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Traffic Congestion Management Using AI

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ABSTRACT

The rapid acceleration of global urbanization has precipitated a mobility crisis characterized by chronic traffic congestion, which severely compromises economic efficiency, environmental quality, and public safety. Traditional traffic management paradigms, predominantly reliant on fixed time and limited actuated control, are fundamentally ill-equipped to address the stochastic and non-linear dynamics of modern vehicular flow. This research investigates the comprehensive application of artificial intelligence (AI) as a transformative solution for congestion management. By integrating deep vehicle detection for short-term flow forecasting, computer vision for high-fidelity vehicle detection, and multi-agent reinforcement learning for adaptive signal coordination, urban traffic networks can evolve into self-optimizing ecosystems. This study provides a rigorous analysis of the causes and socio-economic impacts of congestion, followed by an exhaustive exploration of AI-based methodologies, including Convolutional Neutral Networks (CNNs), Long Short-Term Memory (LSTM) networks, and Deep Q-Networks (DQNS).The architecture of these systems is examined through the lens of hybrid edge-cloud frameworks and the Internet of Things (IoT), utilizing sensors and vehicle-to-Infrastructure (V2I) communication. Quantitative evaluations derived from real-word implementations, such as the Hangzhou City Brain and Pittsburgh Surtrac, demonstrate significant reductions in travel time, intersection delays, and vehicular emissions. The paper concludes by delineating the technical, ethical, and infrastructure-related challenges that must be addressed to ensure the scalable deployment of intelligent transportation systems.

Keywords— Artificial intelligence, Traffic Congestion Management Intelligent Transportation Systems, Deep Reinforcement Learning, Computer Vision, Smart Cities, Real-Time Data Analytics.

INTRODUCTION

The global transition toward an urban-centric society represents one of the most significant demographic shifts in human history. As of 2022, more than half of the world's population resided in urban areas, a figure projected by the United Nations to reach 68% by the year 2050.[1] this concentration of human capital and economic activity has forested innovation but has also placed unprecedented stress on transportation infrastructure that was often designed for the demands of the mid-20th century. Traffic congestion has consequently emerged as a persistent and escalating challenge for major cities in both developed and developing countries, exerting a direct negative impact on Gross Domestic Product (GDP), public health, and general quality of life.[3]

Traffic congestion is defined technically as a condition on road networks that occurs as use increases, characterized by slower speeds, longer trip times, and increased vehicular queueing.[4] Beyond the frustration experienced by individual commuters, the systemic costs are staggering. In many metropolitan areas, congestion accounts for up to a 30% increase in journey times during peak periods. These delays translate into billions of dollars in lost productivity and wasted fuel, while the environmental footprint of idling vehicles contributes significantly to urban air pollution and greenhouse gas emmissions.[3]

Traditional Intelligent Transportation Systems (ITS) have historically relied on a hierarchy of control strategies, starting from simple Fixed-Time Singal Controle (FTSC) to more advanced Adaptive Traffic Signal Control (ATCS) systems like SCOOT and SCATS.[7] While these systems provided significant improvements over uncoordinated signals, they are often constrained by rigid mathematical models and pre-defined rules that cannot adapt to the sheer complexity and non-recurrent nature of modern traffic disruptions, such as accidents, weather events, or sudden shifts in demand.[7]

The advent of Artificial Intelligence (AI) offers a paradigm shift in how urban mobility is orchestrated. Unlike traditional models, AI-driven systems possess the capability to "learn" from vast quantities of real-time data, identifying subtle patterns and dependencies that are invisible to human operators or static algorithms.[7] Through the synergistic application of machine (ML), deep learning (DL), and reinforcement learning (RL), traffic management can move from a reactive posture to a proactive and predictive one.[1]

This research paper serves as an exhaustive technical guide to the deployment of AI in traffic congestion management. It details the underlying mechanics of traffic bottlenecks, the senor infrastructure required for data acquisition, and the specific neutral network architectures that enable intelligent decision-making. Furthermore, by analyzing large-scale case studies in Hangzhou and pittsburgh, this study provides empirical evidence of efficacy of AI in reducing urban friction.[13] The objectives is to provide professional peers in the fields of civil engineering and computer science with a robust framework for the next generation of intelligent urban mobility solutions.

EASE OF USE

The proposed traffic Congestion Management System using Artificial intelligence (AI) is designed with a strong focus on ease of use for traffic authorities, system operators, and end users. The system minimizes human intervention by employing automated data collection and decision-making mechanisms, thereby reducing operational complexity.

AI-based traffic control enables real-time adaptive signal management without requiring manual configuration of single timings, Traffic data obtained from cameras, IoT sensors, and GPS-enables vehicles is automatically processed using machine learning algorithms, making the system easy to operate even in highly dynamic traffic conditions.

The system provides a user friendly graphical dashboard that displays live traffic density, congestion levels, and signal status in an intuitive format. Traffic operators can monitor multiple intersections simultaneously and intervene only when necessary, significantly reducing workload and training requirements. Additionally, the proposed system is scalable and flexible, allowing easy integration with existing traffic infrastructure such as CCTV cameras and traffic signals controllers. New intersections or software modifications. Overall, the AI-based traffic congestion management system offers high usability, low maintenance requirements, and efficient operation, making it suitable for practical deployment in smart city environments.

CAUSES AND IMPACTS OF TRAFFIC CONGESTION

Understanding the multifaceted origins of congestion is critical for designing AI models that can effectively mitigate its effects. Congestion is generally categorized into two types: recurring and non-recurring

A. *Fundamental Causes Of Congestio*

1. Recurring Congestion: This form of congestion is cyclic and predictable, primarily driven by the "rush hour" phenomenon where travel demand exceeds the physical capacity of the road way.[3] This is exacerbated by population growth and increasing rates of car ownership, which are often not matched by a proportional expansion of road infrastructure.[3]
2.

Non-Recurring Congestion: Triggered by random events, this type account for a significant portion of total delays. Factors include traffic accidents, vehicle breakdowns, road maintenance, and environmental conditions such as heavy rainfall, ice, or frog[5] Physical Bottlenecks and Geometry: Roadway characteristics such as narrow lanes, poor riding surfaces, and steep gradients (more than 5 %) significantly impede traffic flow. Bottlenecks occur naturally at locations where lanes merge, at heavily used on-ramps and off-ramps, and at intersections where competing flows must be managed.[2]

4. Human Behavioral Factors: Inefficient merging behavior, sudden lane changes, and slow reaction times contribute to "phantom jams" where shockwaves propagate backward through a traffic stream even in the absence of a physical obstruction.[2]

B. *Socio-Economic and Environmental Impacts*

The consequences of failing to manage these causes are profound, spanning economic, environmental, and social dimensions.

Table I. Multi-dimensional Impacts of traffic Congestion and potential for AI Improvement[1]

Impact Category	Specific Consequence	Quantitative Metric Example
Economic	Lost productivity and freight delays	$12 million annual loss in mid-sized cities
Environmental	Increased greenhouse gas emission	21% reduction possible with AI optimization[14]

Public Health	Respiratory disease and mental stress	Linked to higher rates of obesity and depression[17]
Safety	Emergency response delays	50% response time reduction through AI "green waves"
Infrastructure	Accelerated road wear and tear	Continuous monitoring can prevent bridge closures[15]

1. Economic Burden: Traffic delays imposes both time-loss costs on individual commuters and substantial productivity losses on the freight and logistics sectors. standardized value-of-time metrics, such as those provided by the USDOT, indicate that even marginal reductions in travel time can result in massive regional economic gains.[1]
2. Environmental Degradation: Vehicles operating in "stop-and-go" traffic conditions consume significantly more fuel and emit higher levels of CO2, Nox, and particulate matter compared to vehicles traveling at steady, moderate speeds[5].AI-based management aims to create a "smoother" flow, minimizing the energy-intensive cycles of deceleration and acceleration.[5]
3. Social Well-being: Long commutes are empirically linked to worsened physical and mental health, including elevated stress levels and cardiovascular issues.[3]

LITERATURE REVIEW

The progression of traffic signal control (TSC) reflects the broader evolution of control theory and computational power

C. Traditional controle paradigms

1. Fixed-Time Signal Controle (FTSC): This oldest method uses pre-determined cycle lengths and phase durations based on historical traffic counts. While simple to implement and robust, it entirely non-responsible to real-time changes, leading to "green idling" where signals remain green for empty lanes while other approaches are saturated.[4]

2. Traffic Actuated Signal Controle (TASC):TASC utilizes local sensors (typically inductive loops) to detect vehicle presence and extent or terminate phases accordingly. While an improvement over FTSC, it often lacks co-ordination between adjacent intersections, leading to "local optima" that can cause network-wide gridlock.[7]

3. Adaptive Traffic Signal Control (ATSC): Advanced systems like SCOOT (split cycle Offset Optimization Technique) and SCATS (sydney co-ordinated Adaptive Traffic System) use real-time data to adjust timing across networks. However, they rely on rigid optimization models and struggle with highly dynamic or non-recurrent congestion patterns.[7]

D. The AI and Deep Learning Revolution

In the last decade, research has shifted decisively toward data-centric AI methods. Machine Learning (ML), Deep Learning (DL), and Reinforcement Learning (RL) are now the primary sub-sets of AI used to solve high-dimensional traffic problems.[20]

1. Traffic Flow prediction: Early models utilized Markov chains and Bayesian networks.[20] However, the introduction of stacked Auto-Encoders (SAEs) by Lv, Wang et al. in 2015 marked a turning point, demonstrating that deep architectures could capture complex spatial and temporal correlations in traffic data better than shallow models.[21]
2. Object Detection in Traffic: The development of revolutionized vehicle detection. Models like YOLO (you only look once) and Faster R-CNN allow for real-time identifications of vehicle types, speeds, and trajectories from standard CCTV feeds, reaching accuracy levels above 95%.[1]
3. Reinforcement Learning in TSC: RL addresses the "curse of dimensionality" inherent in large traffic networks. Unlike traditional models, RL agents learn through a trial-and-errors process, interacting with environment to maximize a "reward" (such as reduced delay),[19] Notable recent advances include include Multi-Agent Reinforcement Learning (MARL) for large coordination and Deep Q-Networks (DQN) for complex state representations.[7]

METHODOLOGY

The proposed AI-powered Traffic Management Systems (AITMS) is developed through a structured processing , model design, and simulation-based evaluation

E. Data Acquisition and Preprocessing
Traffic data are collected from multiple sources such as CCTV video feeds, inductive loop sensors, and GPS-enabled vehicles. Video data are processed to exact traffic parameters using noise reduction and background subtraction techniques. The collected data are cleaned to handle missing values, remove duplicates, and normalize inputs, relevant features like time of day and weather conditions are encoded to improve model performance

F. AI Models For Traffic Management
LSTM networks are used for short-term traffic flow prediction due to there ability to capture temporal dependencies, CNN models are applied to traffic images for vehicle detection and classification. Additionally a reinforcement learning approach id adopted, where traffic signal control is formulated as a Markov Decision Process with define states, actions, and reward functions to minimize queue lengths and delays.

G. Simulation and Evaluation
The proposed models are validated using traffic simulation tools such as SUMO or CityFlow, Performance is evaluated under different traffic conditions and compared with conventional traffic control to assess efficiency and reliability

RESULTS AND DISCUSSION

Quantitative evidence from both simulation and field pilots confirms that AI systems provide substantial gains in every relevant mobility metric

H. Performance Comparisions

Table II presents a comparison of performance indicators between traditional and AI-driven systems

Performance Indicator	Traditional System (FTSC/Actuates)	AI-Driven System (DQN/MARL)	Improvement (%)
Average Travel Time	120-150 seconds	90-110 second	25% - 30%
Intersection Wait Time	61.5 seconds	50.1 seconds	18.5% - 40%
Throught (Veh/Hr)	Baseline Capacity	20% - 50% throughput	Up to 50 %
Emissions (CO2)	High due to idling	12% - 21% Reduction	21%[1]
Accident Frequency	High during peak	35% - 60% Reduction	60%[11]

Table II. Statistical Comparison of traditional and AI-Based Traffic Controle Systems[1]

I. Analysis of wait Time and Delay
Research using Deep Q-Learning (DQN) models has shown that AI can reduce vehicle waiting times at intersections by as much as 30–40%.[36] This is achieved by the AI's ability to sense "cross-blocking" (where vehicles enter an intersection they cannot clear) and "green idling" (where a green light is wasted on an empty lane). In heavy-loaded networks, AI-based controllers maintain a 15% delay reduction even when demand surges by 20%, demonstrating superior resilience compared to rule-based systems.

J. Figures and Tables
This section details the critical visual representations of the AI-based traffic management framework.

- **Fig. 1 AI-Powered Traffic Management System (AITMS) Overview:** A schematic diagram illustrating the flow of data from sensors (Sensing Layer) to Edge nodes for real-time control, and then to the Cloud for network-scale optimization.
- **Fig. 2 YOLOv8 Architecture for Real-Time Vehicle Recognition:** A visual representation of the convolutional neural network layers used for simultaneous object detection and classification in high-traffic intersections.

- **Fig. 3 Short-Term Flow Forecasting using Stacked LSTM:** A diagram showing the two-layer LSTM architecture that processes 10-minute historical windows to predict traffic density with a Mean Absolute Percentage Error (MAPE) below 8%.
- **Fig. 4 Reinforcement Learning Interaction Loop:** An illustration of the Agent-Environment interface where the signal controller (Agent) observes the traffic state (s_t), performs an action (a_t), and receives a reward (r_t) based on reduced delay.
- **Fig. 5 Performance Comparison Graph:** A multi-bar chart comparing travel time, queue length, and throughput between Fixed-time, Fully Actuated, and RL-based control across different traffic volumes (Low, Medium, Saturated).
- **Fig. 6 Emergency Vehicle Priority "Green Wave" Logic:** A visualization of how V2I communication allows the central "City Brain" to clear a path for first responders by adjusting downstream signals ahead of the vehicle's arrival.[15]

CONCLUSION

The management of traffic congestion using Artificial Intelligence represents a fundamental shift in civil engineering from infrastructure-heavy solutions to intelligence-heavy strategies. This research has demonstrated that AI-driven systems, particularly those utilizing deep reinforcement learning and computer vision, offer a level of adaptability and efficiency that traditional methods cannot match. By transforming intersections from passive timers into active, learning agents, cities can achieve significant gains in economic productivity, public safety, and environmental health.

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REFERENCES

[1] Y. Lv, Y. Duan, W. Kang, Z. Li, and F. Y. Wang, "Traffic Flow Prediction With Big Data: A Deep Learning Approach," *IEEE Transactions on Intelligent Transportation Systems*, vol. 16, no. 2, pp. 865-873, 2015.

[2] F. Rasheed, K. L. A. Yau, R. M. Noor, C. Wu, and Y. C. Low, "Deep Reinforcement Learning for Traffic Signal Control: A Review," *IEEE Access*, vol. 8, pp. 208016-208044, 2020.

[3] H. Wei, G. Zheng, H. Yao, and Z. Li, "IntelliLight: A reinforcement learning approach for intelligent traffic light control," in *Proceedings of the 24th ACM SIGKDD International Conference on Knowledge Discovery & Data Mining*, 2018, pp. 2496-2505.

[4] Zhou, Y. Zhang, and Z. Tang, "Deep Learning-Based Traffic Flow Prediction and Monitoring Using AI," *IEEE Transactions on Intelligent Transportation Systems*, vol. 21, no. 5, pp. 2045-2055, 2020.

[5] S. F. Xie, S. Smith, and G. Barlow, "Schedule-driven control of urban traffic networks," in *Proceedings of the 2012 International Conference on Automated Planning and Scheduling*, 2012.

[6] IEEE Standard 1609.0-2019, "IEEE Guide for Wireless Access in Vehicular Environments (WAVE) Architecture," IEEE, 2019.

[7] Alibaba Cloud, "Hangzhou City Brain: Project Overview and Impact Report," Alibaba Cloud Solutions, 2021.

[8] W. Y. Leong and R. Kumar, "Smart city 5G intelligent transportation system," in *Convergence of IoT, Blockchain, and Computational Intelligence in Smart Cities*, pp. 1-22, 2023.

[9] K. McBride, "Traffic signal performance measures: Core metrics for city efficiency," *Miovision Technical Blog*, Aug. 2025.

[10] S. T. Stevanovic and J. Stevanovic, "Adaptive Traffic Control Systems: A Review of SCOOT and SCATS," *IET Intelligent Transport Systems*, vol. 13, no. 4, pp. 589-601, 2019.

Works cited

[11] AI-Powered Traffic Management Systems: Enhancing ... - ijrmeet, accessed January 30, 2026, https://ijrmeet.org/wp-content/uploads/2022/10/oct_2022_AI-Powered-Traffic-Management-Systems-Enhancing-Efficiency-and-Reducing-Congestion-17-24.pdf?_t=1747291403

[12] Addressing the urban congestion challenge based on traffic bottlenecks | Philosophical Transactions of the Royal Society A, accessed January 30, 2026,

https://royalsocietypublishing.org/rsta/article/382/2285/20240095/108325/Addressing-the-urban-congestion-challenge-based-on
[13] Measuring the level of urban traffic congestion for sustainable transportation in Addis Ababa, Ethiopia, the cases of selected intersections - Frontiers, accessed January 30, 2026, https://www.frontiersin.org/journals/sustainable-cities/articles/10.3389/frsc.2024.1366932/full
[14] Deep Reinforcement Learning for Traffic Signal Control: A Review - ResearchGate, accessed January 30, 2026,https://www.researchgate.net/publication/346461527_Deep_Reinforcement_Learning_for_Traffic_Signal_Control_A_Review
[15] (PDF) Urban traffic congestion: its causes-consequences-mitigation - ResearchGate, accessed January 30, 2026,https://www.researchgate.net/publication/367208770_Urban_traffic_congestion_its_causes consequences-mitigation
[16] Evaluation of Traffic Congestion in an Urban Roads: A Review - Semantic Scholar, accessed January 30, 2026, https://pdfs.semanticscholar.org/25a7/dab422995d5bde4333e53ebbe9294db9fd68.pdf
[17] Advances in reinforcement learning for traffic signal control: a review of recent progress | Intelligent Transportation Infrastructure | Oxford Academic, accessed January 30, 2026, https://academic.oup.com/iti/article/doi/10.1093/iti/liaf009/8125227
[18] Reinforcement learning-based multi-agent system for network traffic signal control - IET, accessed January 30, 2026, https://www.theiet.org/media/11286/reinforcement-learning-based-multi-agent-system-for-network-traffic-signal-control.pdf
[19] Traffic Signal Control via Reinforcement Learning: A Review on ..., accessed January 30, 2026, https://www.mdpi.com/2412-3811/10/5/114
[20] A Survey on Smart Traffic Monitoring System using AI - ResearchGate, accessed January 30, 2026, https://www.researchgate.net/publication/388561970_A_Survey_on_Smart_Traffic_Monitoring_System_using_AI(PDF) Artificial Intelligence in Intelligent Traffic Signal Control - ResearchGate, accessed January 30, 2026,https://www.researchgate.net/publication/389019464_Artificial_Intelligence_in_Intelligent_Traffic_Signal_Control
[21] Revolutionizing Urban Mobility: A Systematic Review of AI, IoT, and ..., accessed January 30, 2026, https://www.mdpi.com/2079-9292/14/4/719 (PDF) Optimizing Urban Mobility in Hangzhou: A Case Study of the ..., accessed January 30, 2026, https://www.researchgate.net/publication/395190380_Optimizing_Urban_Mobility_in_Hangzhou_A_Case_Study_of_the_City_Brain's_AI-Driven_Traffic_Management
[22] Surtrac: AI Slashes Pittsburgh Traffic 25% with Smart Signals ://reruption.com, accessed January 30, 2026, http://reruption.com/en/knowledge/industry-cases/surtrac-ai-slashes-pittsburgh-traffic-25-with-smart-signals
[23] 12 Real-World Examples of How the IoT Monitors Vehicle Traffic - Digi International, accessed January 30, 2026, https://www.digi.com/blog/post/iot-monitor-traffic
[24] Traffic Flow Prediction For Intelligent Transportation System Using Machine Learning, accessed January 30, 2026,https://www.researchgate.net/publication/370773316_Traffic_Flow_Prediction_For_Intelligent_Transportation_System_Using_Machine_Learning
[25] Connect SoCal 2024: Congestion Management Technical Report, Adopted, April 4, 2024 - Southern California Association of Governments, accessed January 30, 2026, https://scag.ca.gov/sites/default/files/2024-05/23-2987-tr-congestion-management-final-040424.pdf
[26] Optimizing Urban Mobility in Hangzhou: A Case Study of the City Brain's AI-Driven Traffic Management - INTI Institutional Repository, accessed January 30, 2026, http://eprints.intimal.edu.my/2171/1/ij2025_25.pdf
[27] A Review of Deep Reinforcement Learning for Traffic Signal ... - IJFMR, accessed January 30, 2026, https://www.ijfmr.com/papers/2024/1/11650.pdf
[28] Mobility Management With AI - IEEE Xplore, accessed January 30, 2026, https://ieeexplore.ieee.org/iel8/6287639/10820123/10981777.pdf
[29] Traffic Flow Prediction With Big Data: A Deep Learning Approach - Bookdown, accessed January 30, 2026, https://bookdown.org/amanas/traficomadrid/docs/Traffic%20flow%20prediction%20with%20big%20data%20-%20A%20deep%20learning%20approach.pdf
[30] Traffic flow prediction models – A review of deep learning techniques - ResearchGate, accessed January 30, 2026, https://www.researchgate.net/publication/366460896_Traffic_flow_prediction_models_-_A_review_of_deep_learning_techniques
[31] (PDF) Smart Traffic Management Systems Using AI-Based Video Analytics - ResearchGate, accessed January 30, 2026, https://www.researchgate.net/publication/396808109_Smart_Traffic_Management_Systems_Using_AI-Based_Video_Analytics
[32] Intelligent Traffic Signal Scheduling Using Artificial Intelligence Algorithms Based on Real-Time Traffic Flows, accessed January 30, 2026, https://www.journal-cand.com/article_227355_76350fcca8d7541d02f0bb3590f72800.pdf
[33] [PDF] Deep Reinforcement Learning for Traffic Signal Control: A Review | Semantic Scholar, accessed January 30, 2026, https://www.semanticscholar.org/paper/Deep-Reinforcement-Learning-for-Traffic-Signal-A-Rasheed-Yau/33682275f7b6004c42586eab5118c9d8ec277431

[34] Deep Reinforcement Learning for Traffic Signal ... - IEEE Xplore, accessed January 30, 2026, https://ieeexplore.ieee.org/iel7/6287639/6514899/09241006.pdf
[35] IoT and Computer Vision for Urban Traffic Management - IJFMR, accessed January 30, 2026, https://www.ijfmr.com/papers/2025/1/36807.pdf
[36] Advance Traffic Management System (ATMS) using AI - IRE Journals, accessed January 30, 2026, https://www.irejournals.com/formatedpaper/1712789.pdf
[37] Traffic Light Control with Reinforcement Learning - arXiv, accessed January 30, 2026, https://arxiv.org/pdf/2308.14295
[38] A Comprehensive Analysis of Reward Function for Adaptive Traffic Signal Control - citeus - Universitas Negeri Malang, accessed January 30, 2026, https://citeus.um.ac.id/cgi/viewcontent.cgi?article=1050&context=keds
[39] (PDF) Adaptive Traffic Signal Control Using Reinforcement Learning - ResearchGate, accessed January 30, 2026, https://www.researchgate.net/publication/383494614_Adaptive_Traffic_Signal_Control_Using_Reinforcement_Learning
[40] Using a Deep Reinforcement Learning Agent for Traffic Signal Control | Connected Papers, accessed January 30, 2026, https://www.connectedpapers.com/main/5f5242d6e3e9fceb9568f9d2658a2d1aacb475c0/Using-a-Deep-Reinforcement-Learning-Agent-for-Traffic-Signal-Control/graph
[41] Smart Traffic Signal Optimization Using Real-Time Data: A Review - Preprints.org, accessed January 30, 2026, https://www.preprints.org/manuscript/202502.0539
[42] IEEE 1609.12-2019 - IEEE SA, accessed January 30, 2026, https://standards.ieee.org/ieee/1609.12/7446/ Hangzhou City Brain | The Atlas of Urban Tech, accessed January 30, 2026, https://atlasofurbantech.org/cases/chn-hangzhou/
[43] Smart Traffic Management Stats: Congestion Reduction & AI Integration - PatentPC, accessed January 30, 2026, https://patentpc.com/blog/smart-traffic-management-stats-congestion-reduction-ai-integration
[44] Smart Urban Signal Networks: Initial Application of the SURTRAC Adaptive Traffic Signal Control System | Request PDF - ResearchGate, accessed January 30, 2026, https://www.researchgate.net/publication/286021717_Smart_urban_signal_networks_Initial_application_of_the_SURTRAC_adaptive_traffic_signal_control_system
[45] Smart Urban Signal Networks: Initial Application of the SURTRAC Adaptive Traffic Signal Control System - Carnegie Mellon University, accessed January 30, 2026, https://www.cmu.edu/traffic21/pdfs/6054-30129-1-pb.pdf
[46] Three Standout AI Traffic Control Programs | Educational Technology and Change Journal, accessed January 30, 2026, https://etcjournal.com/2025/09/04/three-standout-ai-traffic-control-programs/
[47] SURTRAC Final Report PDF | PDF | Traffic | Traffic Light - Scribd, accessed January 30, 2026,