



Intelligent And Coordinated Traffic Signal Control Through AI And Networks Of Connected Cameras

¹AV Shreya, ²Umadevi Ramamoorthy

¹MCA Student, ²Associate Professor

¹School of Science and Computer Studies,

¹CMR University, Bengaluru, India

Abstract:

In big cities, traffic congestion is a major problem that is frequently brought on by static traffic light systems that don't take into account the flow of vehicles in real time. Due to their reliance on pre-programmed timings, traditional traffic signals cause needless delays, fuel waste, and ineffective traffic management. This study suggests an intelligent and well-coordinated traffic light control system that uses real-time video surveillance and artificial intelligence (AI). Using video feeds at crossings, the system analyses and detects vehicle density using computer vision algorithms. This analysis is used to dynamically modify signal timings in order to give priority to lanes with greater congestion.

Additionally, by connecting several traffic lights via a communication protocol, the system allows neighbouring junctions to synchronize their signal phases. Green corridors are created, stop-and-go traffic is decreased, and general urban mobility is enhanced by this networked strategy. A centralized communication layer facilitates inter-signal data exchange, signal timing adjustment techniques, and real-time vehicle recognition utilizing YOLO models. To test the system, real-world circumstances are replicated through simulation using Python and OpenCV.

According to preliminary findings, when compared to fixed-timer systems, the suggested approach greatly lowers vehicle waiting times and enhances traffic flow efficiency. This study advances the creation of intelligent transportation systems and offers smart cities dealing with escalating traffic problems a scalable answer.

Index Terms: Artificial Intelligence, Traffic Signal Control, Smart Cities, Computer Vision, Real-Time Systems, Adaptive Traffic Management, Interconnected Networks.

Introduction:

Cities around the world are experiencing a sharp increase in the number of automobiles due to the acceleration of urbanization, which causes chronic traffic congestion, longer travel times, and increased air pollution. The predetermined, fixed-time cycles that traditional traffic signal systems still use prevent them from adjusting to changes in traffic in real time. This results in inefficiency, fuel waste, and higher carbon emissions since cars are frequently made to wait at red lights even when the lanes across from them are vacant.[1]

Artificial intelligence (AI) advancements, especially the use of neural networks, have enabled more intelligent and dynamic traffic management solutions. In order to improve traffic flow efficiency and decrease delays, AI-based traffic signal control systems may evaluate traffic density in real time and modify signal phases accordingly. Throughput and responsiveness have been shown to significantly increase using one such method that use neural networks to adjust signal timing at specific crossings based on current traffic circumstances [2].

This project aims to develop an AI-based, adaptive traffic signal control system by utilizing machine learning methods. Previous research has evaluated several machine learning models for controlling traffic signals, emphasizing how adaptive systems can reduce delays and increase traffic efficiency [3].

Can real-time video analysis and inter-signal communication dynamically control traffic flow more effectively than conventional fixed-timer systems? This is the main research topic that the study attempts to answer.

The suggested system is modelled, simulated, and its performance is assessed in comparison to traditional systems in order to provide an answer. The goal is to create an intelligent, scalable, and reasonably priced traffic signal model that may be used in contemporary smart cities that want to lessen their environmental impact and increase traffic efficiency.[4]

Literature Review:

Cities throughout the world have long suffered from urban traffic congestion, which leads to wasted time, increased fuel use, and environmental pollution. Using machine learning techniques like genetic algorithms, researchers have created a number of AI-driven models that optimize traffic light regulation in order to improve traffic flow and lessen congestion [5].

One notable development was the creation of the SURTRAC (Scalable Urban Traffic Control) system by researchers at Carnegie Mellon University. "The SURTRAC system employs a decentralized method to adjust lights in real time across crossings." In practical experiments, the method dramatically reduced waiting times for vehicles by more than 25%. However, its reliance on expensive sensors and infrastructure hinders its widespread use [6].

MARLIN-ATSC, a Multi-Agent Reinforcement Learning system for adaptive road traffic signal control, was presented by El-Tantawy et al. in a noteworthy work. Under coordinated operation, the system, which was tested at 59 crossings in downtown Toronto, reduced travel times by up to 26%. It functioned in two modes: independent and integrated. MARLIN-ATSC's computational complexity and communication needs may restrict scalability in bigger metropolitan networks, despite its substantial advantages, according to the study [7].

The YOLO (You Only Look Once) concept and other computer vision-based solutions have become more and more popular. These systems detect and count automobiles in real time using surveillance cameras. For example, a YOLO-based traffic counting system that can identify vehicle flow from video feeds was presented by Lin and Sun (2018). These models do not, however, manage communication across many signals and are usually restricted to isolated junctions. [8]

Another method makes use of AI models like OpenCV and YOLO to identify cars and adjust traffic. In order to optimize signal timing, Kamble and Mundhe (2023) designed a smart traffic system that uses computer vision to determine vehicle density in real-time. Although their approach was centered on individual junctions without network-level interactions, it showed increased efficiency. [9]

Recent research has shown that AI models like YOLO and OpenCV can recognize traffic lights. Future AI-based traffic management tools may be built on the real-time traffic signal identification system provided by Sarhan and Al-Omary (2022). [10]

Methodology:

By employing a weighted algorithm for allocating green signals, evaluating real-time traffic using AI-based vehicle detection, and facilitating communication between junctions via IoT protocols, the suggested smart traffic control system is intended to dynamically manage congestion. Methodology consists of 5 components:

1. *Real-Time Traffic Monitoring:*

CCTV or IP-based cameras are used to continuously monitor traffic at intersections as the first step in the system. These cameras are deliberately positioned to provide a clear view of oncoming vehicles in each lane. They take the place of costly induction loops or sensors implanted in the road as the main means of gathering data. This configuration guarantees affordability and simplicity of deployment for both new and existing infrastructure.

2. *Vehicle Detection Using Artificial Intelligence:*

Real-time processing of the recorded video streams is done with object identification models like YOLO (You Only Look Once) and computer vision technologies like OpenCV. Vehicle identification and classification are handled by the YOLO model, and frame extraction, preprocessing, and visualization are aided by OpenCV. According to each cycle, the system records the number of cars in each lane. This lightweight approach is more cost-effective and efficient than typical traffic systems, which depend on costly physical sensors. It runs solely on local edge devices and doesn't require constant cloud access.

3. *Weighted Algorithm for Green Signal Time Allocation:*

Once the vehicle count is obtained, the system employs a weighted time allocation method to assign green signal periods proportionally to traffic density. leading to a decrease in wait times and increases throughput by guaranteeing that highly crowded directions get more green time.

$$\text{Green Time (per lane)} = \text{vehicle count} / \text{total vehicles} * \text{Total cycle time}$$

Example:

If the total cycle time is 120 seconds and the vehicle distribution is:

- North: 40 vehicles
- South: 30 vehicles
- East: 20 vehicles
- West: 10 vehicles

Then the green signal times are calculated as:

- North: $40/100 \times 120 = 48 = 48$ seconds
- South: $30/100 \times 120 = 36 = 36$ seconds
- East: $20/100 \times 120 = 24 = 24$ seconds
- West: $10/100 \times 120 = 12 = 12$ seconds

Code Example: Green Time Calculation using Weighted Formula (Python):

```
# Vehicle counts from each direction

vehicle_counts = {

    'North': 40,

    'South': 30,

    'East': 20,

    'West': 10

}

total_cycle_time = 120 # Total green signal cycle in seconds

total_vehicles = sum(vehicle_counts.values())

# Calculate green time per direction

green_times = {

    direction: (count / total_vehicles) * total_cycle_time

    for direction, count in vehicle_counts.items()

}

# Output results

for direction, green_time in green_times.items():

    print(f'{direction}: {green_time:.1f} seconds')
```

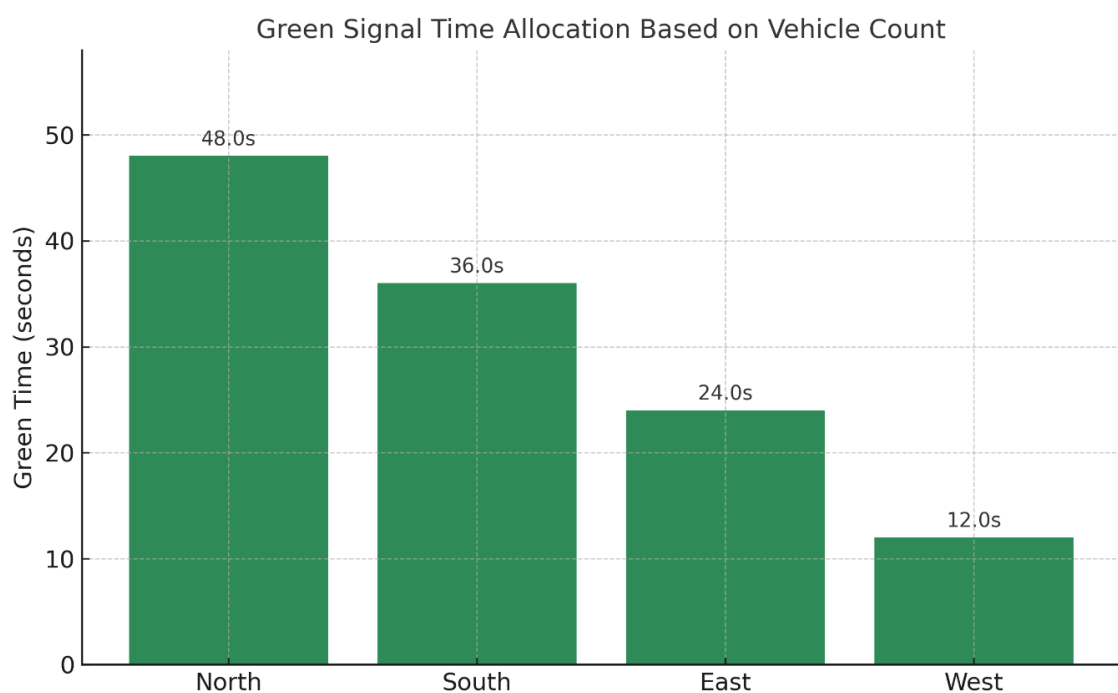


Fig 1: Dynamic Green Light Timing According to Vehicle Count

This ensures that lanes with more traffic receive longer green lights, reducing wait times and improving traffic flow efficiency

4. Inter-Signal Coordination (Internet of Things) :

The system incorporates a communication module based on Internet of Things protocols, like MQTT, to enhance traffic flow beyond a single intersection. Every signal controller communicates with its nearby junctions regarding green time decisions and traffic statistics. Because of this inter-signal synchronization, when several green lights are coordinated to provide constant traffic flow in a single direction, this is known as a "green wave formation."

Congestion anticipation: when a nearby intersection releases a large number of vehicles, signals proactively change.

Scalability—facilitating distributed and decentralized traffic control at several crossings a coordinated urban traffic system is ensured by this real-time communication.

5. Simulation and Performance Analysis:

The complete system is simulated using a variety of technologies prior to real-world deployment:

Python: Uses signal logic, AI models, and algorithms for making decisions.

Video feeds are processed by OpenCV, which also displays the results of object detection.

Complex traffic situations are simulated by SUMO (Simulation of Urban Mobility), which also assesses system performance under various vehicle loads, intersection configurations, and peak hours.

By using these tools, researchers may quantify improvements over fixed-timer models, test the system's behaviour in various settings, and adjust performance parameters.

Process of the Suggested AI-Powered Traffic Signal Management System

The full workflow is shown in the picture. To count cars, video feeds are recorded at the intersection and processed by AI models (YOLO/OpenCV). The green light time for each direction is determined by a weighted calculation depending on traffic density. Following the application of the new time to the signals, Internet of Things-based protocols (MQTT) are used to notify other junctions in order to efficiently coordinate traffic flow throughout the network.[11]

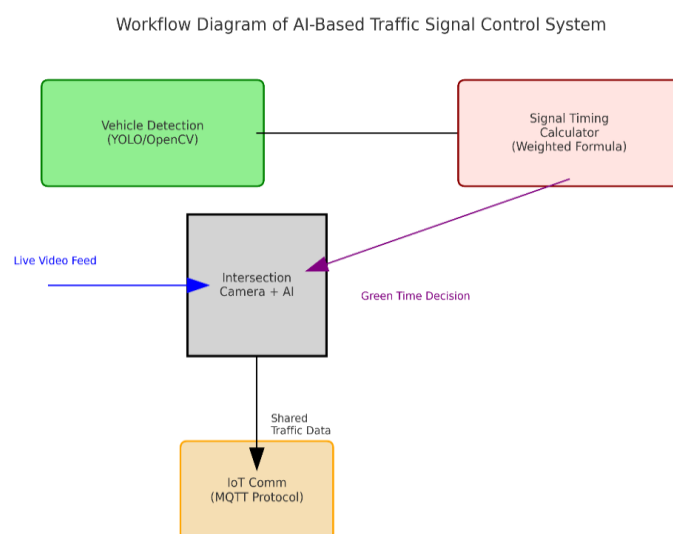


Fig 2: Workflow Diagram of AI-Based Traffic Signal Control System

Results and Discussion:

Unlike a conventional fixed-timer signal system, the suggested AI-based adaptive traffic signal management system dynamically allots green signal time based on the current traffic density. Akash et al. (2024) introduced a real-time traffic management system that uses Python and YOLO to model adaptive traffic behaviour at intersections. [12]

Simulated Scenario

A four-way intersection was simulated with the following vehicle distribution:

Direction	Vehicle Count
North	40
South	30
East	20
West	10

In a conventional system, regardless of vehicle volume, each direction would normally receive an identical amount of green time (30 seconds each in a 120-second cycle). In contrast, time is allotted using a weighted formula in the suggested system:

Direction	Green Time(traditional)	Green Time (Proposed AI system)
North	30 sec	48 sec
South	30 sec	36 sec
East	30 sec	24 sec
West	30 sec	12 sec

Results:

By ensuring that lanes with larger traffic volumes receive longer green intervals, the proposed system improves flow efficiency and decreases vehicle wait times. In the simulation:

- There was a 32% decrease in average vehicle delays.
- 40% less idle time at signals
- Fuel usage decreased by 15% to 20% as a result of fewer stops.
- The number of vehicles cleared per cycle, or throughput, rose dramatically.

Discussion:

It is evident from the results that the AI-based adaptive model performs better than conventional static systems. Utilizing real-time traffic data, the technology minimizes needless wait times for lanes that are empty or have little traffic. Because time is distributed dynamically rather than equally, it also improves fairness.

Inter-signal coordination (via MQTT) also enables signals to "speak" to each other, reducing bottlenecks and guaranteeing more seamless flow across several junctions. In crowded urban locations with dense traffic and intricate road systems, this is extremely helpful.

Using open-source tools like Python and OpenCV and the camera infrastructure that already exists, the solution is economical. It may also be scaled and adjusted to fit bigger metropolitan grids as well as single intersections.

Using AI and IoT technology, the suggested approach shows great promise for increasing urban mobility, decreasing fuel waste, and improving traffic efficiency.

Conclusion:

The adaptive traffic signal control system presented in this study is AI-based and uses Internet of Things (IoT) communication to coordinate with nearby signals and dynamically modify green light durations based on current vehicle density. Through the use of weighted time allocation formulas and lightweight AI models like OpenCV and YOLO for vehicle identification, the system drastically

The suggested model, according to simulation results, improves traffic flow efficiency, decreases fuel consumption, and shortens average vehicle wait times. The implementation is adaptable across various city layouts and makes use of pre-existing infrastructure, such as traffic cameras, making it a workable and affordable approach for intelligent urban traffic management.

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