

Application of Artificial Intelligence in Transportation

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Abstract: Road networks everywhere are under growing pressure from rising vehicle ownership, rapid urban expansion and the human factors behind most crashes. Artificial intelligence (AI) offers a route from fixed, manually operated rules toward transport systems that sense, learn and adjust themselves. This paper reviews how machine learning, deep learning, computer vision, reinforcement learning, LiDAR and radar sensor fusion, edge computing and vehicle-to-everything (V2X) communication are combined in intelligent transportation systems (ITS). It describes a five-stage operating pipeline and a four-tier reference architecture, and examines five application areas: autonomous vehicles, adaptive traffic signal control, logistics route optimization, predictive fleet maintenance and smart parking. Evidence from recent surveys and from published field evaluations of adaptive signal control is summarized, and the Delhi Intelligent Traffic Management System approved in September 2026 is discussed as a current Indian case study. Conventional and AI-enabled operation are compared, and technical, security, ethical and social limitations are listed together with possible mitigations. Finally, the paper specifies Smart-Sync AI, a low-cost edge-based design that pairs weighted queue estimation with emergency-vehicle green-corridor preemption. It is offered as a proposal that has not yet been evaluated, and a simulation-first test plan is outlined

Keywords: Artificial Intelligence, Intelligent Transportation Systems, Autonomous Vehicles, Adaptive Traffic Signal Control, Computer Vision, Reinforcement Learning, Predictive Maintenance, V2X

I. INTRODUCTION

Transport networks move the people and goods that keep cities productive, yet in many regions road capacity grows far more slowly than the number of vehicles using it. The consequences are familiar: long queues at junctions, wasted fuel, higher tailpipe emissions and a steady toll of road crashes. Crash research points to the human element as a dominant factor. In the U.S. National Motor Vehicle Crash Causation Survey, the critical reason behind a crash was assigned to the driver in roughly 94% of the investigated cases [1]. That figure describes the last event in a chain of causes rather than a sole cause, but it explains why so much effort now goes into driver assistance and automation.

AI is increasingly applied to these problems. Machine learning (ML) models forecast demand and detect faults, convolutional neural networks (CNNs) recognize vehicles and pedestrians in camera images, and reinforcement learning (RL) agents learn signal-timing policies by interacting with a traffic environment. Surveys of ML and deep learning in transport describe a field that has grown quickly across prediction, control and perception tasks [2], [3]. This paper gives a structured overview of that landscape, concentrating on traffic management and vehicle automation, and closes with a modest, implementable proposal suited to a resource-constrained city.

A. Evolution of Intelligent Transportation Systems

Transport-management technology can be grouped into four broad phases. In the first, roughly the 1970s to the 1990s, junctions ran on electromechanical fixed-time controllers with buried inductive loops, and dispatching was manual. The



second phase, from about 2000 to 2015, added satellite navigation, cellular telematics and electronic tolling, which made basic digital routing and statistical forecasting possible. The third, from about 2016 to 2023, was driven by graphics processors and deep CNNs and brought driver-assistance features such as automatic emergency braking and lane keeping. The present phase combines multi-sensor perception, edge inference, learning-based signal control and V2X messaging, so that vehicles and roadside units can behave as cooperating nodes. The boundaries are approximate and overlap in practice, because fixed-time signals and advanced driver-assistance systems still share the same roads.

B. Problem Statement and Motivation

The question examined here is how AI can support safer, faster and lower-emission mobility when compared with manual driving and fixed-timer traffic management. Three weaknesses of conventional operation motivate the study. First, human drivers react with a delay and are prone to fatigue and distraction, whereas a sensing-and-inference pipeline can respond within a small fraction of a second, bounded by hardware and model size. Second, fixed signal plans are tuned for typical conditions and cannot follow sudden surges, incidents or special events. Third, standing queues and idling waste fuel and raise emissions of CO₂, nitrogen oxides and particulate matter.

C. Objectives and Contribution

The paper has six objectives: (i) to explain the core AI techniques used in mobility; (ii) to describe how perception-to-actuation pipelines work in autonomous vehicles and adaptive signals; (iii) to compare conventional and AI-enabled operation; (iv) to survey applications and one Indian case study; (v) to discuss limitations, risks and mitigations; and (vi) to specify a low-cost edge-based signal-control prototype for later evaluation. The contribution is a consolidated, source-checked review rather than new experimental data, and statements about performance are limited to what the cited studies report.

II. LITERATURE REVIEW

The literature falls into broad survey work, field evaluations of adaptive signal control, and policy-level deployments. Table I summarizes the sources drawn on in this paper.

A. Survey Literature

Zhang et al. [2] review ML applications in advanced transportation systems, covering trends, techniques and future directions. Nisyrios and Gkiotsalitis [4] systematically review optimization-based approaches to traffic and fleet management for connected and autonomous vehicles, and Bazzan [5] provides a meta-review that maps AI research across transportation topics. Earlier, Wang et al. [3] organized deep-learning applications across transport tasks. A critical note comes from Behrooz and Hayeri [6], whose review of surface-transportation studies found that about 74% concentrate on forecasting, and who point to weak collaboration between ML and transport specialists and to a lack of public spatiotemporal datasets. Taken together, these surveys suggest that methods are plentiful, while reproducible data, deployment evidence and integration across subsystems lag behind.

B. Field Evidence for Adaptive Signal Control

Adaptive signal control technology (ASCT) adjusts signal timing in response to current traffic data and is one of the most mature operational uses of data-driven control [7]. Many commercial ASCT products rely on optimization rules rather than learned models, so the field results below show what adaptive control can deliver and set a benchmark that learning-based controllers must beat. A multi-corridor analysis of 11 corridors found an average 6.4% reduction in travel time and a 31.4% average improvement in travel-time reliability while ASCT was operating [8]. A before-and-after study of eight Florida corridors reported an average overall travel-time reduction of 9.36% [9]. The results are not uniformly positive, however. The Florida work notes that external factors such as tourist traffic also influenced corridor patterns [9], and an Illinois field evaluation reported that the deployed system responded poorly to rising minor-street demand and that travel times increased in some directions [10]. Safety outcomes are mixed too: the Illinois study



estimated a crash modification factor of 0.67 for multiple-vehicle fatal and injury crashes, which was not significant at the 95% level [10], and the South Carolina review found crash reductions in some studies but not in others [8].

C. Research Gap

Studies tend to treat vehicle automation, junction control and fleet analytics separately. Results for deep RL signal controllers are usually reported in simulation, for example in IntelliLight [11], where detector noise, mixed traffic and hardware limits are simplified. Systems that pair low-cost, camera-based queue estimation for mixed traffic with emergency-vehicle preemption on inexpensive edge hardware appear to be less well documented in open literature. The proposal in Section IX targets this gap.

TABLE I: Summary of Principal Sources Reviewed

Source	Focus	Reported finding	Note / limitation
Zhang et al. (2025) [2]	ML in advanced transportation systems	Survey of ML techniques, trends and future directions	Broad survey; not a field validation
Nisyrios and Gkiotsalitis (2025) [4]	Traffic and fleet management for connected and autonomous vehicles	Systematic review of optimization-based approaches	Review only; no new field data
Bazzan (2026) [5]	AI in transportation	Meta-review mapping AI research across transport topics	Coverage depends on the reviews included
Wang et al. (2019) [3]	Deep learning in ITS	Organizes deep-learning applications across transport tasks	Predates recent edge and V2X work
Behrooz and Hayeri (2022) [6]	ML in surface transportation	About 74% of studies focus on forecasting; shared datasets are scarce	Calls for closer ML and transport collaboration
FHWA-SC-21-02 [8]	ASCT on 11 corridors	Average travel time down 6.4%; reliability up 31.4%	Crash effects inconsistent across studies
Florida study (2021) [9]	ASCT on 8 corridors	Average travel time down 9.36%	External factors also affected corridors
Benekohal et al. (2019) [10]	ASCT on one Illinois corridor	CMF of 0.67 for multi-vehicle fatal and injury crashes (not significant at 95%)	Weak response to minor-street surges

III. METHODOLOGY

A. Review Method

The review followed six steps. (1) Topic scoping: applications of AI in surface transportation that are relevant to information technology and smart-city engineering. (2) Source collection: recent surveys and journal articles, U.S. federal transportation reports, the SAE J3016 standard and announcements by the Government of India. (3) Source verification: statistics were taken only from the cited document and reported with its stated scope, and figures that could not be traced to a source were left out. (4) Baseline analysis of fixed-timer control, manual dispatch and mileage-based maintenance. (5) Technical analysis of the main algorithms and sensors. (6) Synthesis of a comparison, a limitations matrix and a prototype specification.

B. Five-Stage Closed-Loop Pipeline

Whatever the application, an AI transport system runs a repeating loop, shown in Fig. 1. Data are collected from cameras, LiDAR, radar, GPS receivers and IoT sensors. They are then filtered, time-aligned and fused on edge hardware, with cloud servers used for heavier analytics. Trained models, such as CNN detectors, recurrent networks for sequences and RL policies, turn the fused data into detections, forecasts or decisions. The decision becomes an



actuation command, for example a steering or braking request sent to an electronic control unit (ECU) or a phase change sent to a signal controller. Finally, logged outcomes are evaluated against safety and efficiency indicators and used to retrain or tune the models, often through over-the-air (OTA) updates.

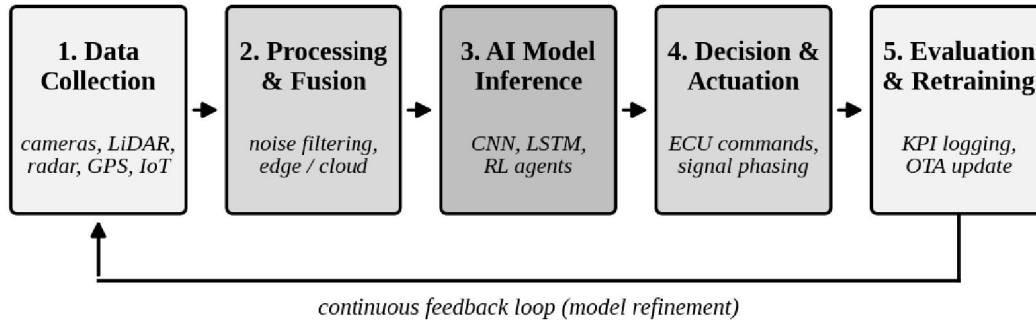


Fig. 1. Five-stage closed-loop operating pipeline of an AI-enabled transportation system.

IV. SYSTEM ARCHITECTURE AND CORE TECHNOLOGIES

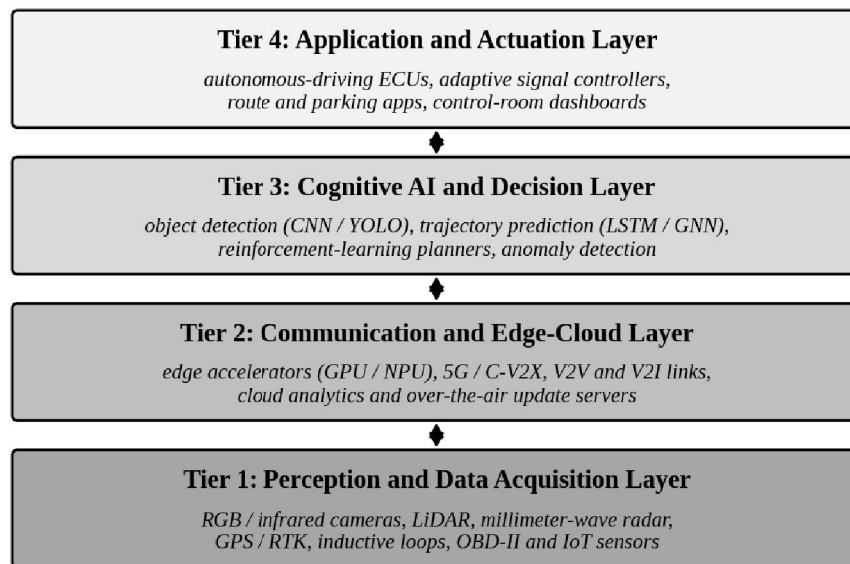


Fig. 2. Four-tier reference architecture of an AI-enabled intelligent transportation network.

A. Conventional versus AI-Enabled Operation

In a conventional network a junction runs a preset cycle, for instance a fixed red and green split, whether or not an approach is empty. Drivers handle perception themselves, and vehicles are serviced at set intervals or after a failure. Upfront cost is low, but the system adapts poorly. An AI-enabled network senses demand, adapts signal phases, supports or replaces driver perception, and schedules maintenance from condition data. It costs more to install and maintain and brings new risks, which are discussed in Section VIII.



B. Four-Tier Reference Architecture

Fig. 2 shows a four-tier reference architecture. Tier 1 acquires data from sensors on vehicles, at the roadside and in fleets. Tier 2 moves the data over V2V and V2I links and cellular or 5G connections to edge nodes and cloud servers. Tier 3 hosts the detection, prediction and planning models. Tier 4 delivers results to actuators, driver or operator interfaces and public information services. Keeping time-critical inference at the edge limits dependence on network latency, while the cloud handles training and fleet-wide analytics.

C. Working Principle: Sense, Perceive, Plan, Act

Autonomous driving stacks and smart junctions share a sense, perceive, plan and act structure. Sensors capture the scene, and synchronized timestamps allow camera, LiDAR and radar data to be fused. Localization methods such as simultaneous localization and mapping (SLAM) align scans with prior maps. Perception models detect and classify road users, estimate their positions and velocities, and track them across frames; single-stage detectors such as YOLO [12] are popular for roadside video because they run in real time on modest hardware. Planning predicts the near-future motion of surrounding agents and selects either a collision-free maneuver in a vehicle or a green-time allocation at a junction. For signal control, the Deep Q-Network idea [13] has been adapted to traffic lights [11], and recurrent networks such as LSTM [14] are widely used for time-series forecasting. Finally, redundant controllers carry out the command, supervised by watchdogs and fallback behavior.

D. Core Technologies and Automation Levels

Table II lists the main technologies. Vehicle automation is classified by SAE J3016 into Levels 0 to 5 [15], summarized in Table III. The levels describe who performs the driving task and who must monitor the environment, not how capable the vehicle seems; NHTSA's public material on automated vehicles also presents these levels [16].

TABLE II: Core Hardware, Communication and AI Software Technologies

Technology	Category	Role in transportation
Computer vision (CNN, YOLO)	AI software	Detects and classifies vehicles, pedestrians, signs and lane markings in camera images [12]
LiDAR and radar	Perception hardware	LiDAR builds 3D point clouds; radar estimates distance and relative speed and is less affected by poor visibility than cameras
ML, LSTM and GNN models	AI algorithms	Forecast traffic and component wear from time-series and network data [14]
Reinforcement learning	AI algorithms	Learns signal-timing or routing policies by interacting with a traffic environment [13], [11]
IoT, GPS and 5G / C-V2X	Communication	Provide position and sensor data and V2V / V2I messaging; achievable latency depends on the network
Edge accelerators (GPU, NPU)	Compute hardware	Run neural-network inference on the vehicle or inside the roadside cabinet

TABLE III: SAE J3016 Levels of Driving Automation

Level	Name	Sustained steering and acceleration	Monitoring of environment	Fallback	Typical example
0	No driving automation	Human	Human	Human	Warnings and momentary assistance
1	Driver assistance	System, one of the two	Human	Human	Adaptive cruise control or lane keeping



Level	Name	Sustained steering and acceleration	Monitoring of environment	Fallback	Typical example
2	Partial automation	System	Human	Human	Combined cruise and lane centering
3	Conditional automation	System	System	Human, on request	Traffic-jam pilot within set limits
4	High automation	System	System	System	Geofenced robotaxi service
5	Full automation	System	System	System	All roads and conditions

V. CORE APPLICATIONS

A. Autonomous Vehicles

Autonomous vehicles combine deep-network perception, sensor fusion and motion planning to drive with limited or no human input inside a defined operational design domain. Current deployments of driverless service are mostly Level 4 operations in geofenced areas, such as shuttles, robotaxis and freight or yard vehicles, whereas most consumer vehicles still offer Level 1 and Level 2 assistance, with a small number of conditional Level 3 systems [15]. Open issues include rare-event handling, performance in poor weather, validation and liability.

B. Adaptive Traffic Management

Cameras and detectors estimate queue length and demand, and a controller changes phase lengths, offsets or coordination along a corridor. Learning-based controllers can, in principle, discover timing policies that fixed plans miss [11], while deployed adaptive systems have reported the modest but real travel-time benefits described in Section II [8], [9]. Outcomes depend on local conditions such as demand variability and detector quality [10].

C. Logistics Route Optimization

Fleet routing is a vehicle-routing problem with delivery time windows and travel times that change with traffic. ML models predict travel times and demand, and optimization solvers, including heuristics and graph-based learning methods, re-plan routes as conditions change, with the aim of fewer empty kilometers, on-time delivery and lower fuel use. Optimization-based fleet management is surveyed in [4].

D. Predictive Maintenance

Onboard sensors and OBD-II telematics record vibration, temperature, pressure and voltage. Sequence models such as LSTM networks [14], or simpler anomaly detectors, learn normal behavior and flag drift before a failure, so that repairs can be scheduled during planned downtime instead of after a roadside breakdown. How far ahead a fault can be flagged depends on the component, the data quality and the history of labelled failures, so lead-time claims should be validated for each fleet before being relied upon.

E. Smart Parking

Cameras or bay sensors maintain a live occupancy map that is shown to drivers through an app or roadside signs, reducing the time spent searching for a space. Drivers circling for parking add to local congestion, although the size of that effect differs from city to city.

VI. CASE STUDY: DELHI INTELLIGENT TRAFFIC MANAGEMENT SYSTEM

On 30 September 2026 the Union Cabinet approved an Intelligent Traffic Management System (ITMS) for Delhi, to be implemented by Delhi Police at an estimated cost of ₹1,789.52 crore [17], [18]. The project covers 42 identified traffic corridors and will be rolled out in three phases over 24 months, followed by five years of operation and maintenance [18]. It includes 1,092 adaptive traffic control locations and 1,029 enforcement locations [17]. Planned functions are adaptive signal timing with coordination along corridors, automated enforcement, real-time detection of congestion and incidents, and green corridors that give priority to ambulances and other emergency vehicles [17], [18]. A master



system integrator selected through competitive bidding will carry out the work, with C-DAC as project management consultant [17].

The Delhi programme is relevant here because it combines adaptive control with emergency-vehicle priority, the same pairing that the prototype in Section IX explores at a much smaller scale. It is, however, an approval and not a completed deployment. No performance results exist yet, and any benefit figures quoted before implementation should be read as projections, not measured outcomes.

VII. COMPARATIVE ANALYSIS

Because published gains differ by site and method, Table IV compares the two approaches by characteristic and quotes numbers only where a cited source supports them.

TABLE IV: Conventional Methods versus AI-Enabled Transportation Systems

Parameter	Conventional manual / fixed-time	AI-enabled
Upfront cost	Low; uses existing legacy hardware	Higher; sensors, edge compute, connectivity and integration are needed
Response to demand	Fixed plans degrade during surges, incidents and events	Signal timing and routing adjust to current conditions
Perception	Depends on human attention; blind spots and fatigue	Multi-sensor detection, but sensitive to weather, sensor faults and unseen situations
Reaction time	Human perception-reaction typically takes about a second or more	Model inference typically takes tens of milliseconds on edge hardware; total response also includes sensing and actuation delay
Maintenance	Fixed intervals or after failure	Condition-based, driven by sensor data and anomaly detection
Evidence of benefit	Long operating record, predictable behavior	Field gains for adaptive control are modest and site-dependent, about 6% to 9% average travel-time reduction in the cited multi-corridor studies [8], [9]; learning-based controllers are mostly evaluated in simulation
Dependence on data	Low	High; relies on data quality, connectivity and cybersecurity

VIII. ADVANTAGES, LIMITATIONS AND MITIGATION

A. Advantages

When implemented well, AI in transportation can improve safety by warning drivers or intervening before a collision, ease congestion through adaptive signals and routing, and cut fuel use and emissions by reducing idling. Condition-based maintenance can improve fleet availability, and automated shuttles or voice-assisted interfaces can widen access to transport for elderly, visually impaired and physically disabled travellers. Each of these benefits is conditional on data quality, sound engineering and appropriate oversight.

B. Limitations and Risks

The main limitations are as follows. Cost: sensors, edge servers, connectivity and signal upgrades need substantial investment and continuing maintenance. Environment: heavy rain, fog, glare and faded lane markings degrade cameras and LiDAR. Security and privacy: connected vehicles and V2X links expose attack surfaces such as message spoofing, GPS interference and ransomware against traffic-management centres. Ethics and liability: responsibility among manufacturers, software providers and operators after a collision is still being settled, and the behaviour of opaque models is hard to audit. Data: models trained on one city's traffic may not generalize to mixed traffic elsewhere, and



public datasets are scarce [6]. Workforce: automation of driving jobs calls for reskilling. Table V pairs the main risks with engineering mitigations.

TABLE V: Challenges in AI Transportation and Possible Mitigations

Challenge	Specific risk	Mitigation strategy
Infrastructure and cost	High cost of LiDAR and roadside edge upgrades	Use lower-cost solid-state sensors and retrofit existing CCTV with lightweight quantized models
Cybersecurity	V2X message spoofing, network outages, adversarial changes to road signs	Authenticated V2X messaging such as IEEE 1609.2 [19], intrusion detection and local fail-safe fallback
Environmental robustness	Glare, rain and fog degrade camera and LiDAR data	Cross-modal fusion with radar and thermal imaging; degrade gracefully to safe behavior
Ethics and accountability	Unclear liability and black-box decisions	Event data recorders, human-in-the-loop oversight and explainable decision logs
Data and generalization	Models fail on unfamiliar traffic mixes	Local data collection, retraining and staged validation before deployment

IX. PROPOSED PROTOTYPE: SMART-SYNC AI

A. Concept

To address the gap identified in Section II, this paper specifies Smart-Sync AI, an edge-based adaptive traffic signal and emergency green-corridor system. Instead of underground inductive loops or cloud-dependent video streaming, it processes live video from a four-way junction locally, using a quantized YOLO-family detector [12] on affordable edge hardware such as a Raspberry Pi 5 with an AI accelerator or a Jetson-class board. Fig. 3 shows the block diagram. The design has two coordinated functions: weighted queue estimation to set green times, and emergency preemption.

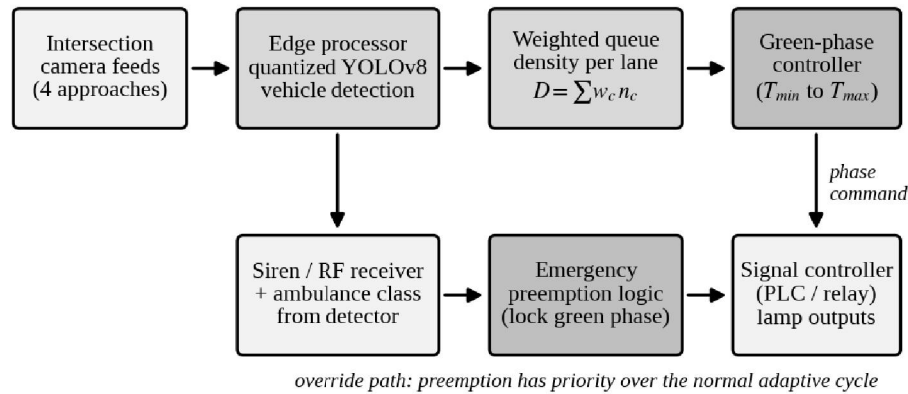


Fig. 3. Block diagram of the proposed Smart-Sync AI controller.

B. Weighted Queue Density and Green Time

Indian junctions carry mixed traffic, so a simple vehicle count is a poor measure of demand. The detector counts vehicles of each class c on an approach, and each class receives a weight w_c that approximates its road-space occupancy. The weighted density D and the green time T_g for that approach are

$$T_g = \min(T_{\max}, T_{\min} + k \cdot D), \quad D = \sum w_c n_c \quad (1)$$



where n_c is the number of detected vehicles of class c , k is a scaling constant in seconds per weighted unit, and $T_{\min}$ and $T_{\max}$ bound the green time. Phases are served in a fixed cyclic order, and the upper bound keeps waiting time on the other approaches limited. The initial design values in Table VI are assumptions to be tuned in simulation; they are not validated results.

TABLE VI: Initial Design Parameters of the Smart-Sync AI Controller

Parameter	Initial value	Purpose
Weight w_c : car	1.0	Reference vehicle class
Weight w_c : motorcycle	0.5	Occupies less road space than a car
Weight w_c : bus and truck	2.5	Occupies more road space and clears slowly
Minimum green $T_{\min}$	15 s	Lets a queue start moving and protects pedestrians
Maximum green $T_{\max}$	90 s	Bounds waiting on other approaches
Scaling constant k	1.8 s per unit	Converts weighted density to extra green time

C. Emergency Green-Corridor Preemption

If the detector reports an ambulance class above a confidence threshold, or an acoustic or radio-frequency receiver reports an active emergency signal, the controller ends the running phase after the normal yellow and all-red clearance intervals and holds green on the emergency vehicle's approach for up to $T_{\max}$. Two safeguards are essential: clearance intervals must never be skipped, and preemption requests must be authenticated to prevent misuse. Siren detection by audio alone is error-prone in noisy traffic, whereas transponder or radio-based preemption is more dependable but needs equipped vehicles.

D. Evaluation Plan

The design will be tested first in microscopic traffic simulation using SUMO [20] against a fixed-time baseline, with average waiting time, queue length, throughput and emergency-vehicle travel time as indicators. A bench test with recorded junction video will then measure detection accuracy and inference speed on the target board. Only after that would a supervised pilot with the traffic authority be considered. No results are reported in this paper.

X. FUTURE SCOPE

Several directions are likely to shape the next stage of research. Cooperative V2X over 5G-Advanced and later networks could let vehicles share perception data with each other and with roadside units, supporting awareness of hazards beyond line of sight. Trustworthy edge AI, with safety validation, explainability, security and human oversight, will matter as systems take on more control authority. Public-transport demand forecasting can help scale fleet dispatch to passenger demand across bus and metro networks. City-scale digital twins could be used to test responses to floods, large events or lane closures before changes are made on the street. Emerging modes such as electric vertical take-off and landing (eVTOL) aircraft will also need AI-assisted traffic management in low-altitude airspace, although their operating models are still being defined.

XI. CONCLUSION

AI is moving transportation from fixed, manually controlled infrastructure toward systems that sense, predict and adapt. The surveys and field studies reviewed here show real but site-dependent benefits: adaptive signal control has reduced average travel time by roughly 6% to 9% across multi-corridor evaluations, while safety and reliability results vary and depend on local conditions. Cost, weather sensitivity, cybersecurity, data quality and unresolved liability questions remain active engineering and policy problems. Delhi's approved ITMS shows that large-scale adoption is under way in India, though its outcomes are yet to be measured. The proposed Smart-Sync AI controller offers a practical, low-cost



direction that combines mixed-traffic queue estimation with emergency preemption, and its value must now be established through simulation, bench testing and supervised trials.

ACKNOWLEDGMENT

The authors thank the Department of Information Technology, Government Polytechnic Awasari (Kh.), for academic guidance and the facilities used in preparing this study.

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