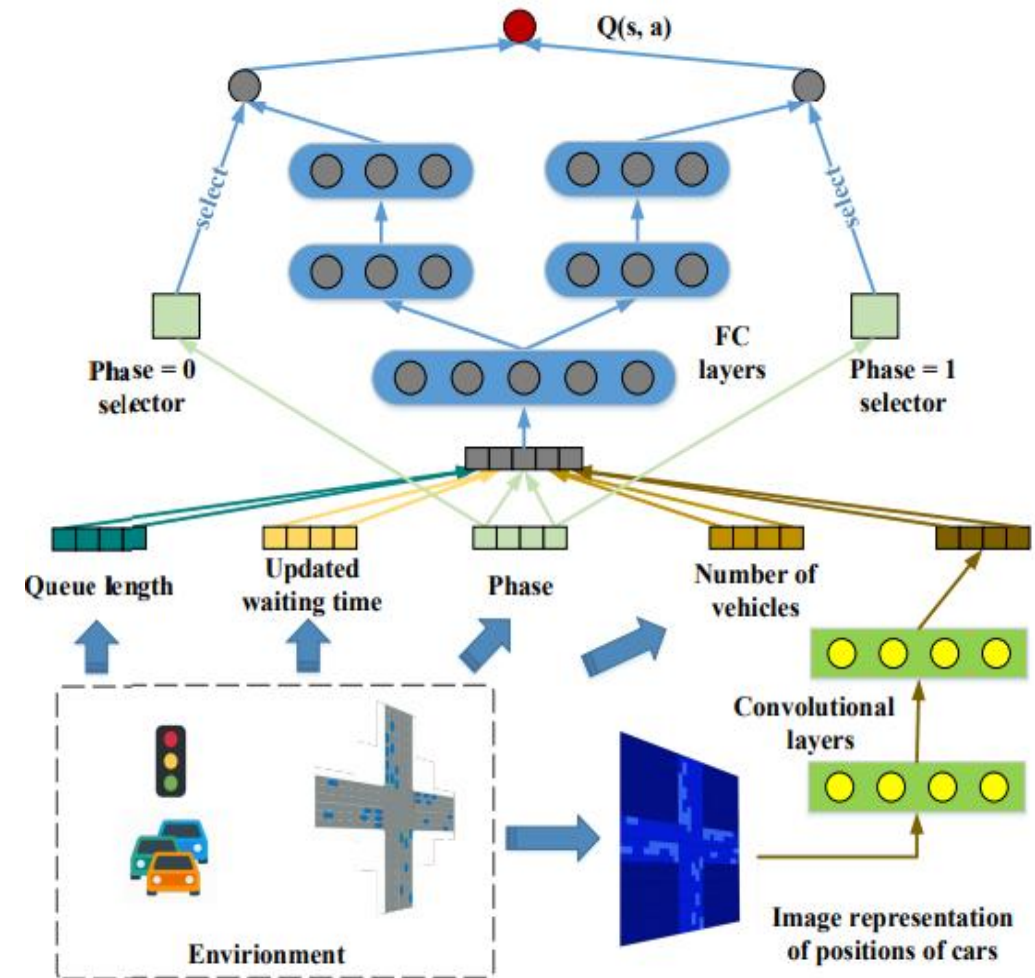
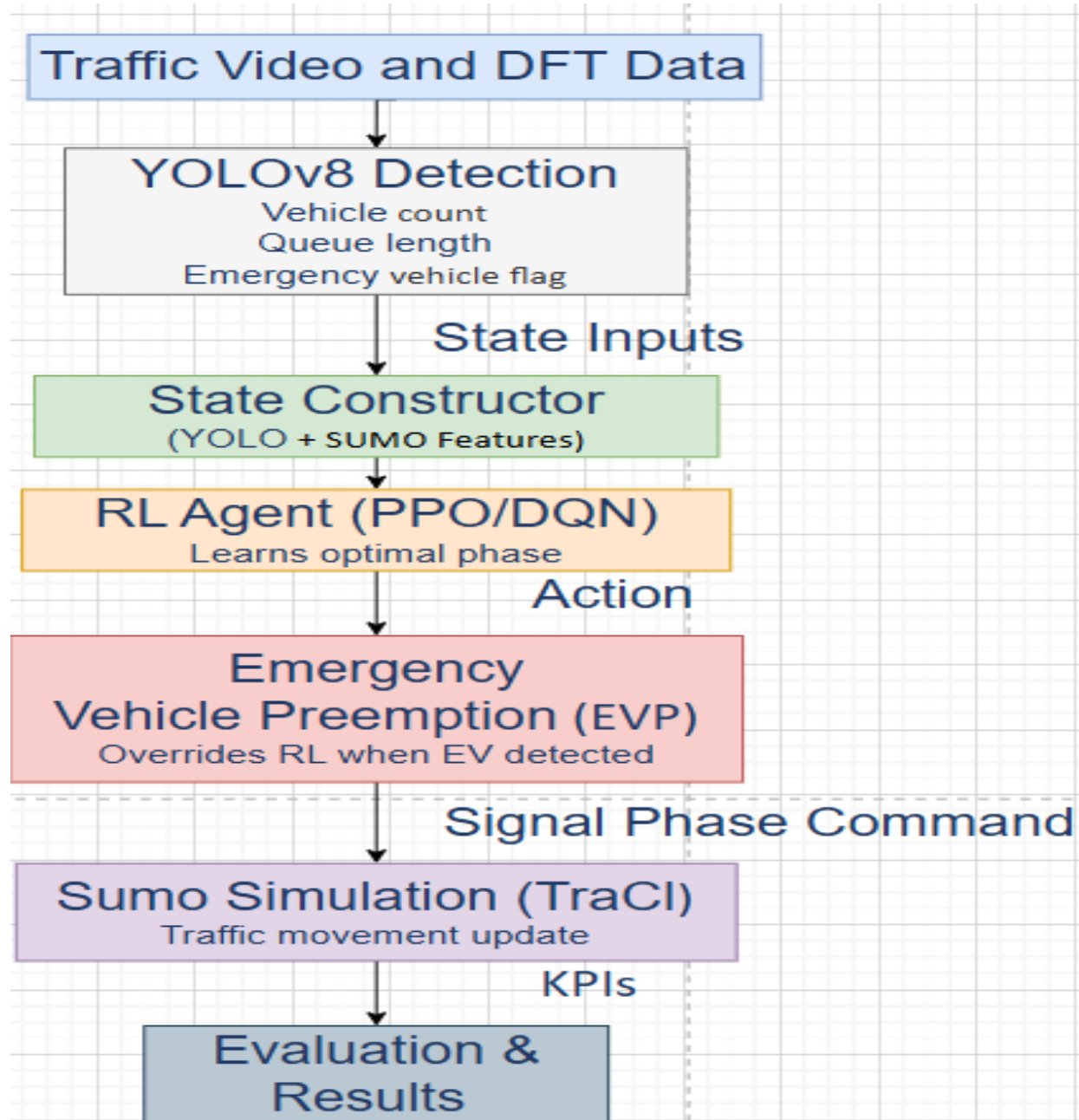


Sim-to-real implementation challenges (noise, lighting, camera calibration) remain unaddressed in current research, creating a practical deployment gap.

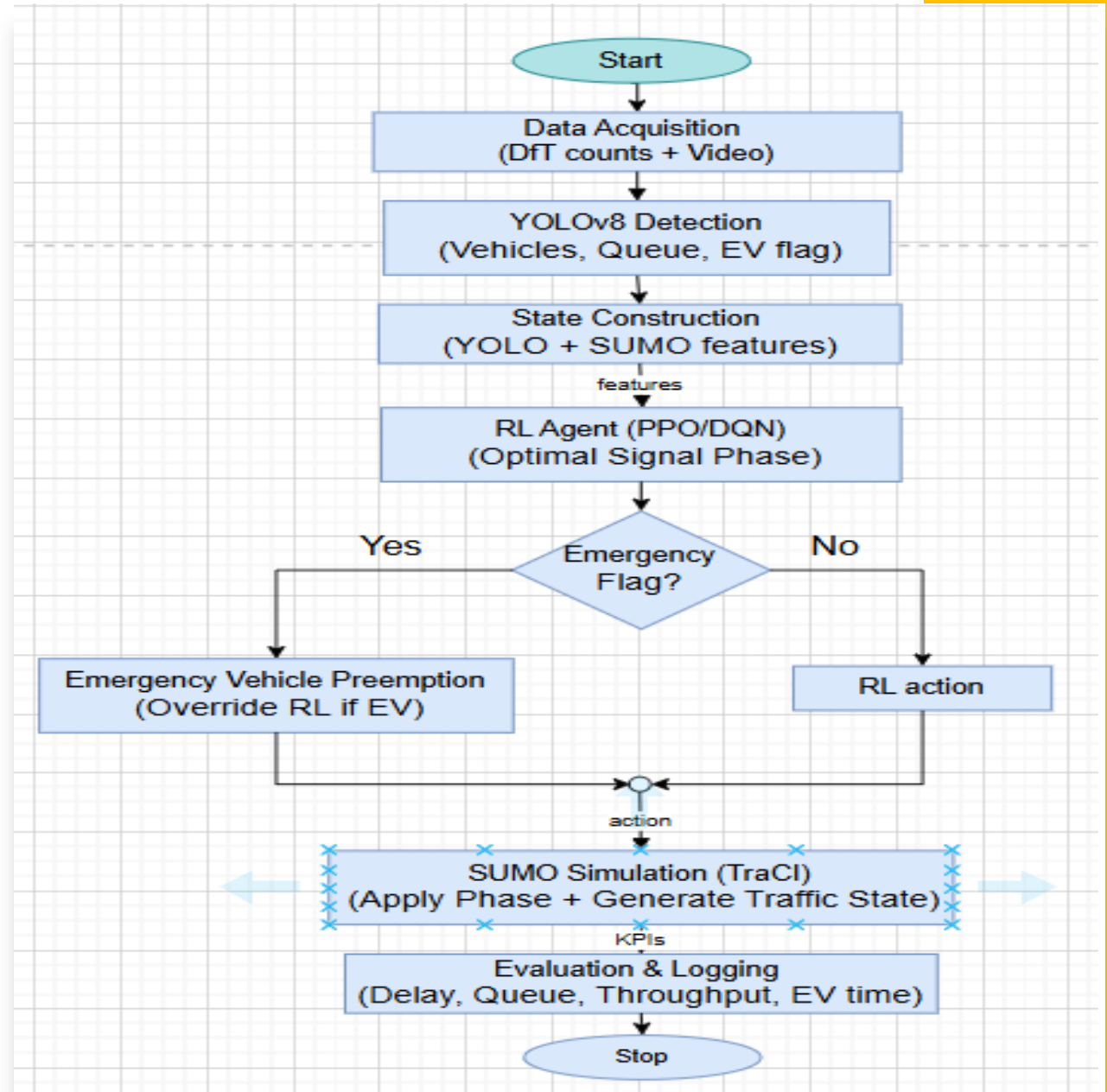
System Design/ Methodology

Workflow

34



Flow Chart



Queue Values (Counting the Vehicles)

$$Q_{L_j} = \underbrace{Q_{L_{j-1}}}_{\text{remaining vehicles from the prev. cycle}} + \underbrace{\lambda_G G}_{\text{vehicles arrive in green time}} - \underbrace{\mu_G G}_{\text{vehicles departure in green time}} + \underbrace{\lambda_R R}_{\text{vehicles arrive in red time}}.$$

Q_{L_j} = Expected queue length of one lane for the next cycle j .

$Q_{L_{j-1}}$ = Queue length for the previous cycle.

G = Arrival Rate in green phase.

λ_R = Arrival rate in red phase.

λ_G = Arrival rate in green phase.

G = The green period of one phase in seconds.

R = Red light period in seconds.

$G - R$ = Difference between the T and green time period.

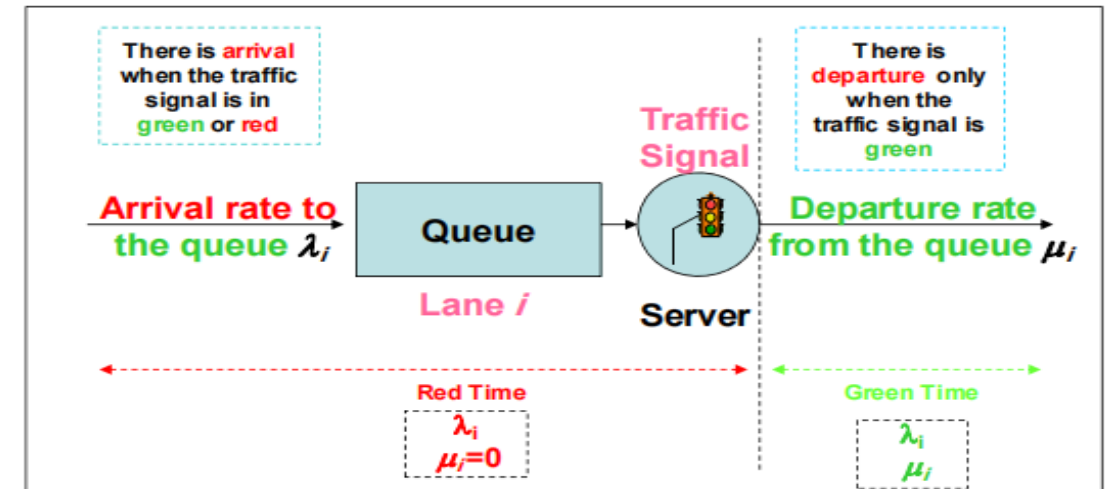


Fig. 7. Traffic signal queue flow.

Integrated Methodology Breakdown

Real-Time Data Acquisition

Collect traffic counts and camera video streams to establish real-time traffic demand and detection inputs.

Perception and State Construction

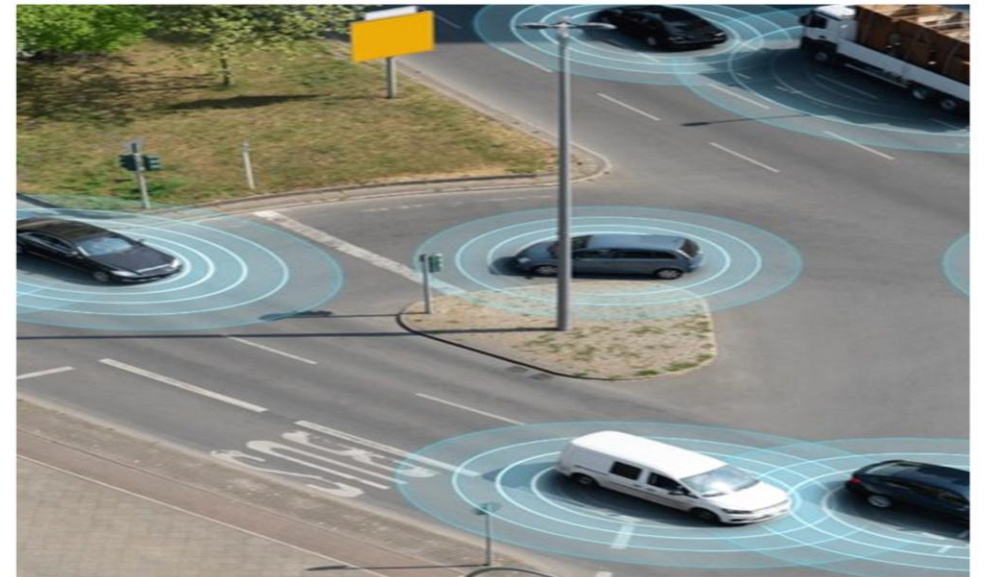
YOLOv8 processes video to detect vehicles and congestion, merging outputs with simulation metrics for RL input.

Reinforcement Learning Optimization

RL agents use algorithms like PPO or DQN to learn optimal signal policies minimizing delays and queue lengths.

Emergency Vehicle Preemption

EVP module overrides RL to prioritize emergency vehicles, adjusting signals for safe and quick passage.

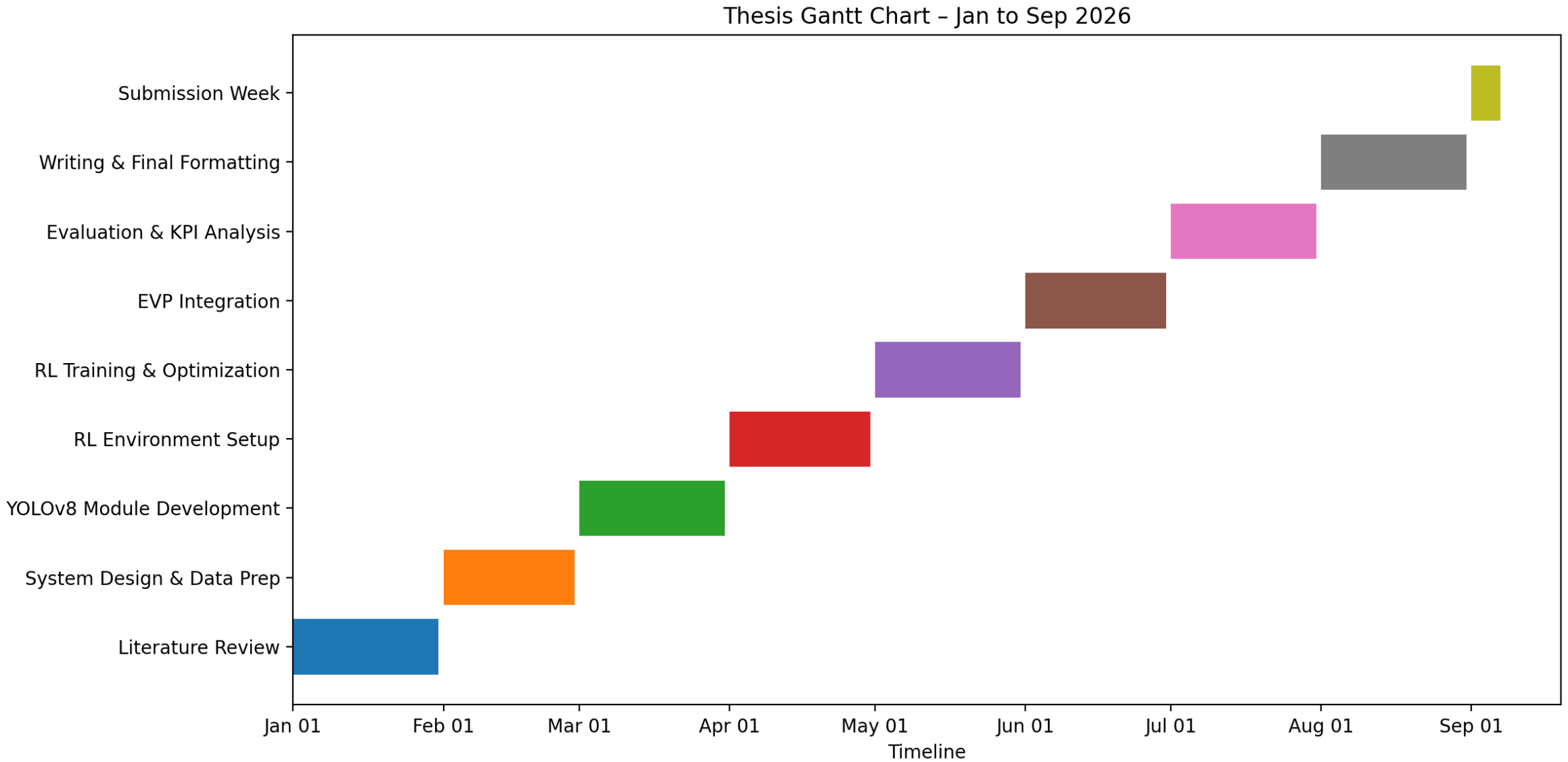


Planning and Resources



Current Progress

- Implementation and Evaluation phase ongoing
- Plan to train RL models (PPO, DQN)
- Plan to utilize YOLOv8 for real-time vehicle & emergency detection analysis
- Early experiments for traffic delay, queue length, and throughput analysis
- Emergency-vehicle preemption logic being testing
- Simulation scenarios and metrics preparing for evaluation phase within SUMO Environment



Resources

Category	Resources Required
Software & Tools	• Python 3.x • SUMO (Simulation of Urban Mobility) • TraCI API • YOLOv8 (Ultralytics) • Stable-Baselines3 (PPO/DQN) • OpenCV, NumPy, Pandas • Jupyter Notebook / VS Code
Datasets	• DfT (UK Department for Transport) Traffic Count Data • Public traffic video datasets for YOLO testing • SUMO-generated synthetic traffic routes
Hardware	• Laptop/PC with 8–16 GB RAM • Multi-core CPU • (Optional) GPU for faster YOLO inference & RL training
Technical Skills	• Reinforcement Learning concepts (state/action/reward) • Computer Vision & Object Detection • SUMO simulation design • Python programming • KPI analysis (delay, queue, throughput)
Documentation & References	• IEEE & Springer research papers • YOLOv8 official documentation • SUMO & TraCI tutorials • RL algorithm documentation (PPO/DQN)
System Integration	• YOLO → State Processor → RL Agent pipeline • SUMO TraCI real-time control • Logging tools for KPIs and training monitoring

The background of the slide features a complex arrangement of interlocking metal gears in various sizes, creating a sense of mechanical complexity. In the upper right quadrant, a circular compass rose is visible, with its face showing cardinal and intercardinal directions (N, NE, E, SE, S, SW, W, NW) and degree markings. The text "Impact and Limitations" is centered over the image in a white, sans-serif font, with a thin white horizontal line positioned directly beneath it.

Impact and Limitations

Impact of Dynamic Traffic Control System

- Improve traffic safety.
- Reduce air pollution.
- Relieve traffic congestion.
- Reducing the average waiting time.
- Minimizing the fuel consumption.
- Maximizing the throughput.
- Increasing energy efficiency.
- Considering emergency vehicles.
- Reduce human direct involvement.



Limitations

- YOLO reliability depends on weather(rain, fog) /light conditions.
- RL training requires long time and careful tuning.
- SUMO-to-real transfer limitations.
- Emergency detection may produce false positives/negatives.
- Requires good hardware (GPU/CPU).
- Single-intersection setup—limited scalability.
- Real-world deployment requires reliable cameras & network.

Conclusion



I proposed to priorities type of vehicles for maximize traffic throughput and minimize average vehicle waiting times at intersections.



An intersection controller control to resolve potential conflicts at intersections in order to assign higher priorities to specific roads.



In normal operation, I priorities based on density of the vehicles.



For Emergency vehicle, I specially priorities the Emergency vehicles like, Ambulance, Police car, vehicles of fire brigade etc.

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*Thank
you*



SOOOOO...

ANY QUESTIONS?