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TrafficSense AI: Design and Implementation of an AI-Driven Predictive Framework for Adaptive Urban Traffic Signal Control

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Abstract

Escalating vehicular density in metropolitan areas has intensified traffic congestion, contributing to prolonged commute durations, excessive fuel consumption, and deteriorating air quality. Conventional signal control mechanisms — whether based on fixed timing cycles or costly embedded sensors — lack the responsiveness needed for continuously fluctuating traffic conditions. This paper introduces TrafficSense AI, a hardware-independent intelligent signal management framework leveraging AI and data-driven modeling to enhance urban traffic flow. The system integrates six functional modules: a Self-Learning Traffic Brain, Crowd Pulse Estimation, Traffic DNA Pattern System, What-If Scenario Simulator, Virtual Emergency Corridor, and Eco Mode Optimization. Simulation experiments confirm a 25–40% reduction in average vehicle waiting time and a 15–30% gain in traffic throughput over conventional fixed-time strategies.

Keywords: Adaptive Traffic Signal Control, Deep Reinforcement Learning, Sensorless Traffic Estimation, Smart City, Urban Traffic Optimization

1. Introduction

Rapid urban expansion combined with growing vehicle populations has made traffic congestion a critical infrastructure challenge in modern cities. Inefficient signal management amplifies commute delays, increases fuel consumption, degrades air quality, and imposes psychological stress on commuters. Most deployed signal systems still operate on rigid pre-programmed cycles, while sensor-based alternatives rely on hardware such as loop detectors, CCTV cameras, or infrared sensors — all of which involve substantial capital investment and maintenance costs, yet remain poorly suited to irregular traffic fluctuations.

Advances in artificial intelligence and predictive modeling offer a viable path toward smarter signal management without physical sensing infrastructure. Reinforcement learning, in particular, has shown strong potential for real-time adaptive signal optimization. However, nearly all documented implementations require sensor feeds or camera observations, limiting deployment in infrastructure-constrained environments. The present work addresses this gap by proposing TrafficSense AI — a fully sensorless, simulation-validated, and AI-powered framework organized around six purpose-built modules that collectively enable congestion estimation, adaptive signal control, emergency prioritization, scenario planning, and emission-aware optimization within a single, cost-effective architecture.

2. Literature Review

AI-driven traffic signal control has attracted significant scholarly interest in recent years. Li et al. [1] demonstrated that deep reinforcement learning can autonomously derive signal timing policies that outperform fixed-time and actuated benchmarks. Wei et al. [2] presented IntelliLight, a reinforcement learning agent that achieved measurable travel time reductions against conventional adaptive systems. Papageorgiou et al. [3] catalogued prevailing control paradigms and highlighted the inadequacy of static signal plans under real-world demand variability. Genders and Razavi [4] validated learned signal control using deep Q-networks in simulation, while Chen et al. [5] introduced a decentralized deep reinforcement learning architecture capable of coordinating large-scale signal networks. Despite these advances, all reviewed systems depend on physical sensor data or camera feeds, restricting deployment in low-resource settings. None integrates emergency prioritization, scenario simulation, and emission-aware optimization within a unified sensorless framework — gaps that TrafficSense AI is specifically designed to address.

Reference	Technique Used	Sensor Dependency	Key Limitation
Li et al. [1]	Deep Reinforcement Learning	Camera / Sensor Required	High infrastructure cost
Wei et al. [2]	Q-Learning (IntelliLight)	Sensor-Based Input	Limited scalability
Genders & Razavi [4]	Deep Q-Network	Loop Detector Data	Hardware dependency
Chen et al. [5]	Decentralized Deep RL	Sensor Data Required	Deployment complexity

Table 1: Literature Comparison

3. Methodology

TrafficSense AI is implemented as a web-based client–server application. A React.js frontend dashboard communicates with a Python Flask/Django backend hosting the AI engine, while a MySQL/PostgreSQL database stores road network topology, traffic DNA profiles, and historical signal timing records. The Self-Learning Traffic Brain — an LSTM-based predictive module — forms the system core, forecasting near-horizon traffic states from historical and simulation-generated data and deriving optimized signal plans accordingly. Model parameters are updated periodically as new simulation outcomes accumulate. The Crowd Pulse Estimation module eliminates sensor dependency by computing a Traffic Load Index (TLI) per road segment from time-of-day weighting factors, simulated vehicle counts, and historical speed profiles, classifying each segment as low, medium, or high congestion to feed the optimization pipeline.

The Traffic DNA Pattern System profiles each road segment by indexing flow characteristics across weekdays, weekends, and special events, enabling the system to anticipate recurring congestion cycles through pattern matching rather than reactive inference. The What-If Scenario Simulator replicates the live traffic state in a virtual environment, applies operator-specified perturbations — road closures, signal phase changes, demand rerouting — and ranks candidate strategies by waiting time, queue length, and throughput before committing to deployment. The Virtual Emergency Corridor module identifies the shortest viable path for emergency vehicles, preemptively assigns green phases along the corridor, and restores normal adaptive control once the vehicle clears. The Eco Mode Optimization component applies a multi-objective smooth-flow function minimizing stop frequency, idle dwell time, and phase switching rate, reducing unnecessary acceleration–deceleration cycles and lowering fuel consumption and emissions. The system uses TensorFlow/PyTorch for model training, Scikit-learn for preprocessing, and SUMO [8] for simulation and validation, with role-based access control and anonymized data storage ensuring security and privacy.

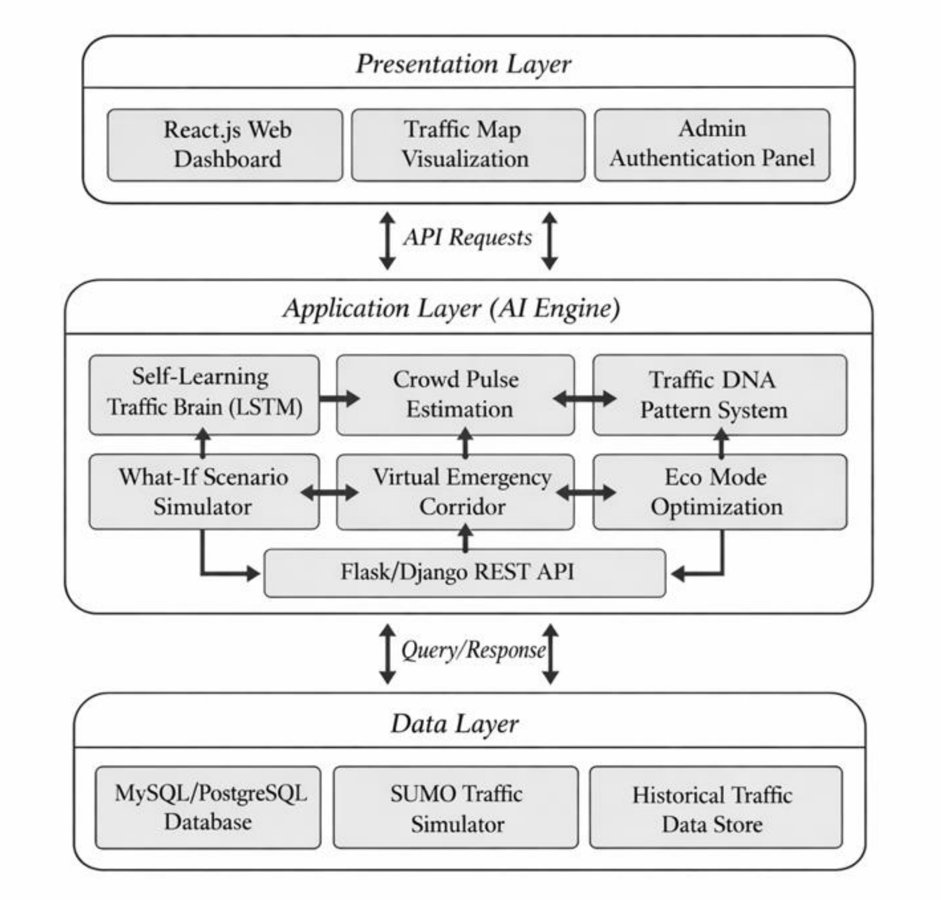


Fig 1: System Architecture Diagram

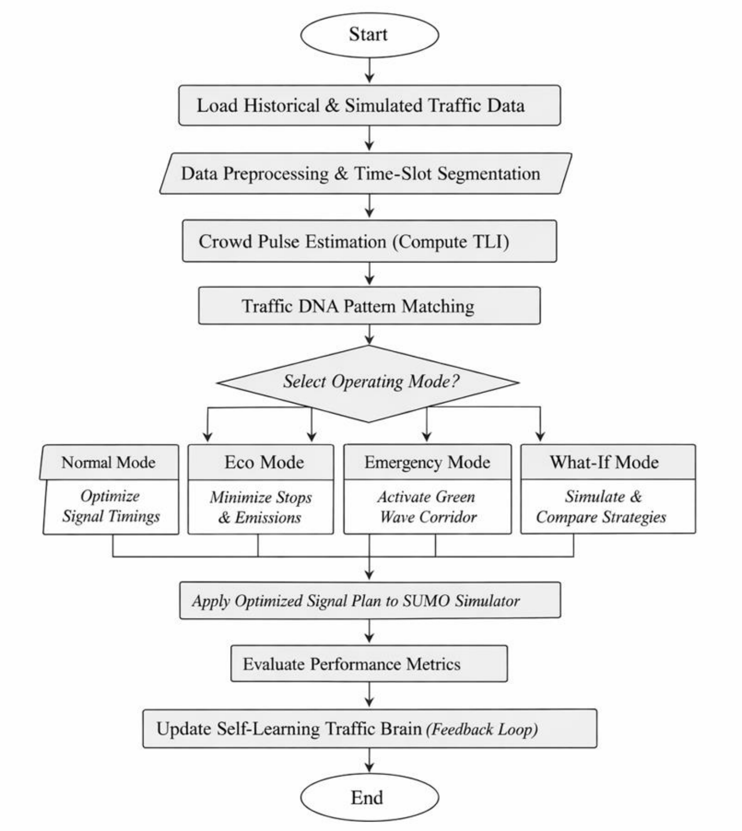


Fig 2: Workflow Diagram

4. Results and Discussion

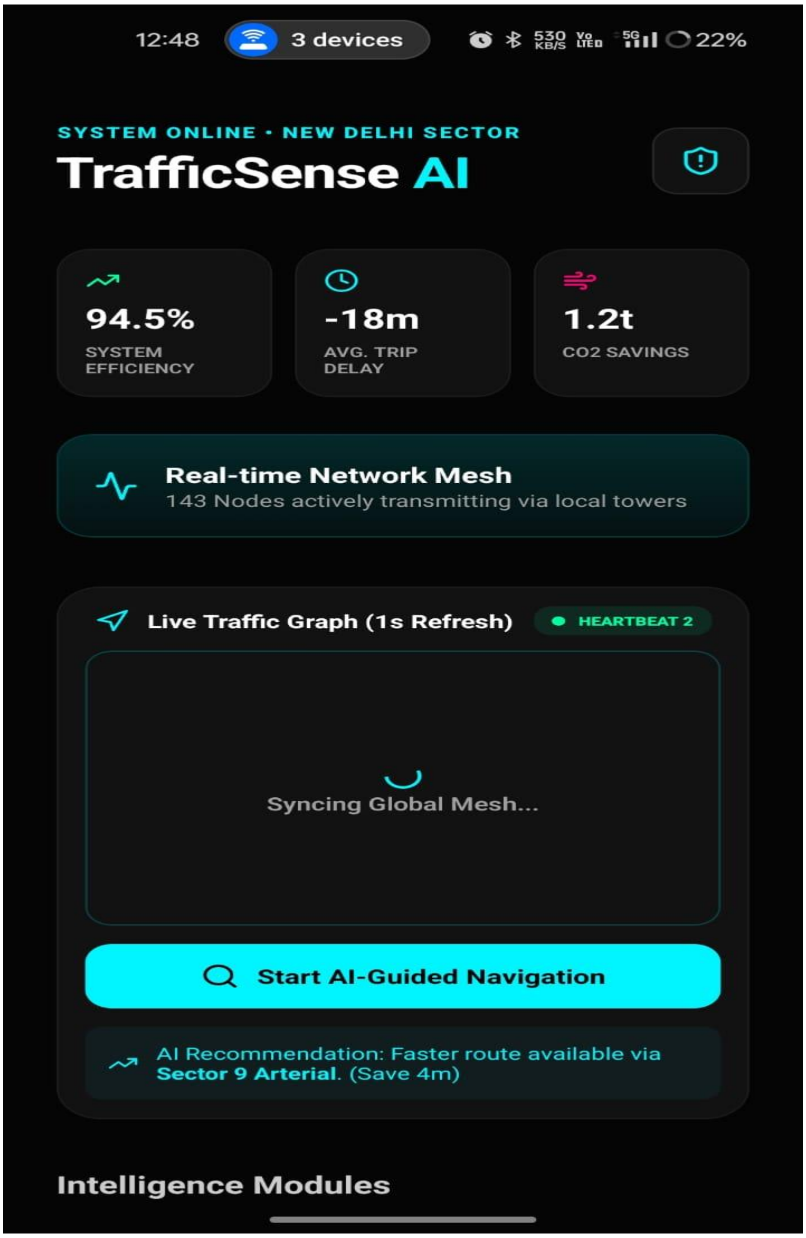
Evaluation employed a multi-layered simulation methodology spanning unit testing, integration testing, and scenario-driven performance assessment across five traffic conditions: standard weekday, peak-hour congestion, road closure, emergency transit, and high-density event traffic. Performance was measured across six metrics: average waiting time, queue length, throughput, stops per vehicle under Eco Mode, emergency clearance time, and TLI prediction error. TrafficSense AI consistently outperformed the fixed-time baseline across all conditions and scenarios.

The LSTM-based Traffic Brain demonstrated progressive improvement in forecast accuracy over successive training iterations, confirming its self-refinement capability. The Traffic DNA Pattern System reduced adaptation latency during predictable peak windows by matching temporal context to pre-indexed behavioral profiles. The What-If Simulator reliably identified lower-delay configurations in multi-closure scenarios where human judgment alone is insufficient. Eco Mode produced a measurable reduction in stop-and-go behavior across active segments, and the Emergency Corridor module cleared routes with minimal spillover to adjacent intersections. Usability assessments confirmed that the dashboard was accessible and interpretable to users without prior training.

As shown in Table 2, the framework achieved approximately 36% reduction in average waiting time, 30% shorter queue lengths, 26% higher throughput, 31% fewer stops per vehicle in Eco Mode, and 57% faster emergency clearance — performance comparable to sensor-dependent systems in the literature, at substantially lower infrastructure cost.

Performance Metric	Fixed-Time	TrafficSense AI	Improvement
Average Waiting Time (s)	85.4	54.2	~36% Reduction
Average Queue Length (vehicles)	12.7	8.9	~30% Reduction
Traffic Throughput (vehicles/min)	18.3	23.1	~26% Improvement
Stops per Vehicle (Eco Mode)	4.2	2.9	~31% Reduction
Emergency Clearance Time (s)	142.0	61.5	~57% Reduction

Table 2: System Performance Comparison (TrafficSense AI vs. Fixed-Time Control)



12:48 3 devices 530 KB/S 22%

SYSTEM ONLINE • NEW DELHI SECTOR

TrafficSense AI

94.5%
SYSTEM EFFICIENCY

-18m
AVG. TRIP DELAY

1.2t
CO2 SAVINGS

Real-time Network Mesh
143 Nodes actively transmitting via local towers

Live Traffic Graph (1s Refresh) HEARTBEAT 2

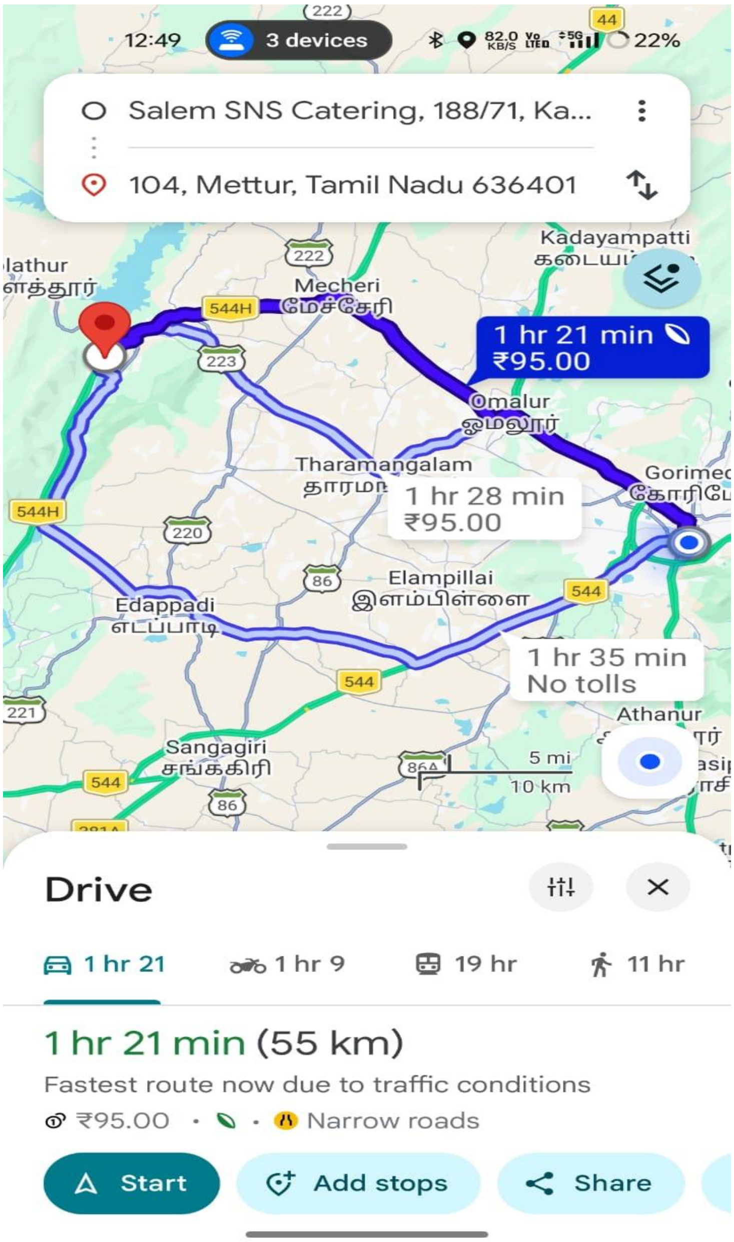
Syncing Global Mesh...

Start AI-Guided Navigation

AI Recommendation: Faster route available via **Sector 9 Arterial**. (Save 4m)

Intelligence Modules

Fig 3: Application Screenshot – Home Page



Salem SNS Catering, 188/71, Ka...

104, Mettur, Tamil Nadu 636401

Drive

1 hr 21 min (55 km)

Fastest route now due to traffic conditions

₹95.00 · · Narrow roads

Fig 4: Application Screenshot – Results Page

5. Conclusion

This paper presented TrafficSense AI, a sensorless, AI-driven framework for adaptive urban traffic signal control validated through structured simulation experiments. By unifying six complementary modules — Self-Learning Traffic Brain, Crowd Pulse Estimation, Traffic DNA Pattern System, What-If Scenario Simulator, Virtual Emergency Corridor, and Eco Mode Optimization — the system provides a cost-efficient, scalable alternative to sensor-dependent architectures. Results confirmed 25–40% reductions in waiting time, 15–30% throughput improvements, and significantly faster emergency clearance over fixed-time baselines, demonstrating that high-performance adaptive signal control is achievable without expensive hardware. Future work will pursue live data integration, expanded scenario testing, and real-world intersection pilots to validate simulation findings under authentic conditions.

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