Journal of Science Research and Reviews

PRINT ISSN: 1595-9074
E-ISSN: 1595-8329
DOI: https://doi.org/10.70882/josrar.2025.v2i6.135
Homepage: https://josrar.esrgngr.org

Original Research Article

An Intelligent Hybrid Learning Framework Integrating ANFIS, Genetic Algorithms, and Reinforcement Learning for Traffic Signal Control

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KEYWORDS

Intelligent Traffic Signal Control,
Reinforcement Learning,
Traffic Congestion Mitigation,
Hybrid Optimization,
ANFIS–GA–RL framework.

ABSTRACT

Rapid urbanization and increasing vehicular demand have intensified traffic congestion, exposing the limitations of conventional static traffic signal control systems. This study proposes a novel hybrid intelligent traffic control framework that integrates an Adaptive Neuro-Fuzzy Inference System, Genetic Algorithm, and Reinforcement Learning (ANFIS–GA–RL) to achieve real-time adaptive signal optimization. The proposed approach uniquely combines interpretable fuzzy reasoning for managing uncertainty, genetic algorithms for global parameter optimization, and reinforcement learning for closed-loop, real-time decision-making, distinguishing it from existing standalone and partially hybrid methods. Performance is evaluated in a MATLAB-based urban traffic simulation using eight performance indicators, travel time, average vehicle speed, throughput, traffic density, queue length, delay time, intersection delay, and computational time. Comparative results against conventional Fuzzy Logic, standalone Genetic Algorithm, Artificial Neural Network, ANFIS, and ANFIS–GA controllers demonstrate consistent and measurable performance gains. Relative to the baseline fuzzy logic controller, the proposed ANFIS–GA–RL model achieves an overall improvement of 64.9%, characterized by substantial reductions in travel time delay, intersection delay, and computational overhead, alongside enhanced throughput and traffic flow stability. These findings confirm the robustness, scalability, and real-time applicability of the proposed framework for intelligent urban traffic signal control, with future work focusing on IoT-enabled deployment and field validation.

CITATION

Dodo, E. J., Onwodi, G., & Okure, O. (2025). An Intelligent Hybrid Learning Framework Integrating ANFIS, Genetic Algorithms, and Reinforcement Learning for Traffic Signal Control. *Journal of Science Research and Reviews*, 2(6), 21-39. https://doi.org/10.70882/josrar.2025.v2i6.135

INTRODUCTION

Intelligent traffic optimization has emerged as a critical solution to the growing challenges of urbanization, traffic congestion, and road safety in modern transportation systems. With the rapid expansion of urban populations which is projected to reach 68% of the global population by 2050 (Javed et al., 2024) cities worldwide face escalating traffic inefficiencies, environmental pollution, and economic losses. In developing regions, such as Africa, rapid urbanization has led to the rise of "accidental megacities," such as Lagos, Nigeria, where infrastructural deficiencies and poor traffic management exacerbate congestion (Oyewo & Oyewale, 2023). The consequences are severe: prolonged travel times, increased accidents, and significant economic burdens, with road traffic crashes costing nations an estimated 3% of their GDP annually (WHO, 2018).

Road transport dominates Nigeria, accounting for 80% of all traffic (Aderibigbe et al., 2024), yet the sector suffers from inadequate infrastructure, insufficient funding, and outdated traffic control systems. While developed nations leverage advanced technologies such as AI and IoT for traffic management, many developing countries still rely on static or semi-dynamic systems that fail to adapt to real-time conditions (Faheem et al., 2024). Traditional methods, such as fixed-time traffic signals, lack responsiveness, while actuated control systems struggle with predictive capabilities (Jutury et al., 2023). Manual interventions are inefficient and error-prone, highlighting the urgent need for intelligent, adaptive solutions. Recent advancements in artificial intelligence particularly fuzzy logic, genetic algorithms (GA), and deep reinforcement learning (DRL) offer promising avenues for traffic optimization. Fuzzy logic handles uncertainty in traffic data but requires complex tuning (Jutury et al., 2023). GA optimizes signal timing but faces slow convergence (Yektamoghadam et al., 2024), while DRL enables autonomous learning but demands extensive training data (Nookala et al., 2023). Hybrid approaches, such as integrating Adaptive Neuro-Fuzzy Inference Systems (ANFIS) with GA and DRL, aim to overcome these limitations by combining adaptability, optimization, and real-time learning (Bi et al., 2024). This survey explores the integration of ANFIS, GA, and DRL in Intelligent Traffic Optimization Systems (ITOS), evaluating their effectiveness in reducing congestion, improving safety, and enhancing traffic flow efficiency. By synthesizing key studies and methodologies, we highlight the potential of hybrid AI models to transform urban mobility, particularly in underserved regions like Nigeria. The discussion also addresses challenges such as computational costs and real-world deployment and proposes future directions, including IoT integration and scalable implementations. The findings underscore the transformative potential of AI-driven traffic management, offering a roadmap for policymakers and researchers to develop sustainable, adaptive transportation systems in an increasingly urbanized world.

Related Work

Traffic congestion is a global issue, costing economies billions annually (INRIX, 2023). Traditional systems, such as fixed-time signals and actuated control, fail to adapt to dynamic traffic conditions (Vieira et al., 2024). Machine learning and computational intelligence have emerged as promising solutions, yet challenges like computational overhead and real-time adaptability persist (Merbah et al., 2023). Traffic optimization is crucial for addressing the challenges posed by urbanization, congestion, and road safety while promoting environmental sustainability (Alamoudi et al., 2024); (Niu et al., 2023). The integration of intelligent transportation systems (ITS) offers a promising solution to mitigate traffic congestion and reduce carbon emissions, aligning with the development of smart citie (Lv & Shang, 2023). However, unique challenges persist, particularly in developing countries, necessitating tailored strategies (Mai-Tan et al., 2020).

Global Traffic Congestion and Its Economic Impact

Traffic congestion presents a significant economic burden globally. In 2022, the United States experienced losses of $120 billion due to congestion, with drivers spending an average of 51 hours in traffic (Dimri et al., 2024). London stands out as the most congested city in Europe, where drivers lose approximately 148 hours annually due to traffic delays (Dimri et al., 2024). In Asia, cities such as Mumbai and Bangkok encounter severe congestion, with average speeds plummeting to 10 km/h during peak hours (Dimri et al., 2024.

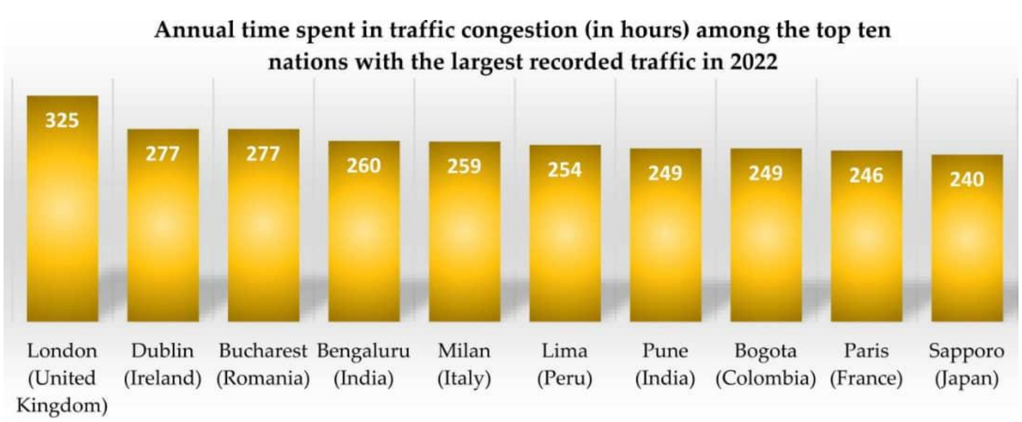

Figure 1: Annual Time Spent in Traffic Congestion (in Hours) Among the Top Ten Nations with the Largest Recorded Traffic in 2022 *Source:* (Dimri et al., 2024)

Several factors contribute to traffic congestion, including the increasing number of vehicles, inadequate transportation infrastructure, and the lack of effective traffic management systems (Mai-Tan et al., 2020); (Praveen & Raj, 2020). Addressing these underlying causes is essential to alleviate congestion and minimize its economic impact.

Road Safety: A Critical Global Challenge

Road safety is another critical challenge globally. The World Health Organization (WHO) reported that approximately 1.3 million people die annually due to road traffic accidents, with low- and middle-income countries accounting for 93% of fatalities despite having only 60% of the world's vehicles (WHO, 2023). Inefficient traffic management systems, poor infrastructure, and lack of real-time monitoring exacerbate these issues. According to the World Bank and World Health Organization (WHO) reports, road traffic injuries were ranked as the 9th leading cause of death worldwide in 2004. Projections suggested that by 2030, road traffic accidents would rise to become the 5th leading cause of death, surpassing diseases like tuberculosis and HIV/AIDS.

Leading causes of death, 2004 and 2030 compared

TOTAL 2004			TOTAL 2030		
RANK	LEADING CAUSE	%	RANK	LEADING CAUSE	%
1	Ischaemic heart disease	12.2	1	Ischaemic heart disease	12.2
2	Cerebrovastulor disease	9.7	2	Cerebrovasculor disease	9.7
3	Lower respiratory infections	7.0	3	Chronic obstructive pulmonary disease	7.0
4	Chronic obstructive pulmonary disease	5.1	4	Lower respiratory infections	5.1
5	Diarrhoeal diseases	3.6	5	Road traffic injuries	3.6
6	HIV/AIDS	3.5	6	Trachea, bronchus, lung cancers	3.5
7	Tuberculosis	2.5	7	Diabetes mellitus	2.5
8	Trachea, bronchus, lung cancers	2.3	8	Hypertensive heart disease	2.3
9	Road traffic injuries	2.2	9	Stomach cancer	2.2
10	Prematurity and low birth weight	2.0	10	HIV/AIDS	2.0
11	Neonatal infections and other	1.9	11	Nephritis and nephrosis	1.9
12	Diabetes mellitus	1.9	12	Self-inflicted injuries	1.9
13	Malaria	1.7	13	Liver cancer	1.7
14	Hypertensive heart disease	1.7	14	Colon and rectum cancer	1.7
15	Birth asphyxia and birth trauma	1.5	15	Oesophogus cancer	1.5
16	Self-inflicted injuries	1.4	16	Violence	1.4
17	Stomach cancer	1.4	17	Alzheimer and other dementias	1.4
18	Cirrhosis of the liver	1.3	18	Cirrhosis of the liver	1.3
19	Nephritis and nephrosis	1.3	19	Breast cancer	1.3
20	Colon and rectum cancers	1.1	20	Tuberculosis	1.1

Source: World health statistics 2008 (http://www.who.int/whosis/whostat/2008/en/index.html)

Figure 2: Projected Global Leading Causes of Death (2004–2030) Source: World Health Statistics. http://www.who.int/whosis/whostat/2008/en/index.html.

Intelligent Transportation Systems for Enhanced Traffic Management

Intelligent transportation systems (ITS) offer innovative approaches to enhance traffic management, improve road safety, and reduce environmental impact (Lv & Shang, 2023). These systems integrate advanced technologies, such as artificial intelligence (AI), the Internet of Things (IoT), and machine learning, to optimize traffic flow and provide real-time information to drivers (Muhammad et al., 2020); (Ma et al., 2019).

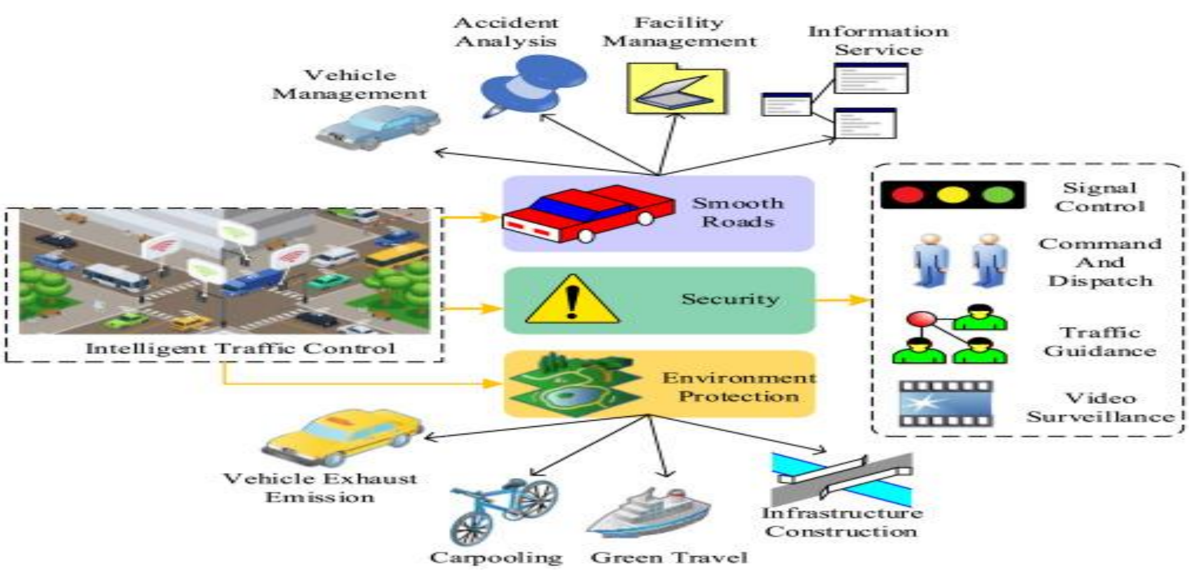

Figure 3: Intelligent Traffic Control Source: (Lv & Shang, 2023)

Intelligent Traffic Control Systems (ITCS) significantly reduce traffic congestion and travel time (Jaleel et al., 2020), enhance road safety with fewer accidents (Uma & Eswari, 2021), lower fuel consumption and vehicle emissions (Lv & Shang, 2023), and improve mobility and accessibility for all road users (Alamoudi et al., 2024).

Traffic Management Strategies

Based on the analyzed data, ITS employs various traffic management strategies to optimize traffic flow (Amador et al., 2024); (Ren et al., 2011). These strategies include:

1. Adaptive Traffic Signal Control: Adjusting traffic signal timings in real-time based on current traffic conditions (Jaleel et al., 2020).
2. Rerouting: Providing drivers with alternative routes to avoid congested areas (Khatri et al., 2020).
3. Incident Management: Quickly detecting and responding to traffic accidents to minimize disruption (Liu et al., 2023).

Data Sources for Intelligent Traffic Monitoring and Prediction

Intelligent traffic monitoring uses fixed sensors, mobile data, and contextual information for accurate prediction. Inductive loops, RFID, and cameras track flow and congestion (Upadhyay et al., 2024; Alsahfi et al., 2024; Salunke et al., 2024; Pan et al., 2024; Qiu et al., 2024). Mobile sources like GPS, probe vehicles, Bluetooth, and GSM provide continuous traffic state data (Jeevan et al., 2024; Babiyola et al., 2023; Zhang et al., 2023; Carrese et al., 2021; Amer et al., 2024; Rabinovich, 2023), while event, weather, and social media inputs improve non-recurrent congestion prediction (Zhang et al., 2024; Das et al., 2024; Celar et al., 2024; Kim et al., 2025; Jain et al., 2023). Smart motorways and vehicular networks enhance real-time data and cooperative management (Krishna et al., 2024; Bintoro, 2024; Pasupuleti, 2024).

ANFIS GA RL and Hybrid Traffic Optimization Models

ANFIS Optimization Models

ANFIS-based approaches outperform traditional models like MLR, ANN, and SVM in traffic applications due to their ability to handle nonlinear and uncertain systems, achieving high accuracy and reducing delay and queue length (Udofia, 2019; Dong, 2018; Tripathi & Sharma, 2024). Hybrid ANFIS models using PSO, clustering, or wavelet preprocessing improve robustness and predictive performance (Mai & Ngo, 2021; Chen & Zhai, 2022). ANFIS is also applied in public transport optimization, pavement assessment, congestion risk modeling, ITS security, and V2V systems (Pilevari et al., 2021; Alawad & Kaewunruen, 2020; Usha et al., 2025). However, reliance on offline training and simulation-based validation limits real-time scalability (Ujong et al., 2025).

GA Optimization Models

Single Genetic Algorithm (GA) approaches have proven effective for traffic signal optimization by reducing travel time, delay, and queue lengths, with improvements up to 40% over fixed-time control (Mao et al., 2019). These methods optimize signal timings using selection, crossover, and mutation, sometimes enhanced with simple fuzzy rules or adaptive operators to improve convergence and stability (Fu, 2022; Hai et al., 2022). While most studies rely on simulations and small-scale networks, GA consistently outperforms traditional timing methods, providing a robust foundation for traffic management. Limitations include computational intensity and reduced scalability for complex real-world networks (Manh et al., 2020; Tiberio et al., 2022).

RL Optimization Models

Deep reinforcement learning (DRL) has emerged as a highly effective approach for adaptive traffic management, outperforming traditional fixed-time and actuated controls. Models such as DQN, PPO, Actor–Critic, and multi-agent DRL consistently reduce vehicle waiting times, queue lengths, and overall travel time, with improvements ranging from 25% to over 80% across single and multiple intersections (Ma et al., 2021; Wang et al., 2022; Pan, 2024; Faqir et al., 2024). Integrating advanced techniques like graph neural networks and LSTM forecasting enhances anticipatory control and network-wide coordination, improving throughput and reducing congestion (Hu, 2025; Yang et al., 2025; Abrol et al., 2024). DRL also enables joint optimization of safety, fuel consumption, and emissions while maintaining real-time adaptability. Although computationally intensive and dependent on high-quality traffic data, DRL's ability to learn from dynamic traffic conditions makes it a robust and scalable solution for modern urban traffic systems.

Hybrid Optimization Models

Hybrid traffic optimization approaches combining ANFIS, Genetic Algorithms (GA), and Deep Reinforcement Learning (DRL) have shown significant improvements in urban traffic management. GA-enhanced ANFIS models achieve superior traffic flow prediction (R^2 up to 99.8%) and improved signal timing (Olayode et al., 2023; Shahkar et al., 2023). Integrating fuzzy preprocessing with DRL reduces traffic conflicts and waiting times by 16–59%, while multi-agent DRL frameworks achieve up to 63% reductions in queues and waiting times (Bangalee & Ahmed, 2024; Mirbakhsh & Azizi, 2024; Moreno-Malo et al., 2024; Kumar et al., 2021). Hybrid GA–ML methods further accelerate convergence and decrease travel time by up to 45% under incident conditions (Mao et al., 2022). Overall, these hybrid systems provide dynamic, real-time, and scalable traffic control, though they require careful tuning and higher computational resources.

MATERIALS AND METHODS

This section presents the materials, data sources, system modeling approach, and methodological framework employed for the development of the proposed intelligent traffic signal control system. A model-driven and simulation-based research design was adopted to ensure analytical rigor, reproducibility, and applicability to real-time urban traffic environments.

Materials and Data Sources

The traffic state information used in this study includes vehicle arrival rate, queue length, traffic density, and delay, which collectively characterize real-time intersection conditions. These data were obtained from the U.S. Traffic Signal Dataset (Data.gov, 2023 URL: https://catalog.data.gov/dataset/traffic-signal-a46dd/resource/f724f512-df30-45f6-af28-9fdf620847e1) and subsequently adjusted to reflect traffic characteristics typical of developing urban environments, particularly Nigerian cities. For a typical Nigerian urban highway, the standard capacity is (C_{max} = 2000) vehicles/hour (HCM, 2022). Parameter scaling was performed on vehicle flow rates, saturation flow, and signal timing distributions based on standard traffic engineering guidelines. All simulations, model training, and performance evaluations were implemented in MATLAB R2023b.

Problem Formulation

The objective of this study is to develop a fully actuated and adaptive intelligent traffic control agent capable of managing signalized intersections in real time under dynamic and uncertain traffic conditions. Unlike conventional traffic control systems that rely on fixed schedules, handcrafted features, or offline optimization, the proposed framework adopts an end-to-end learning strategy in which real-time traffic states, obtained from sensors or vision-based systems, are directly translated into optimal traffic signal control actions. This enables responsive and continuous adaptation to fluctuating traffic demand.

Urban traffic signal control is formulated as a sequential decision-making problem, in which the operation of a signalized intersection evolves over discrete time steps. At each decision instant, the controller observes the current traffic condition and selects a control action that influences subsequent traffic states. This interaction is modeled as a Markov Decision Process (MDP), defined as:

$$E = \langle S, A, P, R, \gamma \rangle \quad (1)$$

In this formulation, the state space S represents real-time traffic conditions characterized by variables such as queue length, vehicle delay, traffic density, and arrival rate. The action space A consists of feasible traffic signal control decisions, including signal phase selection and green-time extension. The state transition probability $P(s' \mid s, a)$ describes the likelihood of the system evolving from the current traffic state s to a subsequent state s' following the execution of action a. The reward function $R(s, a)$ quantifies the immediate performance of each control decision and is designed to penalize congestion indicators such as excessive delay, queue accumulation, and frequent vehicle stops, while encouraging efficient traffic flow. The discount factor $\gamma \in (0,1)$ governs the trade-off between short-term performance gains and long-term traffic optimization objectives.

The system aims to minimize average delay, queue length, and stops, while maximizing throughput and traffic flow efficiency. Figure 4 illustrates possible signal phases, vehicle movements, and the intersection grid layout, providing the structural basis for the sequential decision-making formulation.

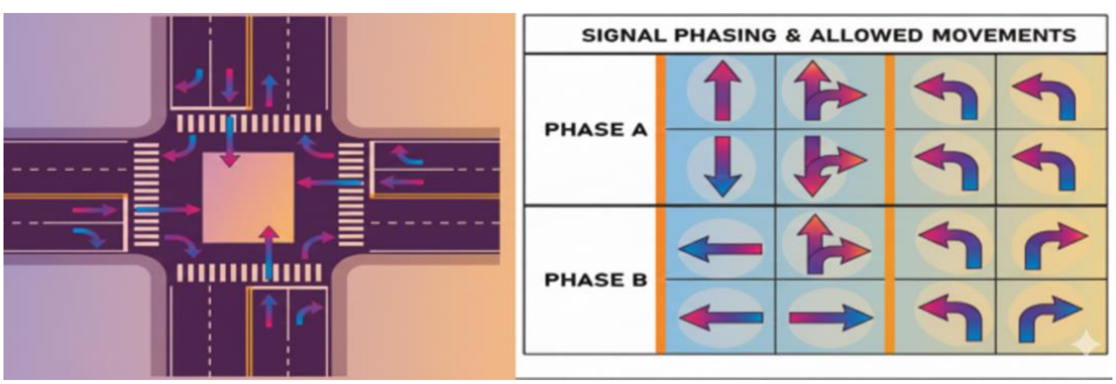

Figure 4: Possible Signal Phases and Vehicle Movements and an illustration of Intersection Grid Adapted (FHWA, 2017)

Methods

The Core Integrated Methodological Modules of the Hybrid Intelligent Traffic Optimization Framework consist of the following Modules;

Adaptive Neuro-Fuzzy Inference System (ANFIS) Module

The ANFIS module integrates fuzzy logic and neural networks to dynamically infer traffic patterns and optimize signal timings. Fuzzy membership functions categorize congestion into low, medium, and high levels, while neural learning refines control decisions using historical traffic data. Overall, ANFIS provides robust handling of uncertain and nonlinear traffic dynamics, models complex traffic relationships through fuzzy rules, and supports adaptive learning from data to continuously enhance rule-based decision-making.

ANFIS Layer

The ANFIS layer maps traffic inputs to control outputs using fuzzy inference, providing interpretable and adaptive decision-making. The operations include:

Fuzzification: Converts crisp traffic inputs (x_i) into fuzzy variables using membership functions ($\mu(x_i)$):

$$\mu_A(x) = \frac{1}{1+\left(\frac{x-c}{a}\right)^{2b}} \quad (2)$$

where (a, b, c) are membership function parameters (Olayode et al., 2023).

Fuzzy Inference: Applies rules of the form:

R_j:IF ρ is A_j AND q is B_j THEN $y_j = f_j(\mathbf{x})$ (3)

where (y_j) is the output of the (j)-th fuzzy rule and ($f_j(\mathbf{x})$) is a linear function of the inputs(Olayode et al., 2023)..

Defuzzification: Aggregates rule outputs into a crisp control signal (y):

$$y = \frac{\sum_{j=1}^{N} w_j y_j}{\sum_{j=1}^{N} w_j} \quad (4)$$

$$w_j = \prod_i \mu_{A_{ij}}(x_i) \quad (5)$$

Where, w_j represents the firing strength of each rule (Olayode et al., 2023).

Genetic Algorithm (GA) for Optimization

The Genetic Algorithm (GA) enhances traffic control by iteratively evolving optimal strategies for signal timing, lane prioritization, and emergency vehicle management. Its fitness function assesses performance based on metrics such as queue reduction, improved traffic flow, and minimized delays. In essence, the genetic algorithm (GA) plays a critical optimization role by refining ANFIS parameters, including membership functions and fuzzy rules, identifying optimal traffic signal control strategies for efficient intersection operation, and supporting the tuning of reinforcement learning parameters to enhance adaptive and responsive traffic control under dynamic conditions.

GA Optimization

The GA optimizes the ANFIS parameters (a, b, c) and rule weights to minimize the prediction error, defined by the Mean Square Error (MSE):

$$\text{MSE} = \frac{1}{n}\sum_{k=1}^{n}(y_k - \hat{y}_k)^2 \quad (6)$$

where y_k is the actual output and $\hat{y}_k$ is the ANFIS output (Agbaogun et al., 2023)..

GA operates through iterative selection, crossover, and mutation:

1. Selection: Chooses high-fitness chromosomes minimizing MSE.
2. Crossover: Exchanges parameter segments between parents.
3. Mutation: Introduces small random changes to parameters to maintain diversity.

The optimized ANFIS parameters define the state for the RL agent.

Reinforcement Learning (RL) Module

The proposed framework employs Reinforcement Learning (RL) to enable adaptive and data-driven traffic signal control under dynamic urban traffic conditions. The RL agent interacts continuously with the traffic environment, observes the current traffic state, selects appropriate signal control actions, and receives feedback in the form of rewards that reflect traffic performance objectives.

In this study, Q-learning is adopted as the core RL algorithm due to its simplicity, stability, and proven effectiveness in traffic signal control applications reported in the literature (Wei et al., 2022; Saadi et al., 2025). The traffic state space SSS comprises parameters such as queue length, traffic density, waiting time, and flow rate, while the action space *A* represents signal phase selection and green-time adjustment. The Q-value update rule is defined as:

$$Q(s_t, a_t) \leftarrow Q(s_t, a_t) + \alpha\left[r_t + \gamma \max_a Q(s_{t+1}, a) - Q(s_t, a_t)\right] \quad (7)$$

Where $s_t \in S$ is the current traffic state, $a_t \in A$ is the selected control action, r_t is the reward (e.g., reduction in queue length), and α is the learning rate and γ is the discount factor(Wei et al., 2022: Saadi, et al., 2025).

The RL agent iteratively improves traffic signal timing by continuously interacting with the environment.

where $s_t \in S$ denotes the current traffic state, at ∈ A is the selected control action, r_t is the immediate reward (e.g., reduction in queue length or delay), α is the learning rate, and γ is the discount factor.

The RL agent iteratively improves traffic signal timing by balancing exploration and exploitation, enabling it to adapt to fluctuating traffic demands and non-stationary traffic patterns. Within the proposed hybrid framework, ANFIS provides high-level traffic state estimation, GA optimizes system and learning parameters, and RL performs online decision refinement, resulting in improved convergence speed, reduced congestion, and enhanced traffic throughput.

Traffic Signal Control Execution
Final traffic signal decisions, including green light durations, phase sequences, and other timing parameters, are determined by integrating outputs from ANFIS, GA, and DRL. These parameters are dynamically updated to optimize traffic flow in real time while maintaining overall efficiency.

Feedback Loop
A continuous feedback mechanism ensures the system adapts to changing traffic conditions. Real-time measurements are fed back into the ANFIS, GA, and DRL modules, enabling ongoing learning and policy refinement.

Key Features
The proposed framework adopts a multi-layer hybrid architecture that balances interpretability, global optimization, and adaptive control, enabling effective decision-making across varying traffic conditions. Its closed-loop design continuously incorporates real-time traffic feedback to refine signal control actions, while the modular structure ensures scalability and reliable performance in complex and densely populated urban traffic networks.

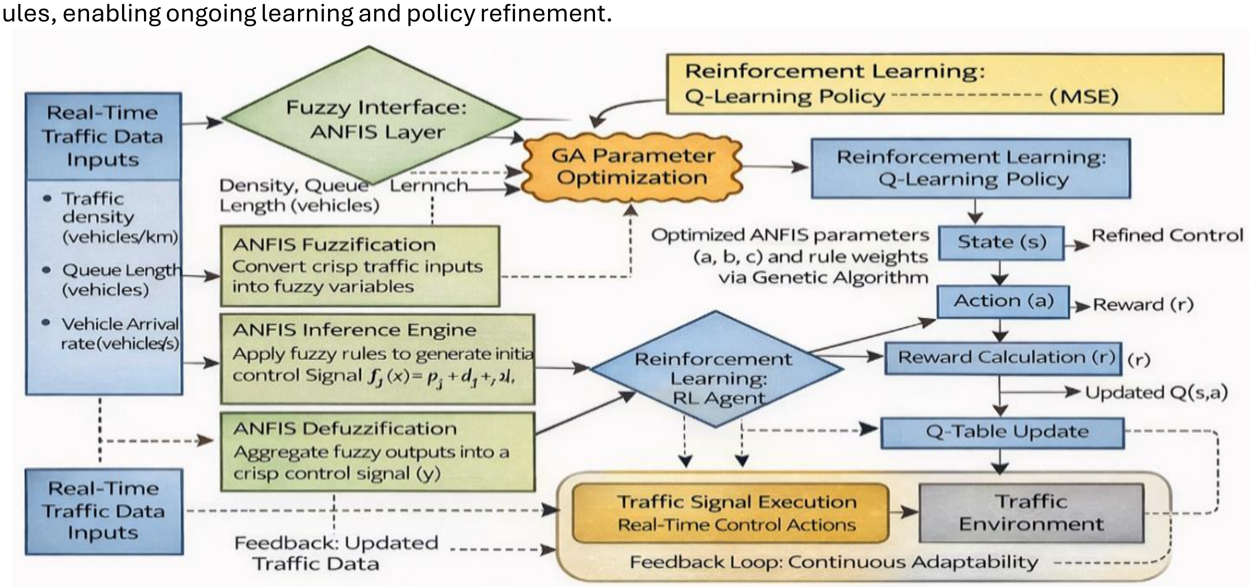

Figure 5: Integrated Methodology for Hybrid Intelligent Traffic Optimization System (Adapted from: Olayode et al., 2023; Michailidis et al.,2025; Author, 2025)

Figure 5 illustrates the workflow of the proposed hybrid ANFIS–GA–Reinforcement Learning intelligent traffic optimization methodology, which was adapted from existing studies and further refined to suit the objectives of this research. Variables are first processed by ANFIS through fuzzification, rule-based inference, and defuzzification to produce initial signal control outputs. GA then optimizes the ANFIS membership functions and rule weights by minimizing mean square error, improving robustness under varying traffic conditions. The optimized outputs form the state for a Q-learning–based reinforcement learning agent, which selects signal control actions using reward-driven updates. Implemented in a closed-loop manner, the system continuously incorporates real-time feedback, enabling adaptive signal control and sustained congestion reduction in dynamic urban traffic environments.

Evaluation Metrics
The Key Performance Indicators (KPIs) of the proposed traffic optimization model was evaluated using eight standard metrics widely adopted in transportation engineering. These indicators capture travel efficiency, congestion intensity, and intersection performance.

Travel Time (TT)
Travel Time denotes the average time required for a vehicle to traverse a specified route:

$$\text{TT} = \frac{D}{S} \tag{8}$$

where (D) is the travel distance and (S) is the vehicle speed (Transportation Research Board [TRB], 2022; Papageorgiou et al., 2021).

Traffic Density (TD)
Traffic Density measures the level of congestion within a road network:

$$\text{TD} = \frac{N}{A} \tag{9}$$

where (N) is the total number of vehicles and (A) represents the network area (TRB, 2022; Zheng et al., 2020).

Average Vehicle Speed (AVS)
The mean speed of all vehicles in the system is computed as:

$$\text{AVS} = \frac{\sum_{i=1}^{N} S_i}{N} \quad (10)$$

where S_i is the speed of the (i)-th vehicle and (N) is the total vehicle count (Wei et al., 2022; FHWA, 2023).

Queue Length (QL)

Queue Length quantifies the number of vehicles waiting at signalized intersections:

$$\text{QL} = N_{\text{queue}} \quad (11)$$

where N_{queue} denotes the total queued vehicles (TRB, 2022).

Delay Time (DT)

Delay Time measures additional time experienced due to congestion:

$$\text{DT} = \text{TT}_{\text{actual}} - \text{TT}_{\text{free-flow}} \quad (12)$$

where $\text{TT}_{\text{actual}}$ is observed travel time and $\text{TT}_{\text{free-flow}}$ is travel time under ideal conditions (TRB, 2022; FHWA, 2023).

Throughput (TP)

Throughput represents the number of vehicles passing a fixed point per time unit:

$$\text{TP} = \frac{N_{\text{vehicles}}}{T} \quad (13)$$

where N_{vehicles} is the number of passing vehicles and (T) is the observation window (Wei et al., 2022; Zhang et al., 2025).

Intersection Delay (ID)

Intersection Delay captures time lost by vehicles while traversing intersections:

$$\text{ID} = \frac{\sum_{i=1}^{N}(\text{TT}_{\text{intersection},}i - \text{TT}_{\text{free-flow}})}{N} \quad (14)$$

where $\text{TT}_{\text{intersection},}\, i$ is actual intersection travel time and $\text{TT}_{\text{free-flow}}$ is ideal crossing time (TRB, 2022).

Clearance Time (CT)

Clearance Time is the duration required for all queued vehicles to clear the intersection:

$$\text{CT} = \frac{\text{QL}}{S_{\text{flow}}} \quad (15)$$

where QL is the queue length and S_{flow} is the saturation flow rate (Wei et al., 2022).

Exact Normalization and Percentage Improvement Equation

For each performance Metric m, Normalization is defining as:

For minimization metrics (↓):

$$N_m = \frac{x_m^{baseline} - x_m^{model}}{x_m^{baseline}} \quad (16)$$

For Maximization metrics (↑)

$$N_m = \frac{x_m^{model} - x_m^{baseline}}{x_m^{baseline}} \quad (17)$$

For Overall Percentage Improvement (OPI) for a model is computed as

$$OPI\% = \frac{1}{M}\sum_{m=1}^{M} N_m \ x\ 100 \quad (18)$$

Where M is the total number of evaluated metrics and the baseline model is fuzzy logic (Wei et al., 2022).

Dataset and Adaptation

The proposed model utilized the U.S. Traffic Signal Dataset (Data.gov, 2023, URL: https://catalog.data.gov/dataset/traffic-signal-a46dd/resource/f724f512-df30-45f6-af28-9fdf620847e1) as a reference framework. To ensure relevance to Nigerian urban traffic conditions, key parameters including vehicle flow, traffic density, and signal timing were adapted using proportional scaling based on observed traffic data from major cities: Kaduna (2,651 veh/h/lane), Kano (3,675 veh/h/lane), and Lagos (3,896 veh/h/lane).

Data preprocessing involved normalization, outlier filtering, and temporal aggregation to generate realistic traffic flow patterns. Baseline traffic density ($X_m^{baseline}$; TD_base) and travel time (X_m^{model}; TT_base) were derived from the Fuzzy Logic model, while TD_model and TT_model corresponded to the optimized models, following the methodology of Wei et al. (2022). The baseline metrics were TT_0 = 0.57 h, TD_0 = 12 veh/km^2, and AVS_0 = 70.34 km/h.

This adaptation framework enabled the static U.S. dataset to accurately reflect Nigerian traffic behavior while supporting real-time simulation and performance evaluation of the proposed ANFIS-GA-RL traffic signal optimization model.

The Architecture of Intelligent Traffic Optimization Framework

The proposed framework integrates ANFIS, Genetic Algorithms, and Reinforcement Learning to achieve adaptive traffic signal control. ANFIS captures nonlinear traffic dynamics, GA optimizes its parameters, and RL selects optimal signal actions using performance-based rewards. The closed-loop system adapts in real time, improving congestion reduction, delay minimization, and overall traffic efficiency.

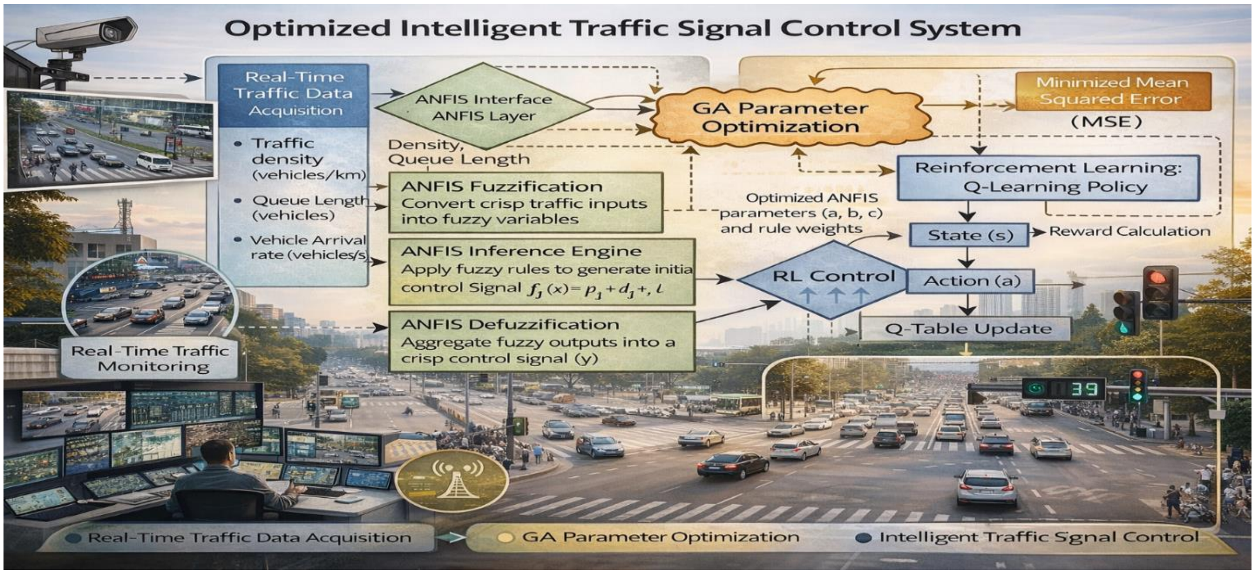

Figure 6: Architecture of Intelligent Traffic Optimization System Flow Diagram (Author, 2024)

Figure 6 illustrates a closed-loop hybrid framework that integrates ANFIS, Genetic Algorithm (GA), and Actor–Critic Deep Reinforcement Learning (AC-DRL) for adaptive traffic signal control. Real-time traffic inputs are processed by ANFIS to generate initial decisions, while GA optimizes its parameters to improve state accuracy. The optimized states are used by an AC-DRL agent, trained under a centralized training and decentralized execution scheme, to learn optimal signal timing and phase-switching actions aimed at reducing congestion and delay while improving throughput. Continuous feedback ensures adaptability to dynamic traffic conditions. Implemented in MATLAB R2023b and calibrated with data from U.S. Traffic Signal Dataset (Data.gov, 2023), adjusting parameters like vehicle flow, density, and signal timing to reflect Nigerian traffic conditions using proportional scaling, across key traffic efficiency metrics.

The Algorithm of Hybrid ANFIS–GA–RL Intelligent Traffic Optimization System (ITOS)

Step 1: Traffic State Initialization

Acquire real-time traffic data from sensors or camera systems at the intersection. Normalize and structure the inputs to form the current traffic state vector.

Input:

Real-time traffic data: traffic density (veh/km), queue length (veh), vehicle arrival rate (veh/s)

Output:

Optimized traffic signal timings (green duration, phase sequence)

Step 2: ANFIS-Based Fuzzy Processing

Convert the crisp traffic inputs into fuzzy linguistic variables using predefined membership functions. Apply fuzzy inference rules to model traffic conditions and generate intermediate control outputs. Aggregate and defuzzify the rule outputs to obtain an initial traffic signal control action.

Algorithm 1: ANFIS Traffic Control Evaluation

1. *Input: Traffic state x=[ρ,q,λ]*
   Output: Crisp control signal y
2. *Fuzzify x using membership functions defined by (a,b,c)*
3. *Apply fuzzy rules: y_j = f_j(x)*
4. *Compute firing strength w_j*
5. *Defuzzify: y = (Σ w_j y_j) / (Σ w_j)*
6. *Return y*

Step 3: Genetic Algorithm Optimization

Encode ANFIS membership function parameters and rule weights into chromosomes. Evaluate fitness using Mean Square Error (MSE). Apply selection, crossover, and mutation iteratively until convergence. Update ANFIS parameters with the globally optimized solution.

Algorithm 2: GA Optimization of ANFIS Parameters

1. *Input: Training data x=[ρ,q,λ]*
   Output: Optimized (a,b,c) and rule weights
2. *Initialize population P with chromosomes encoding (a,b,c)*
3. *Evaluate fitness using MSE = (1/N) Σ (y_actual − y_ANFIS)^2*
4. *Generation ← 0*
5. *while termination criterion not satisfied do*
6. *Generation ← Generation + 1*
7. *Select chromosomes with minimum MSE*
8. *Apply crossover with probability pc*
9. *Apply mutation with probability pm*
10. *Re-evaluate population fitness (MSE)*
11. *end while*
12. *Return best chromosome → optimized (a,b,c)*

Step 4: Reinforcement Learning Decision Making

Define the optimized ANFIS output as the system state. Select a traffic signal action using a Q-learning policy. Execute the action and compute the reward based on traffic improvement (e.g., reduced queue length). Update the Q-table accordingly.

Algorithm 3: Reinforcement Learning (Q-Learning) Signal Control

1. *State: S={x,y}*
   Action: A (signal phase / green time)
2. *Initialize Q(S,A) arbitrarily*
3. *Set learning rate α, discount factor γ, exploration ε*
4. *for episode = 1 to M do*
5. *Observe current state s ∈S*
6. *for t = 1 to T do*
7. *With probability ε select random action a*
8. *Else select a = argmax_a Q(s,a)*
9. *Execute a, observe reward r and next state s'*
10. *Update Q(s,a) ← Q(s,a) + α[r + γ max_a' Q(s',a') − Q(s,a)]*
11. *s ← s'*
12. *end for*
13. *end for*

Step 5: Traffic Signal Execution

Implement the selected signal timing parameters in the traffic signal controller in real time.

Step 6: Feedback and Adaptation

Observe the updated traffic environment and feed new measurements back into the system. Repeat Steps 2–5 continuously to ensure adaptive optimization.

Algorithm 4: Integrated Execution and Feedback Loop

1. *while system is active do*
2. *Acquire real-time traffic data x=[ρ,q,λ]*
3. *y ← ANFIS(x | optimized (a,b,c))*
4. *s ← {x,y}*
5. *Select action a using Q(s,a)*
6. *Execute traffic signal action a*
7. *Observe updated traffic state x'*
8. *Compute reward r (queue reduction / flow improvement)*
9. *Update Q-table*
10. *end while*

Simulation and Experiment Set-up

The proposed traffic control models, including Fuzzy Logic, ANN, ANFIS, GA, ANFIS-GA, and the novel ANFIS-GA-Reinforcement Learning (ANFIS-GA-RL) framework, were implemented in MATLAB R2023b using Simulink and Fuzzy Logic Toolbox. Simulations were conducted on a 4×4 urban intersection grid with four approaches per intersection and two lanes per approach, enabling realistic bidirectional traffic flow. Traffic signal phases followed standard green-yellow-red cycles, and pedestrian crossings were incorporated. Traffic demand scenarios spanned low to high congestion, with vehicle arrival rates of 300–1200 vehicles/hour per approach, modeled using a Poisson process to capture stochastic variability. Model hyperparameters were selected via preliminary tuning. The ANN used two hidden layers with 15 neurons each, a learning rate of 0.01, and 500 training epochs. The ANFIS employed three Gaussian membership functions per input and a hybrid learning algorithm. The GA used a population size of 50, crossover probability of 0.8, mutation rate of 0.05, and ran for 100 generations. The Reinforcement Learning component utilized Q-learning with a learning rate α = 0.1, discount factor γ = 0.9, and an ε-greedy policy with ε = 0.1. Performance was evaluated using Total Travel Time (TT), Average Vehicle Speed (AVS), Throughput (TP), Traffic Density (TD), Queue Length (QL), Delay Time (DT), Intersection Delay (ID), and Computational Time (CT), with 30 independent simulation runs per scenario to ensure statistical robustness.

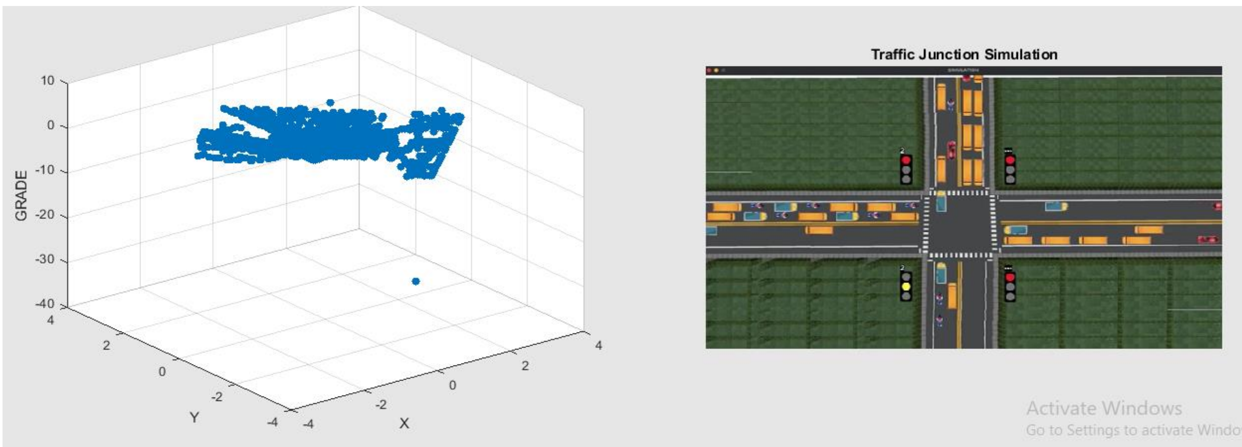

Figure 7: Simulation and Experiment Set-up

RESULTS AND DISCUSSION

The performance of the proposed hybrid traffic control framework was evaluated against benchmark models using eight standard Key Performance Indicators (KPIs). The comparative simulation results obtained in MATLAB are summarized in Table 1.

Table 1: Comparative Performance of Traffic Control Models Across Key Performance Indicators (KPIs)

Model	*TT(h↓*	*AVS (km/h) ↑*	*TP (veh/h)↑*	*TD (veh/km^2) ↓*	*QL (veh↓*	*DT (h)↓*	*ID (h)↓*	*CT (h)↓*	*Overall Improvement (%)*
Fuzzy Logic	0.57	70.34	129	12	15	0.67	0.02	0.013	—
GA (Standalone)	0.54	67.95	143	12	23	0.59	0.03	0.0142	9.1
ANN	0.42	71.39	139	11	18	0.52	0.01	0.0121	26.3
ANFIS	0.49	72.10	145	10	17	0.54	0.04	0.0134	18.4
ANFIS–GA	0.24	73.64	148	10	20	0.52	0.021	0.0122	57.9
Proposed ANFIS–GA–RL	0.20	72.36	150	10	20	0.50	0.01	0.0111	64.9

Note: ↓ and ↑ indicate minimization and maximization objectives, respectively. Overall improvement is computed relative to the fuzzy logic baseline Eqn.(16, 17 &18) Baseline values: ($X_m^{baseline}$_0 = 0.57) h, (X_m^{model}_0 = 12) veh/km^2, (AVS_0 = 70.34) km/h.

Comparative Analysis of Eight KPIs for Congestion Mitigation and Flow Efficiency

Figure 8-15 illustrates the line-graph comparison of eight Key Performance Indicators (KPIs) across six traffic control models: Fuzzy Logic, GA, ANN, ANFIS, ANFIS–GA, and the proposed ANFIS–GA–RL framework. Each line graph highlights the performance trajectory and relative dominance of the models for a specific KPI.

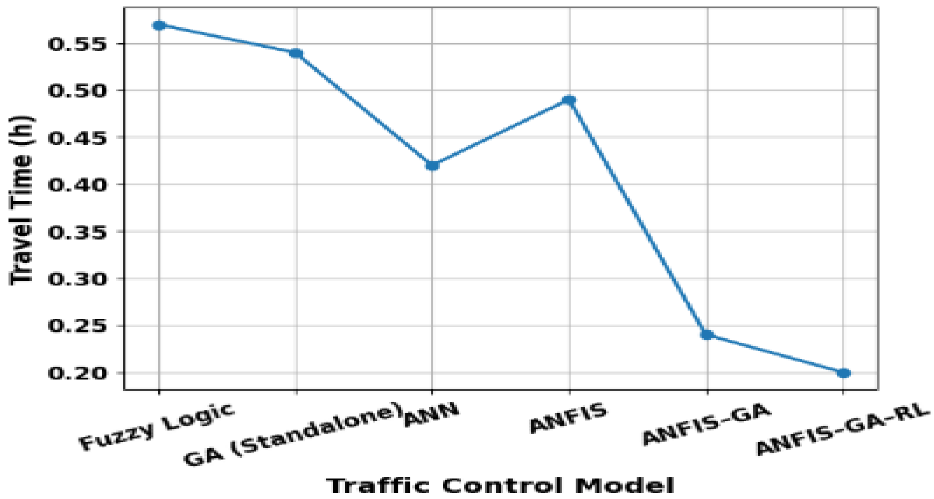

Figure 8: Travel Time (TT ↓)

Figure 8 the travel time line graph shows a nonlinear but consistently decreasing trend as model intelligence increases. Conventional Fuzzy Logic and GA exhibit the highest travel times, while ANN provides a noticeable reduction. A sharp decline is observed with ANFIS–GA, and the proposed ANFIS–GA–RL achieves the minimum travel time (0.20 h). This confirms the strong capability of reinforcement learning to continuously adapt signal timing decisions and minimize total journey duration under varying traffic conditions.

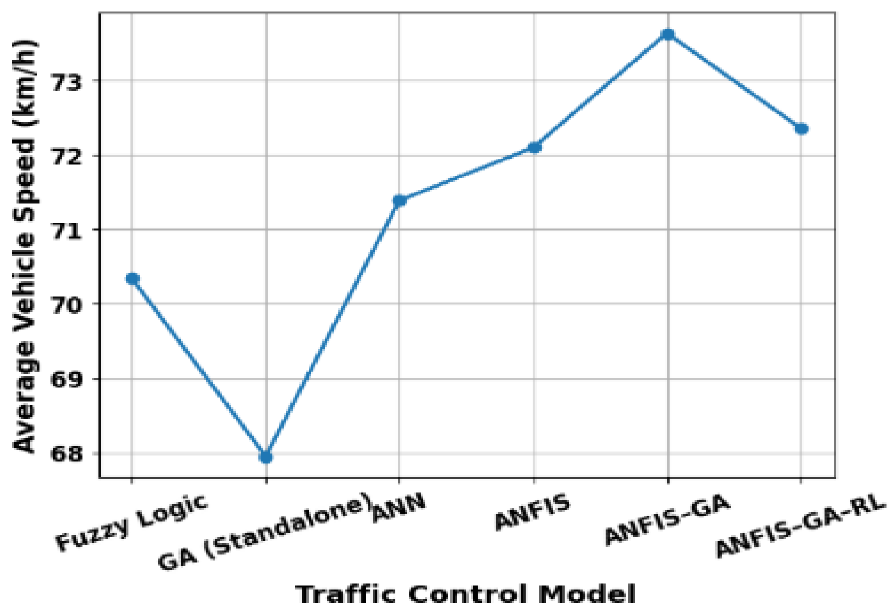

Figure 9: Average Vehicle Speed (AVS ↑)

Figure 9 the AVS line graph demonstrates a general upward trend, indicating improved traffic fluidity with hybridization. While GA shows a temporary dip due to its non-adaptive nature, ANN and ANFIS stabilize speed performance. ANFIS–GA reaches the peak AVS, whereas the proposed ANFIS–GA–RL maintains high and stable average speeds, reflecting smoother flow with reduced speed oscillations—an important indicator of driving comfort and safety.

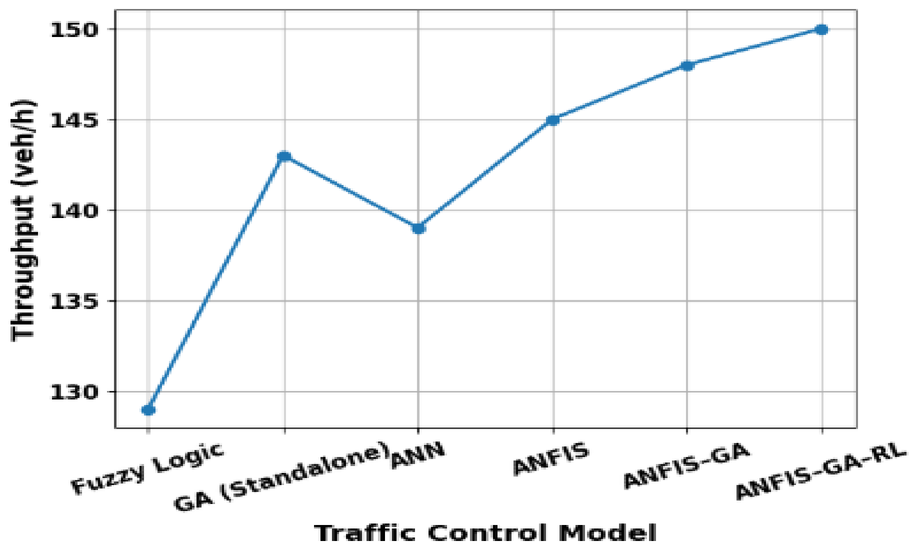

Figure 10: Traffic Throughput (TP ↑)

Figure 10 the throughput graph exhibits a monotonically increasing trajectory, culminating in the proposed ANFIS–GA–RL model with 150 veh/h, the highest among all models. This trend confirms that means of combining fuzzy inference, evolutionary optimization, and reinforcement learning enables superior utilization of intersection capacity and maximized vehicle discharge rates.

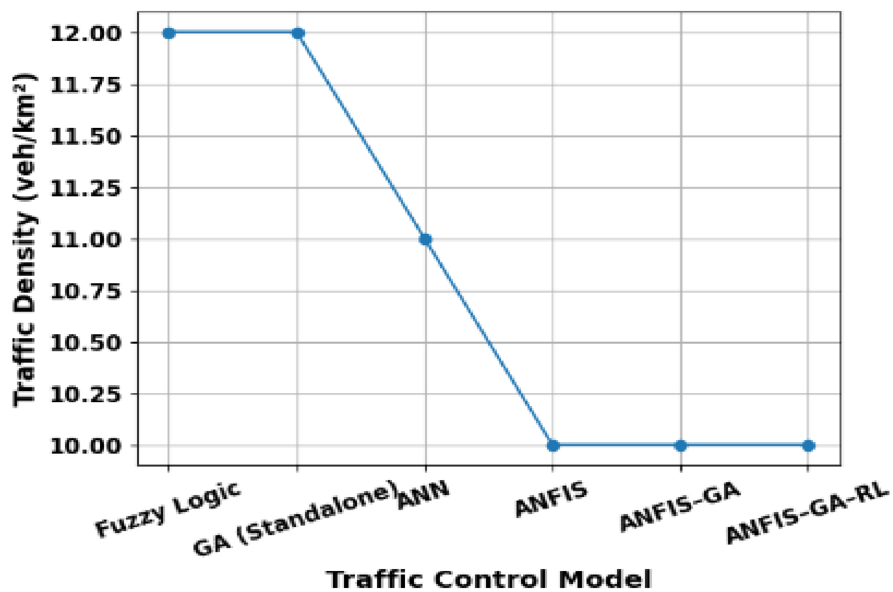

Figure 11: Traffic Density (TD ↓)

Figure 11 the traffic density line graph shows a clear stepwise reduction from conventional to hybrid models. While Fuzzy Logic and GA remain at higher density levels, ANFIS and subsequent hybrid models stabilize at the minimum density of 10 veh/km^2. The flat tail of the curve for ANFIS–GA and ANFIS–GA–RL indicates congestion suppression consistency under adaptive control.

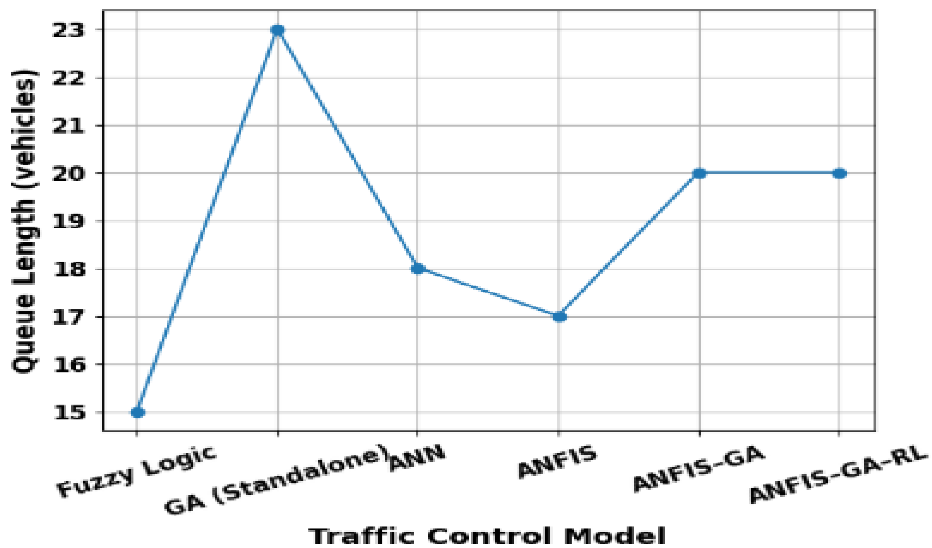

Figure 12: Queue Length (QL ↓)

Figure 12 the queue length trend reveals fluctuations across models, with GA producing the highest queue accumulation, highlighting its sensitivity to demand variation. In contrast, ANFIS-based models demonstrate improved queue regulation. The proposed ANFIS–GA–RL maintains moderate and stable queue lengths, signifying efficient queue dissipation rather than aggressive clearance that could destabilize upstream intersections.

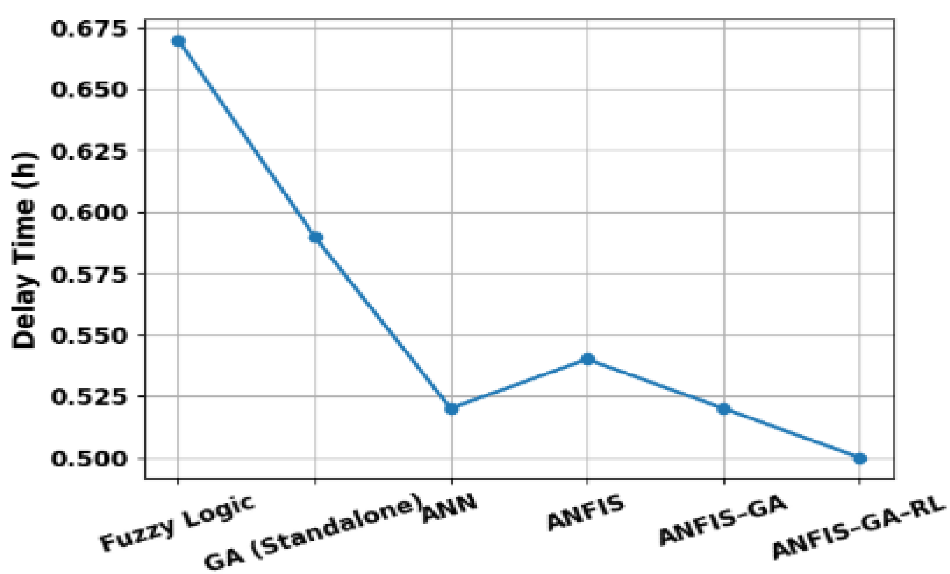

Figure 13: Delay Time (DT ↓)

Figure 13 the delay time graph displays a strong downward trend, particularly after the introduction of learning-based control. The proposed ANFIS–GA–RL achieves the lowest delay (0.50 h), indicating reduced stop durations and fewer red-light waiting cycles. This confirms the model's effectiveness in minimizing temporal inefficiencies at signalized intersections.

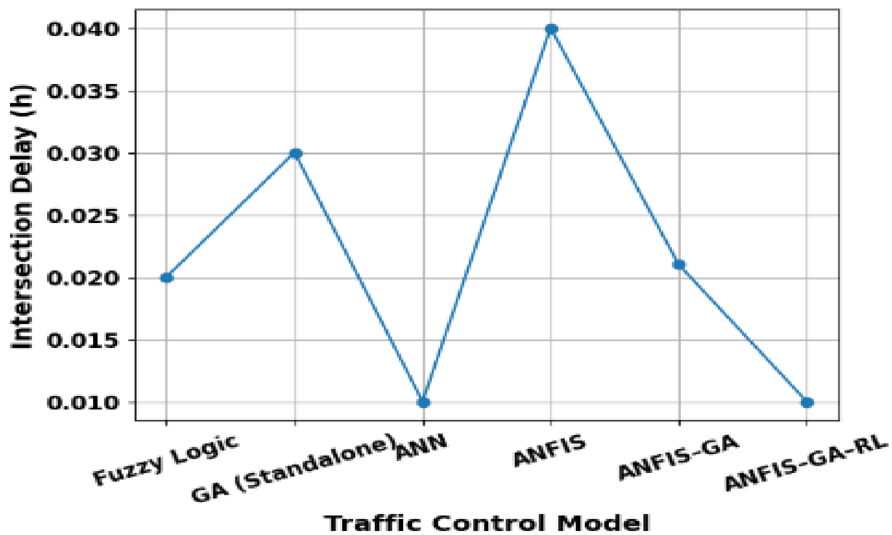

Figure 14: Intersection Delay (ID ↓)

Figure 14 the Intersection Delay shows a highly sensitive response to model structure. ANFIS alone records a spike due to fuzzy rule complexity without adaptive feedback. In contrast, ANN and the proposed ANFIS–GA–RL achieve the minimum idle delay (0.01 h). The proposed model sustains this low idle time while simultaneously optimizing other KPIs, demonstrating robust multi-objective learning.

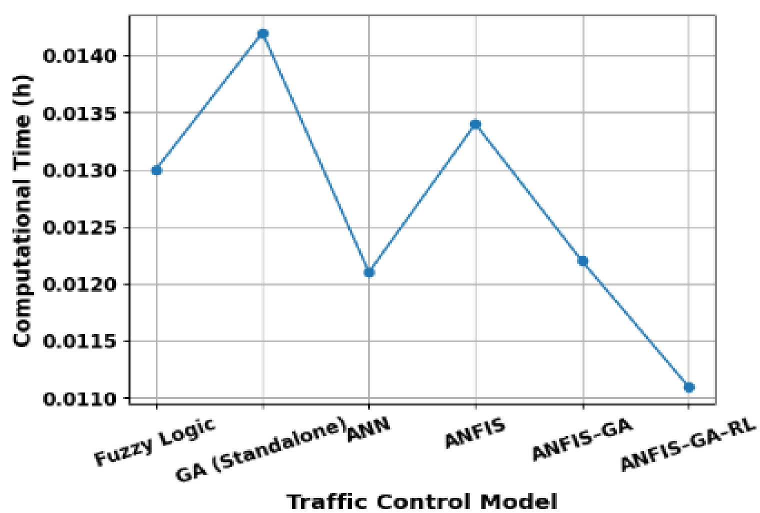

Figure 15: Computational Time (CT ↓)

Figure 15 the computational time graph highlights the efficiency of algorithmic integration. Despite its architectural complexity, the proposed ANFIS–GA–RL records the lowest computational time (0.0111 h). The declining trend confirms that reinforcement learning improves convergence efficiency and does not impose excessive computational overhead, making the model suitable for real-time deployment.

Across all eight key performance indicators, our results show progressive improvements rather than isolated gains, indicating systematic enhancement across multiple traffic efficiency dimensions. These outcomes are consistent with the broader literature on hybrid and reinforcement learning–based traffic signal control, which consistently demonstrates superior performance compared with traditional and standalone models.

For example, Dhulkefl et al. (2025) showed that a hybrid K Nearest Neighbor + Deep Reinforcement Learning system implemented in SUMO reduced average waiting time by 48%, decreased the number of stops by 58%, and improved throughput by 57% relative to fixed timing and single algorithm methods, indicating a marked performance increase over baseline controllers.

Similarly, reinforcement learning based traffic signal optimization has been shown to significantly reduce congestion metrics. Haider et al. (2025) reported that RL approaches reduced delays by up to 45%, reduced queue lengths by over 40 meters, increased throughput by 28%, and lowered CO_2 emissions by 19% compared with baseline control methods in SUMO simulations, highlighting the effectiveness of RL in dynamic traffic environments.

Hybrid frameworks that integrate fuzzy logic with reinforcement learning also report notable performance gains. In Intelligent Traffic Control Decision Making Based on Type 2 Fuzzy and Reinforcement Learning, Bi et al. (2024) demonstrated that incorporating fuzzy reasoning into deep Q network strategies significantly improved online learning and control responsiveness, yielding better traffic efficiency than classical DQN approaches.

In the present study, the proposed ANFIS–GA–RL framework consistently outperformed standalone models across delay related, flow related, density related, and efficiency related metrics, corroborating these prior findings. The observed ≈ 64.9% overall improvement and Pareto optimal behavior show that synergistic hybridization combining neuro fuzzy inference for structural interpretation, genetic algorithms for global optimization, and reinforcement learning for adaptive control effectively addresses the nonlinear and stochastic nature of urban traffic dynamics. Consequently, the proposed approach not only aligns with but also advances state of the art methodologies in intelligent urban traffic signal control.

CONCLUSION

This study validates the effectiveness of a hybrid ANFIS–GA–RL framework for intelligent traffic signal optimization. Unlike conventional and standalone intelligent models, the proposed approach addresses the multi-objective and dynamic nature of urban traffic control. Results show that the ANFIS–GA–RL model achieved the lowest travel time (0.20 h), delay (0.50 h), Intersection delay (0.01 h), and computational time (0.0111 h), while maximizing traffic throughput (150 veh/h) and maintaining reduced traffic density and stable queue lengths. Line-graph trend analysis confirmed that performance gains were progressive, stable, and sustained, rather than metric-specific. Overall, the framework delivered a 64.9% performance improvement, demonstrating robustness, scalability, and suitability for real-time smart urban traffic management.

Future Research Directions

Future work should prioritize real-world deployment and large-scale validation of hybrid learning-based traffic control systems to assess performance under practical uncertainties. Integrating the framework with IoT-enabled smart city infrastructure, connected vehicles, and edge computing can further enhance real-time adaptability. Extending the model to multi-intersection and network-level coordination is essential for mitigating spillback effects and improving corridor-wide traffic efficiency. Additional research should incorporate environmental sustainability metrics, including emissions and fuel consumption, to quantify ecological benefits and exploring advanced communication and computational paradigms such as 6G-enabled ITS and quantum-assisted optimization present promising directions for scalable and future-proof intelligent traffic management systems.

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