LLM-Driven Agents for Traffic Signal Optimization

GitHub repo: https://github.com/NiemaAM/LLM-Driven-Agents-for-Traffic-Signal-Optimization/tree/main

1. Milestone 1: Project inception

1.1. Framing the Business Idea as an ML Problem

Business case description

Urban congestion is one of the most pressing challenges in modern cities, leading to increased travel times, fuel consumption, air pollution, and economic losses. Traditional traffic signal control systems rely on fixed timing plans or rule-based adaptive logic, which often fail to respond efficiently to dynamic traffic patterns.

This project proposes the development of LLM-driven agents for traffic signal optimization, where Large Language Models (LLMs) are used to generate, refine, and optimize traffic signal control policies. The system leverages traffic datasets and simulation environments to evaluate and iteratively improve signal timing strategies.

The LLM functions as an intelligent decision-support agent capable of:

- Generating traffic signal control logic.
- Interpreting traffic state representations.
- Proposing optimized signal phase transitions.
- Iteratively refining policies based on performance feedback.

The system is designed for urban planners, municipalities, and smart city operators seeking AI-assisted traffic optimization solutions.

Business value of using ML

Applying ML and LLM-based agents to traffic signal optimization provides measurable value:

Operational Value

- Smoother traffic flow
- Reduced congestion at intersections
- Shorter vehicle waiting times
- Increased road network throughput

Environmental Value

- Reduced CO_2 emissions
- Reduced idle engine time
- Improved urban air quality

Economic Value

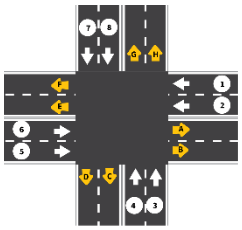
- Reduced fuel consumption
- Lower operational costs
- Reduced time lost due to congestion
- Improved public transportation reliability

Strategic Value

- Scalable across cities
- Adaptable to changing traffic patterns
- Reduced dependency on manually engineered traffic rules

Compared to fixed-time or manually optimized systems, LLM-driven systems can adapt faster and propose alternative strategies automatically.

Data overview



Source: *https://doi.org/10.5281/zenodo.14171745*

This dataset contains simulated multi-lane intersection traffic scenarios with annotated conflict events. It provides structured traffic state variables alongside labeled conflict occurrences and recommended control actions. The dataset is primarily used for conflict detection and safety-aware traffic signal decision modeling.

Input Data Table (Vehicle Scenario Features):

Feature	**Description**	**Example**
vehicle_id	Unique vehicle identifier	V7657
lane	Lane number where the vehicle is	6
speed	Vehicle speed (km/h or m/s)	62.36
distance_to_intersection	Distance to intersection (m)	319.51
direction	Travel direction	south
destination	Intended exit / destination	A

Labels Table (Conflict & Control Information):

Label	**Description**	**Example**
is_conflict	Whether a traffic conflict occurs	yes
number_of_conflicts	Number of conflicts in the scenario	1
places_of_conflicts	Locations of conflicts	['intersection']
conflict_vehicles	Vehicle pairs involved in conflicts	[{'vehicle1_id': 'V7657', 'vehicle2_id': 'V4314'}]
decisions	Recommended actions for vehicles	['Potential conflict: Vehicle V7657 must yield to Vehicle V4314']
priority_order	Vehicle priority ranking (1 = highest)	{'V4314': 1, 'V7657': 2, 'V5246': None, 'V2448': None}
waiting_times	Vehicle waiting time (relative or absolute)	{'V4314': 0, 'V7657': 2, 'V5246': 0, 'V2448': 0}

Project archetype

This project follows the Human-in-the-Loop AI System archetype characterized by:

- The LLM generates signal control strategies.
- A simulation engine evaluates their performance.
- Engineers validate or refine outputs.
- Iterative feedback improves performance.

This positions the system as an AI-Orchestrated Decision Support System for Intelligent Transportation Infrastructure. The LLM does not directly control physical infrastructure without validation but operates within a supervised optimization loop.

1.2. Feasibility Analysis

Literature review

In a subsequent study, Masri et al. (2025) formalize the role of LLMs as centralized traffic controllers through a 4D system model (Detect, Decide, Disseminate, and Deploy) [1]. This methodology integrates traditionally disconnected control processes into a single LLM-driven architecture that can process heterogeneous data from GPS, video imaging, and loop detectors. The authors utilized fine-tuned models and ROUGE-L metrics to confirm that GPT-4o-mini excels in priority assignment and waiting time optimization. This new paradigm demonstrates that LLMs can provide precise, context-aware recommendations that align with established traffic regulations while enhancing overall intersection safety.

Li et al. present LLM-TrafficBrain, an information-centric framework designed for dynamic signal control through semantic reasoning [2]. This architecture transforms structured sensor data—including queue lengths and special events—into semantically rich natural language prompts for processing by an LLM. The framework operates in a closed-loop feedback system, allowing the model to self-correct and adjust timing strategies based on real-time performance metrics like vehicle throughput and average delay. Evaluation via the SUMO simulator showed that the system is highly responsive to emergency vehicle priority requests and unpredictable traffic spikes.

Lai et al. introduce LLMLight, the first framework to directly employ LLMs as decision-making agents for TSC rather than just auxiliary tools [3]. The authors developed LightGPT, a specialized backbone LLM optimized through imitation fine-tuning and a critic-guided policy refinement process. This approach leverages Chain-of-Thought (CoT) reasoning to analyze traffic conditions and execute optimal signal phases. Extensive testing across ten datasets demonstrated that LightGPT offers superior generalization and interpretability compared to traditional heuristic and RL-based methods.

Wang et al. introduce LLM-DCTSC [4], an agent-driven framework that jointly optimizes signal phases and durations to improve traffic management granularity. By incorporating neighboring intersection data, the system avoids local optima and enhances global coordination. The framework employs a two-stage training pipeline featuring supervised fine-tuning and Direct Preference Optimization (DPO), guided by a reinforcement learning reward model. Utilizing Chain-of-Thought reasoning, LLM-DCTSC delivers interpretable decisions and achieves state-of-the-art performance in travel time and queue reduction across varied traffic conditions.

	Direct Agent Decision-Making	Chain-of-Thought (CoT) Reasoning	Specialized/ Fine-tuned Model	Actionable Driver Guidance	Emergency Vehicle Priority	Closed-Loop Feedback System	RL Integration	Conflict Detection & Resolution	Natural Language Rationales
Masri et al. (2025) [1]	✓	✓	✓	✓	✓	✓	✗	✓	✓
LLM-TrafficBrain [2]	✓	◐	✗	✗	✓	✓	✗	✗	✓
LLMLight [3]	✓	✓	✓	✗	✓	✓	◐	✗	✓
LLMDctsc [4]	✓	✓	✓	✗	✗	✓	◐	✗	✓

[1] S. Masri, H. I. Ashqar, and M. Elhenawy, "Large Language Models (LLMs) as Traffic Control Systems at Urban Intersections: A New Paradigm," *Vehicles*, vol. 7, no. 1, p. 11, Jan. 2025. [Online]. Available: https://doi.org/10.3390/vehicles7010011

[2] D. Li, J. Yan, and Q. Yang, "LLM-TrafficBrain: An Information-Centric Framework for Dynamic Signal Control with Large Language Models," in *2025 IEEE Conference*, 2025. [Online]. Available: https://doi.org/10.1109/IEEECONF65522.2025.11137082

[3] S. Lai, Z. Xu, W. Zhang, H. Liu, and H. Xiong, "LLMLight: Large Language Models as Traffic Signal Control Agents," in Proceedings of the 31st ACM SIGKDD Conference on Knowledge Discovery and Data Mining (KDD '25), Toronto, ON, Canada, Aug. 2025, pp. 1–12. [Online]. Available: https://doi.org/10.1145/3690624.3709379

[4] Z. Wang, S. Zhang, J. Li, K. Dong, S. Tan, and S. Zhong, "LLM-DCTSC: LLM as Agent for Dynamic and Coordinated Traffic Signal Control," Preprint submitted to Transportation Research Part B: Methodological, June 15, 2025. [Online]. Available: https://ssrn.com/abstract=5295755

Model choice/ Specification of a baseline

Model Name: *Intersection Conflict Detection LLM*
Repository: *https://github.com/sarimasri3/Intersection-Conflict-Detection/*
Reference Paper: *Masri et al. (2025) [1]*

The selected baseline is a fine-tuned Large Language Model designed for traffic conflict detection at urban intersections. The model predicts whether a conflict is likely to occur based on structured descriptions of vehicle positions, speeds, directions, and distances.

This Baseline Is Appropriate Because:

- It directly addresses intersection-level traffic safety.
- It demonstrates successful LLM adaptation for traffic reasoning.
- It provides an open-source implementation and reproducible setup.

Base Model and Training Setup:

- **Base Model:** GPT-family lightweight variant (GPT-mini architecture)
- **Training Method:** Supervised fine-tuning
- **Task Type:** Binary classification + structured reasoning output
- **Input Format:** Natural language structured vehicle scenario description
- **Output Format:** Conflict status + explanation + action recommendation

The model was fine-tuned on synthetic intersection scenarios generated using simulation data and manually annotated conflict labels.

Availability and Reproducibility:

- **The repository provides:** Training scripts, Dataset formatting pipeline, Fine-tuning configuration, Inference examples.
- **Training:** The model can be re-trained using OpenAI API-compatible infrastructure or equivalent LLM fine-tuning frameworks.
- **Hardware requirements:** GPU-enabled environment (Google Colab or cloud VM sufficient).

Intended Use:

- Conflict detection at urban intersections
- Safety-aware signal control assistance
- Simulation-based traffic optimization experiments

It is not intended for direct autonomous deployment in physical traffic infrastructure without human validation.

Limitations

- Trained on simulated scenarios (may not fully generalize to real-world noisy sensor data).
- Limited to intersection-level reasoning (does not optimize network-wide coordination).
- Performance may degrade under unseen traffic distributions.

Metrics for business goal evaluation

Model evaluation must align with business objectives.

Safety-Oriented Metrics:

Since intersection safety is a primary concern:

- **Precision:** Minimizes false conflict alarms
- **Recall:** Minimizes missed conflicts (critical for safety)
- **F1-Score:** Balanced safety-performance tradeoff
- **False Negative Rate (FNR):** Directly related to accident risk

Reducing false negatives is directly linked to preventing potential collisions, which aligns with the safety and liability reduction objectives of municipalities.

Operational Efficiency Metrics:

To measure congestion reduction:

- **Average Waiting Time (AWT):** The average amount of time vehicles spends stopped or delayed at an intersection before proceeding.
- **Average Travel Time (ATT):** The average total time it takes for a vehicle to pass through the intersection or road segment.
- **Average Queue Length (AQL):** The average number of vehicles waiting in line at an intersection during a given time period.
- **Intersection Throughput:** The total number of vehicles that successfully pass through an intersection within a specified time interval.

Reducing AWT and AQL directly supports:

- Reduced fuel consumption
- Reduced CO_2 emissions
- Improved commuter satisfaction

These metrics reflect measurable economic and environmental impact.

Cost-Sensitive Evaluation:

Different errors have different consequences:

- **False negatives:** Safety risk
- **False positives:** Unnecessary traffic delays

A cost matrix will be used to assign higher penalties to safety-critical errors.