INTELLIGENT TRAFFIC MANAGEMENT SYSTEM WITH REAL-TIME VEHICLE DETECTION AND ADAPTIVE SIGNAL CONTROL

By Group 18

Date - 25/08/2025

TEAM

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INTRODUCTION & MOTIVATION

The Problem: Urban Gridlock

- Traffic congestion is a critical issue in modern cities, leading to significant economic and environmental costs.
- Increased travel times, fuel consumption, and air pollution are direct consequences.
- Traditional traffic light systems use fixed-timers or simple loop detectors, which are inefficient and cannot adapt to real-time, dynamic traffic conditions.

The Motivation: A Smarter Solution

- What if traffic signals could think and adapt like an experienced traffic controller?
- Reinforcement Learning (RL) offers a powerful framework to train an AI "agent" to make intelligent, real-time decisions.
- Our motivation is to create a system that can learn optimal traffic control policies dynamically, reducing congestion with minimal and practical data inputs.

PROJECT OBJECTIVE

- **To Develop a Dynamic Traffic Light Management System:** Design and implement an RL-based system that can intelligently control traffic signal timings.
- **To Minimize Vehicle Waiting Time:** The core goal is to reduce the average and total waiting time for vehicles at intersections, thereby improving traffic flow.
- **To Utilize Minimal Input Data:** Train the RL agent using only easily obtainable data—vehicle counts at intersections—making the system practical and cost-effective to deploy.
- **To Validate Performance using Simulation:** Use the SUMO (Simulation of Urban MObility) environment to build a realistic traffic network and rigorously evaluate the performance of the trained agent against traditional fixed-time controllers.

LITERATURE REVIEW

Paper ID	Title	Publisher	Year	Description
1	Advances in reinforcement learning for traffic signal control: a review of recent progress	Intelligent Transportation Infrastructure, Volume 4, 2025, liaf009, IEEE Transactions on Cybernetics (arXiv:1908.03761)	2025	The paper investigates traffic congestion and signal optimization in urban environments, focusing on how modern techniques can improve traffic flow. It reviews the limitations of traditional fixed-time and vehicle-actuated traffic signals, which struggle with dynamic and uncertain traffic conditions. The study highlights the potential of intelligent systems such as reinforcement learning, fuzzy logic, and adaptive optimization for real-time traffic light management. These methods enable signal controllers to respond adaptively to changing traffic density, reduce waiting times, improve throughput, and lower fuel consumption and emissions. The paper concludes that integrating AI-driven adaptive traffic control offers significant improvements over conventional systems, making urban mobility more efficient, sustainable, and resilient to future transportation demands.

Paper ID	Title	Publisher	Year	Description
2	Deep Reinforcement Learning for Traffic Light Control in Intelligent Transportation Systems	IEEE Transactions on Network Science and Engineering (arXiv:2302.03669)	2025	In early applications of Deep Reinforcement Learning to traffic control, the state was modeled as an image-like matrix encoding vehicle presence and speed, with a Deep Q-Network (DQN) selecting the optimal traffic light phase. While simulations showed DQNs outperforming traditional methods, the approach was constrained by high computational demands and the need for extensive camera infrastructure to supply high-dimensional visual data.
3	Reinforcement Learning Approaches for Traffic Signal Control under Missing Data	IJCAI 2023 (arXiv:2304.10722)	2025	This paper addresses the challenge of deploying RL-based traffic signal control with incomplete data, where many intersections lack sensors. Their two-step approach first imputes missing states and rewards for unobserved intersections using predictive models trained on observed neighbors, then trains a parameter-sharing Deep Q-Network (SDQN) within a model-based RL framework (Dyna-Q style) using both real/imputed and simulated experiences. Tested on synthetic and real-world data and provided better results.

Paper ID	Title	Publisher	Year	Description
4	IntelliLight: A Reinforcement Learning Approach for Intelligent Traffic Light Control	KDD ’18: ACM SIGKDD International Conference on Knowledge Discovery & Data Mining	2018	This paper introduces IntelliLight, a DQN-based framework enhanced with domain-specific innovations—Phase Gate for phase-dependent decision policies and Memory Palace for balanced learning from rare events—to address real-world traffic control challenges. Using a rich state representation combining tabular and image-like data, and a binary action space, the system was trained and tested in SUMO with traffic demand from a large real-world dataset. IntelliLight achieved substantial reductions in queue length (38%) and delay (19%) over baselines.
5	Traffic-Aware Reinforcement Learning for Urban Signal Control	IEEE Transactions on Network Science and Engineering	2024	This approach improved traffic signal control by designing a reward function that not only minimized wait times but also penalized long queues to prevent spillback between intersections. Using a state representation based on queue lengths and time since the last signal change, it showed that well-crafted rewards enhance learning stability and yield more robust policies. However, its reliance on accurate queue length data—difficult to obtain without specialized sensors—makes performance highly sensitive to data quality.

Paper ID	Title	Publisher	Year	Description
6	Multi-Agent Reinforcement Learning for Networked Traffic Signal Control	IEEE Transactions on Cybernetics (arXiv:1908.03761)	2020	This approach models each traffic light as an independent yet cooperative agent in a Multi-Agent Reinforcement Learning framework, where agents make their own decisions while sharing information such as queue lengths and neighboring actions to achieve a network-wide objective. Using an Advantage Actor-Critic (A2C) algorithm, the study demonstrated that coordinated multi-agent systems can substantially reduce overall travel time compared to isolated agents. However, scalability remains a major limitation, as the complexity of coordination and communication grows exponentially with the number of intersections, hindering application to large, real-world city networks.

Paper ID	Title	Publisher	Year	Description
7	Why Online Reinforcement Learning is Causal?	IEEE Transactions on Network Science and Engineering	2024	This method works by combining causal inference with preference-based learning. Instead of relying only on complex reward functions, CPRL can learn from human or simulation-based preferences (e.g., smoother flow vs. reduced wait time) while uncovering the true causal impact of different signal timings. This allows policies that balance multiple objectives, adapt to new traffic conditions, and provide explainable decisions, ultimately improving efficiency, fairness, and safety in urban traffic control.

RESEARCH GAPS

- **Heavy Data & State Complexity:** Current models depend on high-dimensional inputs (video, positioning, raw images), leading to oversized networks, long training, and costly deployment.

- **Poor Scalability & Adaptability:** Multi-agent systems struggle in large urban grids, and models often fail to generalize beyond the conditions they were trained on.

- **The Minimalism Gap:** No robust solution exists that performs well using only simple, universally available inputs like per-lane vehicle counts – the key gap our project addresses.

SIMULATION ENVIRONMENT

Variables Currently in the Environment:

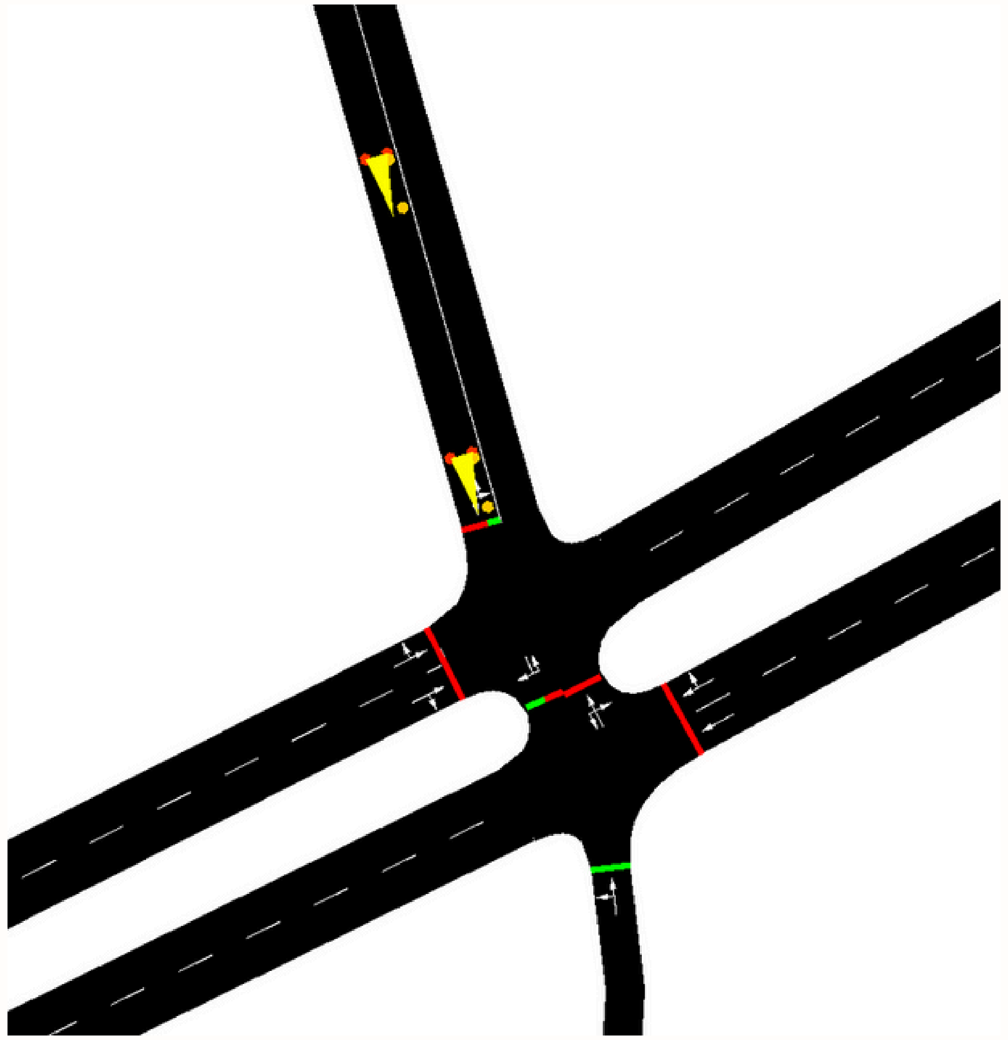
1. **Vehicle Count per Lane:** A list of numbers where each number is the count of vehicles in a specific lane approaching the intersection.

Variables planned to be added for more Realism:

1. **Vehicle Type:** Use SUMO to differentiate between vehicle types. You could change your state to be a count of (cars, trucks) for each lane. This would force the agent to learn that trucks accelerate slower and might need longer green times.
2. **Emergency Vehicles:** Add an ambulance or police car to your routes. You can program the state to include a special flag (e.g., emergency_vehicle_present = 1) which the agent must learn to prioritize above all else.
3. **Pedestrian Crossings:** Add pedestrians to the simulation who press a "walk" button. This adds another demand signal to the state that the agent has to balance against vehicle traffic.
4. **Time of Day / Traffic Patterns:** Instead of one continuous stream of traffic, create different route files for a morning rush hour (heavy traffic in one direction), a midday lull (light traffic), and an evening rush hour (heavy traffic in the other direction). This would test if your agent can learn and apply different policies depending on the time of day.

A GLIMPSE INTO THE SYSTEM

Real world map - Coimbatore(RaceCourse)



With traffic lights and vehicle simulation

PROPOSED METHOD

- Simulates the city map, traffic lights, and vehicle routes.
- Acts as the "real world" for our agent.

SUMO
SIMULATION OF URBAN MOBILITY

- At each decision point, our Python script queries the SUMO environment via the Traci API.
- It extracts a simple state: A vector of vehicle counts for each incoming lane at an intersection.

State Extraction

- This is the "brain" of the system.
- It receives the simple state vector (vehicle counts).
- A Deep Q-Network processes this state and calculates the expected future reward for each possible action.

RL Agent (DQN)

- The agent selects the best action (e.g., "turn phase 2 green").
- The action is sent back to the SUMO environment via the Traci API.

Action Selection

Reward Calculation

After the action is taken, a reward is calculated (negative of the total vehicle waiting time) and fed back to the agent to help it learn.

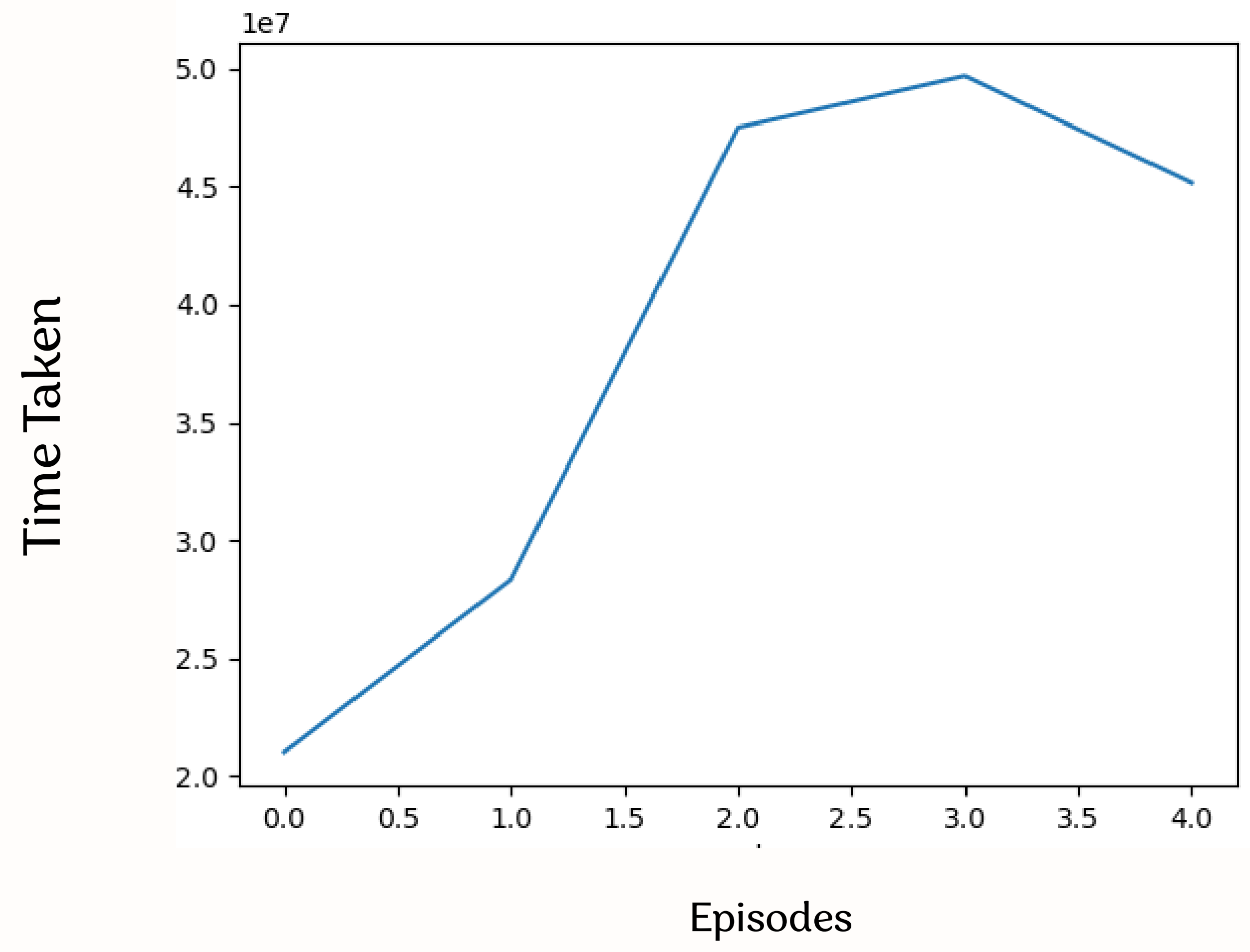
PRELIMINARY RESULT

```
(proj_traffic) D:\College_files\SEMESTER 7\End Sem\Reinforcement Learning\Traffic-Light-Management-system-using-RL-and-SUMO>python train.py --train -m my_first_model -e 5 -s
 3600
***Starting server on port 58140 ***
Loading net-file from 'maps/map.net.xml' ... done (81ms).
Loading route-files incrementally from 'maps/routes.rou.xml'
Loading done.
Simulation version 1.24.0 started with time: 0.00.
Detected intersections. Maximum number of lanes is: 10
Using device: cuda
```

```
total_time 23016048.0
Simulation ended at time: 3601.00.
Reason: TraCI requested termination.
Performance:
 Duration: 1089.29s
 TraCI-Duration: 1075.01s
 Real time factor: 3.30582
 UPS: 1741.699195
Vehicles:
 Inserted: 2818 (Loaded: 3054)
 Running: 1381
 Waiting: 236
 Teleports: 567 (Jam: 282, Yield: 284, Wrong Lane: 1)
***Starting server on port 65091 ***
Loading net-file from 'maps/map.net.xml' ... done (84ms).
Loading route-files incrementally from 'maps/routes.rou.xml'
Loading done.
Simulation version 1.24.0 started with time: 0.00.
```

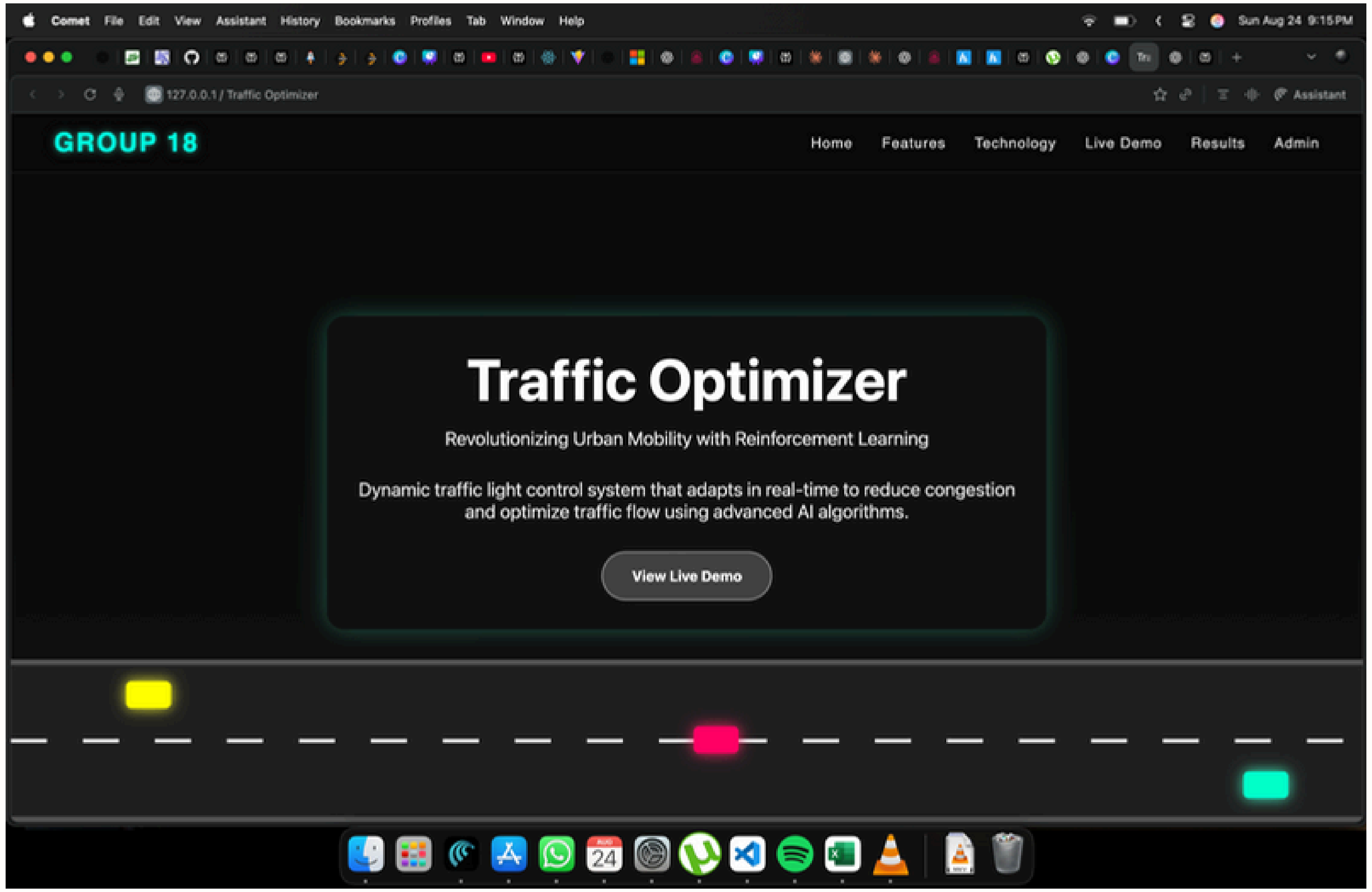
Planned Metrics

1) 📉Queue length
2) 📉 Average time taken for the whole network



→ Unstable Enironment

FRONTEND



Landing Page

SOFTWARE & HARDWARE TOOLS

Software:

- Programming Language: Python 3.8
- Simulation: SUMO (Simulation of Urban MObility) v1.24.0
- RL/ML Library: PyTorch
- Environment: Open Street Map

Hardware:

- CPU: 13th Gen Intel(R) Core(TM) i9-13900H
- GPU: NVIDIA GeForce RTX 4070 Laptop GPU (for accelerating model training)
- Memory: 16 GB RAM

TECH STACK

FRONTEND

React JS

MapBox

D3Js

BACKEND

Python

Node JS

SUMO RL

DATABASE

Postgre SQL

Redis

Cloud Services

- Additionally we will also be using Traci APIs and OpenStreet Map.

PROJECT TIMELINE

Done · In Progress · Upcoming · Milestones

Task	Aug 11	Aug 18	Aug 25	Sep 1	Sep 8	Sep 15	Sep 22	Sep 29	Oct 6
Literature Review & Setup Aug 5 - Aug 7 (Phase 1)	Done								
Building SUMO Environment & Simulation Aug 8 - Aug 10 (Phase 2)	Done								
Model Training & Tuning Aug 12 - Sep 13 (3 Weeks)		In Progress	In Progress	In Progress					
Frontend Development Aug 20 - Sep 10 (3 Weeks)			In Progress	In Progress					
Performance Evaluation Sep 2 - Sep 15 (2 Weeks)					Upcoming	Upcoming			
Final Report Writing Sep 9 - Sep 22 (2 Weeks)						Upcoming	Upcoming		
Final Presentation Prep Sep 16 - Sep 25 (1.5 Weeks)							Upcoming	Upcoming	
Key Milestones	Phase 1&2								

Project Status: Phase 1 (Literature Review) & Phase 2 (SUMO Environment) completed (Aug 10, 2025) • Model Training & Frontend Development in progress
Total Duration: ~6.5 weeks • **Completion Target:** September 25, 2025

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THANK YOU

MISC

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