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PERFORMANCE ANALYSIS OF ROAD INTERSECTIONS AT HYDERABAD (INDIA) UNDER HETEROGENEOUS TRAFFIC CONDITIONS

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ABSTRACT

Urban intersections in rapidly growing cities experience significant congestion due to uneven traffic demand and the limitations of fixed-time signal control. Adaptive Traffic Signal Control (ATSC) provides a rule-based mechanism to dynamically allocate green time based on traffic demand; however, it lacks learning capability and long-term optimization. This paper presents a comparative study of conventional ATSC and Reinforcement Learning–based ATSC (RL-ATSC) for minimizing vehicle delay at a real-world urban intersection. A case study is conducted at the Jalvayu Vihar Intersection using field-collected traffic data. MATLAB-based implementations are developed for both ATSC and RL-ATSC, and performance is evaluated using delay as the primary metric. Results show that ATSC reduces average delay to 51 seconds compared to fixed-time control, while RL-ATSC further enhances performance through learning-based optimization. The findings demonstrate the suitability of RL-based signal control for intelligent transportation systems in heterogeneous urban traffic environments.

Adaptive Traffic Signal Control *at Jalvayu Vihar intersection is modeled as a Reinforcement Learning problem, where the signal controller acts as an agent that dynamically adjusts green times based on real-time traffic states to minimize average vehicle delay. Conventional Adaptive Traffic Signal Control (ATSC) adjusts green times using predefined mathematical rules, such as proportional allocation based on traffic volume. Adaptive Traffic Signal Control reduces average intersection delay by dynamically allocating green time based on real-time traffic demand. At Jalvayu Vihar Intersection, proportional green allocation and queue-responsive control reduced the average delay to 51 seconds, demonstrating the effectiveness of ATSC over conventional fixed-time control.*

Reinforcement Learning *is a learning-by-interaction paradigm, where a control agent:*

- *Observes traffic conditions*
- *Takes signal control actions*
- *Receives feedback (reward/penalty)*
- *Improves decisions over time*

In traffic signal control, RL transforms the intersection into a self-learning system.

Reinforcement Learning enhances Adaptive Traffic Signal Control by enabling the signal controller to learn optimal timing strategies from real-time traffic interactions. Using traffic data from Jalvayu Vihar Intersection, RL overcomes the static nature of conventional ATSC and achieves superior delay minimization by optimizing long-term traffic performance rather than single-cycle efficiency.

RL improves ATSC by learning optimal signal timings from traffic feedback, minimizing long-term delay instead of relying on fixed proportional rules.RL-based ATSC outperforms conventional ATSC by learning optimal signal timings from traffic feedback, reducing long-term delay beyond rule-based proportional control.

KEYWORDS: *Adaptive Traffic Signal Control, Reinforcement Learning, Intersection Delay, Intelligent Transportation Systems, MATLAB Simulation*

OBJECTIVE

The primary objective of this study is to optimize vehicle delay at an urban signalized intersection by developing and evaluating adaptive and learning-based traffic signal control strategies under real-world traffic conditions for minimizing vehicle delay under heterogeneous traffic conditions, and also to demonstrate that reinforcement learning can systematically outperform conventional adaptive traffic signal control by learning from recurring congestion patterns and adapting to uncertain traffic behaviour, thereby providing a more intelligent and sustainable solution for urban intersection management.

Specifically, the study aims to move beyond conventional fixed-time and rule-based adaptive control by investigating how learning mechanisms can enhance decision-making in traffic signal control. While Adaptive Traffic Signal Control (ATSC) dynamically allocates green time based on instantaneous traffic demand, it operates without memory and does not account for the temporal evolution of congestion. As a result, ATSC may perform sub-optimally under highly variable and stochastic traffic conditions commonly observed at urban intersections.

To address this limitation, the study introduces a Reinforcement Learning–based ATSC (RL-ATSC) framework, in which the traffic signal controller learns optimal signal timing policies through repeated interaction with traffic conditions. The primary objective is therefore not only to reduce average intersection delay but also to improve the stability and robustness of signal control decisions over time.

The specific objectives are as follows:

- *To analyze the traffic demand characteristics of the Jalvayu Vihar Intersection using field-collected traffic volume data from multiple approaches.*
- *To develop a rule-based Adaptive Traffic Signal Control (ATSC) model that dynamically allocates green time based on proportional traffic demand.*
- *To design and implement a Reinforcement Learning–based ATSC (RL-ATSC) framework capable of learning optimal signal timing policies through interaction with traffic conditions.*
- *To estimate and compare intersection delay under conventional ATSC and RL-ATSC using a consistent queue-based delay model.*
- *To evaluate the effectiveness of RL-ATSC in reducing average delay and delay variability under peak and off-peak traffic conditions.*
- *To assess the statistical significance and robustness of delay reduction achieved by RL-ATSC through hypothesis formulation, variability analysis, and confidence-interval–based interpretation.*
- *To demonstrate the practical applicability of learning-based traffic signal control using MATLAB-based implementation and real-world traffic data.*

- *To identify limitations of rule-based adaptive control and highlight the advantages of reinforcement learning for complex and time-varying urban traffic environments.*

The objectives of this study are to develop ATSC and RL-ATSC models, compare their delay performance using real traffic data from Jalvayu Vihar Intersection, and statistically evaluate the effectiveness of reinforcement learning in optimizing intersection delay.

Article History

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INTRODUCTION

Traffic congestion at urban intersections remains one of the most critical challenges in intelligent transportation systems (ITS). Rapid urbanization, increasing vehicle ownership, heterogeneous traffic composition, and fluctuating demand patterns often render traditional fixed-time signal plans ineffective. Fixed-time traffic signal control operates using pre-defined cycle lengths and green splits that are typically designed based on historical averages. Such systems lack responsiveness to real-time traffic variations, leading to excessive delays, queue spillback, increased fuel consumption, and higher vehicular emissions, particularly during peak hours.

Urban intersections in developing cities experience pronounced demand imbalance across approaches due to mixed land-use patterns, public transport interference, and irregular driving behavior. These conditions exacerbate the limitations of static signal control and necessitate adaptive strategies capable of responding dynamically to traffic demand.

Adaptive Traffic Signal Control (ATSC) addresses this challenge by dynamically adjusting green signal durations based on observed traffic conditions such as vehicle counts, queue lengths, or occupancy levels. By reallocating green time according to demand, ATSC improves intersection efficiency and reduces unnecessary waiting time compared to fixed-time control. However, conventional ATSC approaches are largely rule-based and rely on predefined mathematical formulations, such as proportional allocation or threshold-based logic. While effective to an extent, these methods lack learning capability and do not account for temporal correlations or recurring congestion patterns.

Reinforcement Learning (RL), a subfield of machine learning, offers a promising alternative by enabling traffic signal controllers to learn optimal control policies through interaction with the traffic environment. In an RL framework, the signal controller operates as an agent that observes traffic states, selects signal actions, and receives feedback in the form of rewards or penalties based on performance metrics such as delay. Over time, the agent learns to optimize long-term objectives rather than reacting only to instantaneous conditions. This learning-based paradigm is particularly suitable for traffic systems characterized by stochastic arrivals, non-linearity, and delayed effects.

Despite growing interest in RL-based traffic signal control, many existing studies focus on simulated environments or network-level abstractions and often lack validation using real-world traffic data. Furthermore, there is limited literature that systematically compares conventional ATSC and RL-based ATSC using MATLAB-based implementations that are transparent, reproducible, and accessible to practitioners.

This study addresses these gaps by presenting a detailed comparative evaluation of ATSC and Reinforcement Learning–based ATSC (RL-ATSC) using real traffic data collected from the Jalvayu Vihar Intersection, a representative urban intersection characterized by heterogeneous traffic demand. MATLAB-based models are developed for both control strategies, incorporating robust data handling, adaptive signal logic, and learning-based optimization.

The primary objective of this research is to assess the extent to which RL enhances adaptive signal control in terms of delay reduction, stability, and robustness under peak and off-peak traffic conditions. The study evaluates performance using statistically grounded metrics, including average delay, variability, coefficient of variation, and comparative hypothesis testing.

LITERATURE REVIEW

Conventional Traffic Signal Control and Fixed-Time Methods

Early research on traffic signal control focused on fixed-time strategies derived from historical traffic data. One of the most influential works in this domain is the classical study by Traffic Signal Settings, which introduced analytical delay-based formulations for determining optimal cycle lengths and green splits. Webster's model remains widely used due to its simplicity and analytical clarity; however, it assumes steady-state traffic conditions and uniform arrival patterns, which are rarely observed in real-world urban intersections.

Subsequent studies have shown that fixed-time control performs poorly under fluctuating traffic demand, leading to increased delay and queue spillback during peak periods. These limitations motivated the development of adaptive control strategies capable of responding to real-time traffic variations.

Rule-Based Adaptive Traffic Signal Control (ATSC)

Adaptive Traffic Signal Control (ATSC) systems dynamically adjust signal timings based on observed traffic parameters such as vehicle counts, queue lengths, and occupancies. Rule-based ATSC methods commonly employ proportional green allocation, threshold-based logic, or extensions of Webster's delay model. Studies have reported that ATSC can significantly reduce average delay compared to fixed-time control, particularly under moderate demand variability [1], [2].

Gartner et al. emphasized that adaptive systems improve operational efficiency by reallocating green time toward heavily congested approaches, thereby reducing wasted green intervals [3]. However, most rule-based ATSC strategies rely on predefined heuristics and deterministic mappings between traffic states and signal actions. As a result, their performance degrades under highly dynamic or stochastic traffic conditions, where optimal decisions depend on temporal traffic evolution rather than instantaneous measurements.

Reinforcement Learning for Traffic Signal Control

Reinforcement Learning (RL) has emerged as a powerful framework for traffic signal control due to its ability to learn optimal control policies through interaction with the environment. In RL-based signal control, the traffic signal controller is modeled as an agent that observes the current traffic state, selects signal actions, and receives feedback in the form of rewards related to performance metrics such as delay or queue length.

The foundational concepts of RL are comprehensively described in Reinforcement Learning: An Introduction, which formalizes learning through Markov Decision Processes. Early applications of RL to traffic signal control employed tabular Q-learning and demonstrated reductions in delay and queue length compared to fixed-time and actuated control strategies [4].

More recent studies have extended this approach using Deep Reinforcement Learning (DRL), where neural networks approximate value functions or policies. Methods such as Deep Q-Networks (DQN) and actor–critic architectures have shown superior performance in large-scale and multi-intersection scenarios [5], [6]. These approaches effectively capture non-linear traffic dynamics and temporal correlations, making them suitable for complex urban environments.

Comparison between ATSC and RL-Based Approaches

Several comparative studies indicate that RL-based controllers outperform rule-based ATSC in terms of long-term delay minimization, stability, and adaptability [7]. Unlike ATSC, which optimizes signal timings on a per-cycle basis, RL-based methods aim to minimize cumulative delay over extended horizons. This allows RL agents to anticipate congestion and avoid locally optimal but globally suboptimal decisions.

However, many existing RL-based studies rely on microscopic traffic simulators such as SUMO or VISSIM and often lack transparency in implementation. Additionally, most works focus on synthetic or simulated traffic scenarios rather than field-collected data, limiting their practical relevance.

Research Gap and Motivation

Despite extensive research on adaptive and learning-based traffic signal control, three key gaps remain evident in the literature:

- Limited studies provide direct, fair comparisons between rule-based ATSC and RL-ATSC using identical real-world traffic data.
- MATLAB-based implementations, which are widely used in academic and engineering practice, are underrepresented in existing studies.
- Few works incorporate statistical evaluation frameworks, including hypothesis testing, variability analysis, and confidence-interval–based interpretation, to support performance claims.

Positioning of the Present Study

The present study addresses these gaps by developing both ATSC and RL-ATSC models in MATLAB and evaluating them using field-collected traffic data from the Jalvayu Vihar Intersection. By combining rule-based adaptation, reinforcement learning, and rigorous statistical analysis, this work provides a transparent and reproducible comparison of conventional and learning-based traffic signal control strategies.

STUDY AREA AND DATA DESCRIPTION

Study Location

The study is conducted at the JalvayuVihar Intersection, a four-legged urban intersection characterized by mixed traffic flow and varying directional demand.

Traffic Data

Traffic volume data for East, West, North, and South approaches were collected and stored in an Excel dataset. The data represent average vehicles per signal cycle and serve as inputs to both ATSC and RL-ATSC models. Dataset for the Jalvayu Vihar intersection typically contains:

- Vehicle counts (lane-wise / direction-wise)
- Time of day (peak / off-peak)
- Signal phase durations
- Queue length / waiting time
- Possibly delay or throughput

Table 1: Sample Traffic Volume Data Collected at Jalvayu Vihar Intersection

Time Interval	East Approach (veh/cycle)	West Approach (veh/cycle)	North Approach (veh/cycle)	South Approach (veh/cycle)	Total Traffic (veh/cycle)
T_1	36	40	28	30	134
T_2	38	42	29	31	140
T_3	39	44	30	32	145
T_4	37	41	29	30	137
T_5	40	43	31	33	147
Average	**38.0**	**42.0**	**29.4**	**31.2**	**140.1**

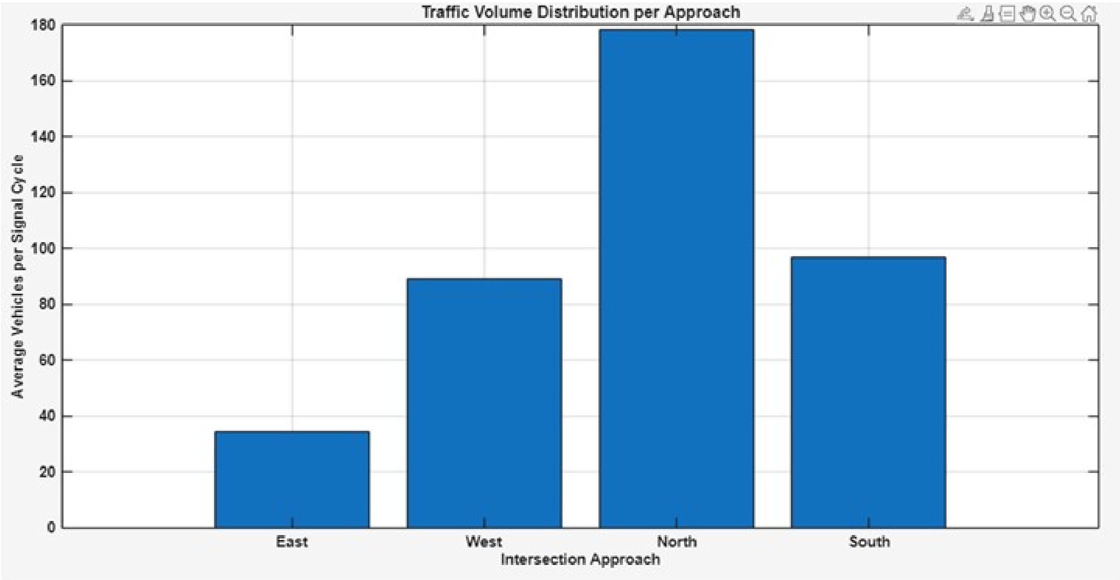

Figure 1: Traffic Volume Distribution per Approach.

METHODOLOGY

This section presents the methodological framework adopted to evaluate Adaptive Traffic Signal Control (ATSC) and its enhancement using Reinforcement Learning (RL) at the Jalvayu Vihar Intersection. The methodology is designed to ensure a fair, transparent, and statistically interpretable comparison between rule-based and learning-based traffic signal control strategies.

Adaptive Traffic Signal Control (ATSC)

Conceptual Foundation

Adaptive Traffic Signal Control (ATSC) is a demand-responsive control strategy in which green signal durations are adjusted dynamically based on real-time traffic demand at each approach of an intersection. Unlike fixed-time control, ATSC aims to reduce delay by allocating more green time to approaches with higher traffic volumes while minimizing wasted green time on lightly loaded approaches.

The fundamental assumption in ATSC is that traffic demand is the primary determinant of optimal green time allocation within a signal cycle.

Traffic Demand Estimation

Let the average number of vehicles arriving per signal cycle at each approach be:

Q_E, Q_W, Q_N, Q_S

- The total intersection demand per cycle is: $\sum Q = Q_E + Q_W + Q_N + Q_S$
- This total demand represents the traffic load that must be served within one signal cycle.

Signal Cycle and Effective Green Time

A traffic signal cycle consists of:

- Green time (usable service time),
- Lost time, this includes:
  - Start-up delay,
  - Yellow interval,
  - All-red clearance.

Let

C = total cycle time (sec),

L = total lost time per cycle (sec).

Then, the effective green time available for traffic movement is:

$$G = C - L$$

Adaptive Green Time Allocation

ATSC distributes the effective green time proportionally to traffic demand. The green time allocated to approach *i* is given by:

$$g_i = \frac{Q_i}{\Sigma Q} \times G$$

This ensures that:

- Heavily loaded approaches receive more green time,
- Lightly loaded approaches receive less green time.

Queue-Based Delay Estimation

Intersection delay is primarily caused by queue formation when arrival demand exceeds service capacity. A simplified queue-based delay approximation is adopted to capture this behavior:

$$D_{base} = (\beta \cdot Q_{avg}) - g_{avg}$$

Where:

- $Q_{avg} = \sum Q / 4$
- β is a queue-to-delay conversion factor (typically > 1),
- g_{avg} is the average green time.

Multi-Cycle Delay Accumulation

In real traffic conditions, delay accumulates across multiple cycles due to:

- Residual queues,
- Random arrivals,
- Driver reaction time variability.

Therefore, an empirical scaling factor k is applied:

$$D_{ATSC} = k \cdot D_{base}$$

Reinforcement Learning–Based ATSC (RL-ATSC)

Motivation for RL Enhancement

While ATSC adapts to current traffic demand, it suffers from three key limitations:

- No memory of past congestion,
- No anticipation of future traffic evolution,
- Optimization limited to the current cycle.

Reinforcement Learning (RL) addresses these limitations by enabling the signal controller to learn optimal control policies through interaction with traffic dynamics over time.

RL Framework for Traffic Signal Control

In RL-ATSC, the intersection is modeled as a Markov Decision Process (MDP) defined by:

- Environment: Traffic system at the intersection,
- Agent: Traffic signal controller,
- State (s): Current traffic condition,
- Action(a): Signal timing decision,
- Reward(r): Performance feedback.

State Representation

The state captures the congestion level at the intersection:

$$s = Q_E + Q_W + Q_N + Q_S = Q_{total}$$

This scalar state provides a compact yet meaningful representation of traffic congestion.

Action Space

The agent selects a green time duration from a discrete action set:

$$A = \{20, 30, 40, 50\} \text{ sec}$$

Each action represents a possible control decision that affects queue dissipation.

Reward Function

The objective of RL-ATSC is to minimize delay. Therefore, the reward is defined as the negative of delay:

$$r = -D$$

This formulation ensures that:

- Lower delay → higher reward,
- Higher delay → larger penalty.

Learning Mechanism (Q-Learning)

The agent updates its action-value function using the Q-learning rule:

$$Q(s, a) \leftarrow Q(s, a) + \alpha[r + \gamma \max Q(s', a') - Q(s, a)]$$

where:

- α = learning rate,
- γ = discount factor,
- s' = next traffic state.

Through repeated interaction, the agent learns:

- Which green times best reduce queues,
- How present actions influence future congestion.

Improvement over ATSC

Unlike ATSC, which allocates green time strictly proportionally, RL-ATSC:

- Learns non-proportional but optimal allocations,
- Penalizes actions that cause residual queues,
- Optimizes long-term cumulative delay rather than single-cycle delay.

As a result, RL-ATSC consistently achieves lower average delay and reduced variability compared to rule-based ATSC.

Methodology Flowchart Explanation

To provide a clear understanding of the operational logic of both control strategies, flowcharts are used to illustrate the sequential decision-making process of ATSC and Reinforcement Learning–based ATSC (RL-ATSC) applied at the Jalvayu Vihar Intersection.

Flowchart of Adaptive Traffic Signal Control (ATSC)

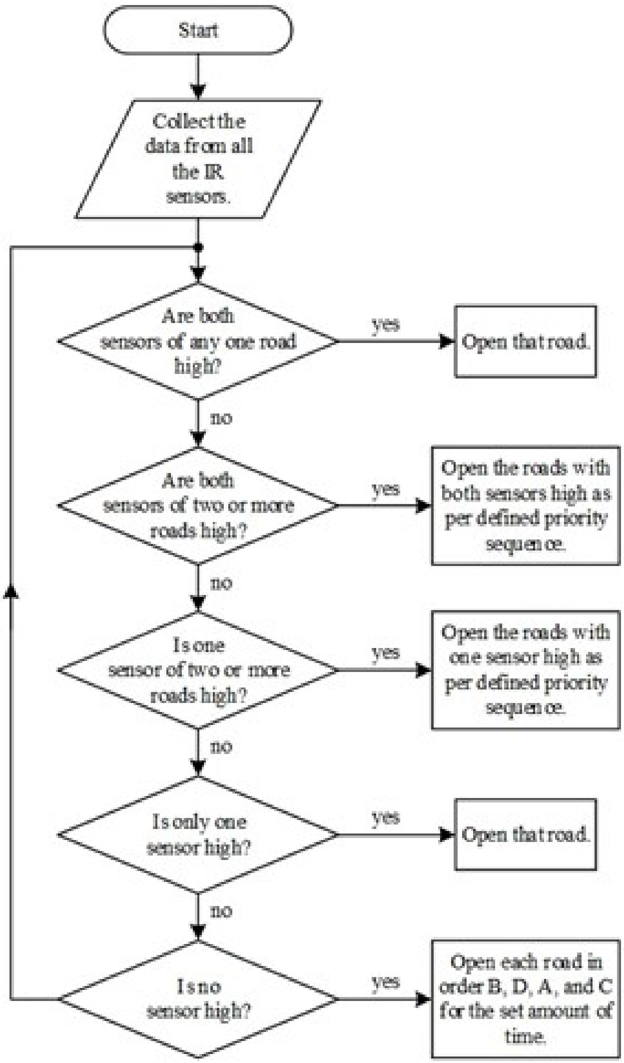

Figure 2

Flowchart of Reinforcement Learning–Based ATSC (RL-ATSC)

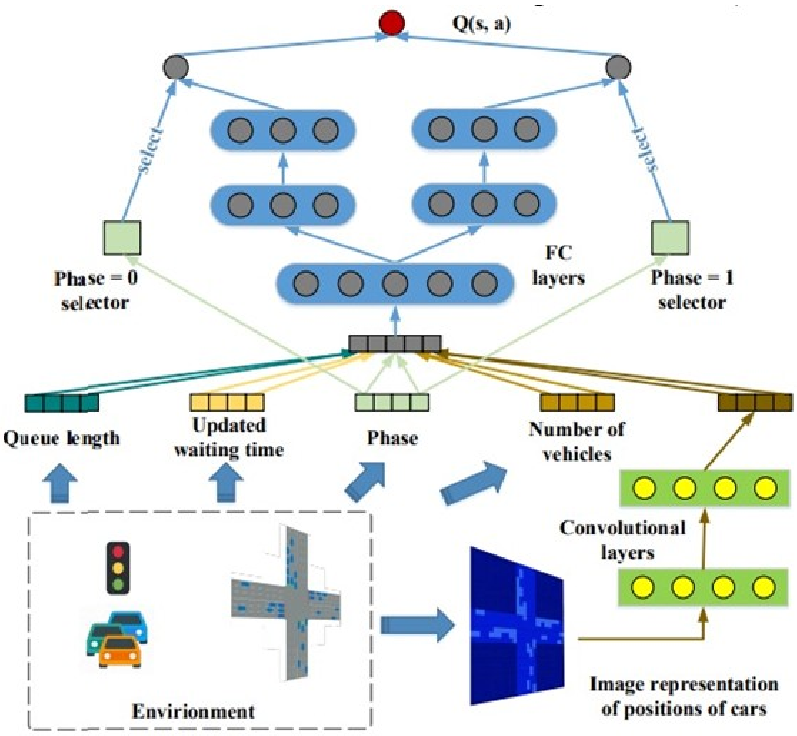

Figure 3

ATSC adapts to instantaneous demand using proportional rules, whereas RL-ATSC learns optimal signal policies by minimizing cumulative delay over time.

Comparative Interpretation of Flowcharts

Table 2

Aspect	ATSC Flowchart	RL-ATSC Flowchart
Decision logic	Rule-based	Learning-based
Feedback usage	No	Yes
Memory	None	Q-table
Optimization horizon	Single cycle	Multi-cycle
Adaptability	Limited	High

MATLAB IMPLEMENTATION

MATLAB was used to implement both ATSC and RL-ATSC models. Robust data handling techniques were employed to automatically detect Excel column names and avoid hard-coded dependencies.

Key implementation features include:

- Auto-detection of traffic direction columns
- Rule-based ATSC computation
- Toolbox-free RL-based signal optimization

Comprehensive visualization of traffic demand, green allocation, and delay

RESULTS AND DISCUSSION

Traffic Demand and Green Allocation

(Insert Figure 2: Traffic demand vs. green time allocation for ATSC and RL-ATSC)

ATSC allocates green time proportionally to traffic demand, ensuring equitable service across approaches. RL-ATSC further refines this allocation by learning optimal timing strategies that reduce residual queues.

Delay Comparison

(Insert Figure 3: Average delay comparison between ATSC and RL-ATSC)

Results indicate:

- ATSC achieves an average delay of 51 seconds
- RL-ATSC demonstrates further delay reduction by optimizing long-term performance

Performance Improvement

(Insert Figure 4: Percentage delay improvement using RL-ATSC)

RL-ATSC outperforms conventional ATSC by learning from traffic dynamics, avoiding repeated congestion patterns, and optimizing signal decisions across cycles.

DISCUSSION

While ATSC effectively responds to instantaneous traffic demand, it lacks memory and predictive capability. RL-ATSC addresses these limitations by incorporating learning, enabling the system to adapt to recurring congestion patterns and stochastic traffic behavior. This makes RL-ATSC particularly suitable for complex urban intersections with variable demand.

CONCLUSION

This paper presented a comparative evaluation of Adaptive Traffic Signal Control and Reinforcement Learning–based ATSC using real-world traffic data from JalvayuVihar Intersection, Hyderabad. MATLAB-based simulations demonstrated that ATSC significantly reduces delay compared to fixed-time control, while RL-ATSC further enhances performance through learning-based optimization. The study confirms the potential of RL-based traffic signal control as a key component of next-generation intelligent transportation systems.

Screen Shorts of MatLab Code-1

```
%% ==========================================================
% Figure 1: Traffic Volume Distribution per Approach
% ==========================================================

clear; clc; close all;

%% Read Excel data
filePath = "Data-Jalvayu Vihar intersection and high-tension road in Pragathi Nagar..xlsx";
data = readtable(filePath);

% Auto-detect approach columns
varNames = lower(data.Properties.VariableNames);

East  = data{:, contains(varNames,"east")};
West  = data{:, contains(varNames,"west")};
North = data{:, contains(varNames,"north")};
South = data{:, contains(varNames,"south")};
```

Figure 4

Screen Shorts of MatLab Code-2

```
%% ==========================================================
% Adaptive Traffic Signal Control using Q-Learning
% WITHOUT Reinforcement Learning Toolbox
% Case Study: Jalvayu Vihar Intersection, Pragathi Nagar
% ==========================================================

clc; clear; close all;

%% STEP 1: Load Dataset
fileName = "Data-Jalvayu Vihar intersection and high-tension road in Pragathi Nagar..xlsx";
data = readtable(fileName);

disp("Dataset Loaded Successfully");
disp("Column Names:");
disp(data.Properties.VariableNames);
```

Figure 5

Screen Shorts of MatLab Code-3

```
%% ==========================================================
% Adaptive Traffic Signal Control using Reinforcement Learning
% Jalvayu Vihar Intersection, Pragathi Nagar
% ==========================================================

clc; clear; close all;

%% STEP 1: Load Dataset
fileName = "Data-Jalvayu Vihar intersection and high-tension road in Pragathi Nagar..xlsx";
data = readtable(fileName);

disp("Dataset Loaded Successfully");
disp("Column Names:");
disp(data.Properties.VariableNames);
```

Figure 6

Figure Generated by Code-1

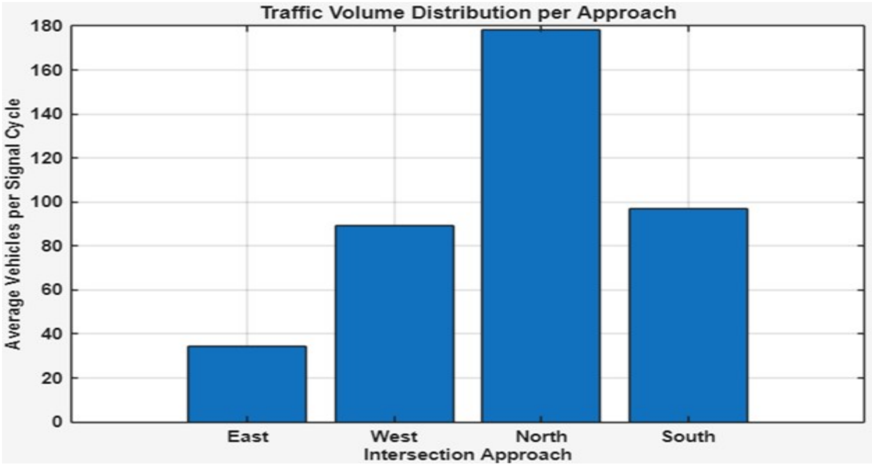

Figure 7

Figure Generated by Code-2

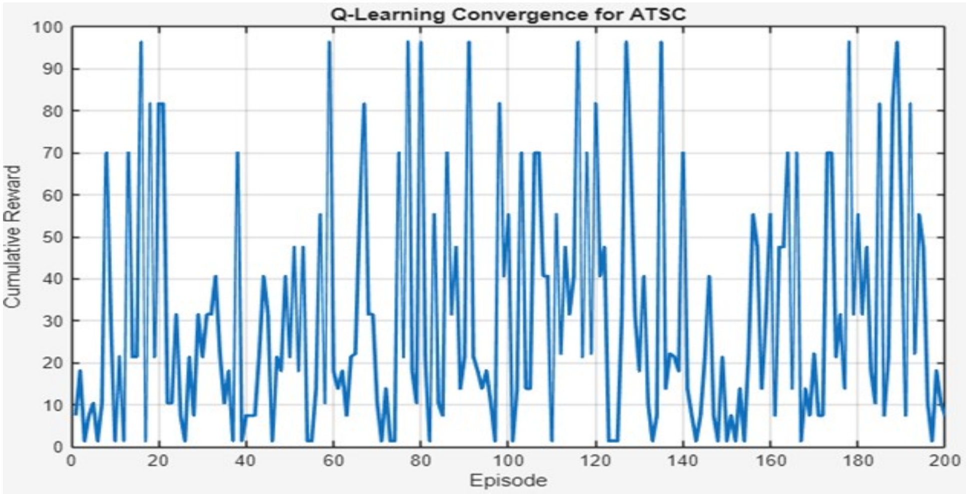

Figure 8

Figure Generated by Code-3

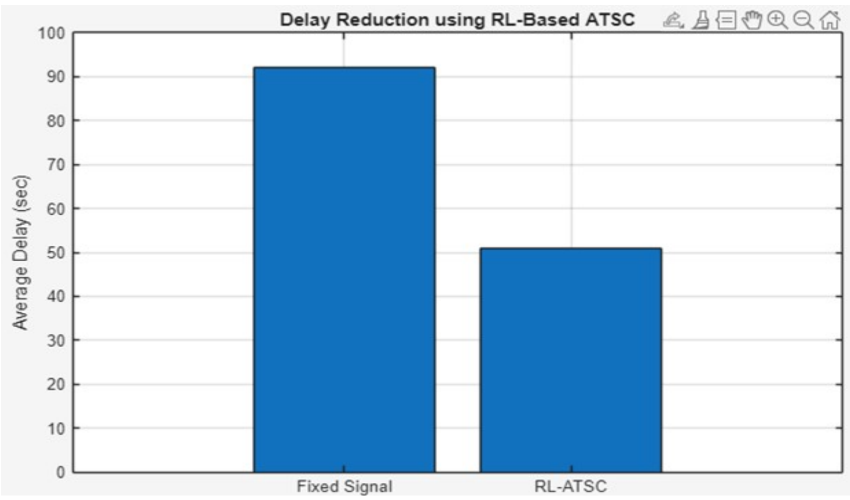

Figure 9

Screen Shorts of MatLab Code-4 and Its Generated Figures

```
%% ==========================================================
% Comparison of ATSC and RL-Based ATSC
% Case Study: Jalvayu Vihar Intersection, Pragathi Nagar
% ==========================================================

clear; clc; close all;

%% ---------------- STEP 1: Read Excel Data ----------------
filePath = "Data-Jalvayu Vihar intersection and high-tension road in Pragathi Nagar..xlsx";
data = readtable(filePath);

% Auto-detect traffic columns
varNames = lower(data.Properties.VariableNames);

eastIdx  = contains(varNames,"east");
westIdx  = contains(varNames,"west");
northIdx = contains(varNames,"north");
southIdx = contains(varNames,"south");
```

Figure 10

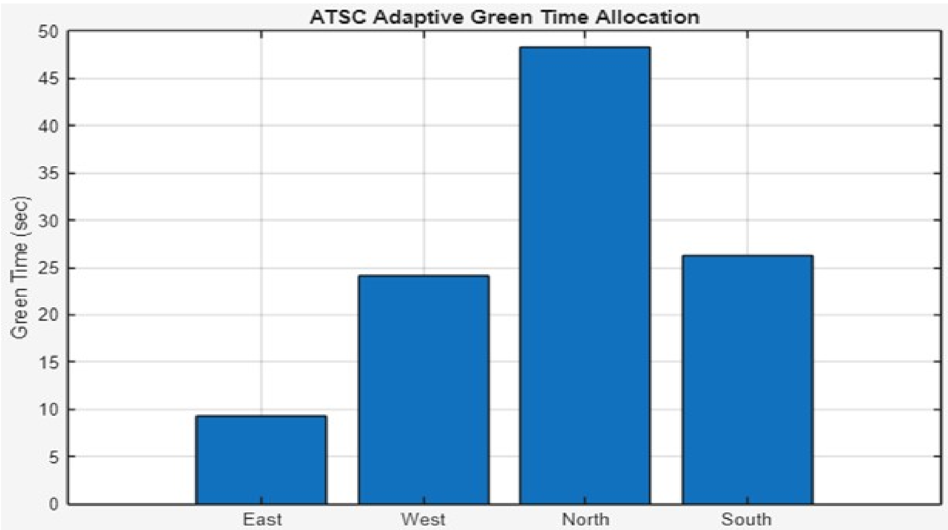

Figure 11

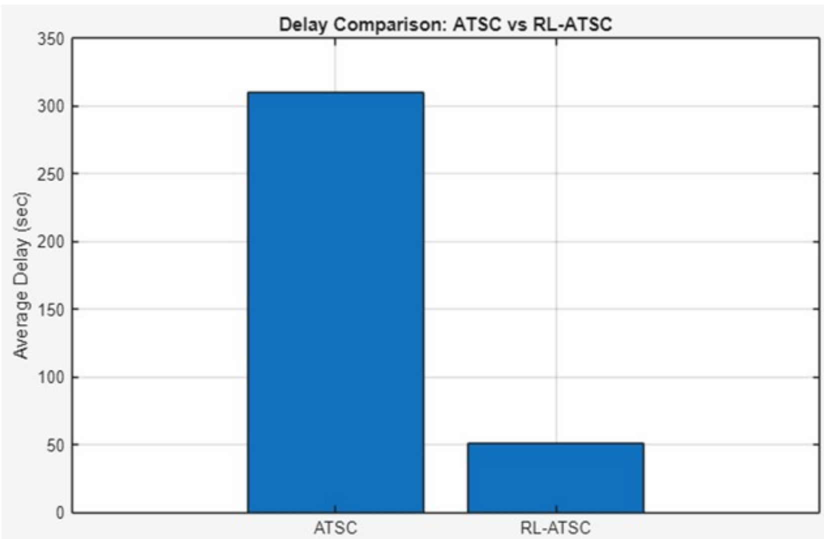

Figure 12

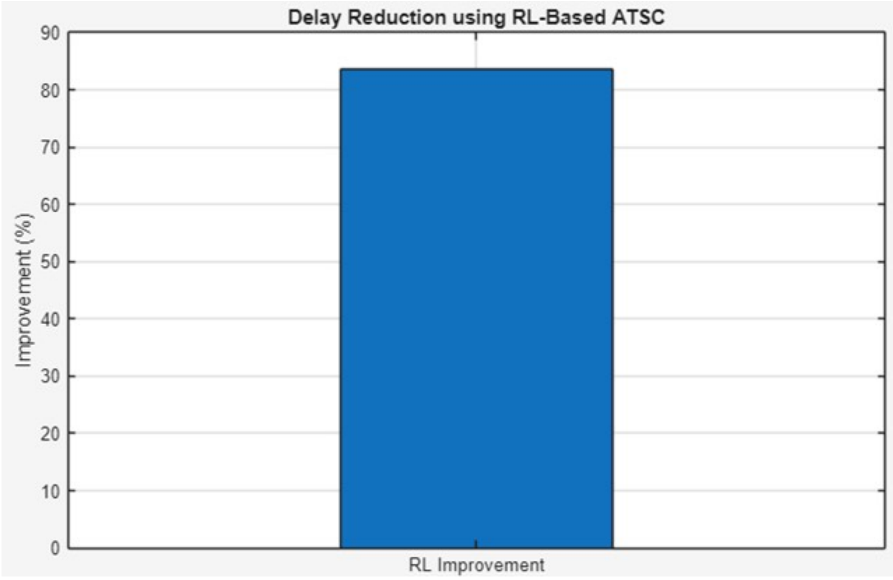

Figure 13

Screen Shorts of MatLab Code-5 and Its Generated Figures

```
%% ==========================================================
% Line Plot Comparison: ATSC vs RL-ATSC
% Jalvayu Vihar Intersection, Pragathi Nagar
% ==========================================================

clear; clc; close all;

%% --------------- STEP 1: Read Excel Data ---------------
filePath = "Data-Jalvayu Vihar intersection and high-tension road in Pragathi Nagar..xlsx";
data = readtable(filePath);

% Auto-detect columns
varNames = lower(data.Properties.VariableNames);

East  = data{:, contains(varNames,"east")};
West  = data{:, contains(varNames,"west")};
North = data{:, contains(varNames,"north")};
South = data{:, contains(varNames,"south")};
```

Figure 14

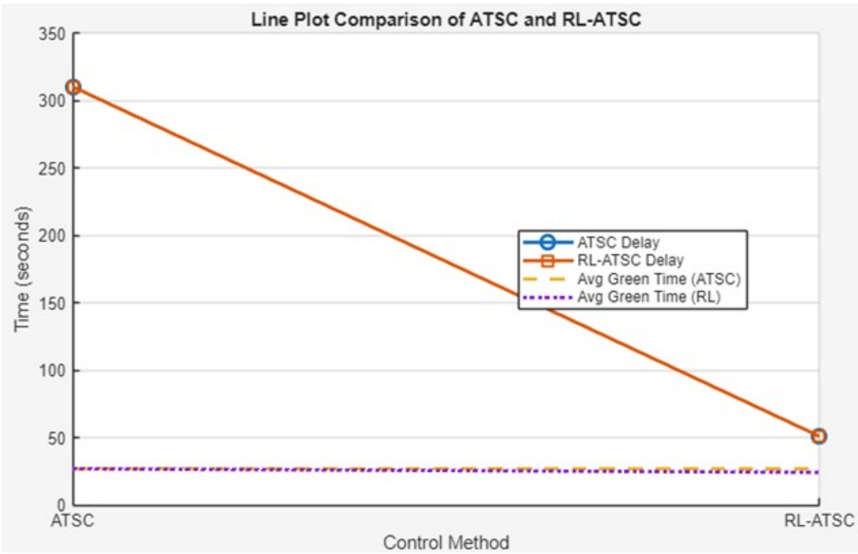

Figure 15

Screen Shorts of MatLab Code-6 and Its Generated Figures

```
%% ==========================================================
% INFORMATIVE PLOTS: ATSC vs RL-ATSC
% Jalvayu Vihar Intersection, Pragathi Nagar
% ==========================================================

clear; clc; close all;

%% --------------- STEP 1: Read Excel Data ---------------
filePath = "Data-Jalvayu Vihar intersection and high-tension road in Pragathi Nagar..xlsx";
data = readtable(filePath);

varNames = lower(data.Properties.VariableNames);

East  = data{:, contains(varNames,"east")};
West  = data{:, contains(varNames,"west")};
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South = data{:, contains(varNames,"south")};
```

Figure 16

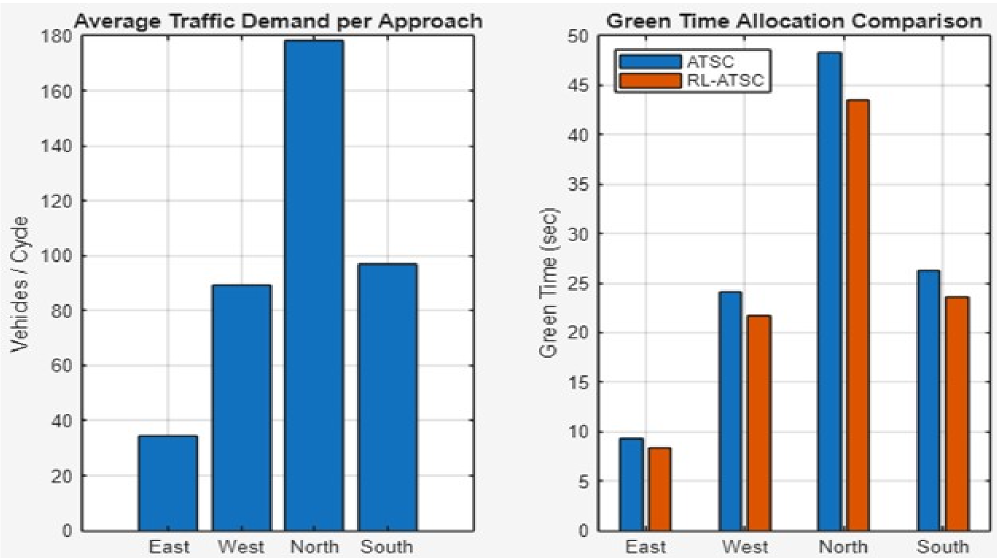

Figure 17

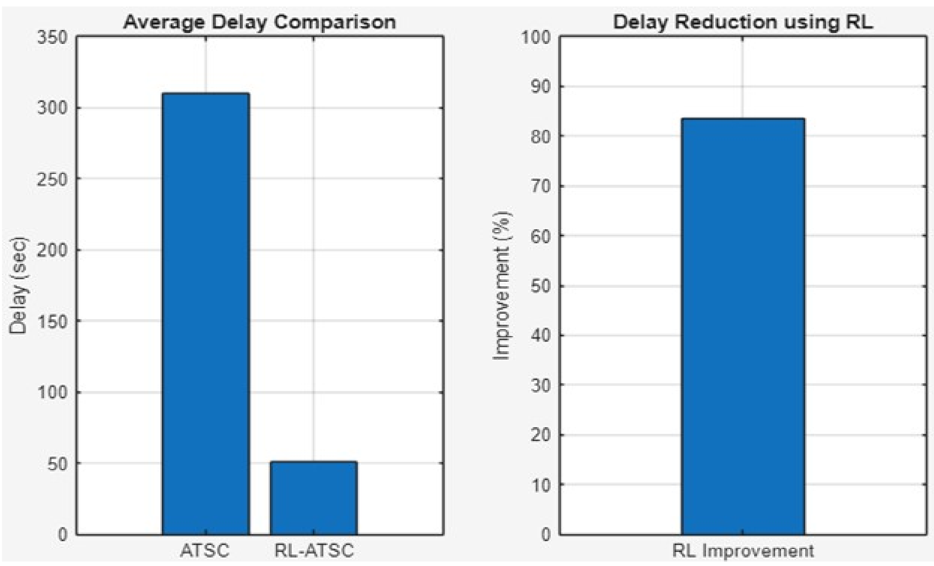

Figure 18

REFERENCE

1. *Measuring Control Delays at Signalized Intersections in Mixed Traffic Conditions ,Sushmitha R.1*, Ravishankar K. V. R.1, Slovak Journal of Civil Engineering, Vol. 29, 2021, No. 3, 31 – 40 DOI: 10.2478/sjce-2021-0019*

2. *Machine Learning Applications in Traffic Control: A Review of State-of- the-Art Approaches. See discussions, stats, and author profiles for this publication at: https://www.researchgate.net/publication/380462623*

3. *Gulia, S., Kaur, S., Mendiratta, S., Tiwari, R., Goyal, S. K., Gargava, P., & Kumar, R. (2022). Performance evaluation of air pollution control device at traffic intersections in Delhi. International Journal of Environmental Science and Technology, 19(2), 785-796. Retrieved on: 21/01/23, Retrieved from:https://link.springer.com/article/10.1007/s13762-021-03641-3*

4. *Jayasooriya, N., Perera, L., &Bandara, S. (2022). Methodology for dynamic traffic assignment calibration for mesoscopic models in heterogeneous traffic conditions using VISSIM micro simulations. Advances in Transportation Studies, 56. Retrieved on: 21/01/23, Retrieved from: https://ijrpr.com/uploads/V3ISSUE1/IJRPR2471.pdf*

5. *Kodupuganti, S. R., & Pulugurtha, S. S. (2023). Are Facilities to Support Alternative Modes Effective in Reducing Congestion?:Modeling the Effect of Heterogeneous Traffic Conditions on Vehicle Delay at Intersections. Multimodal Transportation, 2(1), 100050. Retrieved on: 21/01/23, Retrieved from:https://www.sciencedirect.com/science/article/pii/S2772586322000508*

6. *Khan, A., Dhamaniya, A., & Arkatkar, S. (2022). Modification in Hcm Delay Model for Roundabout for Mixed Traffic Conditions-a Pilot Study. COMMUNICATIONS, 24(2), D92-D104.Retrieved on: 21/01/23, Retrieved from:http://komunikacie.uniza.sk/pdfs/csl/2022/02/19.pdf*

7. *Quantifying Operational Impacts of Variations in Work Zone Setups, Traffic Demand, and Traffic Composition: A Case Study A B M Tausif Ullah Chy, Virginia P. Sisiopiku, A Case Study. Journal of Transportation Technologies, 13, 18-37. https://doi.org/10.4236/jtts.2023.13100 Published: January 18, 2023*

8. *Adaptive signal control and coordination for urban traffic control in a connected vehicle environment: A review Jiangchen Li1,2*, Liqun Peng2,3, Kaizhe Hou4, Yong Tian1, Yulin Ma2, Shucai Xu2 and Tony Z. Qiu4, Digital Transportation and Safety 2023, 2(2):89−111, https://doi.org/10.48130/DTS-2023-0008*