



A Comprehensive Survey On Cognitive AI Approaches For Intelligent Urban Traffic Signal Optimization

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Abstract: Urban traffic congestion causes economic, travel time, and environmental problems. The traditional fixed-timing signals are inadequate for dynamic urban traffic. Recent studies have focused on intelligent adaptive traffic signal control (TSC) systems using AI, particularly deep reinforcement learning (DRL) and multi-agent reinforcement learning (MARL). This survey reviews the progress of AI-driven TSC by examining methodologies such as deep Q-networks, policy gradient, actor critic, graph convolutional networks, fuzzy logic, and hybrid models. It compares techniques based on principles, simulation settings, scalability, and performance indicators. The survey emphasized challenges in coordinating multiple intersections, real-time adaptability, data integration, and safety verification. This highlights the importance of high-fidelity simulators and discusses research gaps, including real-world validation, mixed traffic management, and public transport priority. This study aims to guide future research towards robust, scalable, and sustainable urban traffic management systems using cognitive AI.

Index Terms - Traffic Signal Control, Reinforcement Learning, Deep Reinforcement Learning, Deep Q-Networks, Multihead Attention (MHA), Urban Traffic Management, Adaptive Control Systems, Fuzzy Logic, SUMO, CityFlow, Optimization, Scalability

I. INTRODUCTION

Economic losses, longer travel times, greater fuel consumption, and environmental pollution are consequences of urban traffic congestion. Changing traffic patterns are not adequately managed by conventional traffic lights with set timetables. Researchers have used Artificial Intelligence (AI) techniques, particularly Deep Reinforcement Learning (DRL), to develop intelligent adaptive traffic signal control (TSC) systems. By actively interacting with their environment, DRL algorithms, such as Deep Q-Networks, policy-gradient techniques, and actor-critic models, allow traffic signals to create the best possible control strategies.

Managing linked intersections is complex because actions at one traffic light affect others. Multiagent reinforcement learning (MARL) facilitates cooperation between intersections by utilizing Graph Convolutional Networks and multihead attention for improved communication. Realistic traffic simulators, such as SUMO and CityFlow, are crucial for training AI models. Additional methods include time automata models, genetic algorithms, vehicle-based dynamic user equilibrium, and fuzzy logic for transit signal prioritization, all of which contribute to intelligent TSC systems.

This study introduces an AI-based traffic light control system that combines Deep Q-Learning, multihead attention, and Graph Convolutional Networks. It aims to improve city wide traffic management by learning from real-time data and enhancing intersection coordination. This system addresses the limitations of previous research, which often focused on isolated improvements and struggled with complex urban networks. When

compared to conventional methods, simulation results utilizing real traffic data show the system's ability to enhance traffic flow and minimize congestion.

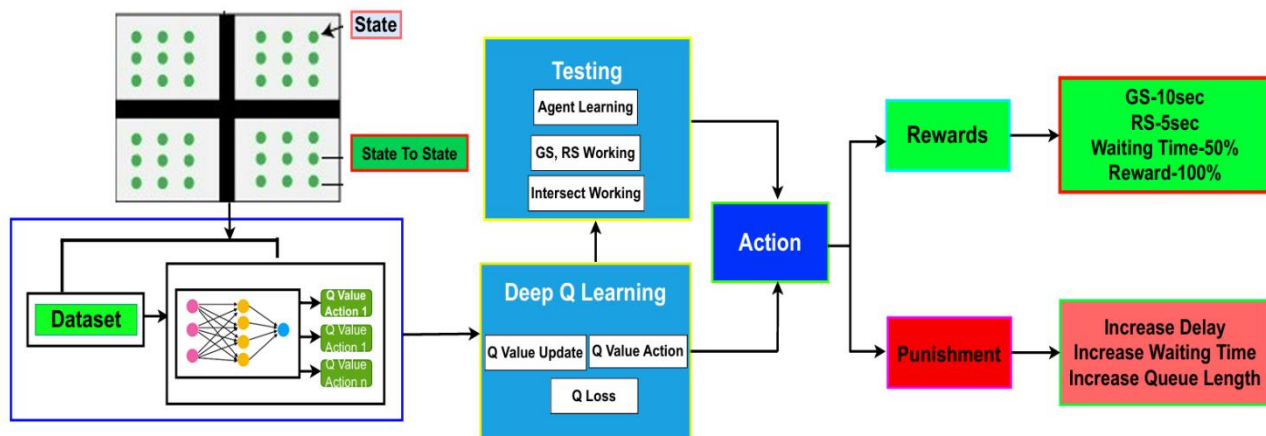


Figure 1: Reinforcement Learning Traffic Signal Management Architecture [16]

II. BACKGROUND

Modern society relies heavily on efficient transportation; however, the rapid growth of urban areas has led to an increase in vehicle numbers and traffic jams. This situation causes delays, greater fuel usage, and air pollution, which in turn lead to economic losses and a decline in the quality of life in cities. To address these challenges and encourage sustainable urban mobility, it is vital to develop smart traffic management solutions.

From fixed-time systems to offset-based coordination and actuator-controlled systems, traffic signal management has changed. Fixed-time systems follow preset timetables and are not flexible enough to adjust to changes in traffic in real time. Actuated control still relies on preset rules but adjusts timings based on vehicle detection. The goal of offset-based coordination is to coordinate many junctions while overcoming obstacles in dynamic and crowded environments. Conventional methods are limited in their ability to manage the intricate and changing patterns of metropolitan traffic.

Traffic signal management has been completely transformed by artificial intelligence (AI) approaches such as machine learning, deep learning, reinforcement learning, and fuzzy logic, which process vast amounts of data and make adaptive choices in real time because they enable agents to improve their decision-making through interactions with their surroundings. Reinforcement learning (RL) and deep reinforcement learning (DRL) have attracted significant attention. Despite the flexibility and automatic feature extraction provided by these approaches, there are still issues in creating efficient state and action spaces, choosing appropriate reward functions, and guaranteeing scalability for large networks.

Despite significant progress, several challenges remain in the pursuit of truly intelligent traffic signal control:

- **Scalability:** Extending control techniques to handle massive traffic networks with numerous intersections is a major challenge.
- **Coordination:** To enhance traffic flow throughout the network, it is essential to effectively synchronize traffic signals at various intersections.
- **Real-time Adaptability:** Traffic management systems need to quickly adjust to abrupt and unforeseen shifts in traffic conditions.
- **Data Requirements:** It is essential to efficiently use a range of traffic data sources, including vehicle positions, speeds, and video footage, in order to appropriately depict traffic conditions.

- **Mixed Traffic:** New levels of complexity are added to traffic management by the increasing integration of connected and autonomous vehicles (CAVs) with conventional human-driven automobiles.
- **Transit Signal Priority (TSP):** Giving precedence to public transport vehicles at intersections is crucial for encouraging sustainable transportation.

III. LITERATURE SURVEY

Li Li, Yisheng Lv, and Fei-Yue Wang proposed a deep reinforcement learning-based solution for optimizing traffic signal scheduling in their study “Traffic Signal Timing via Deep Reinforcement Learning” [1]. Their approach utilized a deep stacked autoencoder to model the Q-function, enabling the system to learn and identify effective signal timing configurations. Through simulation, their model demonstrated a notable performance gain, including a 14% reduction in the average vehicle delay and fewer complete stops during high-congestion periods compared to conventional traffic control methods.

Genders and Razavi explored the use of deep reinforcement learning for adaptive traffic-light regulation. Discrete traffic state encoding (DTSE), a unique state representation devised, records specific traffic data such as vehicle presence, speed, and the current signal phase. The core component of the traffic signal control agent is a deep convolutional neural network, to which the DTSE is fed as an input. The agent uses two parallel neural networks to handle DTSE and fully connected layers for decision-making. It was trained using Q-learning in a SUMO microsimulation environment. With an average cumulative delay reduction of 82%, a queue length reduction of 66%, and a travel time reduction of 20%, their results show notable gains over conventional methods [2].

A study conducted by Gao et al. [3] offers a new strategy for employing artificial intelligence to alleviate traffic congestion. To overcome the shortcomings of the current techniques, the authors proposed a deep reinforcement learning system that learns the best traffic signal control strategies from unprocessed real-time data. To improve stability, the system incorporates target network mechanisms and experiences replayed into deep convolutional neural networks. Compared to conventional approaches, the simulation findings show reduced vehicle delays, flexibility in responding to shifting traffic demands, and fair regulation at crossings.

Mousavi et al. investigated innovative methods to maximize traffic signal control through sophisticated machine learning techniques in [4]. This study proposes two methods for traffic management: a policy-gradient-based agent and a value-function-based agent. This was achieved by combining deep neural networks with reinforcement learning. Deep convolutional neural networks are used in both techniques to optimize the reduction of the overall cumulative latency. Tests conducted using the SUMO traffic simulator showed notable gains over baseline techniques, reducing the average cumulative delay by 67–68% and queue length by 72–73% when compared to shallow neural networks. This study demonstrates how deep reinforcement learning can be used to solve challenging traffic-planning issues.

In [5] Wei et al. presented CoLight as a solution to the problem of coordinating traffic signals at several crossings in metropolitan road networks. To enhance traffic flow, the authors suggest a unique strategy based on graph attentional networks. The limitations of traditional approaches can be overcome by CoLight, which considers the temporal and geographical influences of nearby crossings. This paradigm allows flexible and scalable coordination across large scale networks by utilizing graph attentional networks in reinforcement learning. Tests on both artificial and real-world datasets, such as the Manhattan 196-intersection network, showed that CoLight outperformed the state-of-the-art techniques in terms of performance and scalability.

Wei et al. [6] proposed a new deep reinforcement learning model for traffic light control optimization. It employs real-world data from the city of Jinan, China, presents a phase-gated model learning technique, and discusses the main obstacles to using reinforcement learning for traffic control. The IntelliLight model performs better than other deep reinforcement learning techniques and traditional methods, particularly when it comes to adjusting to complicated and dynamic traffic situations. The novel “phase gate” enables sophisticated decision-making, and the “memory palace” method corrects imbalances in the training data. The experiments provided a realistic assessment of the model’s behavior under different traffic circumstances and showed higher performance in measures, including average queue length, delay, and travel duration.

The study conducted by T. Chu, J. Wang, and their colleagues examines the application of reinforcement learning (RL) for adaptive traffic signal control (ATSC) within complex urban traffic networks. Employing the advantage actor-critic (A2C) methodology, this study introduces a decentralized multi-agent reinforcement learning (MARL) algorithm for ATSC. When evaluated in both synthetic and real-world traffic environments, the proposed multi-agent A2C (MA2C) demonstrated superior performance compared to existing decentralized MARL algorithms, particularly in terms of optimality, robustness, and sample efficiency. By incorporating a spatial discount factor and integrating neighboring policy information, this study addresses the challenges of partial observability and non-stationarity in MARL for ATSC [7].

In order to overcome the shortcomings of current simulators in managing extensive urban traffic situations, Zhang et al.'s research [8] introduces a revolutionary traffic simulator. CityFlow outperforms SUMO in managing vast road networks and high traffic volumes, producing big data samples for deep learning model training in an efficient manner. It offers flexible road network and traffic pattern definitions, providing a user-friendly interface for reinforcement learning applications. The simulator includes a Python interface for multi-agent reinforcement learning experiments, enabling users to manage the simulation components and access state information.

In the research study by Liu et al. [9] The authors presented an agile approach to traffic assignment, a vehicle-based DUE (vDUE) model, and a bi-level optimization problem. The vDUE model uses probabilistic rerouting based on route saturation to integrate macro-level traffic status with micro-level vehicle behavior. The authors developed an effective TSC system that balances speed and accuracy while optimizing signal timing by combining vDUE with an adaptive differential evolution algorithm. Tests conducted on both synthetic and actual networks showed that the suggested agile TSC system performed better, particularly in busy and emergency situations.

The problem of controlling the transit signal priority (TSP) in intricate urban traffic networks was addressed in a study by Xu et al. [10]. The authors suggested a novel method for resolving conflicting TSP requests across several intersections by combining fuzzy logic with multiagent systems. Using fuzzy inference, priority level evaluation, traffic condition assessment, and signal timing adjustment, this architecture employs agents to control crossings. The solution outperformed benchmark methods in minimizing bus and overall vehicle delays, particularly in situations with high traffic demand, as shown by a simulated case study.

Chu et al.'s study [11] is a major step forward for traffic management systems, especially when it comes to solving the enduring problem of traffic jams at intersections. Their method uses deep reinforcement learning to develop a system for controlling traffic lights that are intelligent and responsive to changing circumstances. This method makes urban traffic management more accessible and scalable by using camera images as inputs, instead of expensive sensor equipment. The system can analyze visual information effectively and make decisions about traffic signal timing that are almost optimal because of the creative usage of a background removal residual network (BGR ResNet) as a Q-network. Compared with other deep reinforcement learning techniques and conventional controls, the experiments showed better results in lowering the average waiting times.

Using cutting-edge machine learning techniques, Naoki Kodama, Taku Harada, and Kazutoshi Miyazaki's research [12] tackles the pressing problem of traffic congestion. For multi-intersection situations, the authors suggested a unique method of dynamic traffic signal regulation based on deep reinforcement learning, namely, the dual targeting algorithm (DTA). This technology uses local data to function independently at crossings, enhancing resilience and lowering costs. In comparison with traditional deep reinforcement learning techniques, experiments conducted with the SUMO simulator showed a 33% decrease in waiting times.

Niroumand et al.'s research offers a method for using connected automated vehicles (CAVs) and connected human driven vehicles (CHVs) to manage traffic at signalized crossings. The limits of mixed-autonomy intersection control are addressed in this study, which builds on previous research by proposing a distributed mixed-integer nonlinear program for optimizing vehicle trajectory and signal timing. The authors present the idea of a "white phase" in which CAVs navigate rights of way and guide CHVs through intersections in the role of mobile traffic controllers. To maximize the intersection capacity across a range of CAV penetration rates, this method makes use of each vehicle's computer capabilities for real-time decision-making [13].

According to Kamput et al.'s research, traffic light control systems urgently require efficient modeling and verification [14]. To overcome the considerable difficulties in developing flexible models for various traffic situations and intersection layouts, the authors suggest a novel and scalable approach that uses UPPAAL to model and validate smart traffic light systems. Their method comprised a thorough three step procedure: formal model creation, practical traffic flow modeling, and model property verification. Using this methodology, traffic-light management systems can be thoroughly and methodically examined, guaranteeing their dependability and effectiveness. A case study including six crossings was used to validate the proposed method, proving its resilience and capacity to manage complicated situations, such as the control of priority vehicles, such as fire trucks or ambulances. Although the suggested approach has several benefits in terms of parameterization and scalability, making it simple to adjust to different traffic conditions, the authors admit that there are still some issues. In particular, handling numerous incidents at once or at many intersections poses persistent challenges that call for further study and advancement. These drawbacks demonstrate how intricate real-world traffic networks are and how modeling and verification methods must continue to evolve.

[15] The research work titled "Minimizing Delay at Closely Spaced Signalized Intersections Through Green Time Ratio Optimization: A Hybrid Approach With K-Means Clustering and Genetic Algorithms" by Ruti R. Politi and Tanyel addressed traffic congestion management at closely spaced intersections. This study combines k-means clustering and genetic algorithms to optimize the green time ratios to minimize delays. This research focused on queue spillbacks and traffic signal timing optimization to reduce delays at closely spaced intersections. Using the SIDRA Intersection software for simulation, k-means clustering categorized intersection distances into three groups. Genetic algorithms then optimized the green time ratios for each group, ranging from 0.58 0.69. The results showed significant improvements in both upstream and downstream intersections, with reductions in the delay, degree of saturation, and CO2 emissions.

IV. METHODOLOGY

A. Existing Methodologies

Reinforcement Learning (RL):

- A popular approach is reinforcement learning (RL), in which an agent interacts with the environment (traffic flow) and learns to optimize actions (signal phases) in exchange for rewards.
- The value function or policy was frequently represented using tabular techniques or the linear function approximation in early RL applications.

Deep Reinforcement Learning (DRL):

- DRL combines RL with deep neural networks to handle high-dimensional state spaces and learn complex features.
- Common DRL algorithms include Deep Q-Networks (DQN) , Actor-Critic methods , and Policy Gradient methods.

Multi-Agent Reinforcement Learning (MARL):

- MARL addresses the challenge of controlling multiple intersections by using multiple RL agents that can cooperate or compete.
- Challenges in MARL include partial observability and coordination among agents.

Fuzzy Logic:

- Fuzzy logic is used to handle uncertainty and imprecision in traffic data and control decisions, particularly in Transit Signal Priority (TSP) scenarios.

V. COMPARISON & DISCUSSION

The study contrasted several cognitive AI techniques for optimizing urban traffic signals, such as fuzzy logic, hybrid models, multi-agent reinforcement learning, and deep reinforcement learning. Particularly at remote crossings, DRL techniques such as actor-critic algorithms and Deep Q-Networks show notable decreases in average vehicle delays and queue lengths. MARL frameworks, including those that use multi head attention and graph convolutional networks, allow for scalable coordination across numerous crossings and perform well in both real-world syntheses and simulations. Fuzzy logic works particularly well in situations involving ambiguity, such as transit signal priority, whereas hybrid models, which

combine evolutionary algorithms with clustering, focus on particular problems, such as reducing latency at closely spaced crossings.

The cognitive AI approaches surveyed for traffic signal optimization include deep reinforcement learning (DRL), multi agent reinforcement learning (MARL), fuzzy logic, and hybrid models. DRL methods, such as Deep Q-Networks, reduce delays by 14-82% in simulations but struggle with real-world scalability. MARL frameworks leverage graph neural networks for city-scale coordination, improving traffic flow by 20-33%. Hybrid models that combine clustering and optimization target niche scenarios rely on idealized simulations. Fuzzy logic effectively resolves transit signal priority conflicts, but remains untested in mixed-traffic scenarios.

Table 1: COMPARISON TABLE OF TRAFFIC SIGNAL CONTROL APPROACHES

No.	Approach/Title	Core Algorithm/Method	Test Environment	Key Metrics Improved	Scalability	Real-World Validation
1	Traffic Signal Timing via Deep Reinforcement Learning	Deep Q-Learning (DQN)	SUMO	Avg. delay ↓14%	Moderate	No
2	Using a Deep RL Agent for Traffic Signal Control	Deep Q-Network (DQN)	SUMO	Delay ↓82%, Queue ↓66%	Moderate	No
3	Adaptive TSC: Deep RL w/ Experience Replay & Target Net	Deep RL (CNN, Exp. Replay)	SUMO	Delay ↓, Equitable control	Moderate	No
4	Traffic Light Control Using Deep Policy-Gradient and Value-Function RL	Policy-Gradient, Value-Function RL	SUMO	Delay ↓67–68%, Queue ↓72–73%	Moderate	No
5	CoLight: Learning Network-level Cooperation	GAT + RL (Graph Attention Network)	SUMO, Manhattan	Flow ↑, Delay ↓	High	No
6	IntelliLight: RL for Intelligent Traffic Light	Deep RL (Phase-Gated)	Jinan, China (real)	Queue ↓, Delay ↓, Travel ↓	Moderate	Yes
7	Multi-Agent Deep RL for Large-Scale TSC	Multi-Agent A2C (Actor-Critic)	Synthetic, Real	Optimality, Robustness	High	No
8	CityFlow: Multi-Agent RL Environment	Multi-Agent RL Simulator	CityFlow	Simulation scale, Flexibility	High	No
9	Agile-Vehicle-based Dynamic User Equilibrium for Urban TSC	Bi-level Opt., vDUE, Diff. Evolution	Real, Synthetic	Delay ↓, Speed/Accuracy ↑	Moderate	No

10	Multi-Agent Fuzzy-Based Transit Signal Priority	Multi-Agent Fuzzy Logic	Simulation	Bus/vehicle delay ↓	Moderate	No
11	Traffic Signal Control Using End-to-End Off-Policy Deep RL	Off-Policy Deep RL (BGR ResNet)	SUMO	Wait time ↓	Moderate	No
12	TSC System Using DRL w/ Emphasis on Reinforcing Success	Dual Targeting Algorithm (DTA)	SUMO	Wait time ↓33%	Moderate	No
13	White-Phase Intersection Control Through Distributed Coordination	Dist. Mixed-Integer Nonlinear Prog.	Simulation	Capacity ↑, Delay ↓	Moderate	No
14	Scalable Timed-Automata Models for Traffic Light Control	Timed Automata, UPPAAL	Simulation	Scalability, Verification	High	No
15	Minimizing Delay at Closely Spaced Signalized Intersections	K-Means Clustering + Genetic Alg.	SIDRA Intersection	Delay ↓, CO ₂ ↓, Saturation ↓	Moderate	No

A. Performance and Scalability

Single-agent DRL is effective at reducing delays and shortening queues at individual intersections; however, it faces challenges in dynamic and continuous traffic settings. Conversely, MARL is better suited for large networks, as evidenced by CoLight's simulation of 196 intersections in Manhattan, although it requires substantial computational resources and has not been tested under real-world conditions. Hybrid models are adaptable to complex situations but struggle with scalability owing to incomplete data integration. Simulation tools, such as SUMO and CityFlow, enable large-scale testing, but CityFlow encounters issues with heterogeneous networks.

B. Strengths and Limitations

Deep Reinforcement Learning (DRL) and Multi-Agent Reinforcement Learning (MARL) outperform fixed-timing controls in adapting to dynamic traffic, but lack explainability. Graph-based attention mechanisms enhance intersection synchronization but increase the latency. While some systems use real traffic data, most rely on simulations, creating a gap between the theoretical and practical results. Fuzzy logic manages uncertainty in transit priority well but struggles with scalability. Hybrid models prioritize emission reduction over pedestrian and cyclist requirements.

C. Research Gaps

Key gaps include the limited real-world deployment of AI driven systems, particularly in mixed-traffic environments with connected autonomous vehicles (CAVs) and pedestrians. Few studies have integrated multi-source data (e.g., CAVs and cameras) for comprehensive state representation. Formal verification methods, such as timed automata and computational tree logic (CTL), remain disconnected from adaptive control frameworks, leaving safety guarantees unaddressed. Additionally, hybrid AI strategies combining RL with evolutionary algorithms or fuzzy inference are underexplored despite their potential for robustness.

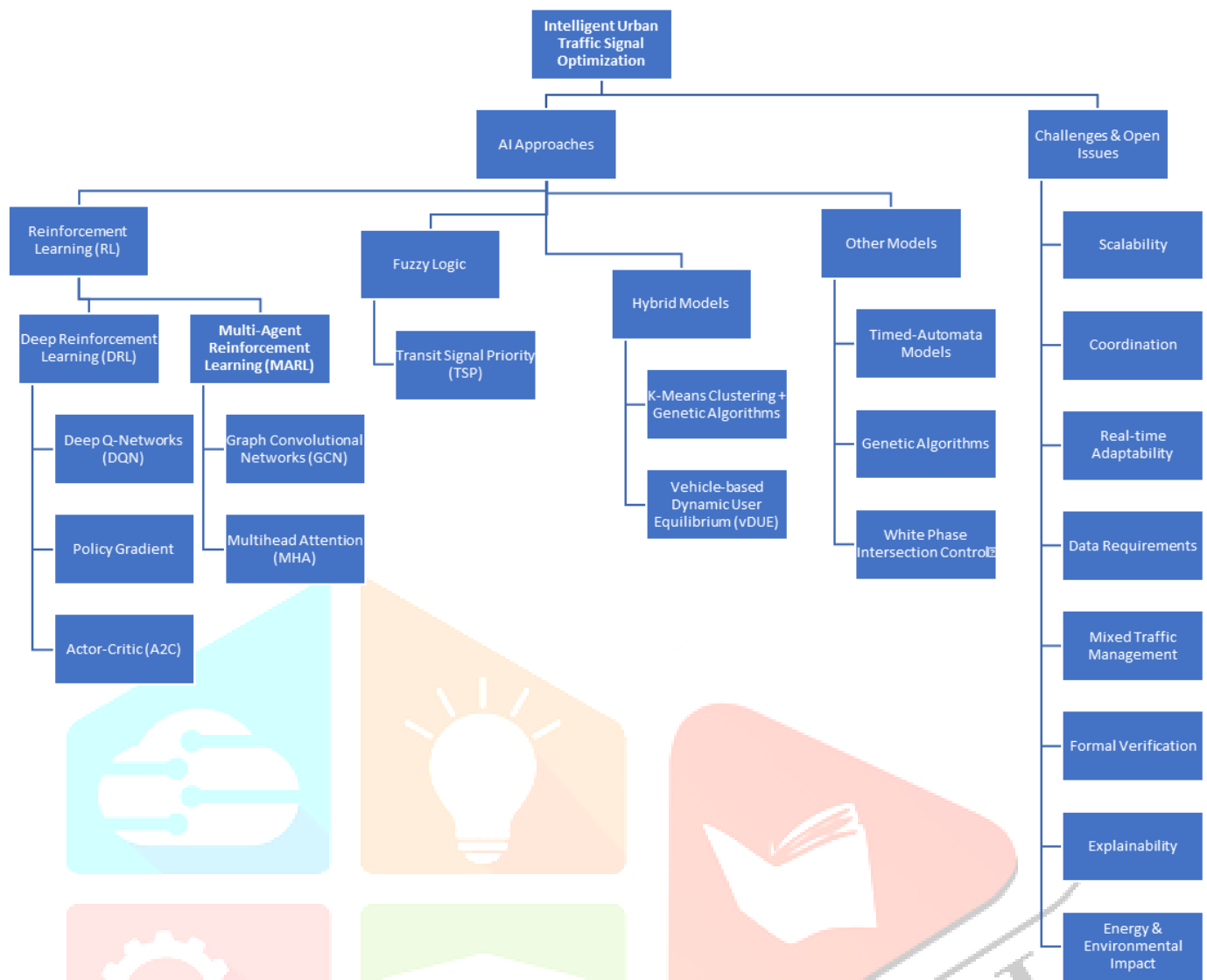


Figure 2: Taxonomy of Traffic Signal Optimization Approaches and Challenges.

VI. CHALLENGES AND OPEN ISSUES

It is critical to address current issues and investigate new avenues as AI technology in the field of traffic light management advances. Scaling AI systems to efficiently handle the intricacies of vast metropolitan transportation networks is the primary challenge. Future research should concentrate on developing frameworks and algorithms that can effectively manage the high dimensionality of these networks' state and action spaces while maintaining real-time performance. This entails investigating methods for efficiently coordinating traffic lights at several crossings, perhaps using sophisticated multi agent reinforcement learning approaches that encourage cooperation and dialogue. To guarantee that AI systems can react to unanticipated events and changes in traffic flow, it is also crucial to increase their resilience and adaptability to dynamic traffic conditions.

In addition to enhancing the algorithms, future studies should focus on integrating various data sources to gain a more thorough understanding of traffic conditions. This involves utilizing information from connected and automated vehicles (CAVs), video streams, and other sensor networks to enhance the representation and forecasting of traffic states. Moreover, investigating hybrid AI methods that combine the advantages of reinforcement learning with other techniques such as fuzzy logic or evolutionary algorithms could result in more sophisticated and effective control strategies. Finally, tackling the challenges of AI decision-making explainability and interpretability, along with incorporating considerations of energy efficiency and environmental impact into the design of traffic control systems, is essential for the broad acceptance and long-term viability of AI-based traffic management solutions.

VII. CONCLUSION

With an emphasis on the revolutionary significance of artificial intelligence, this investigation examined the changing terrain of traffic-signal control approaches. Although conventional approaches have found it difficult to handle the complexity of contemporary urban traffic, artificial intelligence (AI) techniques in particular, deep learning and reinforcement learning offer encouraging prospects for creating traffic management systems that are more flexible, effective, and long lasting. Multi-agent reinforcement learning offers a framework for coordinating signals across several crossings, whereas deep reinforcement learning has proven to be capable of handling high-dimensional traffic data and learning intricate control policies. More complex and context-aware control tactics are indicated by emerging trends, including the incorporation of graph neural networks, application of end-to-end learning from sensory input, and evaluation of dynamic user equilibrium.

However, significant challenges remain. Scalability to large scale networks, robust real-time adaptation, the effective utilization of diverse data sources, and the integration of connected and automated vehicles require further research and development. Future efforts should focus on hybrid AI approaches that combine the strengths of different techniques, the development of scalable and robust architectures with formal verification, and rigorous evaluation in both simulated and real-world environments. AI has the potential to significantly influence how urban mobility develops in the future by tackling these issues, which might result in less traffic, increased safety, and a more sustainable transportation system.

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