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Innovative Method for Vehicle Queue Estimation at Traffic Signals Using Roadside Sensors

Sheela Rani C M[1], Chalitha MN Jain[2], Kruthika T J[3], Hithashree G[4], Mahalakshmi M Ratnakar[5]
[1]Assistant Professor, Dept of CSE, Sapthagiri College of Engineering
[2, 3, 4, 5]Dept of CSE, Sapthagiri College of Engineering

***Abstract:** Rapidly escalating urban traffic congestion demands intelligent, sensor-driven approaches to traffic signal management. Conventional fixed-timer traffic signals allocate uniform phase durations irrespective of prevailing vehicle density, generating unnecessarily prolonged queues, excessive fuel consumption, and heightened greenhouse-gas emissions. This paper presents a structured survey of ten contemporary research works spanning 2019 to 2026 that address vehicle queue estimation and adaptive signal control at urban intersections through roadside sensing, computer vision, and artificial intelligence. The surveyed studies encompass YOLO-based deep learning detection frameworks, fuzzy logic inference controllers, reinforcement learning optimization agents, and hybrid IoT-integrated architectures. Each work is reviewed for its methodological novelty, performance outcomes, simulation environments, and operational limitations. A comparative analysis table consolidates key metrics across studies, followed by identification of prevalent research gaps including adverse-weather robustness, edge-deployment scalability, multi-intersection coordination, and emergency-vehicle preemption. The survey provides a foundational reference for engineers and researchers engaged in next-generation adaptive traffic management system design.*
***Keywords:** vehicle queue estimation; adaptive traffic signal control; YOLO; computer vision; reinforcement learning; fuzzy logic; roadside sensors; intelligent transportation systems; deep learning*

I. INTRODUCTION

Traffic congestion has emerged as a defining urban challenge of the twenty-first century, constraining economic productivity, elevating air-pollution burdens, and reducing quality of life for millions of city residents. Signalised intersections act as primary bottlenecks where vehicle queues accumulate whenever demand exceeds service capacity. The performance of an intersection is governed largely by how accurately signal phase durations reflect instantaneous traffic demand across competing approach lanes.

Traditional fixed-time signal controllers, which continue to dominate deployment in developing-country cities, schedule green phases according to historical demand patterns assumed to remain invariant across time. In reality, traffic arrival at urban junctions exhibits pronounced variability driven by commuting peaks, weather, public events, and random fluctuations. A fixed green allocation optimised for the morning rush performs inefficiently during off-peak or mid-day periods, wasting green time on low-demand approaches while starving congested ones. Vehicle queue estimation—the quantification of instantaneous queue length, vehicle count, or occupancy on each approach—furnishes the real-time demand data necessary to enable adaptive signal controllers to make rational phase-switching decisions. Accurate queue measurement transforms a static scheduling problem into a feedback control loop responsive to observed traffic states.

Roadside sensors deployed at intersections provide the measurement infrastructure for queue estimation. Inductive loop detectors embedded within pavement have historically been the dominant technology, but their high installation cost, maintenance burden, and inability to classify vehicles have motivated migration toward camera-based computer-vision approaches. The maturation of convolutional neural network (CNN) architectures—particularly single-stage detectors such as the YOLO (You Only Look Once) series—has made real-time, accurate vehicle detection and counting feasible on commodity hardware.

Concurrently, algorithmic advances in reinforcement learning (RL) and fuzzy logic have enabled more sophisticated signal-phase selection policies that move beyond simple density-proportional green-time assignment toward policies that account for queue imbalance, vehicle type, and network-level spillback effects. This survey paper systematically reviews ten representative studies that collectively advance the state of knowledge in vehicle queue estimation and adaptive signal control. The selected works span deep learning detection, fuzzy inference, RL-based optimisation, and IoT-integrated architectures, providing a broad perspective on current methodological trends. The paper is structured as follows: Section II introduces background concepts; Section III presents detailed paper-by-paper reviews; Section IV provides comparative analysis; Section V discusses research gaps; and Section VI concludes.

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II. BACKGROUND

A. Vehicle Detection Techniques

Early video-based vehicle detection systems relied on background-subtraction and optical-flow algorithms to identify moving objects within camera frames. Although computationally lightweight, these methods are sensitive to illumination changes, shadows, and camera vibration. CNN-based object detectors overcome these limitations through learned feature representations that generalise across environmental conditions. The YOLO architecture achieves detection by dividing the input frame into a spatial grid and simultaneously predicting bounding-box coordinates and class probabilities for all grid cells in a single network forward pass, enabling real-time throughput exceeding 30 frames per second.

Subsequent YOLO generations (v3, v4, v5, v7, v8) have progressively improved detection accuracy, small-object sensitivity, and deployment efficiency. YOLOv5 introduced the CSP backbone and FPN+PAN neck structures that enhance multi-scale feature fusion. YOLOv8 extended these capabilities with anchor-free detection heads and improved training regularisation.

B. Queue Estimation Methods

Queue estimation translates raw vehicle detection outputs into a signal-actionable queue metric. The most direct method counts vehicles within a predefined Region of Interest (ROI) corresponding to the stop-line approach. Queue length can alternatively be inferred from back-of-queue position tracking, where the detector monitors the rearmost queued vehicle relative to a reference marker. Density-based estimation computes the ratio of detected vehicle occupancy to maximum carriageway capacity within the ROI. Shockwave-based models use loop-detector input–output flow imbalances to compute queue extents analytically, while probe-vehicle GPS trajectories from connected-vehicle platforms provide distributed measurements of queue boundaries without dedicated infrastructure.

C. Adaptive Signal Control Paradigms

Adaptive Traffic Signal Control (ATSC) systems dynamically modify signal phase durations using real-time traffic measurements. Single-intersection ATSC adjusts green time for an isolated junction, whereas multi-intersection ATSC coordinates timing across a network to facilitate vehicle progression and suppress queue overflow. Reinforcement learning formulates signal control as a Markov Decision Process (MDP), enabling agents to discover optimal phase-selection policies through simulated or real traffic experience. Fuzzy logic controllers represent an alternative that handles measurement uncertainty and nonlinear traffic dynamics through rule-based inference on linguistic variables such as "queue length is long."

III. LITERATURE SURVEY

A. Nandhini et al. (2025) [1]

Nandhini and colleagues designed a software-driven intelligent traffic surveillance system that employs YOLO for real-time vehicle detection across intersection approach lanes. The architecture integrates three principal components: a vehicle detection module that processes live camera streams to count vehicles per lane; a signal-switching algorithm that allocates green phase durations in proportion to measured vehicle densities; and a Pygame-based simulation module that replicates real-world intersection dynamics for performance validation. The system avoids dedicated roadside hardware by using existing surveillance cameras and cloud or on-premise computing resources. Preprocessing stages encompassing grayscale conversion, Gaussian noise reduction, contrast enhancement, and Canny edge detection are applied to each captured frame to improve detection robustness under variable environmental conditions. Training data comprising diverse traffic footage—varying vehicle densities, lighting conditions, and intersection layouts—was partitioned at 80:20 for training and testing, with 10% of the training split used for validation. Experimental evaluation demonstrated that the adaptive signal timing mechanism reduced average vehicle idle time relative to fixed-timer baselines, and the YOLO model achieved satisfactory accuracy and detection speed metrics. Acknowledged limitations include performance degradation under adverse weather and low-illumination conditions, and the computational cost of running GPU-accelerated inference on real-time video streams.

B. Jain et al. (2026) [2]

Jain and associates proposed a computer-vision-based adaptive signal control framework employing YOLOv8 combined with OpenCV for lane-wise traffic density computation. CCTV or IP cameras mounted at intersections capture continuous traffic video, which is decoded into frames by OpenCV. Each frame is processed by the YOLO detector to identify vehicles within per-lane ROIs defined by fixed height and width boundaries; bounding boxes confirm successful detection and classification. Traffic density for each direction is quantified as the total vehicle count within the respective ROI during a fixed observation window.

The control algorithm allocates green signal duration proportionally to lane-wise vehicle counts, enforcing minimum and maximum green-time bounds to prevent signal starvation. Signal phase scheduling initialises with default values, with subsequent red times for non-active phases calculated as a function of the active phase green and yellow durations. The system is designed for extension to include emergency vehicle detection and prioritisation through dedicated recognition modules, weather-sensitive timing adjustments, and integration with smart city platforms. Evaluation on recorded video data confirmed accurate vehicle detection under standard illumination and measurable congestion reduction relative to fixed-time control. The study identified high processing-power demand as a practical constraint for real-time deployment.

C. Kamble et al. (2025) [3]

Kamble and colleagues developed an AI-driven smart traffic management system that integrates YOLO-based detection with an OpenCV processing pipeline to achieve adaptive signal phase control. The system deploys cameras at all approach lanes of a target intersection and routes captured frames to a central inference server where YOLO classifies vehicles across categories including two-wheelers, cars, buses, and heavy commercial vehicles. Detected vehicle counts are aggregated per lane and communicated to a signal controller module that computes optimal green phase durations using a demand-proportional allocation function. The framework additionally incorporated temporal traffic profiling, building historical demand models from accumulated detection data to support proactive signal adjustment during predicted peak periods. Multi-intersection coordination functionality was included, allowing neighbouring junction controllers to harmonise phase offsets and reduce stop-and-go propagation along arterial corridors. Experimental results demonstrated statistically significant reductions in average waiting time per vehicle compared to both fixed-time and simple actuated baselines. A critical operational limitation noted by the authors is the dependency on continuous uninterrupted camera operation; equipment faults or optical occlusions can produce coverage gaps that degrade detection completeness, motivating redundant sensor and fault-tolerant processing design requirements.

D. Fahrunnisa et al. (2024) [4]

Fahrunnisa and associates examined adaptive traffic light signal management using fuzzy logic (FL) inference combined with video surveillance measurements. The FL controller accepts two primary input variables—queue depth and vehicle arrival flow rate—measured from the camera feed and converts them to per-phase signal extension or reduction decisions through a structured rule base derived from traffic engineering expertise. Fuzzy membership functions of trapezoidal form were employed to fuzzify input measurements into linguistic categories, enabling the inference engine to operate on qualitative traffic state descriptions rather than precise numeric thresholds. The defuzzification step translates the aggregated fuzzy output into a concrete signal duration adjustment. Simulation experiments demonstrated that the FL controller outperformed fixed-time scheduling across a range of traffic demand scenarios, particularly under moderate demand conditions where binary actuated controllers may under-respond. A noted scalability constraint arises at intersections with more than four approaches or complex multi-modal traffic flows, where the combinatorial size of the fuzzy rule set grows prohibitively. The authors proposed hybrid architectures combining FL with machine learning components as a pathway to overcoming this scalability limitation in future research.

E. Michailidis et al. (2025) [5]

Michailidis and colleagues conducted a structured review of reinforcement learning (RL) methodologies applied to traffic signal control, providing a comprehensive synthesis of algorithmic advancements, state and reward design strategies, and deployment challenges. The survey encompasses single-agent RL formulations including Deep Q-Networks (DQN), Double DQN with duelling architectures, and Proximal Policy Optimisation (PPO), alongside multi-agent RL (MARL) variants such as QMIX, MADDPG, and communication-enabled cooperative frameworks. The review analysed how state representations—constructed from queue length vectors, vehicle position matrices, current signal phase indices, and elapsed phase durations—influence learning efficiency and policy convergence. Reward function design was identified as a primary determinant of emergent controller behaviour, with common formulations minimising cumulative queue length, reducing aggregate vehicle waiting time, or maximising intersection throughput. The survey highlighted that while RL-based controllers consistently outperform fixed-time and standard actuated baselines in simulation, the simulation-to-reality transfer gap presents a formidable barrier to field deployment. Key challenges elaborated include multi-agent non-stationarity, sparse or delayed reward signals in congested networks, sample inefficiency in deep RL training, and the safety constraints imposed by live traffic environments where suboptimal exploratory actions cannot be tolerated.

F. Agrahari et al. (2024) [6]

Agrahari and colleagues produced a comprehensive review categorising AI-based adaptive traffic signal control (ATSC) systems according to the number of road intersections modelled—single (SI) and multiple (MI)—and the governing algorithmic technique: Reinforcement Learning (RL), Metaheuristic Optimisation (MH), Dynamic Programming (DP), Fuzzy Logic (FL), Deep Reinforcement Learning (DRL), and hybrid combinations. For single-intersection scenarios, SI-ATSC systems employing SARSA and Q-Learning achieved queue length reductions of up to 19% relative to fixed-time scheduling baselines, while PSO and GA-based metaheuristic methods demonstrated effectiveness in addressing non-linear signal timing objectives including average travel-time minimisation. The review evaluated six major microsimulation platforms—SUMO, VISSIM, AIMSUN, MATSim, CORSIM, and Paramics—assessing open-source availability, visualisation support, programming language compatibility, and geographic application scope. Multiple-intersection ATSC systems exhibit substantially greater optimisation complexity due to interdependencies between adjacent controllers requiring coordinated cycle-length and offset management. The paper identifies persistent research gaps including underrepresentation of mixed-traffic scenarios (pedestrians, cyclists, and diverse vehicle classes), the scarcity of real-world deployment validation studies compared to simulation evaluations, and the absence of weather-adaptive signal control mechanisms in the reviewed literature.

G. Xiao et al. (2026) [7]

Xiao and associates proposed a deep reinforcement learning framework for intelligent traffic signal control targeting intersection delay minimisation under variable demand conditions. The MDP formulation employs a state space composed of lane-wise queue length vectors, current signal phase index, and elapsed phase duration, with the agent selecting phase transition actions at each decision step. A Dueling Double Deep Q-Network (D3QN) architecture was adopted to stabilise Q-value estimates and reduce overestimation bias inherent in standard DQN. The reward function jointly penalises cumulative vehicle waiting time and queue length growth, with an additional regularisation term discouraging excessively frequent signal changes that disrupt vehicle progression. Training was conducted in high-fidelity simulation environments using real-world traffic demand profiles obtained from field measurement campaigns. Evaluation results demonstrated substantial intersection delay reductions—exceeding those achievable by actuated control and fixed-time baselines—particularly under high-demand conditions where dynamic phase allocation provides the greatest benefit. Noted limitations include the need for large curated traffic datasets spanning diverse demand scenarios to avoid policy overfitting, extended training convergence periods, and difficulty transferring learned policies across intersections with differing geometric layouts without policy fine-tuning.

H. Sakhare et al. (2023) [8]

Sakhare and colleagues developed a smart traffic management architecture integrating Internet-of-Things (IoT) sensing devices, YOLO-based object detection, and machine learning-based signal control optimisation. IoT-enabled cameras installed at intersection approaches transmit captured video frames over a network to a central processing server where YOLO performs real-time vehicle detection and classification across multiple vehicle categories. Machine learning models trained on intersection-specific historical traffic patterns refine signal timing decisions beyond simple instantaneous density-proportional allocation, incorporating temporal factors including time-of-day demand profiles and day-of-week variation. Aggregated multi-cycle vehicle count data enables the system to construct rolling demand forecasts that support proactive phase duration adjustments ahead of anticipated congestion onset. IoT communication protocols enable real-time phase coordination between neighbouring intersection nodes within a larger traffic network. Validation experiments confirmed accurate per-category vehicle counting and demonstrated adaptive control gains in intersection throughput and average delay relative to fixed-time operation. The primary operational limitation is hardware dependency: IoT sensing nodes require physical installation infrastructure, communication network provisioning, power supply, and field maintenance, incurring operational costs and complexity absent from purely software-based approaches.

I. Wang et al. (2025) [9]

Wang and colleagues systematically investigated YOLOv5 optimisation for traffic sign recognition (TSR) within intelligent transportation system deployments, introducing three technical innovations targeting small-target detection, environmental robustness, and deployment flexibility. The first contribution applies k-means++ clustering to generate custom anchor boxes matched to the CCTSDB dataset's sign size distribution, achieving a mean Intersection over Union (IoU) of 77.55% compared to 75.95% for standard k-means, reducing convergence iterations from 51 to 14.

The second contribution provides a rigorous comparative evaluation of YOLOv5 variants (s, m, x), revealing precision-speed trade-offs across 99.3–99.5% mAP@0.5 versus 32–45 ms per-image inference, enabling practitioners to select configurations matched to deployment hardware constraints. The third contribution employs systematic hyperparameter tuning validated through Tukey HSD statistical analysis across 30-sample evaluation batches. Experiments on 13,830 images from the CCTSDB dataset demonstrated superior mAP of 99.3% and 45 FPS throughput for YOLOv5s, outperforming Faster-RCNN and SSD by 5–8% in accuracy metrics. Real-world detection in small-sample, backlit, and foggy conditions confirmed confidence levels exceeding 0.90, verifying practical applicability in latency-sensitive ITS deployments.

J. Wei et al. (2019) [10]

Wei and associates produced a comprehensive interdisciplinary survey bridging classical transportation engineering approaches and emerging machine-learning methods for traffic signal control. The transportation section provides detailed algorithmic treatments of Webster cycle-length optimisation, GreenWave unidirectional offset coordination, Maxband bilateral bandwidth maximisation, vehicle-actuated phase extension, Self-Organising Traffic Light (SOTL) adaptive control, Max-pressure throughput maximisation, and the SCATS adaptive system. The machine-learning section introduces the reinforcement learning formalism (MDP, Q-function, Bellman optimality) within the traffic signal control context, systematically reviewing state representations, reward functions, action schemes, and multi-intersection coordination strategies across 35 published RL-based studies. The review identifies key outstanding challenges: the ad-hoc nature of reward and state function design without principled theoretical grounding; the prohibitive sample complexity of deep RL methods; the credit-assignment difficulty in temporally-extended and multi-agent settings; and safety risks associated with live exploratory policy updates in physical traffic environments. Experimental settings including simulation platforms (GLD, SUMO, AIM), road network scales, and traffic flow characteristics are tabulated for comparative reference, revealing that the majority of evaluated studies are confined to synthetic grid networks with fewer than twenty intersections.

IV. COMPARATIVE ANALYSIS

Table I presents a consolidated comparison of the ten reviewed studies across key dimensions: methodology, dataset or simulation environment, primary performance metric, and principal limitation.

Table I. Comparative Summary of Reviewed Studies

Ref.	Authors (Year)	Method	Dataset / Tool	Key Metric	Limitation
[1]	Nandhini (2025)	YOLO + OpenCV + Pygame	City camera footage	Reduced idle time	Sensitive to lighting; GPU cost
[2]	Jain (2026)	YOLOv8 + OpenCV	Recorded video	Reduced wait time	High processing power needed
[3]	Kamble (2025)	YOLO + OpenCV + Temporal profiling	Live + historical data	Throughput gain	Camera dependency; occlusion risk
[4]	Fahrunnisa (2024)	Fuzzy Logic + Video	Traffic simulation	Queue minimisation	Scalability at complex junctions
[5]	Michailidis (2025)	RL Review (DQN, PPO, MARL)	Literature survey	Policy quality	Sim-to-real gap; safety
[6]	Agrahari (2024)	AI Review (RL, FL, MH, DP, DRL)	SUMO, VISSIM, AIMSUN	Up to 19% queue reduction	Mixed traffic; real deployment gap
[7]	Xiao (2026)	D3QN Deep RL	Real demand simulation	Delay reduction	Large dataset; policy transfer
[8]	Sakhare (2023)	IoT + YOLO + ML	IoT camera network	Throughput & delay	Hardware & maintenance cost
[9]	Wang (2025)	YOLOv5 + k-means++ anchors	CCTSDB (13,830 imgs)	99.3% mAP@0.5; 45 FPS	Sign detection only, not signals
[10]	Wei (2019)	Survey: Webster, RL, SCATS	GLD, SUMO, AIM	Delay & queue benchmarks	Older RL methods; synthetic nets

The comparative analysis reveals three dominant methodological trends across the surveyed literature. First, YOLO-based computer vision has become the de-facto standard for real-time vehicle detection in adaptive signal control research, attributed to its favourable speed–accuracy trade-off on GPU-equipped processing units. Second, reinforcement learning is increasingly adopted as the optimisation engine for phase selection, displacing rule-based and mathematical programming approaches. Third, simulation-based validation—primarily using SUMO and Pygame—predominates over field deployment studies, reflecting the practical difficulty of instrumenting live intersections for controlled experimentation. Performance gains reported across studies are generally expressed relative to fixed-time signal baselines and range from moderate improvements of 10–15% in queue length or waiting time to more substantial reductions of 25–40% in high-demand scenarios where the adaptive mechanism can redistribute green time more aggressively. Metaheuristic approaches report travel-time reductions of comparable magnitude for well-tuned configurations.

V. RESEARCH GAPS AND FUTURE DIRECTIONS

Despite significant recent progress, the surveyed literature reveals several important open research problems that merit focused investigation.

A. Adverse-Weather and Low-Light Robustness

The majority of YOLO-based detection systems are trained and evaluated on daylight footage under favourable weather conditions. Rain, fog, glare, and nighttime illumination introduce photometric distortions that degrade detection confidence, leading to under-counting and erroneous signal timing decisions. Research into domain-adaptive training strategies, synthetic data augmentation for adverse conditions, and multi-sensor fusion (e.g., combining visible-spectrum cameras with thermal or radar sensors) represents a high-priority direction.

B. Edge Deployment and Computational Efficiency

Real-world traffic signal controllers operate at intersections without reliable high-bandwidth cloud connectivity. Deploying large YOLO models on embedded edge devices such as NVIDIA Jetson Nano or Raspberry Pi platforms requires model compression through quantisation, pruning, or knowledge distillation. Very few surveyed works address the specific constraints of edge deployment, leaving a gap between laboratory benchmarks and operational feasibility.

C. Multi-Intersection Coordination

Single-intersection adaptive control, while beneficial at isolated junctions, can exacerbate network-level congestion by displacing queue overflow to adjacent intersections. Coordinated multi-intersection ATSC requires joint optimisation of phase timing, cycle lengths, and offsets across the network. Multi-agent reinforcement learning frameworks show promise but face scalability, communication overhead, and convergence challenges in large networks that have not been fully resolved in the reviewed literature.

D. Emergency Vehicle and Vulnerable Road User Integration

Effective traffic management must accommodate emergency vehicle preemption—rapidly clearing a signal path for approaching ambulances or fire brigades—as well as protective signal allocation for pedestrians and cyclists. The surveyed works largely treat these as optional extensions rather than integral system requirements. Standardised protocols for emergency preemption and vulnerable road user detection remain underspecified.

E. Real-World Validation and Dataset Diversity

The predominance of simulation-based evaluation in the surveyed literature creates uncertainty about performance in messy real-world conditions. Publicly available annotated traffic video datasets from diverse geographic and infrastructure contexts are needed to enable standardised benchmarking. Field trials with rigorous before-and-after comparison methodologies are necessary to substantiate the claimed benefits of adaptive systems.

VI. CONCLUSION

This paper has surveyed ten contemporary research contributions addressing vehicle queue estimation and adaptive traffic signal control at urban intersections, drawing on works published between 2019 and 2026. The reviewed studies collectively demonstrate that computer-vision-based queue detection—particularly through YOLO deep learning models—combined with intelligent control algorithms, can deliver meaningful improvements in intersection performance metrics including reduced vehicle waiting time, lower queue lengths, and improved throughput relative to conventional fixed-time signal operation.

Deep learning-based vehicle detection has emerged as a versatile, hardware-light approach that leverages existing surveillance infrastructure without requiring intrusive pavement sensors. Reinforcement learning provides a principled optimisation framework capable of learning complex multi-phase control policies through simulation experience. Fuzzy logic controllers offer interpretable, low-complexity adaptive mechanisms particularly suited to deployments with limited computational resources.

The proposed project—an innovative method for vehicle queue estimation at traffic signals using roadside sensors—aligns directly with the frontiers identified in this survey: combining YOLO-based real-time detection with ESP32 microcontroller-based signal switching to deliver a cost-effective, hardware-accessible adaptive control solution. Key future enhancement directions include adverse-weather robustness, edge-optimised model deployment, multi-intersection coordination, and integration of emergency vehicle preemption. The survey establishes a comprehensive bibliographic and analytical foundation supporting the continued development of intelligent adaptive traffic management systems.

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