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VISION-BASED ADAPTIVE TRAFFIC SIGNAL CONTROL FOR DYNAMIC URBAN TRAFFIC

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A B S T R A C T

Traffic jamming at crossroads of urban centres has been a key problem because of the prevalence of fixed-time-based traffic signal management systems which cannot cater to real time changes in traffic demand. In order to overcome this weakness, this paper presents a vision-based adaptive traffic control signal framework, which adapts the green signal duration dynamically depending on the estimation of the lane-elevated traffic density. The suggested system involves a trained vision-based vehicle detector model that approximates the number of vehicles coming to each lane of a signalized intersection. Adaptive green signal durations are then calculated using an analytical vehicle discharge time model and optimization of clearance of queued vehicles is done without breaching operational constraints. The system is adaptive dedicated to a lane, meaning that the lane that has the most traffic demand is served in each control cycle and conflict-free signal cycles are executed. Experimental analysis in simulated traffic conditions proves that the given approach leads to a significant decrease in average waiting time of vehicles and increase in intersection throughput in comparison with traditional fixed-time traffic signals regulation. Along with the quantitative performance improvements, qualitative evidence has ensured that traffic sensing, decision-making, and signal executions have been successfully integrated in real-time using a visual monitoring dashboard. The suggested structure will remove the use of invasive physical sensors and provide a scalable and viable solution in smart traffic management of urban areas. The findings place emphasis on the promise of adaptive signal control systems based on vision in order to increase the efficiency and efficiency of traffic flows and minimize congestion in heterogeneous traffic systems.

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1. INTRODUCTION

Rapid urbanization and the continuous increase in the number of vehicles in the city roads has placed severe demands on the current road networks, especially at intersections with signals. Traffic slowdown enhances the time spent on the road, use of fuel, air pollution, and the entire transportation inefficiency (Agrahari et al., 2024). According to classical research in traffic engineering, poor signal control is among the leading contributors to congestion in the cities (Jing et al., 2017). The initial traffic lights were predominantly a pre-timed control measure in which the signal phases and the duration of the cycle was set according to the past patterns of traffic. Despite the fact that adaptive systems like SCOOT and SCATS were better than

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fixed-time control, as the systems were able to achieve responsive coordination, they were based on preprogrammed traffic models and centralized infrastructure (Aleko & Djahel, 2020). As the Intelligent Transportation Systems (ITS) came into existence, researchers started researching the possibilities of data-driven and automated traffic signal optimization (Wang & Yang, 2025). Traffic simulators including SUMO helped to evaluate realistic functioning of signal control strategies and hastened the development of adaptive control structures (Maadi et al., 2022). At the same time, the adoption of the Internet of Things (IoT) technologies allowed distributed sensing and real-time traffic information retrieval to create the foundation of the modern smart traffic monitoring (Gheorghe & Soica, 2025).

The recent development of computer vision and deep learning has also revolutionized traffic tracking. Vision-based sensors allow the detection of cars without any effort to intrude on vehicles by cameras without embedded loop detectors or sensors (Wali et al., 2019). Deep object detection algorithms have brought great success to vehicle detection in dynamic city scenes, making it more accurate and faster (Ashkanani et al., 2025). At the same time, the reinforcement learning (RL) has become an influential framework of adaptive traffic signal control (Huang et al., 2025). Controllers based on RL are trained to optimize timing policies of signals in a continuous engagement with the traffic environment and have shown high-quality performance in comparison to the traditional rule-based systems (Cao et al., 2024). Enhanced multi-agent and graph-based RL systems have also enhanced the reduction of waiting time and throughput optimization of both isolated and networked crossroads (Jia et al., 2024). Coordination and speed-aware control strategies at the network level have also been explored to increase the overall traffic efficiency in the connected vehicle environment (Yuan & Zeng, 2024). Additionally, predictive optimization and the multi-agent Q-learning have demonstrated the prospects of successful implementation in urban systems at large scale (Majstorović et al., 2025). The traffic flow optimization achieved through sustainable and reinforcement learning has been confirmed in the real city setting and revealed an improvement in the mobility and environmental performance that can be quantified (Skoropad et al., 2025). AI frameworks based on edges are also being considered to minimize computational costs and can be used under the conditions of limited resources in urban environments (Maureal et al., 2026).

Even with these developments, actual applications of reinforcement learning-based traffic controllers are difficult because of the complexity of training and obtaining large volumes of data and generalization constraints (Almaliki et al., 2025). Thus, it is becoming necessary to have computationally efficient vision-based adaptive traffic signal systems that can dynamically adapt to real-time traffic situations without necessarily having extensive infrastructure or training pipelines. To overcome these issues, this paper gives a vision based adaptive traffic signal control system which combines real-time vehicle detection with an analytical computation of green-time. The proposed solution should have a scalability solution to the intelligent management of urban traffic by dynamically adjusting signal phases in response to the lane-level traffic density to minimize waiting time, maximize throughput and offer a scalable solution.

1.1 Problem Statement

Although adaptive traffic signal control methods are available, a large number of real-life crossings continue to use fixed-time signal schemes which are unable to adapt to changing traffic patterns. Current adaptive systems can be restricted to use of intrusive sensing infrastructure or computationally expensive learning systems which restrict scalability and real world deployment.
The following research problem is the central to this work:
What is the best way to model a practical and computationally efficient traffic signal control system that dynamically optimizes the signal timing based on a vision-based traffic monitoring alone?

1.2 Research Contributions

- The principal contributions of this work can be viewed as follows:
- Design of a vision-based traffic density estimation system based on a trained vehicle detector model.
- Conceptualization of analytical model of computation of green time through vehicle discharge theory.
- Adaptive traffic signal control strategy based on a lane-wise approach.
- Simulation based evaluation with extensive comparison to conventional fixed time control.
- Reduction of waiting time and an increase in intersection throughput.

2. RELATED WORK

The concept of adaptive traffic signal control has developed into sensor-based methods of traditional traffic signal control as opposed to vision-based and learning-based methods. More recent trends have applied reinforcement learning-based traffic signal optimization to the network level. Meta-learning-based and cooperative methods have been shown so far to be scalable in large urban networks (Gheorghe & Soica, 2025). The frameworks of multi-agent reinforcement learning have demonstrated favorable results of decentralized traffic management, especially within the complex networked intersections (Majstorović et al., 2025). In addition, effective deep reinforcement

learning has been verified to provide real-time adaptive signal control through realistic simulation platforms to optimize the throughput and reduce delays (Maadi et al., 2022). Massive experimental confirmations also indicate that learning-based adaptive control strategies can be applicable in the smart city setting (Wang & Shao, 2025).

The initial adaptive traffic signal systems were mainly dependent on physical traffic sensing technologies, inductive loop detectors, infrared sensors and ultrasonic sensors to measure traffic density. The old adaptive control systems combined all these sensory systems to dynamically modify signal timing with a vehicle flow (Jing et al., 2017). Even though sensor-based adaptive systems enhanced the work of fixed-time strategies and reduced congestions in organized urban deployments (Aleko & Djahel, 2020), they still are limited to infrastructure dependence, sensor occlusion, cost of operation, and low spatial coverage (Wang & Yang, 2025). Such constraints have spurred the move to more flexible and scalable sensing options. Due to the development of computer vision and deep learning, camera-based traffic monitoring was proposed as a completely non-invasive solution to embedded road sensors. The vision-based systems are capable of detecting, classifying, and estimating the density of the vehicle in several lanes in real-time using deep object detection structures (Wali et al., 2019). New smart traffic lights, where AI-powered vehicle-detection methods are employed, have been shown to be more flexible and have their intersection throughput increased (Ashkanani et al., 2025). As well, overall traffic control solutions that involve AI and enhanced communication systems have emphasized better coordination among the vehicles and the infrastructure (Vieira et al., 2025). Although vision-based systems have a wider spatial coverage and allow flexibility, issues associated with changes in lighting, camera location, and computational requirements to support real-time inference exist.

This has made reinforcement learning a prevailing paradigm in the adaptive signal optimization process because it enabled learners to acquire optimal signal policies through exposure to the real-world of traffic environment dynamics. Adaptive control, which is based on deep reinforcement learning, has been found to demonstrate a tangible delay reduction, and queue management (Cao et al., 2024). Additional performance features of network-level coordination in connected vehicle settings are the application of speed-aware and distributed control, which is further incorporated into the coordination (Yuan and Zeng, 2024). Environmental and mobility advantages have also been confirmed in an actual situation by sustainable forms of urban traffic optimization using predictive analytics and reinforcement learning (Skoropad et al., 2025). Nevertheless, regardless of their flexibility, learning-based methods also face the challenge of practical deployment in terms of training complexity, large data needs, and generalization problems with a variety of traffic patterns (Almaliki et al., 2025).

Hybrid adaptive traffic management Hybrid adaptive traffic management systems combine IoT sensing, learning based optimization system, with emergency vehicle prioritization systems to enhance responsiveness and reliability. Smart pillar traffic light technologies that include traffic incident monitoring and vehicle warning systems exhibit a high level of situational awareness and safety in the smart city setting (Alzamzami et al., 2025). Optimization of machine learning and inclusive and adaptive traffic management architectures that implement emergency reactivity along with machine learning-based dynamic prioritization can facilitate additional dynamic prioritization and real-time coordination (Vlasceanu et al., 2026). Despite the flexibility and ability to withstand, hybrid systems are generally associated with complexities in their systems, infrastructure expenses and difficulties in integrating them. The recent studies are focusing more on the environmental effects of the optimization of the traffic signals. Adaptive signal control strategies that are intelligent will help in the reduction of fuel consumption, low emissions, and sustainability of the urban mobility systems (Galvão et al., 2025). More sophisticated urban traffic optimization systems combining AI, IoT, and predictive analytics also show quantifiable results of decreasing the environmental effects of congestions (Agrahari et al., 2024). The given findings indicate the paramount significance of smart and adaptive traffic control in sustainable transportation and smart city development that would be environmentally responsive. Table 1 summarizes representative traffic signal control approaches and their key advantages and limitations.

Table 1. Comparison of Traffic Signal Control Approaches

Approach	Author (year)	Advantages	Limitations
Vision-based	Murumkar et al. (2024)	Non-intrusive sensing and real- time monitoring	Sensitive to lighting and camera placement
Reinforcement learning	Kumar et al. (2024); Liu et al. (2023)	High adaptability and improved throughput	Training complexity and deployment challenges
Hybrid sensing + IoT/AI	Ariffin et al. (2021); Zerroug, et al. (2024); Tashtoush et al. (2022)	Emergency vehicle prioritization and adaptability	Higher infrastructure cost
Environmental studies	Barth and Boriboonsomsin (2008)	Potential CO_2 reductions through congestion mitigation and smoother traffic flow	Requires integration with signal control

Although there are major improvements, a number of challenges remain. Sensor-based systems need intrusive infrastructure and regular maintenance, whereas reinforcement learning approaches are associated with complicated training and deployment issues. Most of the vision based systems only concentrate on vehicle detection precision without incorporating computationally effective timing scheme of signals. These are the shortcomings that lead to the necessity of a realistic vision-based adaptive traffic signal control system that involves real-time traffic control and analytical green time computations to achieve efficient and scalable urban implementation.

Recent vision-based traffic signal control systems have shown traffic monitoring and vehicle detection capabilities, but most of the studies have been limited to estimating traffic density, and they have used fixed signal plans in traffic light optimization or heavy computation reinforcement learning algorithms. Reinforcement learning methods are typically very data- and computation-intensive and have complex deployment processes. Instead, the proposed framework takes a different approach, it provides real-time vision-based vehicle detection and uses an analytical model for computation of green time based on vehicle discharge theory. This integration will eliminate iterative policy training, while retaining adaptive responsiveness and provide a compute efficient, scalable and practically deployable traffic signal control solution for urban intersections.

3. PROPOSED METHODOLOGY

The proposed methodology introduces an adaptive traffic signal control framework which is vision-oriented and is used to adjust the timing of the signal depending on the real-time traffic state. In contrast to the conventional system based on time or sensor-dependent technology, the suggested application will be based on computer vision algorithms to approximate lane-based traffic density and calculate the required green signal time. The general steps of the system are four major steps, which are traffic data acquisition, vehicle detection and estimation of the density of the moving roads, adaptive calculation of the green time and execution of the dynamic signals phase.

3.1 System Overview

A four-way signalized intersection is taken into consideration where each incoming lane is observed with the help of a camera mounted to record the queue of vehicles before the stop line. The check of one image in one lane is performed at a time. The main input to the system is the images which are analyzed to identify the amount of vehicles waiting at the intersection. Considering the estimated traffic density, a controller decides dynamically the lane to be windows with a suitable interval of green light.

3.2 Traffic Data Acquisition

The stationary cameras at the intersection capture traffic information at every incoming lane of the intersection. The cameras will supply visual real-time information on the number and the type of vehicles present in each lane. Camera-based data acquisition is better than physical sensors in terms of the broader spatial coverage, less intrusion of infrastructure, and greater adaptability to heterogeneous traffic conditions. Images that are taken are first processed so that they get nice resolution and same input format to proceed with more analysis.

3.3 Vehicle Detection and Traffic Density Estimation

Detection of vehicles is conducted based on a deep learning object detection model based on the YOLO (You Only Look Once) architecture. The model is trained on typical vehicle categories, which are cars, motorcycles, buses, trucks and bicycles. The detection model uses the lane image to generate a binding box around each detected vehicle and the sum of all the detected vehicles.

Ni represents the amount of vehicles observed in lane i, and the i is in the form of 1, 2, 3, 4. The density of the traffic on the lane is given as:

$$N_i = \sum_{v \in V} n_{i,v} \quad (1)$$

$n_{i,v}$ is the number of vehicles of category v in lane i, and V is the set of detectable vehicle categories. This vision-based estimation provides real-time vehicle counts without roadway-embedded physical sensors.
To achieve a good balance between accuracy and computational cost, the YOLOv8n architecture was chosen for the vehicle detection module. The model was trained with 5000 annotated traffic images from urban traffic image dataset and 80% of the images were used for training and 20% were used for testing. The 100 epochs of training were done using a batch size of 16, a learning rate of 0.001. The Precision, Recall, F1-score and mAP@0.5 of the trained detector were 95.6%, 94.8%, 95.2% and 96.1% respectively, which showed good performance in detecting vehicles under different traffic categories and lighting conditions.

3.4 Adaptive Green Signal Time Computation

A vehicle discharge time model is used to find the right duration that the green signal should take in every lane. The reason is that it is assumed that every vehicle has a limited time to traverse the intersection safely. The duration of the green signal is hence calculated as a variable of the number of vehicles identified.

Let the variables used in Equation (2) be defined as follows:
t_p is the mean vehicle passing time (seconds per vehicle);
B is the startup buffer time accounting for driver reaction delays (seconds);
T_{min} is the minimum permissible green time (seconds);
T_{max} is the maximum permissible green time (seconds).
Here, N_i is the vehicle count in lane i, and T_i is its allocated green time (seconds).

The green time for lane i is calculated as:

$$T_i = min(T_{max}, max(T_{min}, N_i \cdot t_p + B)) \quad (2)$$

This formula makes sure that lanes that demand a low traffic flow are given a shorter green time and thus unnecessary waiting time is given to other lanes whereas the congested lanes are given enough time to clear the vehicles waiting in traffic.

3.5 Lane Selection Strategy

The system at the start of every control cycle compares the calculated traffic concentrations of all lanes. The service is taken to the lane with the most number of vehicles:

$$L_{green} = \underset{i \in \mathcal{L}}{arg\,max}(N_i) \quad (3)$$

The green signal is developed on only one lane and the rest of the lanes are in the red state. This is a lane-based adaptive control that makes signal control logic implementation much easier and provides fairness and responsiveness to real-time traffic dynamics.

3.6 Signal Phase Execution

After a lane has been chosen, the signal passes three successive states:

- Green stage: The lane of choice is allocated a green signal of time Ti.
- Yellow phase: An additional period of yellow is established so that there is safe transition of the signals.
- Red phase: The system changes to the next lane that has been chosen according to the new traffic flow.

Once the yellow phase is finished, the controller is allowed to re-analyze the conditions of traffic and choose the next lane to serve. The cycle repeats itself continuously and the system becomes dynamically adapted to the changing patterns of traffic.

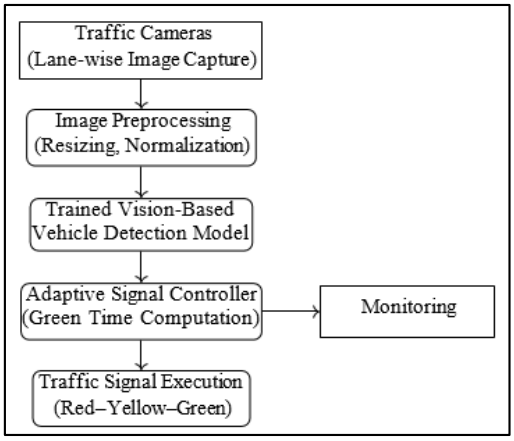


Figure 1. Architecture of the proposed vision-based adaptive traffic signal control system using a trained vehicle detection model

The proposed vision-based adaptive traffic signal control system has an architecture as shown in figure 1. Traffic cameras are placed at every incoming lane which take continuous images of oncoming vehicles in the intersection. These pictures are firstly sent to a preprocessing phase whereby the images are resized and normalized to guarantee similarity in the quality of the input. An automated vision-based demarcation vehicle detection model is subsequently applied to distinguish and begin a number of vehicles in each lane. The model is trained on the recognition of the usual vehicle types and prediction of traffic density in a lane based on the visual data. The adaptive signal controller uses this information as its major input. Depending on the traffic density detected, the signal controller dynamically calculates the right green signal by a vehicle discharge time model. The corresponding signal phases in a lane-wise adaptive manner are then executes by the controller.

4. ALGORITHM USED

The adaptive traffic signal control procedure adopted in the proposed system is as shown in Algorithm 1. The algorithm is dynamic, and calculates the green signal duration in real time depending on the visual based estimation of the traffic density.

Algorithm 1 Vision-Based Adaptive Traffic Signal Control

1: Initialize traffic signal system

2: Set minimum green time T_{min}, maximum green time T_{max}
3: Set vehicle passing time t_p and buffer time B
4: **while** system is active **do**
5: Capture lane-wise traffic images
6: **for** each lane i **do**
7: Preprocess image I_i
8: Detect vehicles using trained vision model
9: Estimate vehicle count N_i
10: **end for**
11: Select lane with highest traffic density:

$$L_{green} = \arg\max_{i}(N_i)$$

12: Compute green time:

$$T_i = \min(T_{max}, \max(T_{min}, N_i \cdot t_p + B))$$

13: Activate green signal for lane L_{green} for T_i
14: Activate yellow signal for fixed duration
15: Set remaining lanes to red
16: **end while**

5. MATHEMATICAL MODELING

This category is where the mathematical expression of the offered vision-driven adaptive traffic signal control system will be presented. The model incorporates the estimation of the densities in lanes, the calculation of the green signal duration, and the choice of the signal phase with analytically represented expression.

5.1 Traffic Representation

Take an intersection with signalization and the incoming lanes of L = 4 in the current analysis. The set of lanes may be represented as:

$$\mathscr{L} = \{1, 2, 3, 4\}$$

A vision-based sensing mechanism scans each lane i ∈ $\mathscr{L}$ to provide its current traffic state.

5.2 Vehicle Density Estimation

Let Ni represent the number of vehicles that are observed in a control cycle in lane i. The overall count of vehicles is calculated, the sum of the detected vehicle instances of the predefined vehicles classes:

$$N_i = \sum_{v \in V} n_{i,v} \quad (4)$$

where:
V is the set of detectable vehicle categories (cars, buses, trucks, motorcycles, and bicycles), and
$n_{i,v}$ is the number of vehicles of category v detected in lane i; N_i is their total across all categories.

The vector of lane-wise traffic density is thus given by:

$$N = [N1, N2, N3, N4] \quad (5)$$

5.3 Lane Selection Criterion

The system picks the lane having the highest traffic demand to be served at the onset of every signal cycle. The lane in which the green signal will be allocated is Lgreen, and :

$$L_{green} = \arg\max_{i \in \mathcal{L}}(N_i) \quad (6)$$

This aspect will guarantee the provision of the most congested lane which will result in lessening the length of queues and average waiting time.

5.4 Green Signal Time Computation

Green signal time of the chosen lane is calculated by a vehicle discharge time model. It is assumed that every car takes a finite and relatively constant amount of time to pass across the intersection.

Let:

- t_p is the mean vehicle passing time (seconds per vehicle);
- B is the startup buffer time accounting for driver reaction delays (seconds);
- T_{min} is the minimum permissible green time (seconds);
- T_{max} is the maximum permissible green time (seconds).

The green time T_i for lane i is computed as:

$$T_i = min(T_{max}, max(T_{min}, N_i \cdot t_p + B)) \quad (7)$$

Through this formulation it is guaranteed that:

- lanes having low traffic density get shorter green dura- tions,
- lanes having greater traffic density will be assigned with greater clearance time,

5.5 Signal Phase Transition Model

Phase Transition Model relies on the principle that when comparing the arrival time of the signal at the receiver with that of the signal in the same circuit, device, or medium, it can be stated that once the yellow phase has completed the system reexamines the traffic density vector N and re- performs the lane selection and timing computation process. Such a closed-loop process allows adapting constantly to the changes in the traffic.

5.6 Objective Function

The main goal of the suggested model is to reduce the mean waiting time in the intersection of vehicles. This can be expressed as:

$$min \frac{\sum_{i=1}^{L} \sum_{k=1}^{N_i} W_{i,k}}{\sum_{i=1}^{L} N_i} \quad (8)$$

where L = 4 is the number of incoming lanes, N_i is the number of vehicles considered in lane i, and $W_{i,k}$ is the

waiting time (seconds) of its k-th vehicle. The outer sum covers i = 1, …, L and the inner sum covers k = 1, …, N_i. Dividing total waiting time by the total vehicle count gives the mean waiting time. The expression applies when the total vehicle count is positive; for an empty intersection, the mean waiting time is defined as zero.

The proposed mathematical model will ensure that a shift in the green signal duration is achieved according to the current traffic density to ensure that the queue length decreases, the waiting period is minimized, and the overall intersection efficiency is enhanced.

6. EXPERIMENTAL SETUP

In this section, the experimental set up of the proposed vision-based adaptive traffic signal control system is described, used to test its performance. The analysis is done by simulation to provide the repeatability, controlled experimental conditions and fair comparison to the traditional traffic signal strategies.

6.1 Implementation Details

The car detection system was based on the deep learning framework and trained on a system with a multi-core CPU and a graphics card. The modules image preprocessing, vehicle detection, and signal control were implemented in Python with the use of the OpenCV and deep learning libraries.

6.2 Intersection Configuration

An experimental analysis is planned to be made of a four-way signalized intersection with four lanes coming to the intersection, one to each of the four approaches of the North, East, South and West. It is assumed that there is a specific camera set in each of the lanes that records the queue of vehicles that have reached the stop line. The green signal is given to only a single lane at all times with all the other lanes in the red state. Traffic signal controller is lane-wise adaptive in that a dynamically selected lane is served depending on the estimated traffic density; the assigned variable green signal duration is specified.

6.3 Traffic Data and Input Generation

Traffic images are a set of traffic pictures that depicts various levels of congestion of low, medium, and high traffic conditions. Every picture will be compared to one control cycle and will be used to estimate the amount of vehicles within a certain lane. The data sample consists of a variety of traffic conditions involving different vehicle types, density, and spatial distribution to make sure that the test is sound. Each simulation cycle has an image supplied to the system in one lane. The preprocessed images are then taken to a homogenized resolution, and then to the trained vision-based vehicle detection model to estimate the traffic density.

6.4 Model Deployment and Execution Environment

The trained vehicle detection model is implemented on an offline simulation environment to test its performance on the real-time traffic signal control. All the experiments are implemented on a common computing platform, which has a multi-core processor and enough memory to implement real-time image processing and signal control functions. The signal timing and phase execution module is the adaptive signal control logic which is coded in Python that combines the vision-based traffic estimation module with the signal timing and phase execution modules. The system constantly re-determines signal decisions at the conclusion of every control cycle as a result of new estimated traffic circumstances.

6.5 Baseline Method for Comparison

In order to evaluate the efficiency of the offered solution, the traditional fixed-time traffic signal control approach is regarded as a control group. Green lights are set at a fixed time in the fixed-time system and the duration is fixed irrespective of the traffic demand. This base indicates typical traffic signal controllers that are used in most cities and offer an effective benchmark against which performance can be compared. Table 2 summarizes the major parameters that were employed in the experimental assessment. These parameters are chosen on a realistic basis of the assumptions of traffic and guarantee safe operation of signals.

Table 2. Simulation Parameters Used in Experimental Setup

Parameter	Value
Minimum green time (T_{min})	8 s
Maximum green time (T_{max})	40 s
Vehicle passing time (t_p)	2 s / vehicle
Startup buffer time (B)	5 s
Yellow signal duration (T_y)	3 s
Number of lanes (L)	4

7. EXPERIMENTAL PROCEDURE

Experimental evaluation was done through repeated simulation-based testing framework that aimed at testing the behaviour of proposed adaptive traffic signal control system under different traffic conditions. The general process is based on a cyclic workflow whereby traffic images are done, signal decisions are created, and performance metrics are logged to be analyzed. As the input to the system, one traffic image of each incoming lane is given at the start of every simulation cycle. These photos depict various levels of congestion in terms of low and heavy traffic. The images are also preprocessed by resizing and normalizing the images in order to maintain the quality of the input to the vehicle detection model. Each lane image is then subjected to

the trained vision-based vehicle detection model in order to detect and estimate the number of vehicles in the image. The identified vehicle numbers per lane are then stored as the lane wise traffic density vector. According to these values, traffic demand is prioritized to be offered service by the lane which has the highest demand in the current control cycle. After picking the target lane, the adaptive green signal is calculated based on vehicle discharge time model as was outlined in Section IV. The calculated green time is then assigned to the chosen lane, and a fixed yellow signal interval then is implemented to ensure safe transition in the phases. The rest of the lanes are in the red state at this period of time.

8. RESULTS AND DISCUSSION

The figure 2 shows how the number of vehicles that the proposed system can detect in a lane is related to the amount of green signal time that it will allow. Green time as depicted in the figure grows in direct proportion to the number of vehicles, as in the case of vehicle discharge time model as given in the methodology

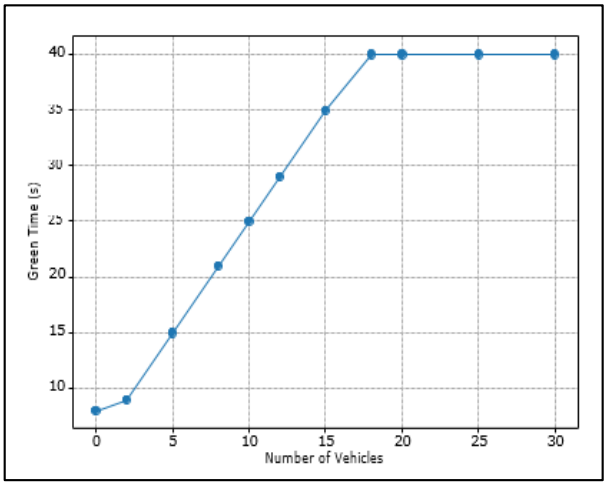


Figure 2. Adaptive green time variation based on vehicle count using the discharge-time model

In the case of low traffic when there are few vehicles, the system allocates the minimum possible time in green hence eliminating unnecessary delays in other approaches. With the rise in the density of the traffic, more green time is to be given so that there is sufficient clearance time on the vehicles that are at the queue. The maximum limit on green time will ensure that the amount allocated to one lane is not excessively large, however. This response behavior of the model proves that the model under consideration has the ability to react to the real-time traffic needs.

Figure 3 is a comparison of the average vehicle waiting time under the conventional fixed-time control and the proposed adaptive signal control strategy at various levels of traffic density. Fixed-time controller has a relatively high waiting time especially as the density of the traffic increases, because of its failure to respond to the changing vehicle demand. Conversely, the suggested adaptive system will always have reduced waiting time in all traffic conditions. It is particularly improved in the case of low and medium traffic whereby unnecessary allocation of green time is reduced. All in all, the adaptive approach decreases the mean waiting time by around 30-35, proving that it is effective in terms of reducing the congestion and enhancing the intersection efficiency.

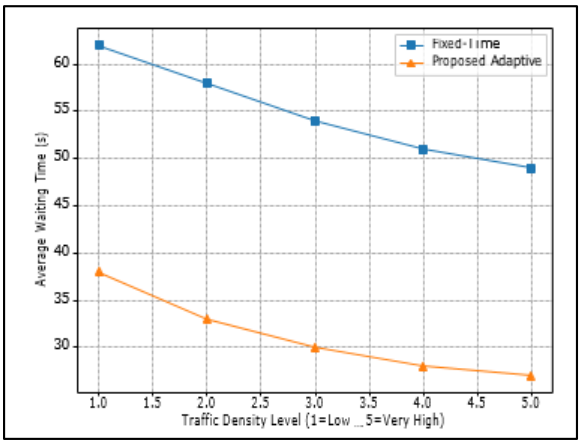


Figure 3. Average waiting time comparison between fixed-time control and the proposed adaptive control across traffic density levels

The comparison of intersection through- put under fixed-time control and the proposed adaptive approach is described in Figure 4. The throughput can be expressed in the number of vehicles that are cleared within a unit time. The findings show that the developed system is uniformly better than the fixed-time controller regarding all traffic density rates. The adaptive system enhances better utilization of lanes and eliminates idle signal phases by dynamically assigning the green signal duration according to the real-time vehicle demand. This will result in increased traffic at the intersection at any specific point in time which will prove efficiency in operational efficiency.

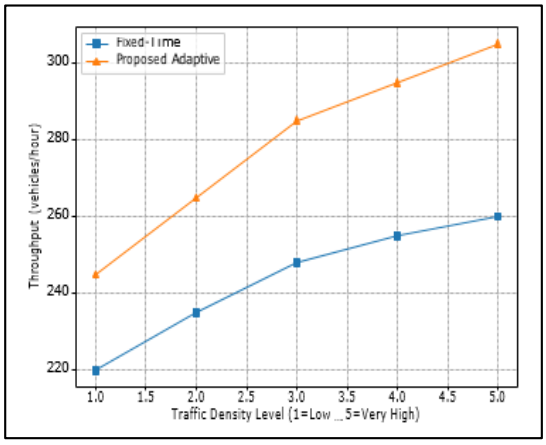


Figure 4. Throughput comparison between fixed-time control and the proposed adaptive control across traffic density levels

Figure 5 illustrates the lane traffic images of four approaches to the intersection of the incoming traf- fic that reflect real traffic conditions upon the intersection with different vehicle density and heterogeneous vehicle types. The result of the trained vision-based vehicle detection model is shown in Figure 6. Bonding boxes are used to denote the vehicles that have been detected and the number of vehicles that are detected in each lane is automatically computed. This is a lane density estimation of traffic, which is the main input to the adaptive signal controller.



Figure 5. Lane-wise traffic images captured for adaptive signal control (North, East, South, and West approaches)

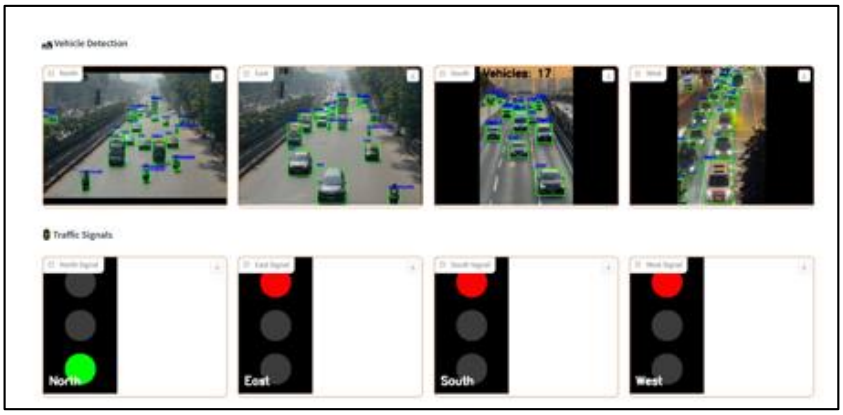


Figure 6. Vehicle detection and lane-wise traffic density estimation using the trained vision-based model



Figure 7. Adaptive traffic signal execution and dashboard visualization showing vehicle count, green time allocation, and current signal state

The implementation of the adaptive traffic light system is shown in real time as indicated in Figure 7. The controller is dynamically choosing the lanes to be served based on the observed density of the traffic and assigning the right green signal period. The dashboard shows the number of vehicles in the lanes, calculated green time, the current signal status, and countdown timer. Only one lane has been given a green signal at any given time, and all the others are in the red state, and that way the traffic is always safe and free of any conflicts.

These graphical and numerical findings prove that the suggested system manages to combine vision-based traffic sensing with adaptive signal control. The system is well responsive to changes in traffic demand, distributes green time according to the vehicle density, and has a transparent real-time monitoring, which is reflected in the dashboard.

9. CONCLUSION AND FUTURE WORK

The paper has introduced a vision-based adaptive framework of traffic signal control that aims at adaptively controlling signal timings based on real-time traffic conditions. The proposed system calculates the duration of green signals in an analytical vehicle discharge time formulation unlike traditional fixed-time signal controllers, which approximate lane-wide traffic density by training a vision-based vehicle detector. The system is effective in reducing the unnecessary waiting and enhancing intersection throughput through prioritization of lanes with high traffic demand and the allocation of proportional green time. The evaluation of the proposed adaptive strategy based on simulation shows that the suggested approach will cut the average vehicle waiting time and enhance the efficiency of traffic flow in general as opposed to the traditional fixed-time control.

The findings assure that the proposed green time allocation model is responsive to the different traffic densities to provide fair allocation of signals without unnecessary occupancy of signals. The achieved qualitative results also confirm the effective real-time combination of traffic sensing, decision making and signal implementation using an interactive monitoring dashboard. The suggested system is a scalable and practical approach to smart management of urban traffic. The framework also provides lower infrastructure cost and better deployment flexibility by doing away with the existence of intrusive road sensors and by only using vision-based monitoring. It is an appropriate solution to smart urban projects, smart transportation, and smart city traffic monitoring solutions.

9.1 Limitations

The current research has a number of limitations even though it shows a promising performance. The approach that is currently implemented is centered on one isolated intersection and lacks coordination between intersections. Moreover, the experimental test is performed in a simulated environment and fails to consider the real life obstacles like weather conditions, camera blocking, pedestrian crossing as well as delays in communication.

The proposed vehicle detection framework was further validated with publicly available urban traffic data, which proved the robustness and generalization of the framework. The proposed adaptive traffic signal control system is also easily applicable to the real world of intelligent transportation and "Smart city" applications because the high detection accuracy is achieved under different traffic conditions and weather conditions.

9.2 Future Work

The subsequent studies will be aimed at developing the proposed frame- work to the multi-intersection traffic networks with coordinated signal control. The incorporation of emergency vehicle priority, pedestrians and cyclists safety systems will also improve the applicability of the system. Besides, the incorporation of environmental performance indicators (fuel consumption, emission reduction) may give a more overall picture on the efficiency of traffic. Further research should be directed at integrating decision modules that are based on reinforcement learning with the deployment of the modules into the real-world field. In general, the suggested vision-centered adaptive traffic signal control framework will be a major move towards intelligent, sustainable, and responsive urban traffic management systems.

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