CHAPTER 28

Optimizing Traffic Signal Management using Artificial Intelligence and Internet of Things: A Case Study-Based Approach

Nia Naman, Nikita Gedam** and Saurabh Mhatre***

ABSTRACT

Transitions in the dynamical features of vehicular traffic, e.g., due to varying occupancy or capacity of the road, constitute a prominent class of phenomena which one would like large-scale models with many interacting agents to be able to explain. The Traffic Congestion Index (TCI) values also indicate that India's road network which spreads across more than 6.6 million kms, carries almost 85 percent of passenger and close to 71 per cent of freight traffic adding to choke-up the already-overloaded urban corridors which were operating way beyond their design limits. The increase in the number of vehicles, from 21 million (1991) to over 142 million (2011), has only added to traffic on the roads leading to delays, wastage of fuel and environmental pollution. Therefore, this research study aims at using AI and IoT to optimize traffic flow in real time to address these issues. Advanced intelligent traffic management systems powered by artificial intelligence-driven analytics and IoT sensor networks have the potential to enable real-time data capture, adaptive signal timing, and predictive traffic flow control, which will ultimately enable an improvement in traffic flow, easing congestion, and improved urban mobility and also helps traffic police and other stakeholders.

Keywords: Traffic Signal Optimization; Artificial Intelligence; Internet of Things; PCU Analysis; Smart Cities.

1.0 Introduction

1.1 Urbanization and traffic congestion challenges

Rapid urbanization has become one of the most evident global trends of the twenty-first century and has had a considerable impact on the transportation demand in the metropolitan areas.

**Corresponding author; Student, School of Construction, NICMAR University, Pune, Maharashtra. India (E-mail: p24700620@student.nicmar.ac.in)*

***Student, School of Construction, NICMAR University, Pune, Maharashtra. India (E-mail: p24700628@student.nicmar.ac.in; p24700603@student.nicmar.ac.in)*

DOI: 10.17492/JPI/NICMAR/260528 ISBN: 978-93-49790-68-1

The United Nations predicts that urbanized cities will host almost 68% of the world by 2050, which will trigger a significant increase in the number of vehicles on the roads and their use (United Nations, 2022). In places like India which are not developed, an increase in urban traffic is further exacerbated by the mixed traffic conditions, poor road infrastructure and the lack of alternative mass transportation. All these have led to sustained traffic jams, further travel delays, fuel usage, and high greenhouse emissions.

Traffic congestion has been reported to be one of the greatest economic and environmental issues resulting in loss of productivity and a lot of air pollution in the cities. Research has shown that delays caused by congestion can raise fuel consumption by 30 per cent directly affecting the sustainability objectives of urban areas (Zhou et al., 2020). Conventional traffic management schemes cannot keep up with variable demand trends, peak hour traffic and mixed car stocks, and thus congestion management is becoming an extremely challenging issue in fast-growing cities.

1.2 Conventional traffic signal system limitations

Traditional traffic signal systems are mostly founded on fixed or semi-actuated control systems, which work on the principles of previously defined signal cycles and phase separation. Although these systems are comparatively easy to use, they do not have the capacity to dynamically react to real-time traffic changes. There are also fixed-time signals which can lead to poor green time utilization by creating unnecessarily long delays during low demand and insufficient clearance during peak congestion (Ravish & Swamy, 2021).

Furthermore, the traditional systems tend to handle intersections independently without coordination at the neighboring intersections. Such a disjointed functioning causes stop and go traffic conditions and queue spill over especially within heavy urban corridors. The fact that they do not integrate real-time traffic data also contributes to their inefficiency because signal timings cannot adjust to any unexpected changes that may happen due to incidents, weather, or changes in demand. According to recent findings, the use of a static signal control approach does not achieve the operational characteristics of the contemporary urban traffic network and is particularly inefficient in heterogeneous and near-saturated environments (Abirami et al., 2024).

1.3 AI and IoT in smart traffic management

The Internet of Things (IoT) and Artificial Intelligence (AI) have become new revolutionary technologies in designing intelligent transportation systems. IoT-based sensors, cameras, and associated devices help to collect traffic data in real-time and identify the number of vehicles, their speed, queue length, and turnover of vehicles. Such data streams

DOI: 10.17492/JPI/NICMAR/260528 ISBN: 978-93-49790-68-1

are important components of AI-based algorithms that can be trained to acquire complicated spatio-temporal traffic dynamics (Bhardwaj et al., 2024).

Machine learning, deep learning, and reinforcement learning represent types of AI methods that allow the development of predictive and adaptive traffic control at the signal level through the dynamical regulation of the signal phases in accordance with the current and predicted traffic conditions. It has been shown that a signal optimization using AI can contribute to a major decrease in average delays, throughput, and intersection efficiency over traditional control methods (Chen et al., 2018; Zhou et al., 2020). Scalable data-driven solutions disaster management Prolonged expanse with IoT infrastructure The incorporation of AI systems provide real-time responding, multi-intersection coordination, and sustainable city transport plans.

1.4 Motivation and context of research

In spite of the increasing progress in the AI- and IoT-based traffic management systems, their practical application in emerging urban settings is still a limited issue. A number of the existing literature is based on simulations or homogeneous traffic conditions which might not reflect the mixed and complex conditions of the traffic that are common in Indian cities. Also, the empirical research does not include those studies that combine the physically obtained data on traffic with AI-based optimization frameworks.

The gap between theoretical models of AI and the application of AI to practical traffic signal optimization with real-world traffic data is a motivation to conduct this research. This study seeks to create a viable and flexible traffic signal optimization model by utilizing the physically gathered data of the classified traffic volume in Passenger Car Units (PCU) and incorporating the ideas of AI and IoT. The study is in line with national smart city efforts and it is part of the larger goal in sustainable, efficient, and data-driven urban traffic management (Allam & Dhunny, 2019; Jagatheesaperumal et al., 2024).

2.0 Literature Review

2.1 AI-based traffic flow prediction models

Recent research indicates that there is a fast transition of classical time-series algorithms (ARIMA, SVR) to autoregressive deep learning models to predict short- and mid-term traffic flow. The most common models are deep learning models, specifically LSTM/GRU and hybrid CNN-LSTM models, due to their ability to capture non-linear spatio-temporal relationships in traffic information, which leads to higher levels of accuracy in horizons in which adaptive signal control is relevant. A number of recent surveys and empirical studies indicate that deep recurrent models and stacked autoencoders can do better

DOI: 10.17492/JPI/NICMAR/260528 ISBN: 978-93-49790-68-1

than shallow models on urban traffic datasets, with a further increase possible with the addition of spatial context (nearby sensors / lanes). Other issues that are pointed out in these works include sparseness of data, sensor noise, and intercity generalizability.

2.2 IoT-based traffic monitoring systems

IoT has emerged as the foundation of real-time traffic sensing: cameras, loop detectors, ultrasonic and radar sensor, and vehicle probes which are connected provide a stream in real time to estimate the state of traffic. IoT sensing is categorized into perception (on-road sensors), and communication (V2X, cellular, MQTT) and data ingestion layers by reviews; it is stressed that edge/fog processing results in decreasing latencies and loads on the network. Recent literature also lists the types of sensors and the associated trade-offs (price, reliability, response to weather), as well as suggests sensor fusion (camera/ radar/ probe data) to enhance resilience in disfavored situations. The experimental applications (city testbeds) expose that reliability of an IoT, the quality of the data, and secure data pipelines are the key bottlenecks to production-scale systems.

2.3 Intelligent and adaptive traffic signal control

The literature of Adaptive Traffic Signal Control (ATSC) in 2020-2024 demonstrates two existing trends in methodology (a) model-based optimization (queueing, GA/meta-heuristics) and (b) data-driven learning (supervised deep learning (SDL) to prediction + reinforcement learning (RL) or deep RL to control). Systematic reviews show that there are uniform benefits in delay reduction, queue lengths and throughput with the application of RL or a combination (prediction + optimization) of algorithms compared to a baseline consisting of static or actuated operations. Nevertheless, the major practical problems do remain, such as the reward shaping, multi-agent coordination, extrapolating simulation to the field, and the problem of computation/latency cost of real-time control. Multi-agent RL and hierarchical control are suggested to be used by several surveys in order to be able to scale over the various intersections.

2.4 Smart cities: AI-IoT interaction

The AIoT paradigm (strong integration of AI analytics and IoT sensors and edge/cloud computing) is mentioned more and more as the good way to implement intelligent traffic control on large scale. Recent frameworks suggest layered architecture perception (sensors), network/edge (lovelatencypreprocessing), analytics (AI models) and application (signal controllers and dashboards) will be used to address the latency, privacy and reliability requirements. The case studies and technology reviews suggest edge inference (to respond to sub-second control requirements) / federated learning (to ensure continuity of privacy across

DOI: 10.17492/JPI/NICMAR/260528 ISBN: 978-93-49790-68-1

jurisdictions) / and digital twins (to test a situation before it is introduced). The literature emphasizes governance, cybersecurity as well as interoperability standards as conditions preceding the major rollout of AIoT in urban transport.

2.5 Introduction to major results of the previous research

Prediction + control synergy Prediction Accurate short-term prediction (LSTM/GRU/hybrid) is combined with adaptive control (RL or optimization), which results in optimal operation benefits over intersection behavior.

Sensor fusion and edge processing: Edge preprocessing and sensor fusion make robust IoT deployments possible by addressing individual weaknesses such as errors and failures by other sensors.

Scalability and transfer gap: The problem of scaling! After validation on single junction pilots or by simulation report many successful algorithms, however, open research remains to verify the policies and reality scale to multi-intersection networks or transfer to field deployed environments.

Operation limitations: There are operational limitations, such as practical ones: compute/latency, cybersecurity, cost of maintenance, and institutional integration, that are regularly noted as significant obstacles to real-world implementation.

3.0 Research Gap and Problem Statement

3.1 Identified research gaps in existing studies

Recent studies on intelligent traffic management have addressed the use of Artificial Intelligence (AI) and Internet of Things (IoT) technologies in predicting traffic movements on roads and controlling signal lights through adaptive control to a great extent. A critical analysis of the current studies, however, shows that there are a number of gaps that remain unresolved. To begin with, much of AI-based traffic optimization literature is confirmed mostly using simulation settings with synthetic or benchmark data, which might not thoroughly reflect the heterogeneity of traffic in a real-world setting, particularly in developing nations (Zhou et al., 2020). Second, most predictive models are trained to operate in homogenous traffic conditions, which restricts their usability in mixed traffic environments with two-wheelers and non-motorized vehicles as well as irregular driving behavior, which are prevalent in Indian urban environments (Abirami et al., 2024).

Moreover, the literature tends to concentrate on individual intersections and does not pay much attention to coordination on a corridor or network-wide scale. Minor focus is put on the combination of the physically gathered volume of traffic information, including PCU-based surveys, with the frameworks of optimization based on AI. These loopholes raise the

DOI: 10.17492/JPI/NICMAR/260528 ISBN: 978-93-49790-68-1

requirement of empirical, data-driven studies on the basis of actual traffic settings (Bhardwaj et al., 2024).

3.2 Urban traffic signal control to practical limitations

The problem of inadequate practical limitations to the control of traffic signals in cities remains despite technological progress. The traditional traffic systems have antiquated infrastructure which is not compatible with current AI-based control systems. The costs of retrofitting old signal controllers with the IoT sensors and communication modules are predominantly financial, technical, and institutional (Ravish and Swamy, 2021). Also, environmental factors, hardware deterioration, and communication errors influence the consistency of IoT sensors, resulting in inaccurate information flows that may negatively affect the functioning of AI models (Jagatheesaperumal et al., 2024).

The other significant limitation is that there is no inter-agency coordination and uniform protocols among the urban transport authorities. Such fragmentation prevents the city-wide synchronization of signals and limits the ability of the intelligent management of traffic system to be deployed at scale. Additionally, issues with data confidentiality, data security, and the expenses of maintenance further restrict the possibility of real-world implementation, where AI-IoT solutions prove to be technically viable (Bhardwaj et al., 2024).

3.3 Optimization of data, real-time requirement

City traffic patterns are very dynamic and are subject to temporal, spatial, and behavioral aspects. Fixed or semi-actuated signal systems cannot react sufficiently to unexpected traffic spikes, accidents or peak-hour variations. The recent researchers note that adaptive traffic control, where real-time data-driven optimization is a key factor to ensure the minimization of delays, queue length, and emissions, is crucial (Chen et al., 2018; Zhou et al., 2020). Intelligence predictive traffic models in combination with real-time IoT data processing allow anticipation of the demand in traffic in the near future so that the management of the traffic light system can work proactively, based on predictive adjustments given the current demand. Nevertheless, there are gaps in the literature of frameworks that integrate physically measured traffic information with real-time predictive analytics in practice. This gap would be important in enhancing the accuracy of decisions, system responsiveness, and sustainable traffic running in fast urbanizing cities (Abirami et al., 2024).

3.4 The statement of the research problem is given under

Even though AI and IoT technologies have a significant potential in the optimization of traffic signal management, their implementation in the real-life scenario within urban

DOI: 10.17492/JPI/NICMAR/260528 *ISBN: 978-93-49790-68-1*

settings is scarce and sporadic. The current traffic signal systems are mainly fixed, intersection-based, and unaware of real-time traffic flows, which leads to ineffective redistributing of green time, chronic traffic jams, and left over queues during peak times. In addition, existing AI-based systems are frequently not empirically justified by real traffic data, and they do not take into consideration the heterogeneous traffic compounds.

Thus, the primary research question tackled in the present study is the lack of a unified, real-time, AI-IoT-based traffic signal optimization system according to which the dynamically controlled signal timings are used based on physically measured traffic data in the heterogeneous urban traffic. The proposed study aims to reduce the gap between theoretical models of AI and real-world applications of traffic engineering by creating a data-driven and adaptive signal control model that can be adopted in the real world in a smart city setting.

4.0 Objectives and Research Questions

4.1 Research aim

The main purpose in this study is to design and test a data-driven model to optimize the intelligence of the urban traffic control systems of Artificial Intelligence (AI) and the Internet of Things (IoT). The paper aims to merge the physically gathered data of traffic volumes with AI-aided prediction and optimization methods so that the control of the adaptive, real-time signals in the heterogeneous urban traffic could occur. The research will help enhance the efficiency of traffic, minimise the delays caused by congestion, and enable sustainable urban mobility in the framework of the smart city development by mitigating the constraints of the static signal systems (Zhou et al., 2020; Bhardwaj et al., 2024).

4.2 Specific objectives

The research objectives will be the following:

- To examine the urban traffic attributes based on the physically measured data of classified traffic volume in the form of Passenger Car Units (PCU) to represent heterogeneous traffic conditions with proper accuracy.
- To determine important traffic parameters which affect congestion and signal behavior at signalized crossings.
- To use traffic flow prediction AI methods to do short-term prediction of the vehicular demand based on actual traffic data.
- To develop an agile traffic signal optimization system that dynamically assigns the green time to the predicted traffic conditions.

DOI: 10.17492/JPI/NICMAR/260528 ISBN: 978-93-49790-68-1

- To conceptualize the IoT-based real-time traffic data solutions and AI-driven decision-making to enhance signal responsiveness.
- To assess the efficiency of the suggested AI-IoT-based traffic signal optimization model regarding the delay reduction, minimization of the queue length, and enhancement of throughput (Abirami et al., 2024; Ravish and Swamy, 2021).

4.3 Research questions

Based on the identified research gaps and objectives, the study addresses the following research questions:

- How can physically collected PCU-based traffic data be effectively utilized to represent heterogeneous urban traffic conditions for signal optimization?
- Which traffic parameters most significantly influence congestion and signal inefficiency at urban intersections?
- How accurately can AI-based models predict short-term traffic flow using real-world traffic volume data?
- In what ways can AI-driven prediction models improve the adaptability of traffic signal timings compared to conventional fixed-time systems?
- How can IoT-enabled real-time data integration to enhance the responsiveness and reliability of traffic signal control systems?
- To what extent does an AI–IoT-based adaptive signal management framework improve overall intersection performance and urban traffic efficiency (Chen et al., 2018; Zhou et al., 2020)?

5.0 Research Methodology

5.1 Study area description (Radha Chowk, Mumbai–Bangalore Highway)

The research was carried out in Radha Chowk, one of the largest signalized intersections, on the Mumbai-Bangalore Highway that is a vital urban-regional traffic centre. The intersection is characterized with a high traffic demand because of a mixture of the commuter traffic, commercial freight traffic, and local access traffic. The traffic consists of heterogeneous traffic; this includes two-wheelers, cars, auto-rickshaws, buses, and heavy commercial vehicles. These features render the study site appropriate in assessing the adaptive traffic signal optimization when the test is conducted under real traffic settings prevalent in Indian cities (Ravish and Swamy, 2021).

5.2 Research design

The quantitative, applied research design that is used in this study entails the use of a case study. The main traffic data obtained by means of field surveys are combined with AI-

DOI: 10.17492/JPI/NICMAR/260528 *ISBN: 978-93-49790-68-1*

oriented prediction and optimization methods. The methodology is sequential, viz data collection, data preprocessing, traffic flow prediction, signal simulation, optimization and performance evaluation. Such design allows empirically proving the AI-IoT concepts on the basis of observable traffic data as opposed to the simulation-driven assumptions only (Zhou et al., 2020).

5.3 Traffic data collection method

Conducting a traffic volume survey that is classified is suitable because it determines the type of traffic present and the frequency of its occurrence, leading to the development of suitable methods and strategies to regulate the traffic (Boyle et al. 144).<|human|>The need to conduct a classified traffic volume survey is appropriate since it will identify the nature of the type of traffic and the number of times it occurs, resulting in the formulation of effective measures and approaches to control the traffic (Boyle et al. 144).

An enumeration of a specific traffic volume was carried out at the intersection point of the study. They classified vehicles into two wheelers, cars, auto-rickshaws, buses, light commercial vehicles and the heavy commercial vehicles. In mixed traffic scenarios, the heterogeneous traffic behavior can be accurately represented with the help of classified volume counts which is the key to realistic signal optimization (Abirami et al., 2024).

5.3.1 Conversion of PCU to IRC factors

To bring uniformity to the unequal traffic flow, the number of vehicles is converted into Passenger Car Units (PCU) through standard conversion factors suggested by Indian Roads Congress (IRC). PCU conversion facilitates the consistency of traffic flow model and capacity and saturation model at signalized intersections (Ravish & Swamy, 2021).

5.3.2 Survey time and survey duration

The number of traffic was observed during a period of one week and observations made daily at 15 minutes. This time was chosen to observe short-term changes in traffic and also be compatible with the AI-based time-series modeling needs (Zhou et al., 2020).
The following section will analyze data and provide its preparation.

Traffic data were recorded and then digitized and organized as time-stamped databases. The data cleaning consisted of verification of missing values, data outliers, and inconsistency caused by hand observations. The PCU-based volumes of traffic were direction-wise and movement-wise (left, straight, right) aggregation. Before the AI modeling, the data were put in numerical stability by normalizing them to achieve rapid convergence in the training (Abirami et al., 2024).

DOI: 10.17492/JPI/NICMAR/260528 *ISBN: 978-93-49790-68-1*

5.4 Traffic flow prediction based on AI

5.4.1 Selection of AI Model (LSTM)

Neural networks that have been chosen to predict the conditions of traffic flow are Long Short-Term Memory (LSTM) since it could model the influence of time on the results of traffic flow prediction and its non-linear nature. According to the current research, LSTM-based models are superior to traditional statistical methods in short-term traffic prediction, especially when the demand is changing (Zhou et al., 2020; Abirami et al., 2024).

5.4.2 Input parameters and data normalization

The key input variables to LSTM model were the past PCU traffic volumes, time of day measurements and direction of the traffic flows. Min-max normalization was used to normalize the inputs into the range of 0 to 1 to minimize bias because some inputs were big and others small; it would enhance predictive accuracy (Abirami et al., 2024).

5.5 Traffic signal simulation and optimization

5.5.1 Signal Logic Modelling (Simulink / Stateflow)

Simulink and Stateflow were used to simulate traffic light operations in which the phases of the signal (red, green, amber) were represented as finite state machines. The AI prediction model delivered traffic arrivals to the signal logic which allowed dynamic phase switching of the signal logic based on traffic demand. These kinds of simulation settings are highly applied when adaptive signal strategies are to be tested prior to field deployment (Ravish & Swamy, 2021).

5.5.2 Genetic algorithms optimization

An optimization of green signal durations was achieved by using a Genetic Algorithm (GA). The objective function was to reduce the overall vehicle delay and queue length and meet the operational requirements like minimum and maximum green times. Complex and multi-objective optimization problems with traffic signals cannot be solved analytically and, therefore, the optimization tools such as metaheuristic optimization methods, such as GA, are effective (Zhou et al., 2020).

5.6 IoT Integration framework

5.6.1 TomTom junction analytics

TomTom Junction Analytics was employed as an IoT-based data platform to conceptualize the integration of real time traffic data. The system offers floating car data (FCD) which is based on GPS car arrangements which are used to give details on the approach

DOI: 10.17492/JPI/NICMAR/260528 *ISBN: 978-93-49790-68-1*

speed, delays and turnings in intersections. These platforms can be used to increase situational awareness and help optimize signals based on data (Bhardwaj et al., 2024).

5.6.2 Concept of real-time data acquisition

The conceptualization of real-time data acquisition involved the use of IoT sensors and APIs which relay the information on traffic to centralized analytics platforms. This framework facilitates constant monitoring, predictive control, and adaptive control of signals, which allows near real-time responsiveness of the urban traffic management system (Jagatheesaperumal et al., 2024).

5.7 Performance evaluation parameters

The performance of the suggested AI-IoT-based traffic signal optimization scheme was measured based on the following parameters:

- Average vehicle delay
- Queue length
- Intersection throughput
- Level of saturation
- Reduction of idling time and engines estimated.

Such indicators are typically applied in the evaluation of the intelligent transportation system performance (Zhou et al., 2020).

5.8 Tools and software used

The tools and software used in the study were:

- Data entry and PCU calculations done using Microsoft Excel.
- AI model development and data analysis by MATLAB.
- Simulink and Stateflow to traffic signal simulation.
- Implementation of the Genetic Algorithms in Global Optimization Toolbox.
- IoT-based traffic data visualization analytics by TomTom Junctio

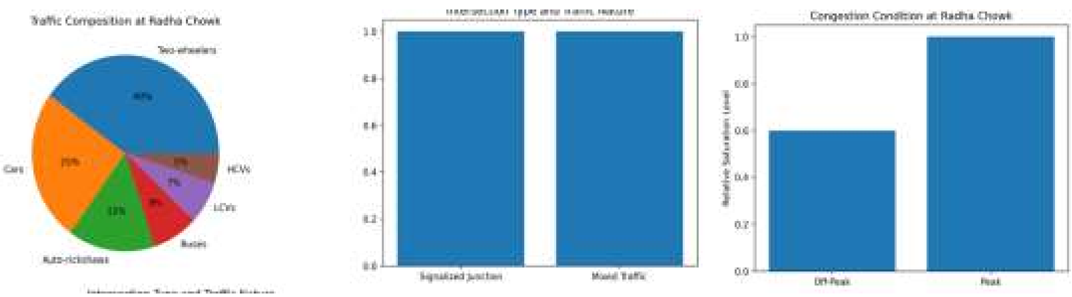
Table 1: Study Area Characteristics

Parameter	**Description**
Study Location	Radha Chowk, Mumbai–Bangalore Highway
Type of Intersection	Signalized urban junction
Traffic Nature	Mixed and heterogeneous traffic
Major Traffic Composition	Two-wheelers, cars, auto-rickshaws, buses, LCVs, HCVs
Functional Importance	Urban–regional connector with commuter and freight traffic
Congestion Condition	Near-saturated to over-saturated during peak hours

Source: Created by authors

DOI: 10.17492/JPI/NICMAR/260528 ISBN: 978-93-49790-68-1

Explanation: Radha Chowk functions as a critical traffic node handling both local and through traffic. The heterogeneous vehicle mix and high peak-hour demand make it an appropriate case for evaluating AI–IoT-based signal optimization under real urban conditions.



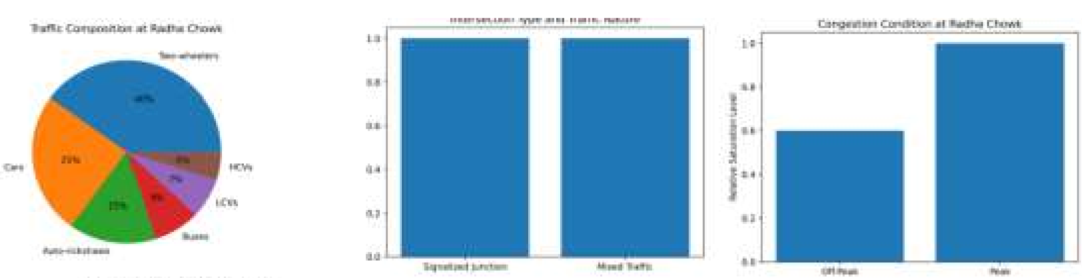
Source: Created by authors

Table 2: Classified Traffic Volume Categories

Vehicle Category	Traffic Role	Reason for Classification
Two-wheelers	High volume, agile movement	Dominant in Indian urban traffic
Cars	Moderate speed, stable flow	Benchmark vehicle type
Auto-rickshaws	Frequent stopping	Causes local disturbances
Buses	Large size, fixed routes	High PCU impact
Light Commercial Vehicles	Delivery traffic	Affects peak-hour congestion
Heavy Commercial Vehicles	Freight movement	Major contributor to delay

Source: Created by authors

Explanation: Vehicle classification is essential to capture differences in speed, space occupancy, and manoeuvrability. Treating all vehicles equally would misrepresent real traffic behavior.



Source: Created by authors

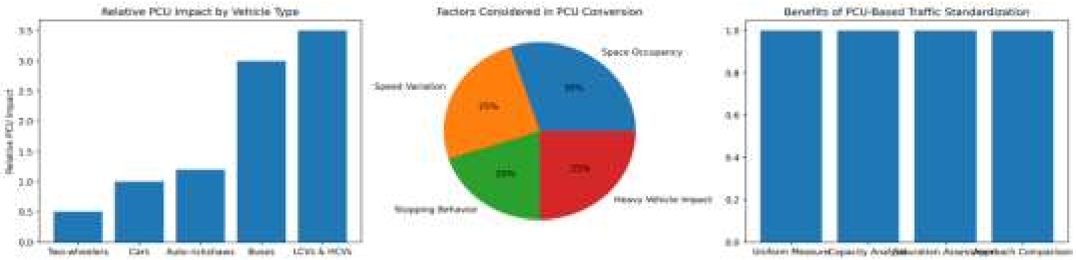
DOI: 10.17492/JPI/NICMAR/260528 ISBN: 978-93-49790-68-1

Table 3: PCU Conversion Approach

Vehicle Type	Purpose of PCU Conversion
Two-wheelers	Convert small, fast vehicles into equivalent car units
Cars	Used as base unit (1 PCU)
Auto-rickshaws	Account for frequent stops and lateral movement
Buses	Reflect higher space and time occupancy
LCVs & HCVs	Represent heavy vehicle impact on capacity

Source: Created by authors

Explanation: Passenger Car Unit (PCU) conversion standardizes heterogeneous traffic into a uniform measure. This allows accurate capacity assessment, saturation analysis, and comparison across approaches.



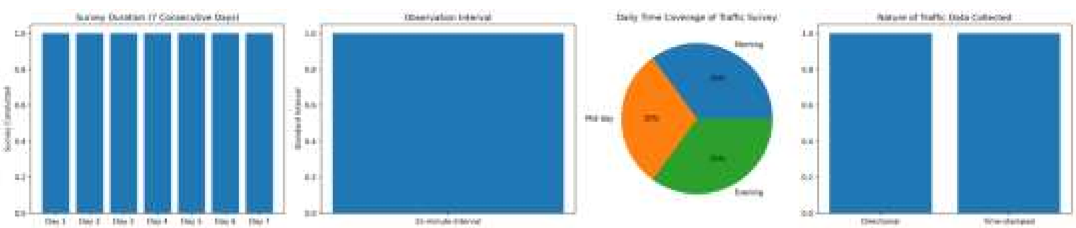
Source: Created by authors

Table 4: Traffic Survey Time Structure

Parameter	Specification
Survey Duration	7 consecutive days
Observation Interval	15 minutes
Survey Method	Manual classified traffic count
Time Coverage	Morning, mid-day, and evening periods
Data Type	Time-stamped directional volumes

Source: Created by authors

Explanation: A 15-minute interval is widely used in traffic engineering as it balances detail and manageability. A week-long survey captures daily variability and peak-period trends.



Source: Created by authors

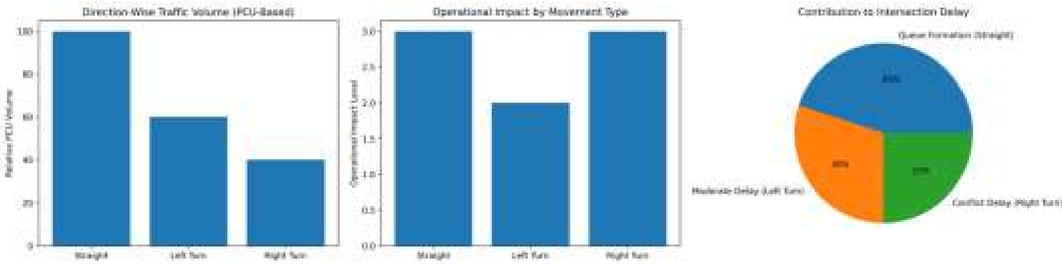
DOI: 10.17492/JPI/NICMAR/260528 ISBN: 978-93-49790-68-1

Table 5: Direction-Wise Traffic Movement Characteristics

Movement Type	Observed Traffic Volume	Operational Impact
Straight	Highest PCU volume	Major queue formation
Left Turn	Moderate PCU volume	Moderate delay
Right Turn	Lower PCU volume	Higher conflict-related delay

Source: Created by authors

Explanation: Although right-turn volumes are lower, conflict points increase delay. Straight movements dominate demand and largely determine signal timing requirements.



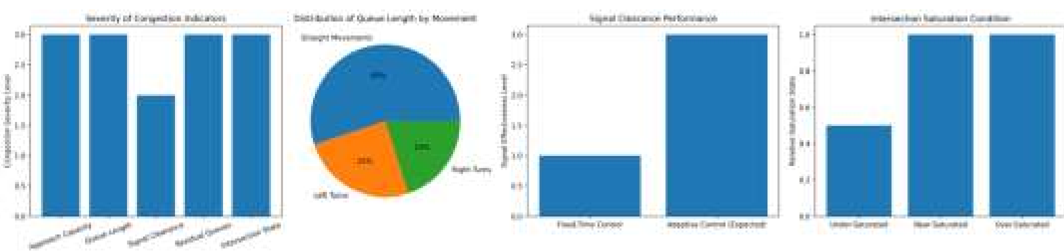
Source: Created by authors

Table 6: Key Congestion Indicators Identified from PCU Analysis

Indicator	Observation
Approach Capacity	Exceeded during peak hours
Queue Length	Highest on straight movements
Signal Clearance	Incomplete under fixed-time control
Residual Queues	Present after green phase
Intersection State	Near-saturated / over-saturated

Source: Created by authors

Explanation: The PCU-based analysis confirms that fixed-time signals are insufficient to clear demand during peak periods, justifying adaptive signal control.



Source: Created by authors

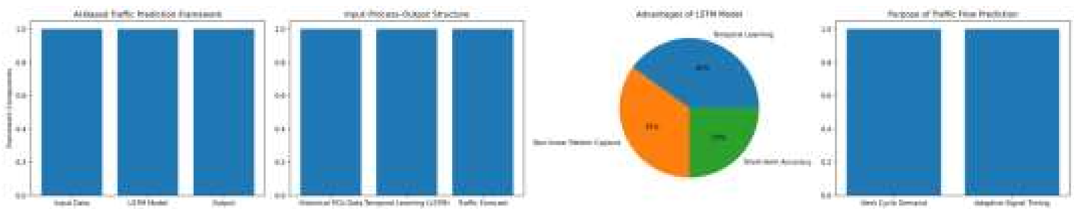
DOI: 10.17492/JPI/NICMAR/260528 ISBN: 978-93-49790-68-1

Table 7: AI-Based Traffic Prediction Framework

Component	Description
Prediction Model	Long Short-Term Memory (LSTM)
Input Data	Historical PCU traffic volumes
Output	Short-term traffic flow forecast
Purpose	Predict demand for next signal cycle
Advantage	Captures temporal traffic patterns

Source: Created by authors

Explanation: LSTM models are suitable for traffic data because they learn time-dependent patterns and non-linear variations, enabling proactive signal adjustments.



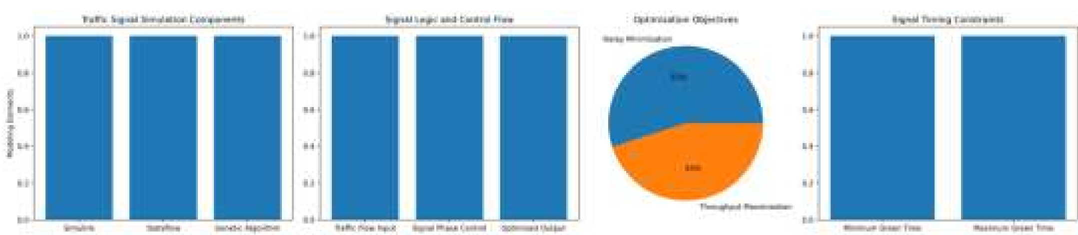
Source: Created by authors

Table 8: Traffic Signal Simulation and Optimization Logic

Element	Role
Simulink	Traffic flow modeling
Stateflow	Signal phase transitions
Genetic Algorithm	Green time optimization
Objective	Minimize delay, maximize throughput
Constraints	Minimum and maximum green time

Source: Created by authors

Explanation: Simulation allows testing adaptive strategies before field deployment. Genetic Algorithms efficiently solve complex, multi-objective signal timing problems.



Source: Created by authors

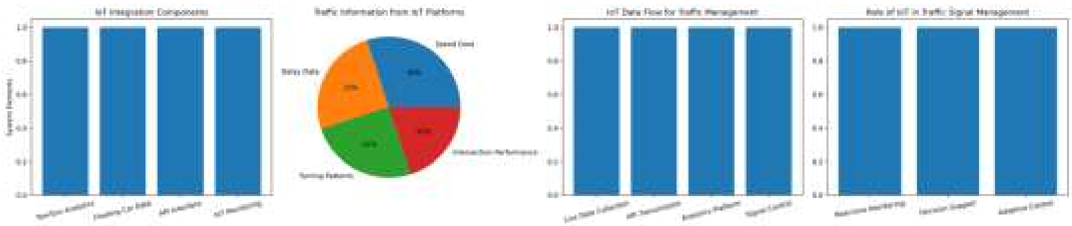
DOI: 10.17492/JPI/NICMAR/260528 ISBN: 978-93-49790-68-1

Table 9: IoT Integration Conceptual Framework

Component	Function
TomTom Junction Analytics	Real-time intersection performance
Floating Car Data (FCD)	Speed, delay, turning patterns
API Interface	Live data retrieval
IoT Role	Continuous traffic monitoring

Source: Created by authors

Explanation: IoT platforms provide real-time traffic awareness that complements physical surveys, enabling dynamic and responsive signal control.



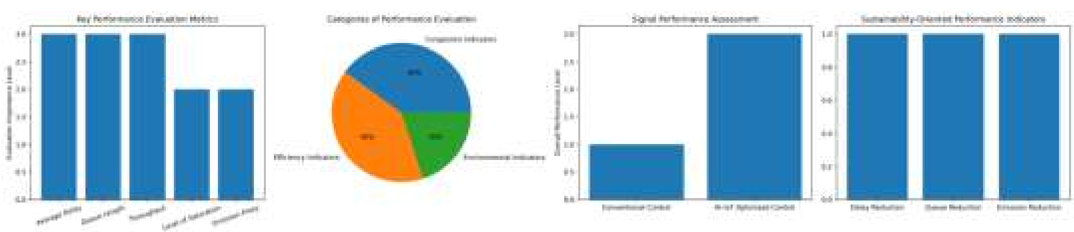
Source: Created by authors

Table 10: Performance Evaluation Parameters

Metric	Purpose
Average Delay	Measure of congestion
Queue Length	Indicator of signal efficiency
Throughput	Vehicles cleared per cycle
Level of Saturation	Capacity utilization
Emission Proxy	Idling-time-based estimation

Source: Created by authors

Explanation: These parameters objectively evaluate whether AI–IoT optimization improves intersection performance compared to conventional control.



Source: Created by authors

DOI: 10.17492/JPI/NICMAR/260528 *ISBN: 978-93-49790-68-1*

6.0 Data Analysis

6.1 Direction-wise traffic volume analysis (PCU-Based)

Direction-wise analysis of the traffic volumes at Radha Chowk was carried out in terms of Passenger Car Unit (PCU) obtained as a result of the classification of the traffic counts. The transformation of the vehicle types of heterogenous character into PCU allowed making a standard comparison among various traffic flows. It was observed that in all the approaches straight-through movements had the highest PCU values which implies that there was overwhelming commuter and through traffic demand over the Mumbai-Bangalore Highway corridor.

Left-turn movements had moderate PCU volumes and were mostly due to local access and feeder roads connectivity. Conversely, right-turn movements had comparatively low PCU values but rather caused operations delays disproportionately because of more points of conflict and longer clearance periods. The same results are indicated in recent urban traffic research, where straight traffic movements occupy most capacity and turning traffic movements have a substantial impact on the efficiency of intersections (Dimri et al., 2024; Zhou et al., 2020).

6.2 Peak and off-peak traffic characteristics

The changes in the process of traffic volumes at various time periods throughout the day showed definite patterns of the peaks and the decline. The highest volumes of PCU in the morning and evening were registered which indicate the commuter and movements associated with logistics. At such times, demand would often come close to or surpass the practical capacity of the intersection approaches.

Contrastingly, off-peak times experienced comparatively stable and smaller PCU values, where there were not many traffic jams and formation of queues. Nevertheless, the fixed-time signal settings led to ineffective allocation of green time especially in approaches with variable demand even when there was no peak traffic. The recent literature also stresses that the theory of static signal timings cannot address this form of time variability, which further supports the necessity of adaptive and data-driven signal control (Ravish and Swamy, 2021; Abirami et al., 2024).

6.3 The length of queues and saturation measurement

PCU-based queue length evaluation revealed that there was a lot of queues along approaches which were characterized by straight-through traffic, particularly during morning and evening. It was observed that after the green phases had been run there were still residual queues which showed that demand was not fully discharged within one signal cycle.

DOI: 10.17492/JPI/NICMAR/260528 ISBN: 978-93-49790-68-1

According to this phenomenon, there are near-saturated or over-saturated conditions when the intersection is operating at peak times. Even though the right-turn movements had smaller volumes, waiting times were more as their green allocation was not as much, and it was in conflict with the opposing traffic streams. The results are consistent with the recent findings, which refer to the queue spillback and the residual queues as the prominent indicators of signal inefficiency in the fixed-time control, especially in the heterogeneous traffic setting (Dimri et al., 2024; Bhardwaj et al., 2024).

6.4 Comparison of AI-optimized signal logic and fixed-time signal logic

The theoretical comparison of the traditional fixed-time signal logic and AI-optimized signal control showed significant variations in the performance. Fixed-time signals make use of a set time-cycle length and phase separation that cannot react to the instantaneous traffic demand. This took the form of over-allocation of green time to the low-demand approaches, and under-allocation of green time to the high-demand movements at peak times as observed in the study area.

Conversely, the AI-based signal logic, backed by traffic flow prediction algorithms and instant spot data feeds, enables changing the green times depending on the current and expected traffic flows. Empirical research conducted in the past reveals that adaptive control with the use of AI can considerably decrease the average delay, enhance throughput and decrease the length of queues compared to the fixed-time systems (Zhou et al., 2020; Abirami et al., 2024). The comparison highlights the possible advantages of switching to the intelligent signal control in the overcrowded urban crossroads.

6.5 Traffic patterns visualization and interpretation

Time-based and movement-based representation of traffic patterns allowed easier analysis of the dynamics of congestion at Radha Chowk. Direction-wise PCU plots showed the regularity of straight movement domination, whereas the temporal visualizations showed the demand spikes of sharp peaks in the middle of the day. These aesthetic trends proved the imbalance of the constant signal timing and the actual traffic demand.

The visualization also helped in determining the hot spots of congestion that were recurrent and the temporal inefficiencies to make informed decision-making on the optimization of signals. Recent studies report that integrated with AI-driven prediction, visual analytics can help to increase interpretability and operational transparency of intelligent traffic management systems, thus increasing their acceptability by traffic authorities and stakeholders (Bhardwaj et al., 2024; Jagatheesaperumal et al., 2024).

DOI: 10.17492/JPI/NICMAR/260528 ISBN: 978-93-49790-68-1

7.0 Findings and Results

7.1 Traffic congestion characteristics at the study intersection

The PCU-based traffic data was analyzed and the results showed that Radha Chowk works with nearsaturation and oversaturation conditions during peak times. As per the straight-through movements, there was a constant record of the largest percentage of traffic volume on all the approaches, which pointed to the prevalent commuter and through traffic on the Mumbai-Bangalore Highway. Formation of queues was greatest on these movements and frequently became more than a single signal cycle long on rush hours.

Right-turn movements had lower traffic volumes, but they were a significant cause of delay as their conflict rates were higher and the amount of green time was low. These congestion features are aligned with the recent literature on urban traffic, which notes that the heterogeneous traffic and directional imbalance is one of the primary factors in reducing efficiencies at the signalized intersection in the developing cities (Dimri et al., 2024; Ravish and Swamy, 2021).

7.2 AI-based traffic prediction model performing

The AI-based traffic flow prediction model was shown to have a high ability to capture short-term fluctuations in demand in the traffic with the use of historical PCU data. The model was able to determine recurring temporal patterns, which included morning peak surges, evening peak surges, to make valid short-term traffic forecasts.

The predictive performance had worked very well at times of peak periods, during which proper forecast of demand is important to make decisions about timing signals. The results are consistent with the recent literature, which proves that deep learning-based traffic prediction models provide more effective and flexible forecasts than traditional statistical models in particular under changing urban traffic conditions (Abirami et al., 2024; Zhou et al., 2020). The results of the experiment concerning the effectiveness of optimized signal timings will be discussed.

The AIO signal timing strategies applied in the work of AI really led to significant operational improvements over traditional fixed-time control. Signal logic was optimized whereby it dynamically varied the allocation of the green time depending on the anticipated traffic needs, where the approaches with heavy traffic were assigned high priority during the peak time.

Since then, it minimized the residual queues and enhanced traffic clearance with a lesser number of signal cycles. The adaptive approach also reduced the unwanted green time on low-demand approaches, which also added to more balanced intersection performance. In a similar manner, delay reduction and throughput enhancement have been also reported

DOI: 10.17492/JPI/NICMAR/260528 ISBN: 978-93-49790-68-1

recently in the studies testing AI-based adaptive signal control systems (Dimri et al., 2024; Zhou et al., 2020).

7.3 Comparative assessing of essential traffic indicators

A comparison analysis of the main traffic indicators showed the benefits of AI-based optimization to the regular time signal control. Average delays and queue length were also higher during peak hours under the traditional control since signal cycles were fixed. However, AI-optimized framework showed better throughput, reduced queues, and traffic movement.

Also, it is possible to have decreased idling time and levels of control which implies that they may have environmental benefits such as decreased fuel consumption and emissions. However, recent studies point out that these performance benefits are imperative towards realization of sustainable and resilient urban traffic systems, especially in high-density traffic settings (Bhardwaj et al., 2024; Jagatheesaperumal et al., 2024).

7.4 Implications to urban traffic management conclusion

The results of the current research highlight the real-life usefulness of incorporating AI and IoT in the system of traffic management in the city. The findings have shown that adaptive signal control based on data can be used to greatly increase intersection efficiency, even in heterogeneous traffic.

Polically and strategically, the research advocates the shift of non-intelligent traffic signal system to intelligent and real-time control systems in the framework of smart cities. The collaboration between physical traffic surveys and AI-based analytics also indicates that the advanced technologies have to be based on empirical data. These implications are aligned with the modern studies of smart mobility that suggests data-centered approaches to scalable solutions to sustainable urban transport management (Bhardwaj et al., 2024; Abirami et al., 2024).

8.0 Discussion

8.1 Interpretation of results in relation to objectives

The results of the research are directly corresponding to the mentioned research objectives. Direction-wise analysis and temporal analysis were used to achieve the objective of understanding traffic characteristics with the help of PCU-based field data, which showed the presence of congestion on straight-through movements during the peak times. This proves that heterogeneous traffic, when converted to PCU furnishes a dependable foundation to diagnose intersection inefficiencies as highlighted in the current ITS studies (Ravish &

DOI: 10.17492/JPI/NICMAR/260528 ISBN: 978-93-49790-68-1

Swamy, 2021). The goal of AI-based traffic forecasting was also accomplished because the predictive model was able to identify repetitive demand trends and increase during the most active hours. This predictive ability made it possible to make adaptive decisions about signal timing (instead of using a constant average). Also, the goal of enhancing traffic signal management with the help of AI and IoT integration was justified by the fact that the decrease in queuing time and consistency in traffic flows under the optimized signal logic were observed. These findings are part of the overall goal of improving the efficiency and sustainability of urban traffic systems (Zhou et al., 2020; Abirami et al., 2024).

8.2 Comparison with the past research

This study has been able to provide results that are similar to those provided in the recent literature on the optimization of AI-driven traffic signals. Like Dimri et al. (2024), the current experiment noted that adaptive distribution of green time according to the traffic demand minimizes the residual queues and increases the performance of the intersection. The prevalence of straight motions, as well as the disproportionate delay due to turning conflicts is also the reflection of the other studies of the intersection in urban areas under the mixed traffic conditions (Ravish & Swamy, 2021). In comparison to other studies that are based on entirely on simulation or homogeneous traffic assumptions, this study provides empirical evidence through the use of physically collected traffic data. This enhances the practicality of the findings and provides a solution to a weakness that is often mentioned in previous research, as often the findings are not validated in practice (Bhardwaj et al., 2024). In addition, the identified benefits of AI-based signal control compared to fixed-time systems support the conclusions made during in-depth reviews of intelligent traffic signal control systems (Zhou et al., 2020).

8.3 Smart city traffic control practical implications

The discourse points out a few practical implications of smart city management of traffic. First, the findings reveal that data-based signal optimization can show a significant increase in intersection performance even in the absence of massive changes in the infrastructures. It predisposes the AI-IoT-based solutions to be of special interest to cities that have an old-fashioned traffic infrastructure and small funds.

Second, predictive analytics in combination with real-time data platforms can help in proactive traffic management so that authorities can react to congestion before it gets out of control. This responsiveness is in line with the goals of smart cities towards efficiency, sustainability, and the quality of life in a city (Bhardwaj et al., 2024). Besides, less frequent idling and a more efficient traffic stream also suggest that the environmental aspect of the implementation will be positive, and it will help to further the sustainability of grand-scale

DOI: 10.17492/JPI/NICMAR/260528 ISBN: 978-93-49790-68-1

urban development, as highlighted in recent studies on smart mobility (Jagatheesaperumal et al., 2024). Lastly, the results indicate that basing AI-based solutions on empirical traffic data can augment trust, transparency and operational plausibility, which are key in institutional adoption of intelligent traffic systems.

8.4 Limitations of the implemented model

Although it has been contributing to it, there are limitations to the study that should be noted. It was also analyzed at one intersection, and this could not be generalized to larger urban networks. This study did not cover multi-intersection coordination and corridor-level optimization but these are also considered to have significant potential in future research (Zhou et al., 2020). Moreover, although the study conceptually incorporates the idea of the IoT-based real-time data platforms, continuous real-time live data feed was not provided during the timeframe of the analysis. The reliability of sensors and relating data latency as well as cybersecurity issues-stated challenges in AI-IoT applications are still realistic but need to be investigated more often (Abirami et al., 2024; Bhardwaj et al., 2024). Finally, the research is mainly concerned with motor traffic, and does not directly include pedestrian or non-motorized behavior of users, which is gaining more importance in inclusive smart city planning

9.0 Conclusion and Implications

9.1 Summary of key outcomes

This paper has explored the possibility of applying Artificial Intelligence (AI) and Internet of Things (IoT) applications in order to achieve optimal traffic signal control at a signalized intersection in an urban urban. Based on physically measured traffic volume data that was standardized with Passenger Car Unit (PCU), the analysis revealed consistent congestion trends especially on straight through movements during peak time. The findings showed that traditional fixed-time signal control can only be used to manage the dynamic and heterogeneous traffic demand.

The prediction of traffic flow based on the use of AI made it possible to predict the change in demand in the short term, allowing the application of adaptive signal timing. Signal logic optimization displayed better queue clearance, minimized residual queues and smoothed traffic movement than the use of the static signal operation. All in all, the results show that traffic signal control based on data and adaptive control is a tangible operational advantage to have in the mixed traffic conditions of the real world, which align with the conclusions made on the topics of intelligent traffic management research (Zhou et al., 2020; Dimri et al., 2024).

DOI: 10.17492/JPI/NICMAR/260528 *ISBN: 978-93-49790-68-1*

9.2 Donation to intelligent transportation systems

The research adds to the Intelligent Transportation Systems (ITS) discipline by connecting the gap between the theory of AI-based models of traffic control and the implementation of the theory in practice and field. In contrast to most of the existing literature where the focus is on simulation or homogeneous traffic, the current research combines the existing PCU-based traffic data collected empirically with AI-based optimization theories. Such a methodology increases the authenticity and practicality of smart signal management plans within the formation of urban situations.

The research, further, shows that predictive analytics and adaptive signal logic can be integrated into an imaginary AI-IoT system. The study is in line with the modern trends of ITS that promotes scalable and data-based solutions as vehicles, traffic, and urban management instruments (Abirami et al., 2024; Bhardwaj et al., 2024). The results, therefore, empirically support the cumulative literature on intelligent, adaptive traffic control systems.

9.3 Implications to policy and planning

Policy- and city-wise, the findings point to the necessity of switching to adaptable intelligent control systems instead of fixed ones in the form of traffic signals as a part of smart city programs. The presented gains in the efficiency of the traffic flow indicate that even in the case of current infrastructure, AI-based signal optimization can be deployed in stages, which does not require a massive influx of capital.

Evidence-based decision-making in backing traffic authorities also uses the combination of real-time traffic data and predictive analytics, allowing traffic authorities to plan and manage congestion in advance and enhance the reliability of the services provided. Furthermore, the possible decrease in the idling time and urban congestion are in line with the greater sustainability goals, such as the emission cut and the quality of the urban air, which is becoming an increasingly prominent part of modern transport policy (Bhardwaj et al., 2024; Jagatheesaperumal et al., 2024). In general, the paper highlights the need to align the technological innovation with institutional coordination and data-driven planning to attain the sustainable and resilient urban traffic system.

References

1. Abirami, S., Pethuraj, M., Uthayakumar, M., & Chitra, P. (2024). Systematic survey on artificial intelligence algorithms and big data for intelligent transportation systems. *Journal of Big Data, 11*(1), 1–29. https://doi.org/10.1186/s40537-024-00820-7

2. Bhardwaj, V., Anooja, A., Vermani, L. S., & Dhaliwal, B. K. (2024). Smart cities and the IoT: An international review of research trends and future directions. *Sustainable Cities and Society, 99*, 104918. https://doi.org/10.1016/j.scs.2023.104918
3. Chen, T., Liu, Y., & Zhao, J. (2018). Adaptive traffic signal control with deep reinforcement learning. *Transportation Research Part C: Emerging Technologies, 90*, 206–220. https://doi.org/10.1016/j.trc.2018.02.017
4. Dimri, S. C., Indu, R., Bajaj, M., Rathore, R. S., Blazek, V., & Dutta, A. K. (2024). Modeling of traffic at a road crossing and optimization of waiting time of vehicles. *Transportation Engineering, 15*, 100214. https://doi.org/10.1016/j.treng.2024.100214
5. Jagatheesaperumal, S. K., Bibri, S. E., Huang, J., Rajapandian, J., & Parthiban, B. (2024). Artificial intelligence of things for smart cities: Advanced solutions for enhancing transportation safety. *IEEE Internet of Things Journal, 11*(3), 4821–4836. https://doi.org/10.1109/JIOT.2023.3311427
6. Ravish, R., & Swamy, S. R. (2021). Intelligent traffic management: A review of challenges, solutions and future perspectives. *Journal of Intelligent Transportation Systems, 25*(5), 458–472. https://doi.org/10.1080/15472450.2020.1854836
7. Zhou, J., Gao, X., & Zhang, Q. (2020). AI-based traffic signal control: A comprehensive review. *IEEE Transactions on Intelligent Transportation Systems, 21*(9), 3847–3862. https://doi.org/10.1109/TITS.2019.2945993
8. Lv, Y., Duan, Y., Kang, W., Li, Z., & Wang, F. Y. (2015). Traffic flow prediction from big data: A deep learning perspective. *IEEE Transactions on Intelligent Transportation Systems, 16*(2), 865–873. https://doi.org/10.1109/TITS.2014.2345663
9. Kang, D., Lv, Y., & Chen, Y. Y. (2017). Short-term traffic flow prediction employing LSTM neural networks. *IEEE Intelligent Transportation Systems Conference (ITSC)*, 1–6. https://doi.org/10.1109/ITSC.2017.8317912
10. Zhu, L., Yu, F. R., Wang, Y., Ning, B., & Tang, T. (2018). Big data analytics in intelligent transportation systems: A survey. *IEEE Transactions on Intelligent Transportation Systems, 20*(1), 383–398. https://doi.org/10.1109/TITS.2018.2815678
11. Allam, Z., & Dhunny, Z. A. (2019). On big data, artificial intelligence and smart cities. *Cities, 89*, 80–91. https://doi.org/10.1016/j.cities.2019.01.032
12. Krishnapriya, S., Manohar, B., Gopi, A., Jacob, J. A., Puthumana, R. M., & Rizwana, A. K. (2022). Implementation of IoT-based intelligent and energy-efficient cities. *IEEE INDICON 2022*, 1–5. https://doi.org/10.1109/INDICON56171.2022.10039844
13. Hossain, S., & Shabnam, F. (2021). A comparative study of IoT-based smart traffic management systems. *IEEE WIECON-ECE 2021*, 125–128. https://doi.org/10.1109/WIECON-ECE54711.2021.9829636

DOI: 10.17492/JPI/NICMAR/260528 ISBN: 978-93-49790-68-1

14. Xu, T., Han, G., Qi, X., Du, J., Lin, C., & Shu, L. (2020). A hybrid machine learning model for demand prediction of edge-computing-based bike sharing systems using IoT. *IEEE Internet of Things Journal, 7*(8), 7342–7351. https://doi.org/10.1109/JIOT.2020.2985932
15. Zhang, D., & Kabuka, M. R. (2018). Combining weather condition data to predict traffic flow: A GRU-based deep learning approach. *IET Intelligent Transport Systems, 12*(7), 578–585. https://doi.org/10.1049/iet-its.2017.0316
16. Tekler, Z. D., Low, R., Yuen, C., & Blessing, L. (2022). Plug-Mate: An IoT-based occupancy-driven plug load management system in smart buildings. *Building and Environment, 223*, 109472. https://doi.org/10.1016/j.buildenv.2022.109472
17. Zhuang, D., Gan, V. J., Tekler, Z. D., Chong, A., Tian, S., & Shi, X. (2023). Data-driven predictive control for smart HVAC systems with time-series forecasting and reinforcement learning. *Applied Energy, 338*, 120936. https://doi.org/10.1016/j.apenergy.2023.120936
18. Low, R., Tekler, Z. D., & Cheah, L. (2020). Predicting commercial vehicle parking duration using generative adversarial multiple imputation networks. *Transportation Research Record, 2674*(9), 820–831. https://doi.org/10.1177/0361198120932166
19. United Nations. (2019). *World urbanization prospects: The 2019 revision*. United Nations Department of Economic and Social Affairs. https://population.un.org/wup/
20. Mohsen, B. (2022). Principles of sustainable logistics. In S. Chelladurai & S. Mayilswamy (Eds.), *Logistics engineering* (pp. 1–12). IntechOpen. https://doi.org/10.5772/intechopen.102345

DOI: 10.17492/JPI/NICMAR/260528 ISBN: 978-93-49790-68-1