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Enhancing Traffic Signal Management through Hybrid Models

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Abstract

Modern-day urban traffic management is turning complex with increasing traffic volumes and intricate intersection dynamics, demanding advanced control methodologies. Traditional solutions in Traffic Signal Control (TSC), such as the Webster technique and Self-Organizing Traffic Light Control (SOTL), are severely limited since they rely on predesigned rules and assumptions, thereby showing comparative ineffectiveness in dynamic environments. While existing Reinforcement Learning-based TSC systems are more flexible, they still have significant challenges to overcome in imperfect observation handling-like degraded communication- and rare events not covered by the designed reward functions. In this respect, this project proposes a new framework that integrates RL with LLMs to improve the strength of the process of traffic signal control. It operates in two major steps: the first one involves an RL agent optimizing traffic light timing based on the recorded traffic flow data; the second invokes an LLM evaluating and further refining the decisions of the RL agent by the prompt engineering to obtain the optimal outputs. This integrated approach offers a much more adaptive and robust solution to TSC, with a view toward tackling the complexities of modern urban traffic. While this work presents a pointing concept of combining LLMs with RL. for TSC, this is just the beginning in the exploration of its applications. Further work may include increasing the capacity of the framework for handling more challenging intersections and other situations.

Keywords: Traffic management, TSC, SOTL, vehicle detection system etc.

1. Introduction

The management of urban traffic systems has evolved into an increasingly complex challenge in modern metropolitan areas. As cities continue to expand and vehicular density rises exponentially, traditional traffic control methodologies are proving inadequate in maintaining efficient traffic flow and reducing congestion. Traffic Signal Control (TSC), a critical component of urban traffic management, faces unprecedented challenges in adapting to dynamic traffic patterns, unexpected events, and complex intersection topologies.

Conventional TSC approaches, such as the Webster technique and Self-Organizing Traffic Light Control (SOTL), operate on predetermined rules and static assumptions about traffic behavior. While these methods have served as the backbone of traffic management systems for decades, their effectiveness is severely limited in contemporary urban environments characterized by unpredictable traffic patterns and rapidly changing conditions. These traditional systems lack the adaptability required to respond to real-time traffic fluctuations, leading to suboptimal performance during peak hours and unusual events.

Recent advances in Reinforcement Learning (RL) have shown promising results in TSC applications, offering more flexible and adaptive solutions compared to conventional methods. RL-based systems can learn optimal control strategies through interaction with the environment, potentially improving their performance over time. However, these systems still face significant challenges in handling imperfect observations and degraded communication scenarios. They struggle particularly with responding to rare events not adequately covered by designed reward functions, generalizing learned policies across different traffic conditions and intersection layouts, and incorporating domain knowledge and human expertise into the decision-making process.

To address these limitations, this paper proposes a novel framework that integrates Reinforcement Learning with Large Language Models (LLMs) to enhance the robustness and adaptability of traffic signal control systems. The framework operates through a two-stage process where an RL agent first optimizes traffic light timing based on historical and real-time traffic flow data, learning patterns and developing initial control strategies. In the second stage, an LLM evaluates and refines the RL agent's decisions through sophisticated prompt engineering, incorporating contextual understanding and domain knowledge to produce optimal control outputs.

This integrated approach offers substantial advantages over existing solutions through its enhanced adaptability, where the combination of RL's learning capabilities with LLM's

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contextual understanding enables better adaptation to diverse traffic conditions. The dual-stage decision process improves robustness by helping mitigate the impact of imperfect observations and communication issues. Furthermore, LLMs can incorporate domain expertise and historical insights into the decision-making process, complementing the RL agent's learned policies. The framework's architecture also allows for extension to more complex intersection configurations and traffic scenarios, ensuring scalability for future applications.

While this work presents a promising direction in combining LLMs with RL for traffic signal control, it represents just the initial step in exploring the potential of this integrated approach. The framework demonstrates significant potential for expanding its capabilities to handle more challenging intersection topologies, incorporating multi-modal transportation considerations, and developing more sophisticated prompt engineering techniques for LLM integration. Future research directions could focus on enhancing the system's ability to handle increasingly complex urban traffic scenarios and improving the integration between RL and LLM components.

2. Related Works

i). **Fixed-Time Control Methods:** The basic method for traffic management includes fixed-time traffic signal control systems which operate using unmoving signal timings during complete periods of daily operation. Peter Geoffrey Webster created the Webster method in the 1960s which serves as the critical example of this approach by using mathematical models to determine optimal signal timing from traffic records. The calculation process uses advanced mathematical methods for determining cycle lengths and setting green times and saturation flow rate criteria. The structured method of fixed-time control does not successfully adapt to dynamically changing conditions inside urban traffic areas.

The implementation method works optimally within environments showing steady traffic patterns even though modern cities have inconsistent and hard-to-predict traffic movements. These systems cause poor signal durations during periods of low traffic and unforeseen traffic patterns that worsens congestion and degrades total traffic performance.

ii). **Actuated Control Systems:** Actuated control systems proved to be a better choice than fixed-time systems through their real-time traffic detection capabilities which dynamically modify signal timing according to current vehicle conditions. Signal extensions with added green light duration and red phase truncations are possible through road-based inductive loop detectors that monitor both queue lengths and vehicle occupancy levels.

Free-control and whole-control represent the two main categories of actuated control systems because free-control uses detection mechanisms for minor roads while whole-control applies detection mechanisms to all approaches. The limitations of actuated control systems include their fixed operating framework because they cannot fully optimize networks containing multiple interconnected intersections. The traffic management system provides better signal response than previous systems yet facesrestrictions because decisions happen at individual locations.

iii). **Self-Organizing Traffic Light Control (SOTL):** SOTL provides an evolved decentralized system of traffic signal control which allows specific intersections to modify their light-cycles according to local traffic volumes through algorithm-based adjustments. The real-time signal timing decisions utilize heuristic rules together with local optimization techniques for responding to present traffic queues while also minimizing intersection delays. SOTL excels by choosing waiting vehicles for preference followed by tactical decisions that benefit traffic conditions in single intersections. SOTL operates through rules-based local tactics that restrict comprehensive executive control among multiple intersections. The localized optimization process tends to cause unnecessary traffic congestion in neighboring zones that suggests major hurdles in deploying intelligent traffic solutions across an entire metropolitan region.

SOTL demonstrates an advanced decentralized method to manage urban traffic because it transforms how single intersections generate signals based on live traffic conditions. The main capability of SOTL consists of self-contained decision-making for intersections that enables dynamic real-time modifications to signal cycles for live traffic quantity and pattern recognition. This system achieves its capabilities through predictive algorithmic methods which process real-time traffic data to execute immediate adjustments of signal times. SOTL implements an algorithmic structure that consists of heuristic rules together with local optimization methods to convert conventional static traffic signal control into a modern system. The flexible method of SOTL provides immediate traffic condition awareness to traffic signals through its dynamic response system which differs from fixed-time approaches. Multiple input parameters like vehicle queue length and waiting time with occupancy rate together with directional traffic flow information enable the algorithms to perform quick intelligent signal timing adjustments. Decision-Making Mechanisms SOTL conducts decision-making through a system that optimizes traffic by using multiple layers of evaluation methodology. The main goal of this operation focuses on waiting vehicles' priority alongside the reduction of total intersection delays.

Multiple assessment rules allow the system to create tactical decisions which optimize local traffic flow for achieving this objective. The algorithms develop their decision-making methods using machine learning concepts which improve through learning from previous traffic data and current observations. The system collects detailed information regarding vehicle movements by using sensor equipment such as inductive loops together with video detection tools and modern traffic monitoring devices. In real time the sensors stream data to SOTL algorithms so the algorithms can track vehicles with accuracy through queue management and speed along with direction evaluation. Stringent computational models used by SOTL allow the system to interpret data patterns into subtle adjustments in signal timing beyond the capability of traditional signal control systems.

iv). **Adaptive Control Methods:** Traffic signal management through adaptive control employs advanced computational methods for real-time control of signal timings to reach optimal control. The systems SCOOT (Split Cycle Offset Optimization Technique) and TRANSYT manage complex algorithms which function continuously by using real-time and historical traffic data to adjust signal parameters. The procedures take into account diverse factors such as traffic load alongside waiting vehicle queues and journey delays as well as individual vehicle advancements.

The main strength of adaptive control systems rests in their capability to change sequences of signal timing components in real-time thus creating quick traffic management solutions. These systems achieve better traffic flow through their integration of various data points and sophisticated mathematical models. Implementing adaptive control systems needs substantial computing power and advanced infrastructure even though they have the capability to function effectively.

3. Preliminary

The objective of Traffic Signal Control Optimization is to forecast and adjust signal schedules using actual-time coupled with historical traffic records for urban traffic route management.

The goal of this system involves learning a function f : T -> Tn+1 to find optimal next-time-interval signal control strategies Tn+1 from an input scenario T = {i1, i2,..., in} which includes each intersection state. The existing traffic methods that employ fixed-time or rule-based systems prove inadequate to handle the intricate traffic patterns which develop within urban areas. Hybrid Reinforcement Learning with Large Language Model approaches provide an advanced solution that adapts learning through contextual understanding because they enhance traffic signal control performance.

Notation and Definitions

The set I contains each intersection which appears only once in the urban traffic network. The traffic scenario T contains information about all intersections appearing in sequence T = {i1, i2,..., in} which functions with elements ik belonging to I. Traffic interaction matrix X contains values Xij = 1 to represent the connection between intersections i and j or else 0 to mark no influence between them. The intersection transition matrix P defines how moving conditions shift between different areas in the network based on traffic movements and signal synchronization practices.

4. Proposed Method

Our proposed method in this project aims revolutionize traffic signal control by combining the real-time optimization capabilities of reinforcement learning with the contextual understanding and reasoning abilities of large language models.

i). Reinforcement Learning (RL) Agent: Advanced Traffic Flow Optimization

The Reinforcement Learning (RL) agent adopts Proximal Policy Optimization (PPO) algorithm as its core framework to build an adaptive traffic control system within an intelligent traffic management framework. The modern traffic control method operates unlike static traffic system rules since it develops real-time knowledge while adapting to unpredictable urban roadway behaviors. The system operates through two neural networks connected in a single architecture which produces decision-making outputs for intelligent traffic management.

The primary decision-making part of the policy network deals with multiple inputs which involve present-time traffic density and lane vehicle distribution together with history-based data and live sensor measurements. Through this process the system develops complex recommendations which adjust the traffic signal sequence as well as practical transition methods to reach peak traffic efficiency. The value network functions as an assessment unit by evaluating how proposed actions will affect the long-term outcomes. This network makes calculations of average vehicle waiting times along with intersection congestion levels and potential queue formation risks to guarantee decisions consider present and upcoming traffic conditions.

The learning mechanism enables advanced operation because it was specifically made to work within the continuous and dynamic conditions of urban traffic systems. A properly engineered reward mechanism of the system works to decrease total vehicle delay time and stop congestion while fostering continuous movement through traffic networks. The algorithm includes emergency vehicle prioritization features while managing a complex decision-making process which serves the social responsibility needs of society.

ii). Emergency Vehicle Detection System: Intelligent Vehicle Classification

The emergency vehicle detection system functions as an advanced method to detect vital vehicles and establish their priority status in city traffic environments. Through modern computer vision technology such as deep learning methods and complex neural network systems this system achieves exceptional accuracy when differentiating vehicles. The system employs YOLO 8 object detection approaches to exceed 95% detection precision which enables it to separate emergency vehicles from other vehicles such as ambulances alongside fire trucks and police vehicles and standard passenger cars.

Multiple advanced technological features enable the system to determine its position in addition to vehicle tracking abilities. Real-time high precision vehicle tracking relies on the detection mechanism which operates at half a meter position accuracy while monitoring multiple frames per second. Different sensors integrate through camera technology and radar technology with GPS systems to create both precise and dependable tracking and identification of vehicles. The system's core strength emerges from an automatic emergency vehicle detection system which operates with intelligent prioritization features.

The system operates on detection signs to make immediate changes to traffic signal phases and establish transit pathways and decrease intersection waiting times. Such emergency vehicle navigation enhances speed and safety through this approach which ensures critical life-saving minutes in dangerous circumstances.

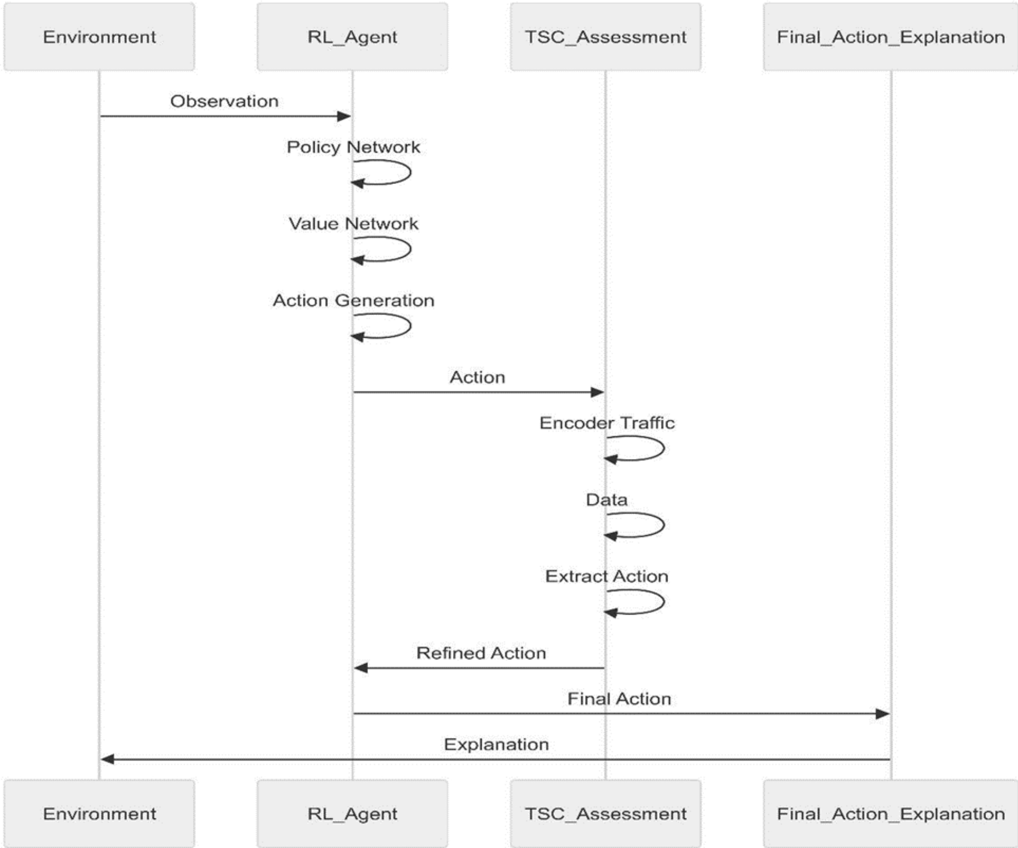

Fig 1: Sequence diagram of the proposed

iii). Large Language Model (LLM) Integration: Contextual Decision Intelligence

By integrating the Large Language Model (LLM) system with GPT-4 capabilities traffic management receives enhanced contextual capabilities. The component provides traffic management systems with superior understanding and reasoning capabilities to analyze complex driving conditions. The LLM performs tasks beyond data processing because it understands and contextualizes information while generating sophisticated support for decisions which account for wide-ranging traffic management impacts.

A prompting system functions as part of the architectural framework to convert numerical traffic data into human-readable narratives so the AI system can develop human-level understanding of traffic situations. The decision parameters along with ethical limits defined by the LLM enable it to conduct detailed analysis of emergency vehicles and traffic densities while using historical data and present intersection conditions. The LLM integration requires its core functionality to operate through a reasoning chain mechanism. The system validates RL agent suggestions while also generating various strategy alternatives and anticipating signal adjustment implementation outcomes and giving detailed explanations for its recommendations. Through this approach the traffic management system creates effective choices which besides being efficient also displays their underlying rationale to stakeholders.

iv). Integrated Workflow: Synergistic Decision Making

The integrated workflow represents the pinnacle of the traffic signal control system's intelligent design, bringing together three sophisticated technologies in a seamless, dynamic decision-making process. At its core, the workflow is engineered to provide rapid, intelligent, and contextually aware traffic management that prioritizes emergency vehicle movement while maintaining overall network efficiency.

a) Emergency Vehicle Detection Initiation

- The process begins with the advanced computer vision system continuously monitoring traffic intersections.
- High-precision sensors and cameras instantly identify and classify emergency vehicles with over 95% accuracy.
- Precise location tracking and vehicle type recognition trigger the initial response mechanism.

b) Reinforcement Learning Agent's Initial Analysis

- The RL agent rapidly processes the emergency vehicle detection data.
- Generates preliminary traffic signal control recommendations based on:
  - Current traffic density
  - Vehicle distribution
  - Historical traffic flow patterns
- Develops initial strategy for signal phase adjustments

c) Large Language Model Contextual Refinement

- LLM receives recommendations from the RL agent
- Applies advanced contextual understanding to:
  - Validate proposed actions
  - Identify potential unforeseen consequences
  - Propose nuanced optimizations
- Incorporates broader urban traffic dynamics into decision-making.

d) Final Signal Control Execution

- Integrated system synthesizes recommendations

- Implements most effective traffic management strategy
- Prioritizes emergency vehicle movement

The final stage represents the culmination of the system's intelligent design. By combining the precise detection capabilities, the learning-driven recommendations of the RL agent, and the contextual refinement of the LLM, the system can execute a traffic management strategy that is simultaneously immediate, intelligent, and holistic.

5. Dataset

The first component of the dataset is designed for analyzing traffic patterns and vehicle behavior using intersection camera data. This dataset includes various vehicle attributes such as unique identifiers, vehicle types, position data, temporal measurements, and environmental metrics. Each entry in the dataset captures a comprehensive profile of vehicle journeys, enabling the system to provide detailed traffic analysis and environmental impact assessments.

An extensive dataset was carefully prepared to detail the varied aspects of traffic monitoring and control. It played an imperative role in the development of the traffic analysis system, providing both real-time monitoring capabilities and historical pattern analysis. The construction considered every possible parameter of vehicle movement and environmental impact. Preparation involved the following steps:

i). Each vehicle's profile includes crucial features such as: Unique vehicle ID and type, Lane positions and movements, Journey timestamps, Speed and route data Environmental metrics (emissions, fuel consumption, energy usage)

ii). Vehicles were categorized based on their types and movements, which helps in identifying traffic patterns. For example:

iii). Measurements were further categorized into three main groups:

Temporal Data: Capturing all time-related measurements (departure/arrival times, waiting duration, total journey time, stop time)

Spatial Data: Recording position-related information (lane positions, route length, queue positions, speed measurements)

Environmental Metrics: Monitoring ecological impact (CO, CO_2, HC, PMx, and NOx emissions, fuel consumption, energy usage)

The data collection achieves high accuracy with: Vehicle detection rate exceeding 95%

Position accuracy of ±0.5 meters

Speed measurement accuracy within ±5% Minimum capture rate of 10 FPS

6. Result Analysis

Through iLLM-TSC (Integration of Reinforcement Learning and Large Language Models for Traffic Signal Control) the efficiency of traffic management increases because signal phases adapt dynamically to current traffic conditions. Interaction between reinforcement learning and large language models works as an optimal mechanism to control signal timing yet simultaneously minimizes congestion and ensures emergency vehicle priority. The iLLM-TSC system achieved a significant 17.5% reduction in average vehicle waiting times compared to traditional reinforcement learning methods, particularly in scenarios with degraded communication conditions.

i). Vehicle Detection and Classification

One of the fundamental components of the proposed framework is its vehicle detection system, which enables real-time monitoring of traffic at intersections. The system effectively detects and classifies vehicles based on their position and lane distribution. The key aspects of vehicle detection include:

Object Detection and Classification

- The model accurately detects vehicles approaching an intersection using computer vision-based deep learning techniques.
- Each vehicle is categorized based on type (e.g., car, bus, truck, emergency vehicle), allowing the system to make informed decisions on signal control.

Lane-Wise Vehicle Distribution

- The detected vehicles are mapped to specific lanes, ensuring that traffic flow is evenly distributed across available road space.
- The system keeps track of lane occupancy, dynamically adjusting green signal durations to optimize throughput.

Emergency Vehicle Identification

- A priority-based classification ensures that emergency vehicles (ambulances, fire trucks, police cars) are detected in real-time.
- When an emergency vehicle is identified, the system immediately modifies the signal phase to provide a clear path, significantly reducing response time.

ii). Adaptive Signal Control for Congestion Management

A key advantage of the iLLM-TSC framework is its ability to handle congestion dynamically. Unlike traditional fixed-time signal control systems, this model continuously learns from real-time traffic conditions and adjusts signal phases accordingly. The benefits observed include:

- Reduced bottlenecks: By redistributing green-light durations across lanes with higher vehicle densities, congestion is minimized.
- Balanced traffic flow: Vehicles are evenly spread across different lanes, preventing excessive queuing in specific areas.

Improved throughput: The adaptive signal system ensures that maximum vehicles cross an intersection within the shortest time frame, improving road network efficiency.

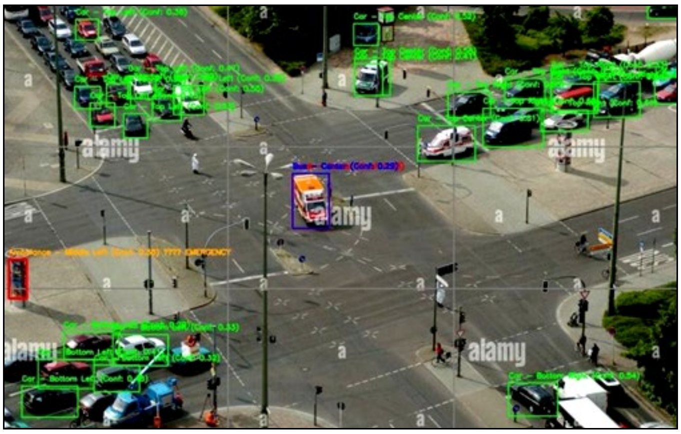

Fig 2: Sample Scenario

Table 1: Performance Metrics

Category	Metric	Value
Detection Metrics	Precision Recall F1-Score	0.92 0.88 0.90
Tracking Metrics	MOTA MOTP ID Switch Rate	0.85 0.87 0.03
Classification Metrics	Emergency Classification Accuracy	0.95
Lane Assignment Metrics	Lane Assignment Accuracy Lane Transition Consistency	0.89 0.91
Performance Metrics	FPS	25.6

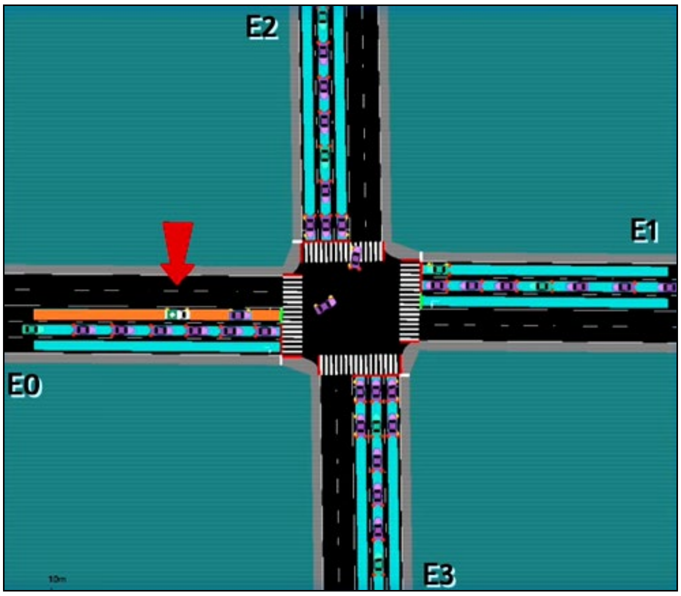

Fig 3: Thought: The decision to activate Phase 2 is justified by the need to prioritize the emergency vehicle and the manageable congestion levels on the movements controlled by this phase

Final Answer:

Decision: Signal Phase Phase-2

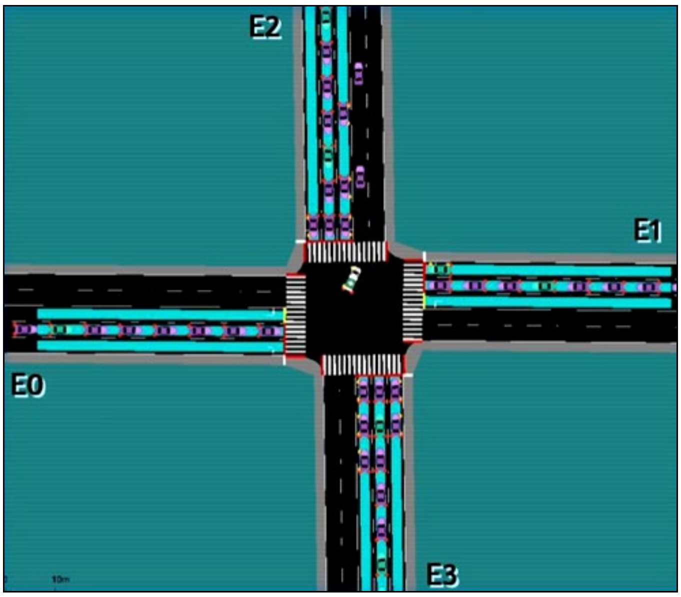

Fig 4: Due to the decision in the previous step the Emergency vehicle cleared the traffic from phase-2 quickly.

Conclusion

The iLLM-TSC framework provides an intelligent traffic control advancement through the application of reinforcement learning with large language models to create dynamic signal timing protocols based on present traffic conditions. The integrated methodology delivers superior traffic control because it unites both prompt congestion relief methods and generalized operational factors concerning emergency vehicle safety and the ability to adapt signal patterns throughout lanes. The vehicle detection system operates in real-time to identify different vehicles for the purpose of maximizing traffic lane allocation efficiency and improving system throughput. The system uses deep learning-based object detection and classification methods to identify vehicles correctly which enables the generation of decisions for traffic signal control systems. Emergency vehicles obtain prioritized clearance in priority-based classification so they can reach their destinations faster thus benefiting urban mobility. iLLM-TSC stands out from conventional fixed-time signal control systems because its adaptive learning ability helps it minimize traffic bottlenecks to provide continuous movement of vehicles. The system achievements show that vehicle waiting times have dropped while lane use effectiveness has improved alongside decreased congestion throughout the area. Operational reliability of this system exists because it includes fallback features that maintain functioning even during diverse traffic conditions.

Future research will concentrate on enhancing the detection precision of this model while extending its application to multiple city traffic scenarios to solidify its role as the next-generation traffic control system. One significant area of future expansion involves implementing iLLM-TSC across multiple interdependent traffic junctions, where signal decisions are coordinated collectively rather than in isolation. This networked deployment will allow for cross-junction communication and synchronization, enabling the system to optimize vehicle flow across a broader urban region. By considering dependencies between junctions— such as traffic inflow/outflow patterns and peak-hour directional congestion—the framework can adapt signal timings dynamically on a larger scale. This distributed yet collaborative approach will enhance overall traffic fluidity, reduce city-wide congestion, and enable emergency routing strategies that span across multiple control points. Integrating such cooperative junction control can contribute significantly toward realizing fully intelligent, interconnected urban traffic ecosystems.

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