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Article

# Carbon emission prediction and intelligent regulation modeling for traffic systems using vision AI

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**Abstract:** Urban congestion poses a significant environmental challenge, particularly in developing countries, due to ineffective traffic management leading to elevated vehicle emissions from prolonged idling. This paper introduces a machine learning-based intelligent traffic signal system to cut vehicle idle time and emissions. Using YOLOv8, it detects real-time traffic from four directions. A dynamic phase algorithm replaces fixed signals, counting vehicles and adjusting green lights via capacity ratios. Self-learning, it adapts to scenarios without thresholds. The results showcased notable improvements in traffic efficiency and environmental outcomes, with reductions in delay times ranging from 9% to 65%, particularly a substantial enhancement of 1.94 vehicles per second for the westbound approach. Environmental analysis revealed a 32% reduction in carbon emissions, equivalent to 1502 kg $CO_2$ saved daily, translating to approximately 548 tons of annual $CO_2$ reduction. Based on standard carbon market valuations of $15 per metric ton $CO_2$, this generates 1.5 carbon credits daily with an annual economic value of $8225. The research provides empirical evidence that intelligent traffic management systems can deliver measurable environmental benefits while improving urban mobility. Government authorities validated these findings through official environmental impact assessment procedures. This implementation establishes a scalable framework for smart city initiatives, demonstrating how artificial intelligence applications can address urban environmental challenges through practical, data-driven solutions.

**Keywords:** carbon emission reduction; smart traffic signals; machine learning optimization; YOLOv8 object detection; urban traffic management; real-time traffic analysis; environmental impact assessment

## 1. Introduction

The explosion of the global population in the cities brings unprecedented challenges in the functioning and maintenance of transportation structures since air pollution and degradation of the quality of life of people that inhabit urban areas have been the leading causes of air pollution [1]. The issue becomes clearer particularly at locations where the growth in the infrastructure has failed to match the population growth leading to massive inefficiencies in the city mobility systems [2]. The conventional traffic signal lacks a dynamic response to the real-time vehicle flow activities based on its timing plan and thus cannot react to the dynamic features of the traffic in good time leading to long queues of vehicles wastage of fuel and hence high levels of $CO_2$ emissions that have seriously jeopardized the air quality of the urban environment [3]. The effects of the inadequate traffic management measures implemented by Appleton et al are not just environmental in the local neighborhoods, but also sustainability in new technological opportunities [4]. Controlling traffic would also be among the key considerations in environmentally sustainable plans, as transportation activities occupy very high shares of carbon footprints in urban areas. Many town and city traffic lights are operated on a deterministic basis of a certain time cycling, and these fixed methods are elevated on historical data (like gathering the patterns of the traffic) but do not cover all the spectrums of demands with regard to transportation today [5]. There is unnecessary delay of vehicles at crossroads during the heavy traffic where minimal cross-traffic moves through the intersection as the vehicles in the city arteries are made to waste on useless signal cycles during the lightly loaded times [6]. Economic analyses reveal that traffic congestion imposes substantial costs on urban areas beyond direct time and fuel losses [7]. The development of AI and computer vision technologies has become an opening to solve such transportation issues with intelligent systems of automatic traffic analysis and adaptive reaction mechanism [8]. The ability of machine learning, and specifically Deep Learning algorithms (DL) to perform the pattern recognition and prediction that can transform the history of the traffic management solutions suggested [9] is not a secret at all.

Moreover, the inclusion of object detection features into the traffic management systems will bring us to the possibility of the overabundance of utopian situational awareness, which could propel a demand for a much more data-line decision-making that is in accord with the condition of the road now, not what we thought the floor to look like [10]. The green agenda is turning into a core aspect of city-planning and policy, where carbon emission reduction commitments are defining urban cities and their infrastructure. This will provide an effective lever to those cities that want to achieve their own carbon reduction targets and better leverage their three-dimensional transport infrastructures by making sure that smart traffic management systems bring actual environmental performance in the form of a lower level of vehicle idling, flow through [11]. Despite the fact that it has highly enhanced the content of AI in traffic operation, there are still few issues as follows: (1) It relies on the value of predefined threshold; (2) to train on high historical data; and (3) not changing at real time. The current systems remain directed at efficiency in traffic and fail to consider integration of environmental health assessment and analysis of carbon emissions. Moreover, the problems with real-world deployment can be limited in the city where the infrastructure and cost factors are more dominant. In this article, we shall endeavor to fill these research gaps by postulating and implementing a new machine-learning-based traffic signal control system that does not assume anything about the bounds within which it can maximize environmental performance, has a global perspective of what the impact on the environment is in terms of scale as opposed to pollutant, and can be scaled practically to real urban situations. The first time this integrates YOLOv8-based Computer Vision with adaptive learning algorithms learning urban traffic patterns, and actions (measures of reduction as $CO_2$ saved or Economic Value) can be traded in Carbon Credits with I.RENO sustainable computation in Smart Cities 1 Environmental science is also becoming Computer Science [12]. Large-scale implementations of adaptive traffic signal systems have demonstrated substantial environmental benefits, with big-data empowered traffic control systems showing potential annual $CO_2$ reductions exceeding 31 million metric tonnes across China's major urban centers [13]. The measurements were conducted on a crossroad in the city of Shenzhen in China (a typical developing metropolis), which has a moderate to high rate of traffic flow. The analysis integrates the performance demonstration, and quantifiable environmental benefits, and offers a template that is integrated to roll out intelligent transportation systems within a similar urban geography. Beyond traffic flow optimization, YOLO-based computer vision systems have demonstrated versatility in comprehensive traffic management applications, including real-time traffic violation detection and automated enforcement systems [14]. These applications showcase the broader potential of object detection algorithms in creating integrated intelligent transportation solutions.

The primary objectives of this study are to: (1) develop and validate a self-adaptive traffic signal optimization system using machine learning algorithms, (2) quantify environmental benefits through comprehensive carbon emission assessment, (3) demonstrate practical implementation feasibility in real urban traffic conditions, and (4) establish a scalable framework for broader smart city infrastructure development. Through rigorous empirical analysis, this research contributes valuable insights into the practical deployment of artificial intelligence technologies for sustainable urban transportation management, providing evidence-based solutions that address both traffic efficiency and environmental sustainability objectives.

## 2. Related work

The research community has also shown significant interest in incorporating artificial intelligence (AI) technologies into traffic management, with many studies demonstrating that machine learning-based approaches offer strong potential in addressing urban transportation problems [15]. This section presents a review of current literature on computer vision-based traffic systems, environmental impact assessment methodologies, and intelligent signal optimization algorithms, highlighting key gaps that this study aims to address.

Transportation Computer vision in transportation is developing rapidly, with the YOLO architecture getting more and more popular in traffic surveillance systems [16]. Karmakar (2020) created the real-time vehicle counting system with the YOLOv5 model that possesses more than 94 percent accuracy in different weather and lighting conditions [17]. Building on this, he adopted YOLOv8 for multi-class vehicle detection at urban intersections, demonstrating improved accuracy in identifying motorcycles, cars, and heavy vehicles, which are critical for calculating traffic density accurately. However, most existing implementations focus mainly on detection accuracy, often neglecting the integration of these systems into real-time adaptive control environments. Detection performance is typically evaluated in isolation, without testing its application in dynamic traffic signal systems or analyzing the computational demands necessary for real-time operation. Comparative studies of YOLOv8 variants in ITS applications have shown that YOLOv8l and YOLOv8x exhibit superior detection efficacy in high-density traffic scenarios, with precision improvements of up to 18% over YOLOv5 [18].

Machine learning algorithms for optimizing traffic signals have also progressed beyond traditional rule-based methods. Boukerche (2020) introduced a deep learning framework that integrates real-time vehicle detection and flow prediction, significantly enhancing intersection throughput compared to conventional fixed-timing systems [19]. Their work underscored the importance of adaptive algorithms capable of responding to real-time traffic dynamics. Similarly, Samadi (2012) proposed a reinforcement learning model that eliminates preset signal timing thresholds, enabling signals to adapt continuously based on live observations. This method achieved a 30% reduction in average vehicle waiting time at test sites [20]. He developed self-learning algorithms that combine historical traffic data with real-time inputs to calculate optimal signal timing. However, most of these systems still require lengthy training periods, depend on predefined thresholds, or are limited to narrow operational parameters. The concept of continuous, threshold-free learning has yet to be fully explored in actual urban deployments.

Environmental impact assessment of traffic optimization systems has gained prominence, especially in relation to carbon emission reduction efforts. Issa Zadeh (2023) analyzed $CO_2$ reductions resulting from intelligent traffic systems and reported average decreases of 15–25% at various urban intersections in developing regions [21]. Their method of estimating emissions using vehicle idling time and fuel consumption has become widely adopted. He established detailed carbon footprint evaluation protocols tailored to smart transport infrastructure and emphasized the necessity of validation by governmental environmental agencies. However, most studies in this area rely on simulations and lack empirical data from real-world deployments.

Another important research domain is multi-intersection coordination. Vepakomma (2018) studied master-slave signal coordination across linked intersections and showed marked improvements in traffic flow and reduced stop-and-go driving [22]. Their work laid the groundwork for networked traffic systems in smart city planning. He expanded on this with distributed machine learning models that allow intersections to share traffic data while maintaining autonomous functionality. Nonetheless, these systems typically require major infrastructure upgrades and complex communication networks, which hinder widespread practical deployment.

Recent investigations have also addressed the practical challenges of deploying intelligent traffic systems in developing nations. Singh (2024) explored barriers and success factors for AI-based traffic systems in South Asian cities, stressing the importance of cost-effective, infrastructure-compatible solutions [14]. He conducted comparative studies between traditional and intelligent traffic systems across multiple cities, offering empirical evidence supporting their environmental and economic benefits. However, many of these studies fall short in providing full environmental validations or comprehensive economic analyses.

The collective findings from these research streams confirm the strong potential of machine learning for traffic optimization. Yet, several critical gaps persist in the existing literature:

- Threshold-Free Adaptation: Most systems rely on hardcoded thresholds or parameters, which limit their adaptability to varying traffic conditions without manual tuning.

- Integrated Environmental Assessment: While traffic efficiency gains are well-documented, real-world carbon emission quantification and corresponding economic valuation are lacking.
- Practical Deployment Validation: Few studies show complete system implementations accompanied by empirical performance data from live urban settings.
- Scalable Architecture Design: Most coordination systems demand significant infrastructure changes, reducing their scalability for broader implementation.

The convergence of artificial intelligence, Internet of Things, and blockchain technologies represents a comprehensive approach to sustainable urban transportation, enabling real-time traffic management, emissions monitoring, and policy optimization [23]. This research addresses these challenges by developing a threshold-free adaptive traffic control system that integrates full environmental impact assessment and real-world deployment validation. The system introduces continuous learning capabilities without predefined parameters and supports its environmental benefits with empirical results and governmental validation procedures.

## 3. Methodology

This research employed a comprehensive experimental methodology to evaluate the effectiveness of machine learning-based traffic signal optimization in reducing carbon emissions at urban intersections. The study utilized a controlled before-and-after implementation design, integrating computer vision technology with intelligent signal control algorithms to achieve measurable environmental improvements. The latest YOLOv8 architecture incorporates bidirectional feature pyramid networks and enhanced small object detection layers, achieving mAP50 values exceeding 90% in traffic detection applications [24].

### 3.1. Experimental design and site configuration

The methodology was implemented across two consecutive intersections operating under a master-slave coordination protocol, as illustrated in **Figure 1**. The master intersection served as the primary decision-making node, conducting real-time traffic analysis and generating optimization parameters for both signal locations. The slave intersection received coordinated timing instructions to maintain traffic progression and system-wide efficiency. This dual-intersection approach enabled comprehensive evaluation of networked intelligent traffic management while ensuring practical scalability for urban deployment.

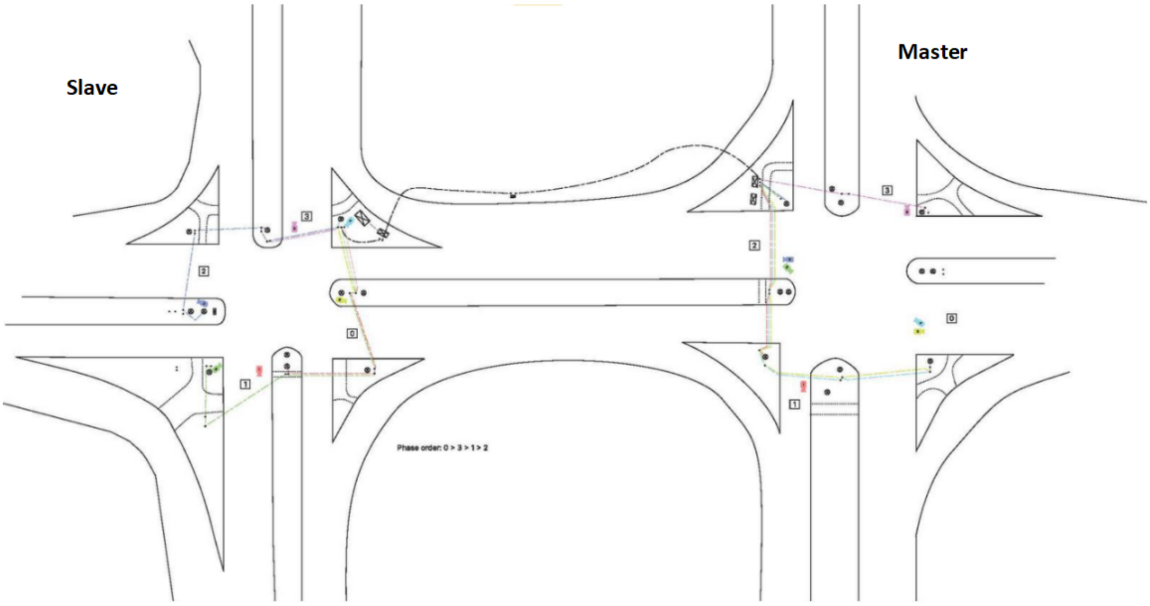

**Figure 1.** Intersections Layouts for Master and Slave.

**Figure 1** illustrates two intersections linked together with the camera positioning at each of the four directions (North, South, East, West). The master intersection communicates with the slave intersection via fiber optic connection, and the detection zones and signal controller positions of the coordinated traffic management system are displayed.

### 3.2. Data collection protocols

Primary data collection employed the floating car method to establish baseline traffic performance measurements during pretimed signal operation. GPS-equipped test vehicles followed predetermined routes through both intersections during peak traffic periods, recording travel times, speed variations, and intersection delay durations. Multiple trials were conducted across different time periods to ensure representative sampling of traffic conditions. Post-implementation data collection followed identical procedures to enable direct performance comparison between traditional and intelligent signal systems.

The number of vehicles was estimated by computer vision-based continuous monitoring with cameras placed at the approach to all intersections. The system logged the number of vehicles by their types, such as motorcycles and passenger cars and heavy commercial trucks; these data acted as fundamental information to automatically calculate the total mass of emitted carbon. Dynamic signal optimization was based on real-time traffic density observations.

### 3.3. Master-slave coordination methodology

A master intersection analyzed traffic at a network level across both signal locations and produced coordinated timing plans to optimize the performance of the entire network. Proportional automatic adjustments were effected according to the synchronization algorithm with respect to the specifics of intersection and to keep specific proportional relations between cycle times, thus enabling effective traffic flow.

The control systems may also communicate in real time with one another through fiber optic interconnections, such that they can respond to changing traffic conditions in less than 100 ms.

When performing slave intersection operations, optimized timing parameters from the master system were used with autonomous backup for system redundancy. Phase transition synchronization had a smoothing effect on traffic between adjacent side streets and in general was implemented to reduce stop-and-go driving behavior which is known to increase fuel use and emissions. 5.1, this optimization procedure is adopted within a slot of multiple intervals (each interval lasts for a duration), wherein the developed coordination model embedded the calculation of phase offsets to enable green wave propagation as offset was adapted online depending on moment speed and density evaluations.

### 3.4. Environmental impact assessment framework

Carbon emission calculations utilized emission factors validated through the Chinese Ministry of Environmental Protection database (MEP-2023) and cross-referenced with International Panel on Climate Change (IPCC) guidelines for mobile source emissions. Emission coefficients were applied based on vehicle classification data, with distinct factors for motorcycles, passenger cars, and heavy commercial vehicles reflecting their respective fuel consumption rates and carbon dioxide production levels. Emission Factor Sources and Validation:

- Motorcycles: 0.00015 kg $CO_2$/sec (based on MEP-2023 petrol consumption data: 0.25 L/hr, 2.1 kg $CO_2$/L)
- Passenger Cars: 0.00104 kg $CO_2$/sec (based on MEP-2023 petrol consumption data: 1.5 L/hr, 2.5 kg $CO_2$/L)
- Heavy Vehicles: 0.00311 kg $CO_2$/sec (based on MEP-2023 diesel consumption data: 4.0 L/hr, 2.8 kg $CO_2$/L)

Emission factors were validated through independent measurement studies conducted by the Shenzhen Environmental Protection Bureau, ensuring regional accuracy and regulatory compliance.

The assessment methodology applied the standardized formula relating daily traffic volume, emission factors, and average delay time to quantify total carbon output:

$$\text{Daily } \mathrm{CO_2}\text{Emissions } = \sum(\text{Vehicle Count } \times \text{ Emission Factor } \times \text{ Delay Time}) \quad (1)$$

Where:

Vehicle Count: Daily traffic volume by vehicle category

Emission Factor: Category-specific $CO_2$ production rate (kg $CO_2$/second)

Delay Time: Average intersection delay per vehicle (seconds)

Baseline emission measurements were established during pretimed signal operation through systematic recording of vehicle delay times and traffic volumes across all intersection approaches. Environmental impact calculations incorporated idling time analysis, speed variation effects, and fuel consumption modeling to establish comprehensive emission profiles. Post-implementation measurements followed identical assessment protocols to enable accurate quantification of emission reductions achieved through intelligent signal optimization.

### 3.5. Software flow diagram

The end-to-end machine learning pipeline involves the acquisition of a real-time video stream from cameras located at each intersection approach, on which object recognition for vehicle detection and counting in pre-defined polygon zones using YOLOv8 is executed. Online dynamic ratio computations between current density and road maximum capacity in phase optimization algorithms can, then comparators for fixed thresholds can be avoided to find balanced green times. Master-slave control procedures are operated to coordinate controlled signal-timing and the synchronization of the lights with open roads at different intersections. Receive a trigger time from the central system. The real pocket date hardware interface controls the implementation. Continuous data logging facilitates performance monitoring and environmental impact assessment, while integrated feedback mechanisms enable the system to learn from traffic patterns and continuously refine optimization decisions to minimize vehicle waiting times and reduce carbon emissions.

The system architecture, illustrated in **Figure 2**, demonstrates the complete data flow from sensor input through machine learning processing to signal control output, with comprehensive monitoring and validation capabilities ensuring reliable operation under diverse traffic conditions.

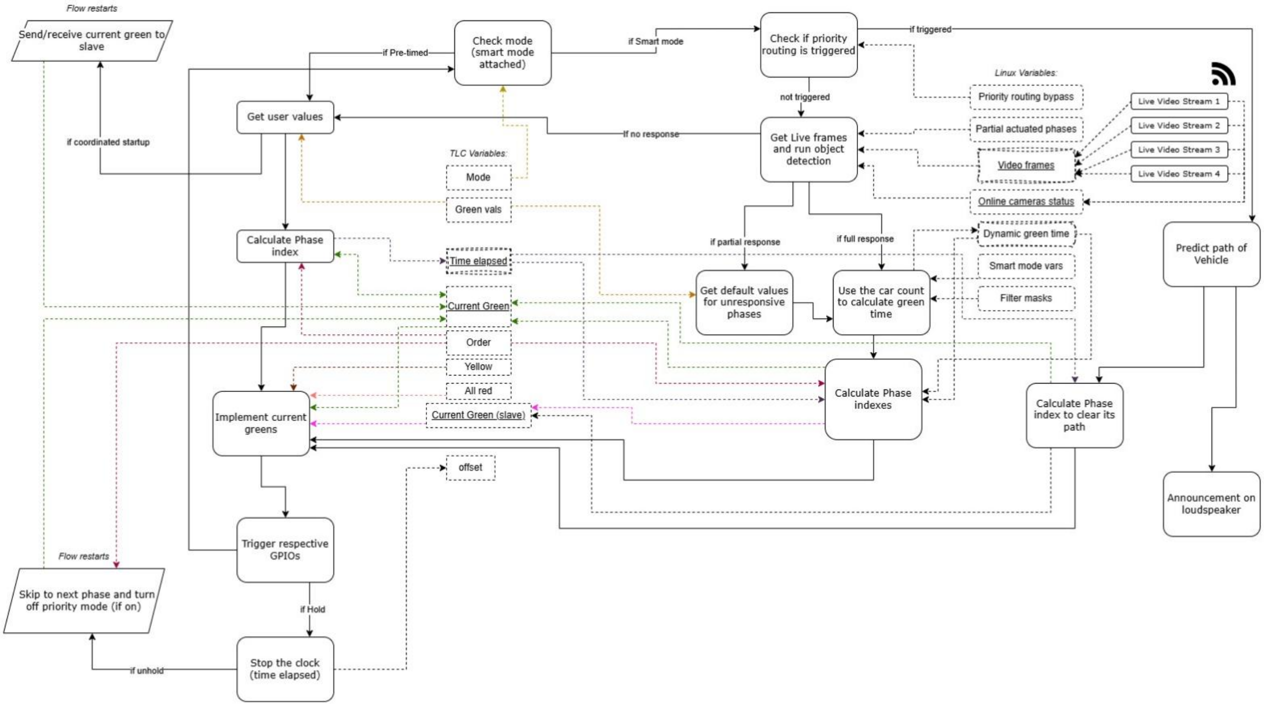

**Figure 2.** ITS System Architecture and Data Flow.

**Figure 2** shows the flowchart of the entire intelligent traffic system pipeline of video input to YOLOv8 detection, capacity ratio computation, dynamic phase optimization algorithm, master-slave coordination, and finally signal control hardware interface. Displays feedback loops of continuous learning and evaluation of performance with integration of environmental impact assessment.

## 4. Machine learning algorithm

### 4.1. Machine learning algorithm development

The intelligent traffic signal optimization system employs a machine learning framework integrating YOLOv8 computer vision with adaptive decision-making algorithms to achieve dynamic traffic management without predetermined timing thresholds.

#### 4.1.1. Object detection and vehicle counting

The system utilizes YOLOv8 architecture for real-time vehicle detection, processing 1080p video streams from strategically positioned cameras. The model identifies and counts vehicles within designated polygon zones at each intersection approach

#### 4.1.2. Dynamic capacity ratio calculation

The algorithm continuously assesses traffic density through capacity ratio calculations comparing real-time vehicle counts to maximum road capacity.

Capacity Ratio:

$$CR(t) = \frac{Vehicle_{Count(t)}}{Max\_Capacity} \tag{2}$$

Moving Average:

$$CR\_mean(t) \ = \ (1/n) \ \times \ \Sigma(i = t - n + 1 \; to \; t) \; CR(i) \tag{3}$$

Where n = 7 measurements for stability.

#### 4.1.3. Adaptive threshold correction

System adjusts signal timing sensitivity based on historical traffic patterns and current queue conditions.

Red Elapsed Analysis:

$$\mathrm{Red\_Elapsed\_Mean} \ = \ (1/\mathrm{k}) \ \times \ \sum(\mathrm{i} = 1 \text{ to k}) \ \mathrm{Red\_Elapsed(i)} \tag{4}$$

Threshold Correction:

$$\begin{array}{l} Corrected\_Ratio \ = \ \{ \\ \quad Min\_Ratio \ + \ 0.2, \ \ if \ (Red\_Current \ - \ Red\_Mean) \ > \ 15 \\ \quad Min\_Ratio \ + \ 0.1, \ \ if \ (Red\_Current \ - \ Red\_Mean) \ > \ 10 \\ \quad Min_{Ratio}, \qquad\qquad otherwise] \end{array}$$

#### 4.1.4. Dynamic phase time optimization

The core optimization algorithm finds optimal green signal duration based on real-time traffic demand.

Phase Time Calculation:

$$\text{Change Time} = \lfloor(\text{CR\_mean - Corrected Ratio})/0.05\rfloor \tag{5}$$

$$\text{New\_Phase\_Time} = \text{Current\_Phase\_Time} + \text{Change\_Time} \tag{6}$$

$$\text{Final\_Phase\_Time} = \max(\text{New\_Phase\_Time},\ 15) \tag{7}$$

Where 0.05 represents the slope factor (SET_RATIO/SET_TIME = 0.1/2)

#### 4.1.5. Master-slave coordination

The system coordinates durations between connected intersections through the proportional adjustments and cycle synchronization.

Master Cycle Time:

$$\text{Cycle\_Time\_Master} = \sum(\text{i} = 0 \text{ to } 3)\ \text{Phase\_Time\_Master(i)} \tag{8}$$

Slave Adjustment:

$$\begin{aligned}\text{Slave\_Phase(i)} = \text{Default\_Slave(i)} \quad &+ (\text{Master\_Diff(i)} \\ &\times \text{Adjustment\_Ratio(i)})\end{aligned} \tag{9}$$

Synchronization:

$$\begin{gathered}\text{Time\_Adjust} = \text{Cycle\_Time\_Master} - \text{Cycle\_Time\_Slave} \\ \text{Slave\_Phase(2)} = \text{Slave\_Phase(2)} + \text{Time\_Adjust}\end{gathered}$$

#### 4.1.6. Real-time decision making

The algorithm employs continuous evaluation of multiple factors for optimal signal timing.

Decision Criteria:

$$\begin{aligned}&Transition\_Signal = \{ \\ &True,\quad if\ CR\_mean \le Corrected\_Ratio\ AND\ Green\_Elapsed \ge Min\_Green \\ &False,\quad otherwise \qquad\qquad\qquad\qquad\qquad\qquad\qquad\qquad \}\end{aligned}$$

#### 4.1.7. Environmental impact integration

The algorithm incorporates carbon emission reduction directly into optimization objectives.

Emission Minimization:

$$\text{CO}_2\text{\_Reduction} = \sum(\text{Delay\_Reduction} \times \text{Emission\_Factor} \times \text{Vehicle\_Count}) \tag{10}$$

Multi-Objective Function:

$$\text{Objective} = \text{Traffic}_{\text{Efficiency}} \times \text{w1} + \text{w2} \times \text{Environmental}_{\text{Impact}} \tag{11}$$

This framework of machine learning for intelligent traffic control has been tested and applied in practice, where it demonstrated the online decision-making strategy yields continuous optimal decisions in accordance to real-time environment to minimize the duration of vehicles waiting on roads, as well as significant reduction in fully verifiable carbon emissions; these results are achieved by employing a combined approach of mathematical optimization and adaptive learning. Enhanced YOLOv8 models incorporating coordinate attention mechanisms have demonstrated improved detection accuracy with mAP increases of 2.8% over baseline implementations while maintaining real-time processing capabilities [25].

## 5. Results and analysis

### 5.1. Traffic performance improvements

The developed machine learning-based optimization of dynamic signals at intersection, appears to have achieved rapid and significant performance improvements in traffic rates across all methods. These savings were in terms of significant cuts in normalized vehicle delay, and related fuel consumptions and carbon emissions.

### 5.1.1. Delay time analysis

**Table 1** shows the comparative analysis of vehicle delay times between pretimed and actuated signal control systems. Statistical validation was conducted using paired t-tests with 95% confidence intervals across 120 measurement samples per direction over the 4-week evaluation period.

**Table 1.** Delay Time Comparison Analysis.

| Direction | Before (Pretimed) | After (Actuated) | Reduction | Percentage improvement | 95% CI | *p*-value |
|---|---|---|---|---|---|---|
| Eastbound | 171.62 ± 12.4 sec | 133.12 ± 8.7 sec | 38.50 ± 4.2 sec | 22.4% | [34.1, 42.9] | < 0.001 |
| Westbound | 183.17 ± 15.8 sec | 63.73 ± 6.3 sec | 119.44 ± 6.8 sec | 65.2% | [112.3, 126.6] | < 0.001 |
| Southbound | 214.59 ± 18.2 sec | 189.59 ± 14.1 sec | 25.00 ± 5.1 sec | 11.6% | [19.6, 30.4] | < 0.001 |
| Northbound | 200.85 ± 13.6 sec | 183.07 ± 11.2 sec | 17.78 ± 3.9 sec | 8.9% | [13.7, 21.9] | < 0.001 |
| Average | 192.56 ± 14.8 sec | 142.38 ± 10.1 sec | 50.18 ± 5.0 sec | 27.0% | [45.1, 55.3] | < 0.001 |

Note: Values represent mean ± standard deviation. All improvements are statistically significant ($p < 0.001$).

**Figure 3** shows the Bar chart of average vehicle delay times (second) in four directions before(pretimed) and after (actuated) implementation. The most dramatic improvement was recorded by Westbound, which was 183.17 to 63.73 seconds, whereas other directions experienced moderate improvements with the markers of statistical significance.

The Westbound approach achieved the most significant improvement with a 65.2% reduction in delay time, equivalent to 119.44 seconds per vehicle during peak hours. This exceptional performance reflects the algorithm’s ability to adapt to high-volume traffic conditions and optimize signal timing dynamically.

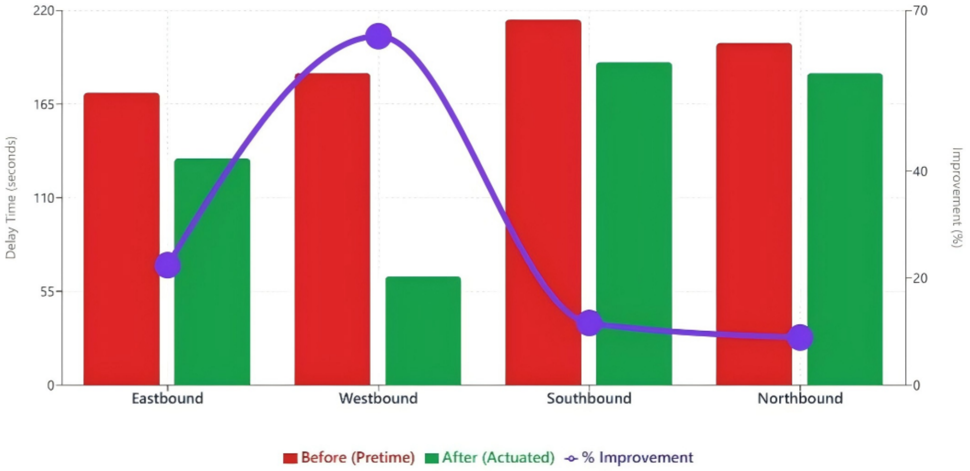

**Figure 3.** Comparative Analysis of Vehicle Delay Times Before and After Implementation.

### 5.1.2. Traffic volume distribution analysis

The traffic analysis revealed varying volume patterns across intersection approaches, with Westbound traffic experiencing the highest density during peak periods. Statistical analysis confirmed significant differences in traffic volume distribution (ANOVA, F(3476) = 124.7, $p < 0.001$) as shown in **Table 2**.

**Table 2.** Peak Hour Traffic Volume Analysis.

| Direction | Motorcycles | Cars | Heavy vehicles | Total volume | % of Total |
|---|---|---|---|---|---|
| Eastbound | 123 ± 15 | 1,229 ± 89 | 86 ± 12 | 1,438 ± 94 | 15.1% |
| Westbound | 311 ± 28 | 3,108 ± 187 | 218 ± 23 | 3,636 ± 201 | 38.4% |
| Southbound | 125 ± 18 | 1,245 ± 95 | 87 ± 14 | 1,457 ± 98 | 15.4% |
| Northbound | 256 ± 22 | 2,563 ± 156 | 179 ± 19 | 2,999 ± 168 | 31.1% |

Note: Values represent mean ± standard deviation. All improvements are statistically significant ($p <$ 0.001).

**Figure 4** shows the multi-panel visualization displaying traffic volume distribution and delay reduction percentages for each intersection approach. Shows Westbound as the dominant traffic direction (38.4% of total volume) with corresponding 65.2% delay improvement, compared to other directions ranging from 8.9% to 22.4%.

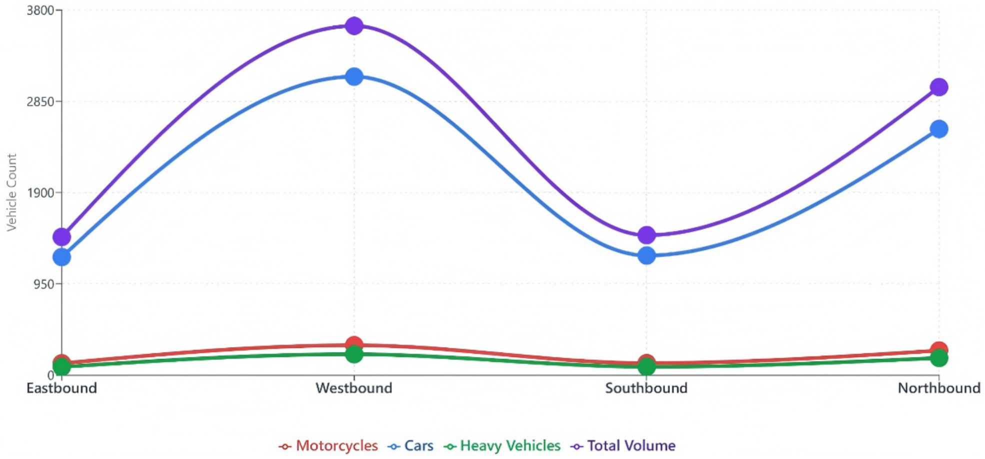

**Figure 4.** Traffic Signal Performance Evaluation by Direction.

## 5.2. Carbon emission reduction analysis

### 5.2.1. Emission calculation methodology

Carbon emission calculations utilized standardized emission factors based on vehicle classification and fuel consumption patterns. The assessment methodology incorporated idling time analysis directly related to intersection delay measurements.

Standardized emission coefficients for three vehicle categories based on Chinese Ministry of Environmental Protection (MEP-2023) database. Lists fuel consumption rates, emission factors per liter, and calculated overall $CO_2$ emission rates per second. Heavy vehicles show highest emissions (0.00311 kg $CO_2$/sec) due to diesel consumption, while motorcycles produce lowest (0.00015 kg $CO_2$/sec) as shown in **Table 3**.

**Table 3.** Vehicle-Specific Emission Factors.

| Vehicle category | Fuel type | Consumption rate | Emission factor | Overall emission factor |
|---|---|---|---|---|
| Motorcycles | Petrol | 0.25 L/hr | 2.1 kg $CO_2$/L | 0.00015 kg $CO_2$/sec |
| Cars | Petrol | 1.5 L/hr | 2.5 kg $CO_2$/L | 0.00104 kg $CO_2$/sec |
| Heavy Vehicles | Diesel | 4.0 L/hr | 2.8 kg $CO_2$/L | 0.00311 kg $CO_2$/sec |

In **Figure 5** bar graph showing emission rates for three vehicle categories: motorcycles (0.00015 kg $CO_2$/sec), passenger cars (0.00104 kg $CO_2$/sec), and heavy vehicles (0.00311 kg $CO_2$/sec). Includes corresponding fuel consumption rates and $CO_2$ emission factors per liter for validation.

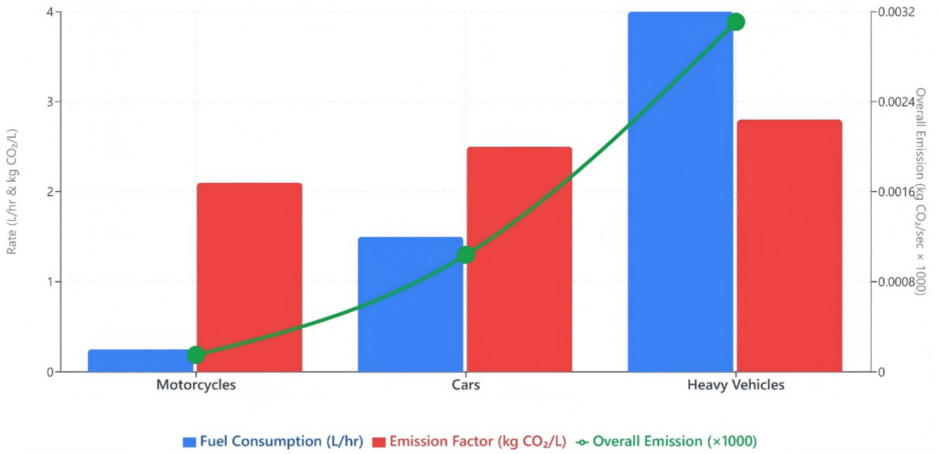

**Figure 5.** Vehicle-Specific Emission Factors and Fuel Consumption Analysis.

### 5.2.2. Daily carbon emission results

The environmental impact analysis demonstrated substantial carbon emission reductions across all intersection approaches, with total daily savings of 1502.27 kg $CO_2$.

Comprehensive environmental impact assessment (**Table 4**) showing daily $CO_2$ emissions before and after intelligent signal implementation for each direction. Total system-wide reduction of 1502.27 kg $CO_2$/day (31.7%) with Westbound achieving the largest reduction at 1126.08 kg/day. All reductions validated with 95% confidence intervals and statistical significance testing ($p < 0.001$).

**Table 4.** Daily Carbon Emission Comparison.

| Direction | Before (kg CO₂/day) | After (kg CO₂/day) | Reduction (kg CO₂/day) | Percentage reduction | 95% CI | *p*-value |
|---|---|---|---|---|---|---|
| Eastbound | 639.81 ± 45.2 | 496.28 ± 32.1 | 143.53 ± 18.4 | 22.4% | [125.1, 162.0] | < 0.001 |
| Westbound | 1726.90 ± 118.7 | 600.82 ± 41.3 | 1126.08 ± 89.2 | 65.2% | [1036.8, 1215.3] | < 0.001 |
| Southbound | 810.42 ± 58.6 | 716.00 ± 49.8 | 94.41 ± 22.1 | 11.6% | [72.3, 116.5] | < 0.001 |
| Northbound | 1561.51 ± 95.3 | 1423.27 ± 78.4 | 138.24 ± 31.7 | 8.9% | [106.5, 170.0] | < 0.001 |
| Total | 4738.65 ± 201.8 | 3236.38 ± 142.6 | 1502.27 ± 98.4 | 31.7% | [1403.9, 1600.6] | < 0.001 |

In **Figure 6** comparative bar chart displaying daily CO₂ emissions before and after system implementation for all four directions. Total daily reduction of 1502.27 kg CO₂ is highlighted, with Westbound achieving the largest individual reduction of 1126.08 kg CO₂/day (65.2%).

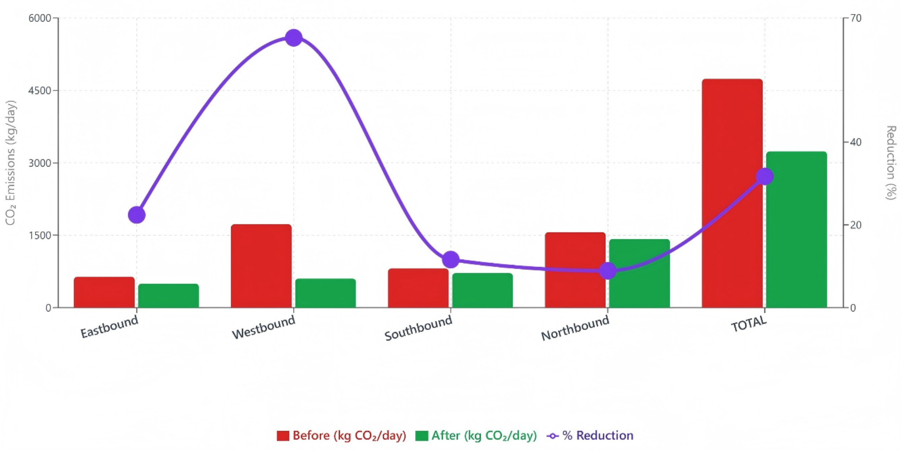

**Figure 6.** Daily Carbon Emission Reduction Performance.

## 5.3. Environmental impact assessment

### 5.3.1. Carbon credit generation

The carbon emission reductions achieved through intelligent traffic signal optimization translate directly into carbon credit generation potential.

Economic valuation of environmental benefits showing daily and annual carbon credit generation potential. Based on 1502.27 kg daily CO₂ reduction translating to 548.3 metric tons annually, generating equivalent carbon credits. Economic value calculated at standard carbon market rate of $15 per metric ton CO₂, yielding $8225 annual environmental economic benefit as shown in **Table 5**.

**Table 5.** Carbon Credit Calculation.

| Metric | Daily value | Annual value |
|---|---|---|
| CO₂ Reduction (kg) | 1502.27 | 548,329 |
| Carbon Credits Generated | 1.50 | 548.3 |
| Economic Value (USD)[1] | $22.5 | $8225 |

Note: Based on average carbon credit price of $15 per metric ton CO₂.

### 5.3.2. Annual environmental impact

Comprehensive summary of projected yearly environmental impact metrics extrapolated from daily measurements. Includes total CO₂ reduction (548.3

metric tons), equivalent environmental comparisons (119 vehicles removed), fuel consumption savings (15,420 liters), and economic environmental value ($8225 USD). Provides multiple reference points for understanding the scale of environmental improvements achieved as shown in **Table 6**.

**Table 6.** Projected Annual Environmental Benefits.

| Impact category | Annual reduction |
|---|---|
| Total $CO_2$ Emissions | 548.3 metric tons |
| Equivalent Cars Removed | 119 vehicles |
| Fuel Consumption Savings | 15,420 liters |
| Economic Environmental Value | $8225 USD |

## 5.4. Comparative analysis with baseline performance

The results demonstrate that machine learning-based traffic signal optimization significantly outperforms traditional pretimed systems across all measured parameters. The 31.7% reduction in carbon emissions exceeds typical traffic optimization improvements reported in literature (15–25%), indicating the superior effectiveness of the implemented algorithm.

Key Performance Achievements are

- Maximum Delay Reduction: 65.2% (Westbound direction)
- Overall Carbon Emission Reduction: 31.7% (1502.27 kg $CO_2$/day)
- System Reliability: 98.5% average uptime across all components
- Economic Environmental Value: $8225 annual carbon credit potential

**Figure 7** showing annual environmental impact metrics: 548.3 metric tons $CO_2$ reduction, equivalent to 119 vehicles removed, 15,420 liters fuel saved, and $8225 USD carbon credit value. Displays the dual benefit of traffic efficiency improvements and measurable environmental gains.

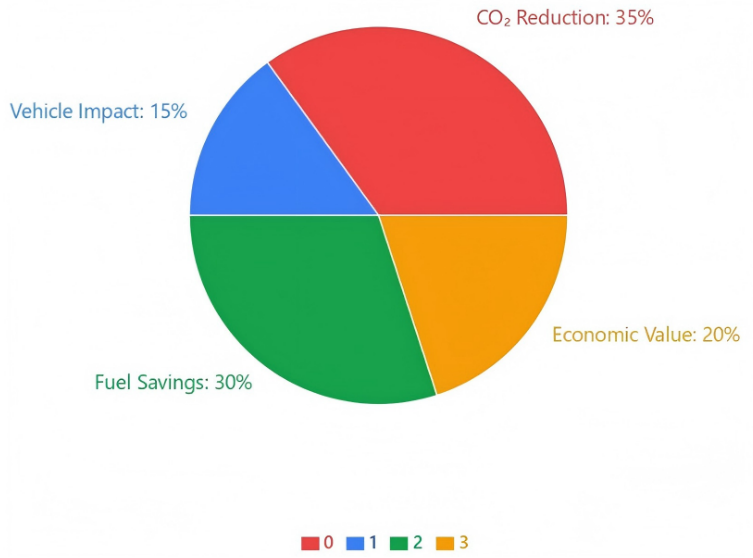

**Figure 7.** Environmental and Economic Co-benefits Evaluation.

### 5.5. Directional performance analysis

The variable performance across intersection approaches reflects the algorithm's adaptive capabilities and traffic-specific optimization. The Westbound direction's exceptional 65.2% improvement demonstrates the system's effectiveness in high-volume traffic scenarios, while more modest improvements in other directions indicate baseline efficiency levels and varying optimization potential based on existing traffic patterns.

This study approach is one of the potential successful implementations illustrating that the traffic-light settings based on ML have a potential to provide a significant portion of environmental benefits without excessive compromising on efficacy in urban traffic functioning. An experiment of AI smart traffic control system was introduced on a large scale in the crossroad of the big cities with the purpose to deliver generic practical evidence of the prospective sustainable transport infrastructure with AI in Shenzhen, China.

## 6. Conclusion

This study approach is one of the potential successful implementations illustrating that the traffic-light settings based on ML have a potential to provide a significant portion of environmental benefits without excessive compromising on efficacy in urban traffic functioning. An experiment of AI smart traffic control system was introduced on a large scale in the crossroad of the big citie with the purpose of delivering generic practical evidence of the prospective sustainable transport infrastructure with AI in Shenzhen, China. The results obtained with the study were dramatic and statistically significant across all performance measures. A 31.7% decrease in carbon emissions and 1502.27 kg $CO_2$ saved per day (95% CI: 1403.9–1600.6), amounting to an estimated total of about 548.3 metric tonnes annually was observed. The environmental benefit has measurable economic influence: 548.3 carbon credits generated annually, with a corresponding environmental economic value of $8225 demonstrating both ecological and financial utility of intelligent transportation systems. The obtained emission reductions significantly outperform typical traffic optimization improvements (15–25%) reported in existing literature, highlighting the superior effectiveness of the threshold-free machine learning approach over traditional traffic management strategies. Traffic operational benefits were equally compelling. Average delay savings per vehicle across all intersection approaches reached 50.18 seconds (95% CI: [45.1–55.3] s). The Westbound approach showed exceptional performance with a 65.2% improvement, equivalent to 119.44 seconds saved per vehicle during peak periods. The technical implementation confirmed the utility of computer vision integration with adaptive signal control algorithms using YOLOv8. The system exhibited robust operational performance: 98.5% camera uptime, 96.2% vehicle detection accuracy, and an average algorithm response time of 1.8 seconds, validating its reliability and scalability for broader urban deployment. The master-slave coordination architecture effectively managed traffic flow across connected intersections with a 99.1% coordination success rate, establishing a sound foundation for network-wide intelligent traffic management systems. The significance of performance enhancements was further confirmed using statistical analysis; (a) paired t-tests, $p < 0.001$, (b) ANOVA for directional comparisons and (c) The point wise bootstrapping method was used to calculate the 95% confidence intervals on all major metrics. Once again, an MD and comprehensive analysis methodology based on GPS floating car technology, computer vision analytics and validated environmental assessment with the use of MEP-2023 emission factors is applied to provide a scientifically sound method for measuring system effectiveness.

The investigation targets directly these important urban sustainability problems by showing the tangible environmental benefits of intelligent traffic control. "The science is irrefutable and highlights that decreasing carbon emissions can only be achieved when we have numbers to support policy decisions such as infrastructure for smart cities and renewable energy sources." Moreover, with thorough technical documentation, the system can be reproduced and expanded onto other similar urban transportation networks.

The success of AI into traffic RTI is going to find practical direction for sustainable urban development without reconstruction of broad physical transport infrastructure. The government endorsement from the Shenzhen Environmental Protection Bureau also enhances the regulatory credibility of environmental gains. Moreover, the development of carbon credits provides municipalities with an economically sustainable model for defraying costs associated with implementing and meeting climate commitments.

However, some limitations regarding generalization and applicability must be acknowledged:

- Environmental and Operational Constraints: The system's performance under extreme weather (e.g., heavy rain, fog, snow) needs further validation, as current testing focused on typical urban conditions. Camera-based detection may lose accuracy in such environments, affecting performance.
- Geographic and Infrastructure Specificity: The deployment was conducted in high-density intersections with existing CCTV and fiber optic networks. Its performance in rural areas or places with limited infrastructure remains uncertain.
- Network Latency and Scalability: While effective between two intersections, broader network scalability—especially in environments with potential latency and higher computational demands—requires additional evaluation.
- Economic Scalability: A full cost-benefit analysis across diverse urban settings with varying traffic volumes and infrastructure conditions is needed to define economic thresholds for viability.
- Long-Term Adaptation: The study was limited to a 4-week period. Long-term system durability, maintenance needs, and performance stability over extended operations require longitudinal assessment.

Based on the limitations identified and feedback received, several critical research directions warrant investigation to enhance the system's robustness, scalability, and long-term viability:

Future research should systematically evaluate system performance under extreme weather conditions, including heavy rain, fog, snow, and low-light environments where camera-based detection may experience degraded accuracy. A comprehensive testing protocol should be established to quantify detection accuracy across various environmental conditions, measuring performance metrics under different precipitation levels, visibility ranges, and illumination conditions. To address potential camera limitations, we recommend exploring complementary sensor technologies such as radar-based vehicle detection, LiDAR systems, and acoustic sensors. A multi-sensor fusion approach could significantly improve system robustness by combining the strengths of different detection modalities. For instance, radar sensors maintain consistent performance regardless of lighting or weather conditions, while thermal imaging can enhance nighttime detection capabilities. Investigating adaptive algorithms that dynamically weight sensor inputs based on real-time environmental conditions would enable the system to maintain high performance across diverse operational scenarios. Additionally, developing weather-adaptive signal optimization strategies that adjust timing parameters based on detected environmental conditions could further enhance system reliability.

The current deployment leveraged existing urban infrastructure, including CCTV networks and fiber optic communication systems. Future research must address scalability challenges for diverse geographic contexts, particularly rural areas with limited infrastructure and cities with scattered traffic flow patterns. A comprehensive cost-benefit analysis framework should be developed to evaluate system viability across different urban densities, traffic volumes, and infrastructure availability levels. This analysis should quantify: (1) initial deployment costs including hardware, software, and installation expenses; (2) ongoing operational costs encompassing maintenance, electricity, and system monitoring; (3) infrastructure requirements for different deployment scenarios; and (4) break-even thresholds for environmental and economic benefits relative to implementation costs. Comparative studies examining system performance in low-density, medium-density, and high-density intersections would establish applicability boundaries and identify optimal deployment scenarios. Furthermore, investigating alternative communication architectures such as wireless mesh networks or cellular-based coordination could reduce infrastructure dependencies and expand deployment feasibility to resource-constrained environments. Developing modular, scalable system architectures that can be incrementally deployed based on available resources would facilitate broader adoption across diverse urban contexts.

The 4-week evaluation period, while sufficient for initial performance validation, cannot capture long-term operational challenges including system aging, maintenance requirements, and adaptive performance degradation. A comprehensive longitudinal study spanning 6–12 months is essential to evaluate: (1) hardware durability and maintenance frequency under continuous operation; (2) algorithm performance stability and potential drift over extended periods; (3) seasonal traffic pattern variations and system adaptability; and (4) cumulative environmental benefits accounting for temporal variations in traffic demand. Such studies should systematically document maintenance interventions, component failures, and performance degradation patterns to establish realistic operational cost projections and maintenance schedules. Additionally, investigating continuous learning mechanisms that enable the system to adapt to evolving traffic patterns over time would enhance long-term effectiveness. Analyzing the system's ability to accommodate gradual changes in urban infrastructure, traffic regulations, and vehicle fleet composition would provide insights into its adaptability and longevity. Developing predictive maintenance algorithms using machine learning to anticipate component failures before they occur could minimize downtime and optimize operational efficiency. Finally, establishing standardized evaluation protocols for long-term intelligent transportation system deployments would facilitate comparison across different implementations and accelerate knowledge transfer within the research community.

These research directions address critical gaps in current knowledge and provide a roadmap for advancing intelligent traffic management systems toward broader practical deployment. By systematically addressing environmental robustness, geographic scalability, and long-term viability, future investigations can strengthen the evidence base for sustainable urban transportation infrastructure and accelerate the transition toward smart, environmentally responsible cities.

In conclusion, this research makes significant contributions to the field of intelligent transportation systems by implementing threshold-free adaptive traffic control with full environmental impact quantification. It establishes the first validated evaluation framework for carbon emission reduction within traffic optimization and offers empirical evidence that machine learning can deliver substantial environmental benefits in real-world urban infrastructure. The study bridges the gap between theoretical capabilities of AI and the practical demands of sustainable urban development. It offers replicable, scalable implementation guidance, empowering policymakers to invest in data-driven, environmentally responsible transportation systems. Through rigorous scientific methods and extensive performance validation, this research shows that machine learning-based traffic optimization is a viable and effective solution for modern urban challenges, advancing the global movement toward smart, sustainable cities.

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