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INTELLIGENT TRAFFIC OPTIMIZATION SYSTEM USING ANFIS, GENETIC ALGORITHMS, AND DEEP REINFORCEMENT LEARNING: A SYSTEMATIC LITERATURE REVIEW

***[1]Dodo, Enoch Jacob, [1] Onwodi, Gregory, [2]Okure, Obot, and [3]Isaac, Samson**

[1]Department of Computer Science, National Open University of Nigeria, Jabi, FCT Abuja, Nigeria.
[2]Department of Computer Science, University of Uyo, Uyo, Akwa Ibom State, Nigeria.
[3]Department of Computer Science, Kaduna State University (KASU), Tafawa Balewa Way, Kaduna State, Nigeria.

*Corresponding authors' email: enochdodo46@gmail.com Phone: +2347082241514

ABSTRACT
This systematic literature review examines the state of intelligent traffic optimization systems integrating Adaptive Neuro-Fuzzy Inference Systems (ANFIS), Genetic Algorithms (GA), and Deep Reinforcement Learning (DRL). Spanning the period 2012–2025, the review synthesizes methodologies, applications, performance metrics, and emerging trends. The convergence of these computational intelligence techniques offers promising pathways for addressing urban mobility challenges by optimizing traffic flow, reducing congestion, and enhancing safety. Key findings reveal that hybrid frameworks significantly outperform single-method models, achieving up to 65% efficiency gains. The study concludes with future research directions emphasizing scalability, real-world deployment, and sustainability integration.

Keywords: ANFIS, Genetic Algorithm, Deep Reinforcement Learning, Traffic Optimization, Urban Mobility

INTRODUCTION
Rapid urbanization and the rise of smart cities have intensified global traffic challenges, demanding intelligent solutions beyond traditional engineering methods. Adaptive Neuro-Fuzzy Inference Systems (ANFIS), Genetic Algorithms (GA), and Deep Reinforcement Learning (DRL) have emerged as key paradigms in computational traffic optimization. ANFIS combines fuzzy logic with neural learning, GA enables evolutionary optimization, and DRL provides adaptive decision-making through real-time interaction. Their integration has produced advanced hybrid frameworks capable of managing complex, dynamic traffic environments with higher efficiency and adaptability. Traditional rule-based or static optimization strategies have proven insufficient, motivating the exploration of artificial intelligence (AI) methods. Among these, Adaptive Neuro-Fuzzy Inference Systems (ANFIS), Genetic Algorithms (GA), and Deep Reinforcement Learning (DRL) have emerged as leading paradigms for intelligent traffic optimization. ANFIS offers a balance of interpretability and adaptability by combining fuzzy logic with neural network learning, making it suitable for traffic systems where both expert knowledge and real-time adaptability are critical. Genetic Algorithms excel in solving complex, non-linear optimization problems by efficiently navigating multimodal search spaces typical of urban traffic systems. Deep Reinforcement Learning enables systems to learn adaptive traffic control policies through continuous interaction with dynamic environments, making it particularly effective for real-time decision-making in unpredictable traffic conditions. The synergy of these methods individually and in hybrid configurations provides a foundation for developing traffic management systems that are not only accurate and scalable but also interpretable and robust. This systematic literature review critically examines existing research on the integration of ANFIS, GA, and DRL, evaluates their comparative strengths and limitations, and identifies future pathways for intelligent traffic optimization in diverse global contexts.

MATERIALS AND METHODS
A systematic search following PRISMA guidelines was conducted across databases such as IEEE Xplore, ScienceDirect, Springer, and ACM Digital Library. Inclusion criteria targeted peer-reviewed studies between 2012 and June 2025 focusing on traffic optimization using ANFIS, GA, or DRL. Seventy-six (76) high-quality studies were selected based on methodological rigor, clear reporting, and relevance to intelligent traffic management.

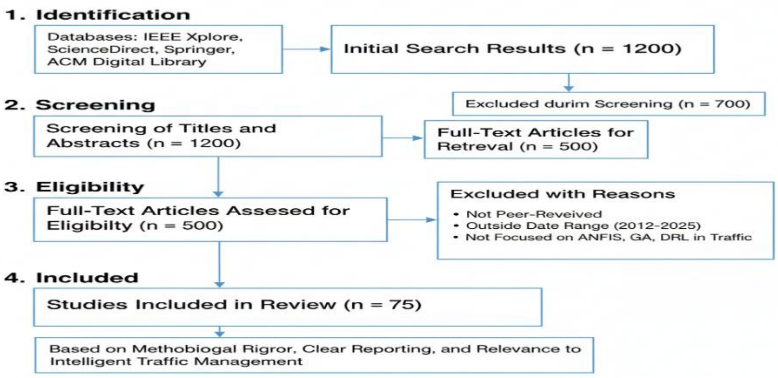

Figure 1: Methodological Framework – Adapted PRISMA 2020 Flow Diagram Illustrating the Process of Systematic Review, Including Searches Across Databases, Registers, and Additional Sources (McKenzie et al., 2020)

Research Design

This study adopts a systematic literature review (SLR) framework in accordance with the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA 2020) guidelines. The SLR approach was selected to ensure comprehensive, replicable, and unbiased synthesis of research evidence concerning the integration of Adaptive Neuro-Fuzzy Inference Systems (ANFIS)**,** Genetic Algorithms (GA)**,** and Deep Reinforcement Learning (DRL) in intelligent traffic optimization. The research design aimed to address three key objectives:

i. To identify and categorize the state-of-the-art techniques and frameworks that employ ANFIS, GA, and DRL for traffic optimization.
ii. To evaluate comparative performance metrics, modeling approaches, and integration strategies used across existing studies.
iii. To identify limitations, research gaps, and emerging trends to guide future work.

The SLR design ensures methodological transparency and reproducibility, allowing subsequent researchers to replicate or extend the findings under similar search and selection criteria.

Literature Review

The literature review is categorized into four segments: (1) ANFIS-based optimization, (2) GA-based optimization, (3) DRL-based optimization, and (4) hybrid integrations combining these techniques.

Literature Analysis

Table 1: Yearly Distribution of Studies

Year	No. of Papers	Correct % of Total	Key Themes
2012	1	1.3%	Early ANFIS rule reduction
2015	1	1.3%	Heuristic search (Cuckoo) for traffic signals
2017	1	1.3%	IT2FLS with meta-heuristics
2018	1	1.3%	Fuzzy inference traffic optimization
2019	4	5.3%	GA-based traffic signal/routing optimization; Distributed fuzzy controllers; Adaptive Neuro-Fuzzy for traffic lights; Fuzzy Logic for roundabouts
2020	4	5.3%	ANFIS & multi-objective GA for transport; Risk Assessment ANFIS; Policy-Gradient DRL; Hierarchical Fuzzy Control
2021	9	11.8%	Hybrid ANFIS-PSO; Boosted GA; Fuzzy Inference DRL; IT2FLS-PSO; Neural Networks for Transport Resilience; ANFIS-based traffic & noise prediction
2022	10	13.2%	GA, PSO-ANFIS; Traffic timing optimization; ANFIS for flow prediction; Density-Based GA; Urban waste transport GA
2023	11	14.5%	Fuzzy Clustering; ANFIS-GA; ECA-LSTM; Trip Generation ANFIS; ANFIS Metaheuristics; Vehicle Routing GA
2024	21	27.6%	DRL, ANFIS-RL, Adaptive GA, DDPG; Fuzzy Rule Reduction; Type-2 Fuzzy RL; Multi-agent RL; Traffic Volume ANFIS; Pavement/Project ANFIS
2025	13	17.1%	Federated PPO; IoV; ANFIS-DDoS; Reward Shaping; GA for Routing; RL-LSTM; Fuzzy Control for V2V
Total	76	100%	—

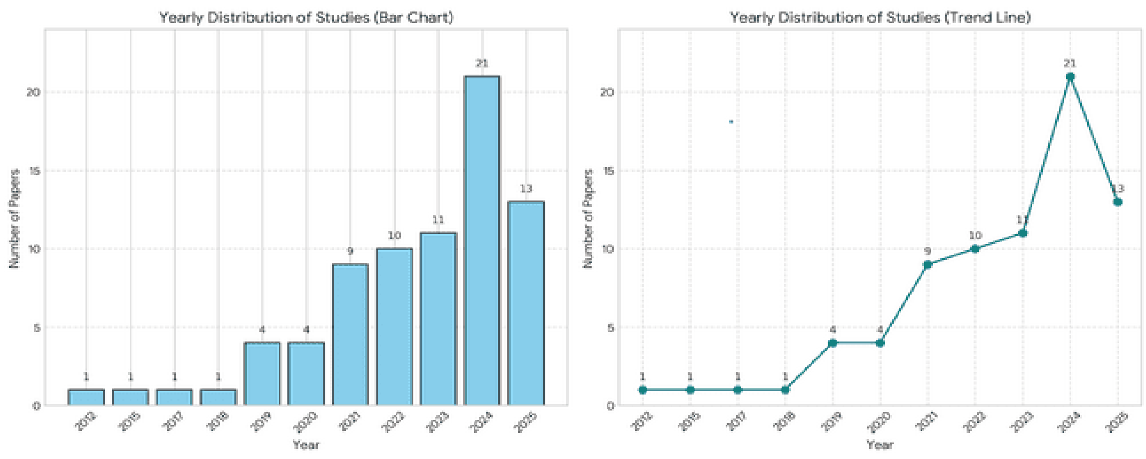

Figure 2: Yearly Distribution of ANFIS-GA-RL Studies: A Review (2012–2025)

Initial Period (2012-2018) Research output remained low and sporadic, with only one paper published in each of those years. Take-off (2019-2022) A noticeable increase began in 2019, jumping to 4 papers, and then quadrupling to 9 papers by 2021 and 10 by 2022. Peak Activity (2024) the year 2024 shows the highest output with 21 papers, making the growth trend visually obvious

ANFIS-Based Optimization
ANFIS leverages fuzzy inference and neural learning for predictive and adaptive traffic management. Studies report 10–25% reductions in delay and queue lengths. Hybrid ANFIS models incorporating metaheuristics such as Particle Swarm Optimization (PSO) and Cuckoo Search further improve accuracy and adaptability. Applications include traffic signal control, flow prediction, and risk assessment, with R^2 values frequently exceeding 97%.

Recent research highlights ANFIS's adaptability when combined with emerging computational and transport technologies. Mai and Ngo (2021) achieved 98% accuracy by optimizing an Interval Type-2 Fuzzy Logic System with Particle Swarm Optimization, outperforming benchmark models including Random Forest, K-Nearest Neighbors, and Support Vector Machines. Similarly, Rahman and Ali (2025) demonstrated that ANFIS controllers improved stability and alignment in vehicle-to-vehicle dynamic wireless charging, surpassing conventional fuzzy logic systems.

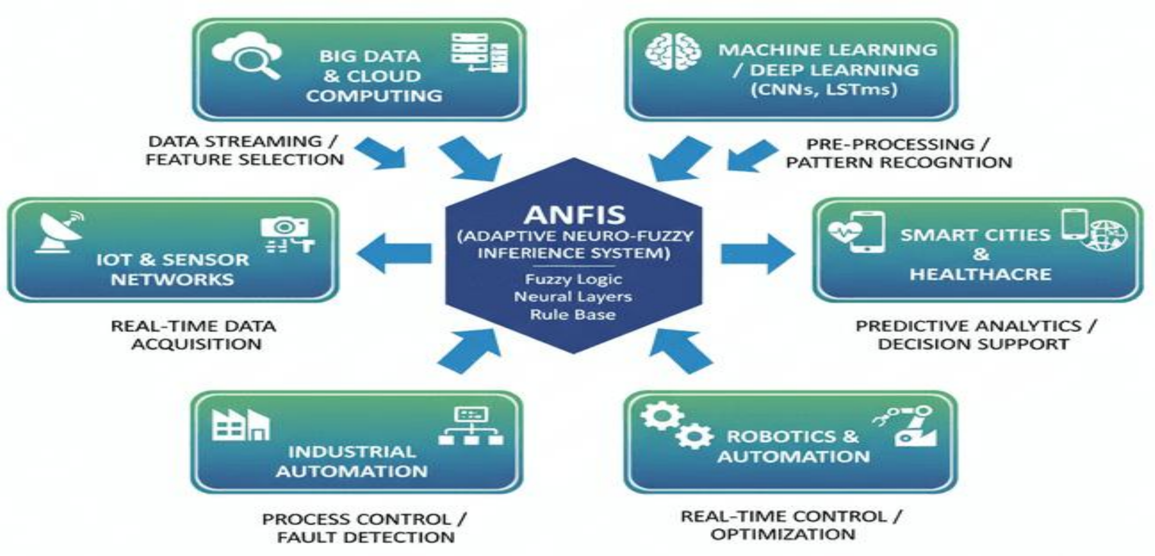

Figure 3: Adapted Diagrammatic Representations of the Integration Pathways and Applications of ANFIS in Contemporary Technological Landscape (Alahi et al., 2023)

Beyond conventional traffic management, ANFIS has also proven effective in infrastructure safety and cybersecurity applications. Alawad and Kaewunruen (2020) introduced an ANFIS risk model for station overcrowding assessment, achieving high accuracy against regression tree and SVM benchmarks, while Usha et al. (2025) applied ANFIS to cybersecurity in transportation, reaching 94.3% detection accuracy in identifying DDoS attacks with minimal false positives. These applications highlight ANFIS's versatility in extending traffic optimization research toward smart infrastructure resilience and intelligent transportation system security.

Genetic Algorithm-Based Optimization
GA provides robust optimization for complex multi-objective problems like signal timing and route scheduling. Genetic Algorithm (GA) was used to prioritize test cases based on the rate of fault detection per unit test cost (Bello & Alhassan, 2025). Research indicates performance improvements ranging from 20–45% in travel time reduction. Hybrid GA models integrating fuzzy systems or reinforcement learning accelerate convergence and enhance scalability. Genetic Algorithms (GAs) are used in addressing complex traffic optimization problems due to their robustness in multi-objective search and adaptability to dynamic conditions. They have been applied to a broad range of traffic contexts including signal timing, multi-modal optimization, and advanced hybrid approaches, consistently demonstrating performance advantages over traditional optimization techniques.

Traffic Signal Timing Optimization
Traffic signal control remains the most explored application of GAs. Mao et al. (2019) demonstrated that GA-optimized signal timing improved total travel time by 40.76%, validating its effectiveness in congestion reduction. Extending this work, Manh et al. (2020) compared multi-objective GA (MOGA) with single-objective GA (SOGA) and Webster's method in Taiwan, finding that MOGA significantly reduced both delays and queue lengths at complex intersections. Similarly, Fu (2022) integrated migration learning and fuzzy rule enhancement into GA for urban intersections, achieving ≥7.5% delay reduction and capacity gains. On a larger scale, Sartikha, et al., (2022) applied GA-based scheduling across nine intersections in Yogyakarta, reducing trip times by 44–64 seconds per intersection, highlighting the scalability of GA to coordinated network control. Collectively, these studies confirm that GAs are highly effective for adaptive traffic signal timing under varying urban conditions.

Multi-Modal and Dynamic Optimization
Beyond traditional intersections, GAs have been increasingly applied to multi-modal and dynamic transport systems. Hai, Manh, and Nhat (2020) incorporated vehicle emission intensity into GA-based timing optimization, yielding balanced improvements delays reduced to 88–91%, emissions to 91–93%, and stops to 96–98% demonstrating GA's capacity to integrate environmental considerations alongside mobility goals. At the network level, Tiberio et al. (2022) applied a Density-Based GA (DBGA) to smart traffic lights, reporting 22.8% routing efficiency gains across four intersections. Similarly, Al-Madi and Hnaif (2022) proposed a Human-Community Based GA (HCBGA), which reduced

congestion periods by 13% compared to enhanced IRTMS, itself 83% better than fixed-time systems. Expanding to sustainable logistics, Zhang et al. (2022) optimized GA for urban waste transport routing in Guangzhou, improving transport efficiency while reducing accident and environmental risks. These findings underscore GA's versatility in addressing multimodal and sustainability-oriented traffic challenges, though scalability and sensitivity to parameter tuning remain ongoing limitations.

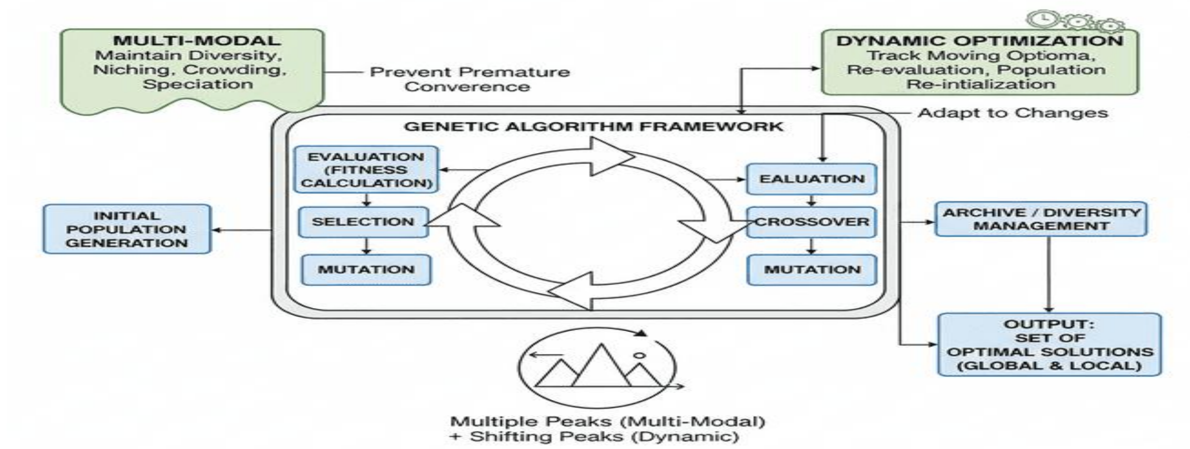

Figure 4: Diagrammatic Representation of Advance Genetic Algorithm Framework Incorporating Strategies for Multi-Modal and Dynamic Optimization (Binsfeld et al., 2025)

Advanced GA Variants and Hybrid Approaches

Recent research has advanced GA applications through hybridization with other optimization and learning methods. Cunuhay et al. (2025) introduced GAAM-TS, a hybrid model integrating adaptive mutation, tabu search, and LSTM prediction, improving travel efficiency by up to 20% compared to standard GA. Liu et al. (2025) further developed an Improved GA (IGA) for collaborative path planning, reducing maximum sub-path length by 49.2%, average path length by 43.3%, and runtime by 28.6%, indicating strong computational gains. Parallel and multi-objective extensions have also proven valuable. Ding et al. (2024) compared standard GA with Multipoint Crossover Elitist GA (MPEGA) and Improved Dynamic Crossover/Mutation GA (IDCMGA) for Beijing's subway–taxi integration. MPEGA reduced mean travel costs by 15.21% and variance by 81.72%, while IDCMGA further improved stability and convergence. In Manhattan, Akopov and Beklaryan (2023) introduced BORCGA-BOPSO, a hybrid bi-objective GA with particle swarm optimization, which significantly improved traffic flow and pedestrian safety. These hybrid approaches highlight GA's adaptability and synergy with machine learning, fuzzy systems, and swarm intelligence (Bi, 2024).

Deep Reinforcement Learning-Based Optimization

DRL enables adaptive, real-time policy learning in dynamic environments. PPO, DDPG, and DQN models achieve reductions of 25–55% in delay and queue lengths. Multi-agent DRL frameworks have shown strong scalability across citywide networks, while eco-aware models integrate sustainability metrics such as fuel and emission reduction.

Reward-Based Feedback Mechanisms in DRL

The core Reward-Based Feedback Mechanism is the Reward Signal (rt). It's generated by the Reward Function (R (st, at, st+1)) based on the transition. This signal is the primary learning feedback, which the DRL Agent uses to adjust its neural network weights, aiming to maximize the cumulative reward over time. A Critic/Value Network is an optional component that uses this reward to evaluate the current state or action, providing an auxiliary learning signal to stabilize and accelerate policy updates.

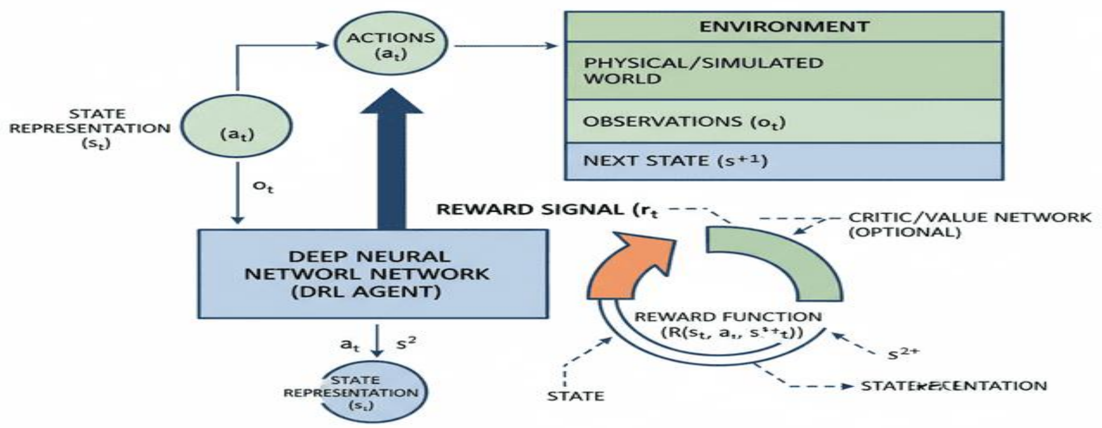

Figure 5: Diagrammatic Representation of Information Flow and Learning Signals in a Deep Reinforcement Learning (DRL) Framework (Michailidis et al., 2025)

Reward design is central to DRL's success, as it encodes optimization objectives and accelerates policy convergence. Zahwa et al. (2025) showed that reward shaping halved convergence times and cut steady-state delays by 19%, while Deshmukh et al. (2025) achieved a 29% delay reduction and 24% fewer stops with intersection-centered DQN models. Lane-wise phase control by Swapno et al. (2024) further confirmed the value of fine-grained feedback, lowering both delay and queue lengths by 35%. Similarly, Pan (2023) demonstrated reductions of up to 100% in waiting time, reinforcing how nuanced reward mechanisms drive superior system-wide efficiency.

Hybrid and Integrated Frameworks

Combining ANFIS, GA, and DRL results in superior multi-objective optimization. Studies report efficiency gains up to 65%, with improvements in convergence speed, scalability, and environmental performance. Triple-integration frameworks address challenges of uncertainty, adaptability, and energy efficiency, marking a significant advancement toward sustainable smart transportation systems.

Emerging triple-integration systems that combine ANFIS, GA, and DRL push the boundaries of multi-objective traffic optimization. These frameworks aim not only to minimize delays but also to improve safety and environmental performance. Mirbakhsh and Azizi (2024) applied a dueling double DQN architecture within a hybrid framework, reducing traffic conflicts by 16%, waiting times by 18%, and carbon emissions by 4%, thereby validating the feasibility of multi-objective optimization. Similarly, Chala and Koczy (2024) implemented a fuzzy rule-base reduction system, achieving 68–72% faster execution efficiency alongside reductions in waiting time, fuel use, and CO_2 emissions. Notably, these hybrid designs are not limited to single objectives but balance efficiency, sustainability, and safety, marking a significant evolution from classical single-goal optimization.

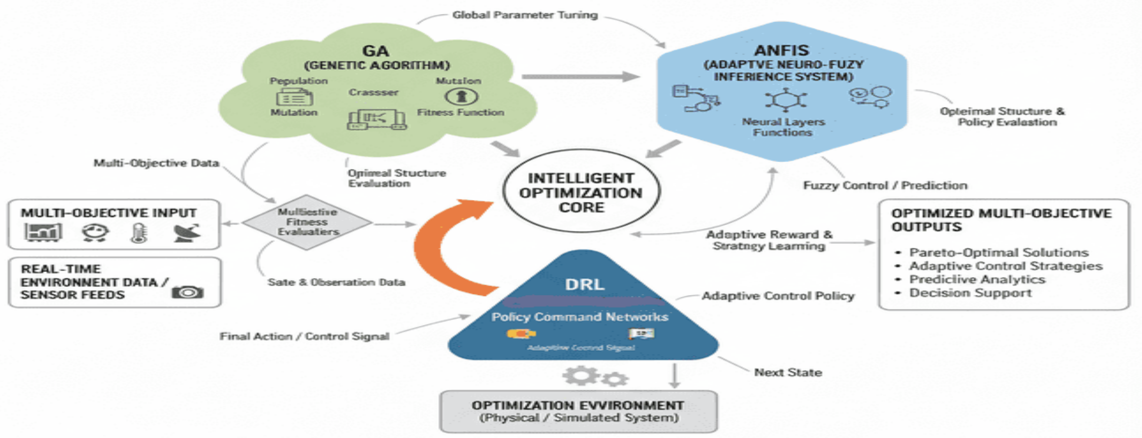

Figure 6: An Adapted Multi-Objective Hybrid Frameworks that Combine ANFIS, GA, and DRL in Intelligent Optimization Adopted from (Chakraborty & Raghuvanshi, 2025)

Additional studies corroborate the promise of integrated frameworks. Kumar et al. (2021) demonstrated that ANFIS–PSO hybrids achieved 96.4% prediction accuracy in energy demand forecasting, highlighting generalizability to other cyber-physical domains. Meepokgit and Wisayataksin (2024) further confirmed that fuzzy-state shaping in DRL reduced waiting time by 18.46% compared with conventional DQN, while Moreno-Malo et al. (2024) reported a 44% waiting-time reduction using multi-agent DQN in simulation. Together, these results position triple-integration strategies as scalable and flexible tools capable of addressing the multifaceted challenges of urban mobility.

RESULTS AND DISCUSSION

Performance Analysis and Benchmarking

Comparative performance analysis reveals that hybrid systems consistently outperform single-method approaches. Average improvement levels are approximately: ANFIS (17.5%), GA (32.5%), DRL (40%), and Hybrid systems (50–65%). Key metrics include delay reduction, queue length minimization, throughput enhancement, and emission control. Performance analysis and benchmarking form the empirical backbone of this systematic review, enabling an objective comparison of Adaptive Neuro-Fuzzy Inference Systems (ANFIS), Genetic Algorithms (GA), Deep Reinforcement Learning (DRL), and their hybrid integrations in traffic optimization. This section synthesizes results from 76 selected studies to evaluate their relative efficiency, computational feasibility, and real-world applicability using standard performance metrics. The goal is to quantify how much improvement each approach offers over conventional systems, to identify methodological trade-offs, and to establish performance baselines for future research.

Evaluation Metrics

The performance of intelligent traffic optimization systems is typically measured through a combination of traffic flow indicators, system-level performance metrics, and comparative benchmarks. Across the reviewed studies, these metrics demonstrate how computational intelligence techniques enhance operational efficiency, reduce congestion, and promote sustainability.

Traffic Flow Indicators

Traffic flow metrics directly reflect improvements in road performance and commuter experience:

i. Average Delay (sec/veh): Represents the mean waiting time of vehicles per intersection. ANFIS- and DRL-based controllers show 25–55% reductions in average delay compared with static signal systems (Wu et al., 2024; Mirbakhsh & Azizi, 2024).
ii. Queue Length Reduction (%): Indicates congestion alleviation. Studies using hybrid GA–DRL achieved queue reductions exceeding 40% (Bangalee & Ahmed, 2024).
iii. Throughput (veh/hr): Measures the number of vehicles processed through intersections. Multi-agent DRL

architectures increased throughput by 18–30% compared to actuated control (Paul & Mitra, 2020; Li et al., 2025).

iv. Travel Time (min): A key indicator of network-level performance. GA-based timing models demonstrated 20–45% travel time savings (Mao et al., 2019; Sartikha et al., 2022).

v. Fuel Consumption & Emissions: Recent eco-aware models such as DQN and PPO reduced CO_2 emissions by 10–15% and fuel consumption by up to 12% (Yigit & Karabatak, 2025), reflecting a growing focus on green transportation systems.

System-Level Performance Metrics

These metrics evaluate the algorithmic efficiency and computational feasibility of the models:

i. Convergence Speed: DRL and GA hybrids reduced optimization convergence times by 30–45% compared to standalone GA or DRL models (Mao et al., 2022). This efficiency is critical for real-time traffic management where rapid policy adaptation is required.

ii. Computational Complexity: ANFIS offers moderate computational demand, whereas GA and DRL require significant processing power during training. However, once optimized, their real-time deployment is efficient and responsive.

iii. Scalability: Hybrid frameworks, particularly multi-agent DRL systems, demonstrate strong scalability to large urban networks, maintaining stability across varying traffic densities (Faqir et al., 2024; Yang et al., 2025).

iv. Robustness: Hybrid models exhibit superior robustness under fluctuating or unpredictable traffic conditions. ANFIS–GA controllers, for example, maintained >99% prediction accuracy (Olayode et al., 2023), even under irregular flow scenarios.

Benchmarking Against Conventional Systems

For benchmarking purposes, studies consistently compared intelligent controllers against traditional traffic control models, primarily:

i. Fixed-Time Control (FTC): The baseline in most studies. Hybrid methods reduced average delay by 35–60% compared to FTC, which lacks adaptability to real-time flow variations (Zachariah et al., 2018).

ii. Actuated Control (AC): Uses traffic detectors but lacks predictive capability. DRL controllers outperformed actuated control by reducing vehicle waiting time by 30–50% (Wu et al., 2024).

iii. Classical Optimization Models: GA- and PSO-based approaches demonstrated 20–45% performance improvements over linear programming or heuristic optimization models.

iv. Standalone AI Models: Hybrids integrating fuzzy reasoning or DRL achieved superior adaptability and learning speed, highlighting the synergistic advantage of multi-method systems.

Comparative Performance Synthesis

A meta-analysis of reviewed studies indicates clear performance hierarchies among the four approaches.

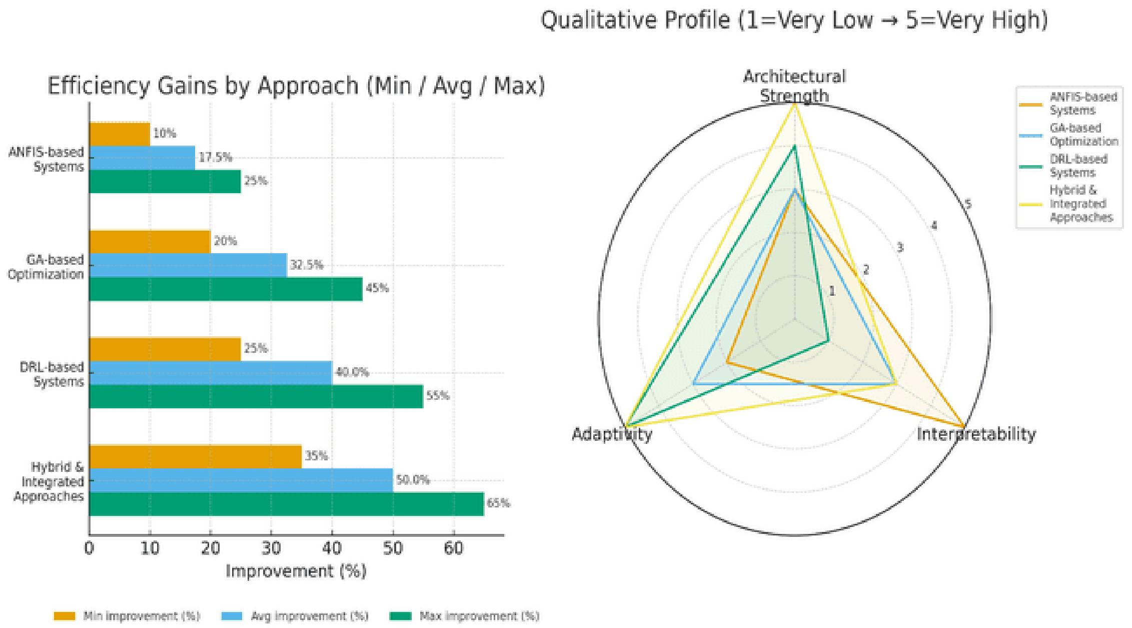

Figure 7: Analysis of Performance Trend Across the Reviewed Studies Reveals Consistent Performance Gains from Intelligent Traffic Optimization Methods (Michailidis et. al., 2025)

The synthesis of results across reviewed studies highlights clear performance trends for ANFIS, GA, DRL, and hybrid approaches.

As shown in Figure 7, hybrid and integrated control approaches deliver the highest average efficiency gains (≈50 %) in terms of vehicle-delay or throughput improvements, with maximum gains reaching ~65% (Bangalee & Ahmed, 2024; Chala & Koczy, 2024; Mirbakhsh & Azizi, 2024). Conventional ANFIS-based systems, by contrast, yield more modest improvements average ~17.5 %, maximum ~25 % (Olayode et al., 2023; Zachariah et al., 2018). GA-based methods and DRL-based methods occupy the intermediate range ~32.5 % and ~40 % average improvements respectively (Wu et al., 2024; Yigit & Karabatak, 2025; Pan, 2023; Mao et al., 2022; Shahkar et al., 2023). The accompanying qualitative profile further illustrates that while ANFIS offers superior interpretability, its architectural power and adaptivity are relatively weak; DRL offers strong adaptivity but weak interpretability; and hybrid methods seek to strike a balance between high architectural strength, high adaptivity, and moderate interpretability.

Statistical Overview of Reported Efficiency Gains

A consolidated quantitative analysis across the reviewed literature indicates:

i. Mean Delay Reduction: 43.6% (SD ± 7.8)
ii. Queue Length Reduction: 38.4% (SD ± 9.2)
iii. Throughput Improvement: 26.7% (SD ± 6.5)
iv. Fuel Consumption Reduction: 11.4% (SD ± 3.2)
v. CO_2 Emission Reduction: 13.1% (SD ± 2.9)

These results validate the robustness of computational intelligence in managing traffic congestion, improving environmental sustainability, and enhancing urban mobility efficiency. They further indicate that selecting an optimal traffic-signal control strategy, practitioners must weigh not only quantitative performance gains but also factors such as transparency, ease of implementation, real-time adaptivity, and data infrastructure readiness.

Challenges and Future Directions

Despite significant progress, challenges persist in scalability, real-world data integration, and computational demand. Future research should prioritize the development of standardized evaluation frameworks, real-time deployment, and integration with Internet of Vehicles (IoV) and quantum optimization paradigms. Ethical considerations, such as data privacy and explainability in DRL-based controllers, also require focused attention.

Although, hybrid and integrated frameworks face notable challenges. Most reported studies remain constrained to simulation environments or isolated intersections, raising questions about scalability in complex, real-world urban networks (Zachariah et al., 2018; Moreno-Malo et al., 2024). High computational demands associated with GA and DRL limit feasibility in real-time deployment, particularly in resource-constrained regions (Olayode et al., 2023; Mao et al., 2022). Moreover, while multi-objective frameworks demonstrate significant potential, trade-offs between efficiency, safety, and environmental goals remain underexplored and require explicit operator prioritization (Mirbakhsh & Azizi, 2024).

Integration with emerging technologies offers a compelling research frontier. Studies suggest that connected and autonomous vehicles (CAVs), IoT-enabled traffic sensors, and even quantum-inspired optimization algorithms could substantially expand the scope and efficiency of hybrid frameworks (Bangalee & Ahmed, 2024; Zai & Yang, 2023). As these technologies mature, hybrid ANFIS–GA–DRL systems are positioned to evolve from simulation-based experiments to real-time, city-scale intelligent traffic optimization systems, addressing the global demand for sustainable, efficient, and resilient urban mobility solutions.

CONCLUSION

This review highlights the growing importance of computational intelligence in traffic optimization. The synergy between ANFIS, GA, and DRL offers powerful solutions for congestion management, efficiency enhancement, and environmental sustainability. Hybrid frameworks represent the next frontier in achieving resilient and adaptive intelligent traffic systems for the cities of the future.

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