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DEEP REINFORCEMENT LEARNING FOR INTELLIGENT TRAFFIC SIGNAL CONTROL IN SMART CITIES: A COMPREHENSIVE REVIEW

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ABSTRACT

The city is getting crowded and more people are buying cars, which is making the traffic really bad. This is why we need to have traffic lights that can control the traffic flow. The old ways of controlling traffic lights like using a fixed schedule or sensors do not work well because they cannot adjust to the changing traffic conditions. This means that cars have to wait there is more traffic people use more fuel and the air gets polluted. A new way to control traffic lights is by using something called Deep Reinforcement Learning. This is a type of computer program that can learn how to make decisions by trying different things and seeing what works best. We looked at how this type of program has been used to control traffic lights from 2016 to 2026. We saw how different types of computer programs like Deep Q-Network, Double DQN and Graph Neural Network have been used to control traffic lights. We talked about how these programs work, what they are good at and what their limitations are. We also looked at how new technologies, like self-driving cars the Internet of Things and smart transportation systems can be used to make traffic flow better. However, there are still some challenges that need to be solved like making sure the programs can handle a lot of data do not use too much computer power and can be used in the real world. Overall, we think that Deep Reinforcement Learning can be used to create traffic light systems that're smart, efficient and good for the environment but more research is needed to make sure they can be used in big cities. Deep Reinforcement Learning and traffic signal control systems are really important for the future of cities. Deep Reinforcement Learning can help traffic signal control systems to be more adaptive and efficient. Traffic signal control systems that use Deep

Reinforcement Learning can reduce traffic congestion, fuel consumption and environmental pollution. We need to do research, on Deep Reinforcement Learning and traffic signal control systems so that we can use them in big cities.

KEYWORDS: Deep Reinforcement Learning, Deep Q-Network, Traffic Signal Control, Smart Cities, Intelligent Transportation Systems.

1. INTRODUCTION

Rapid urbanization has growing fast has changed the way people move around. More than half of the people in the world live in cities now. That number will go up a lot in the next few years. As more people move to cities and get jobs and more people buy cars the roads are getting very crowded. This is putting a lot of pressure on the roads. It is causing big problems. One of the problems is that the roads are getting too crowded. This is bad for the economy the environment and the people who live in cities. When the roads are crowded it takes a time to get anywhere people use more gas and there is more pollution. There are also car accidents. Traffic lights are very important for keeping cars moving at intersections. They help make sure the roads are used well. For a time, traffic lights were controlled by timers. They would turn red or green at the time every day. This is simple. It does not work well when there is a lot of traffic or an accident. These old traffic lights cannot handle things. They do not use the roads well. There are some traffic light systems like SCOOT and SCATS. They can change when they turn red or green based on the traffic. These systems need a lot of setup and special equipment. They also need to be able to guess how much traffic there will be. This makes it hard to use them in cities where the traffic is always changing. Traffic signal control systems like these are not very good at handling changes in traffic. The traffic signal control systems are very important for cities like these. Traffic signal control is used to control the traffic lights. Traffic signal control is necessary, for keeping the roads safe and moving. Traffic signal control systems are used to make sure traffic signal control is done well. Traffic signal control is a part of keeping cities moving

2. Literature Review

Li et al. [1] introduced one of the earliest Deep Reinforcement Learning (DRL)-based traffic signal control frameworks using a Deep Q-Network (DQN). The proposed model learned optimal signal timing policies by interacting with a simulated traffic environment and observing traffic states such as queue length and waiting time. The reward function was designed to reduce vehicle delay and congestion. Experimental results demonstrated that the

DQN-based controller outperformed conventional fixed-time traffic signal systems, establishing the foundation for applying DRL in intelligent traffic management.

Van der Pol et al. [2] proposed a decentralized multi-agent Deep Reinforcement Learning framework for coordinated traffic signal control. In this approach, each intersection was treated as an independent learning agent capable of optimizing local traffic conditions while cooperating with neighboring intersections. The framework improved traffic coordination without relying on centralized control, making it suitable for large-scale urban road networks. Simulation results showed reduced vehicle waiting time and improved traffic throughput compared with traditional traffic control strategies.

Gao et al. [3] enhanced Deep Reinforcement Learning for adaptive traffic signal control by integrating experience replay and target networks into the Deep Q-Network architecture. These techniques improved training stability and accelerated convergence during learning. The proposed controller continuously optimized signal timing based on traffic conditions, minimizing queue length and vehicle delay. Experimental evaluations demonstrated superior performance over conventional reinforcement learning methods, highlighting the effectiveness of stable DQN training for intelligent traffic management.

Genders et al. [4] investigated the application of Deep Q-Networks for intelligent traffic signal control at isolated intersections. The proposed agent learned optimal signal phase selection directly from real-time traffic observations without requiring predefined traffic models. The reward function focused on minimizing queue length and vehicle waiting time while avoiding unnecessary signal switching. Simulation results confirmed that the DRL-based controller significantly outperformed fixed-time and actuated traffic signal systems under varying traffic demand conditions.

Wei et al. [5] proposed **IntelliLight**, an advanced reinforcement learning framework based on a Double Dueling Deep Q-Network for adaptive traffic signal control. The study introduced an improved state representation and reward function that better captured real-time traffic conditions. The proposed model effectively minimized vehicle delay, queue length, and intersection congestion while achieving faster convergence than conventional DQN approaches. The results demonstrated significant improvements in traffic efficiency across different urban traffic scenarios.

Rasheed et al. [6] developed a Deep Reinforcement Learning-based traffic signal control framework for disturbed urban traffic conditions using a real-world case study of Sunway City, Malaysia. The proposed system adapted signal timings according to continuously changing traffic patterns and unexpected disturbances. Experimental results indicated improved traffic flow, reduced average waiting time, and enhanced robustness under fluctuating traffic demand, demonstrating the practical applicability of DRL for intelligent urban traffic management.

Yen et al. [7] proposed a deep on-policy reinforcement learning framework for coordinated control of multiple traffic intersections. The study employed an on-policy learning strategy to improve policy stability and adaptability under dynamic traffic environments. By enabling cooperation among neighboring intersections, the proposed model achieved better traffic coordination, reduced congestion, and improved network-wide traffic efficiency compared with isolated intersection control strategies and conventional reinforcement learning approaches.

Li et al. [8] introduced a fairness-aware Deep Reinforcement Learning framework for adaptive traffic signal control. Unlike conventional approaches that primarily focused on minimizing vehicle delay, the proposed model also considered fairness among different traffic movements. A modified reward function balanced traffic efficiency and equitable signal allocation across competing directions. Simulation results demonstrated that the proposed controller successfully reduced congestion while providing a more balanced distribution of vehicle waiting times.

Yu et al. [9] proposed a safer and smarter Deep Reinforcement Learning approach for intelligent traffic signal control by incorporating traffic efficiency and safety considerations into the learning process. The developed framework optimized traffic signal timing while reducing potential traffic conflicts and excessive delays. Experimental evaluations showed that the proposed controller improved traffic throughput and minimized congestion without compromising operational safety, making it suitable for future intelligent transportation systems.

Guzmán et al. [10] developed a distributed reinforcement learning-based cooperative traffic signal control framework for urban intersections. The proposed decentralized approach enabled neighboring traffic signals to share information and collaboratively optimize signal timings without centralized supervision. The distributed learning strategy improved scalability, reduced vehicle delays, and enhanced traffic flow across interconnected intersections. The study demonstrated that cooperative reinforcement learning can effectively address the complexity of large urban transportation networks.

Liao et al. [11] proposed an LSTM-based Deep Q-Network framework for adaptive traffic signal control to balance traffic capacity and safety at urban intersections. By integrating Long Short-Term Memory (LSTM) networks with reinforcement learning, the model effectively captured temporal traffic variations and historical traffic patterns. A time-difference penalty was incorporated into the reward function to reduce unnecessary signal switching while improving traffic flow. Experimental results demonstrated lower vehicle delay, improved intersection capacity, and enhanced decision-making compared with conventional DQN-based approaches.

Liu et al. [12] developed an optimized Deep Q-Learning framework for intelligent traffic signal control by improving the exploration strategy and reducing the complexity of the action space. The proposed model efficiently learned optimal signal timing policies under varying traffic conditions while maintaining stable convergence during training. Simulation results indicated significant reductions in average vehicle delay, queue length, and travel time compared with traditional Q-learning and conventional traffic signal control methods, demonstrating the effectiveness of the optimized learning strategy.

Lu et al. [13] introduced a Dueling Recurrent Double Deep Q-Network (DRDQN) for adaptive traffic signal control in complex urban traffic environments. The proposed architecture combined recurrent neural networks with Double DQN and Dueling Network structures to capture both temporal traffic variations and accurate action-value estimation. The model achieved faster convergence, improved learning stability, and better traffic optimization than conventional DQN algorithms. Experimental analysis showed considerable improvements in traffic throughput and reduced vehicle congestion.

Zhang et al. [14] investigated intelligent traffic signal control under partial vehicle detection using reinforcement learning. Unlike previous studies requiring complete traffic information, the proposed framework effectively operated with limited detection data collected from connected vehicles. A Deep Reinforcement Learning model was developed to optimize signal timing despite incomplete observations. Experimental results demonstrated that the proposed controller maintained satisfactory traffic performance even under low vehicle detection rates, making it suitable for practical smart city applications.

Ibrokhimov et al. [15] proposed a Biased Pressure-based Cyclic Reinforcement Learning model for intelligent traffic signal control. The proposed approach integrated the traditional max-pressure traffic control principle with reinforcement learning to improve traffic coordination across intersections. By considering traffic pressure imbalance during policy learning, the model effectively reduced queue length, vehicle delay, and congestion. Simulation results confirmed that the proposed framework achieved higher traffic efficiency and more stable signal control than conventional reinforcement learning methods.

Wang et al. [16] presented a model-based Deep Reinforcement Learning framework integrated with traffic inference for adaptive traffic signal control. Unlike model-free reinforcement learning approaches, the proposed system incorporated traffic prediction mechanisms to improve learning efficiency and decision-making accuracy. The model successfully reduced training time while maintaining high traffic optimization performance. Experimental evaluation demonstrated lower average vehicle delay, shorter queue lengths, and better traffic flow compared with conventional DQN-based controllers.

Wang et al. [17] developed a Deep Reinforcement Learning model for optimizing traffic light timing in urban transportation systems. The proposed framework continuously adjusted traffic signal phases according to real-time traffic conditions, minimizing vehicle waiting time and congestion. The study evaluated different traffic demand scenarios and demonstrated that DRL-based optimization significantly improved traffic efficiency over traditional fixed-time signal control methods. The proposed approach also exhibited stable learning behavior under varying traffic densities.

Liu et al. [18] proposed an improved Deep Reinforcement Learning algorithm for single-intersection traffic signal control. The study focused on enhancing policy learning through improved state representation and reward function design. The proposed controller effectively reduced queue length and vehicle waiting time while maintaining smooth traffic flow under dynamic traffic conditions. Comparative analysis revealed that the improved DRL model achieved better convergence and higher traffic efficiency than conventional reinforcement learning algorithms.

Zhao et al. [19] introduced a Deep Reinforcement Learning framework for the joint optimization of vehicular flow direction and traffic signal control across urban road networks. Instead of optimizing traffic signals independently, the proposed method simultaneously considered road direction planning and signal timing decisions. The integrated optimization strategy significantly improved traffic distribution, reduced network congestion, and enhanced overall transportation efficiency. Experimental results demonstrated superior network-wide performance compared with traditional signal optimization approaches.

Gokasar et al. [20] proposed the SWSCAV framework for real-time traffic management using connected autonomous vehicles and intelligent traffic signal control. The framework combined vehicle-to-infrastructure communication with reinforcement learning to improve traffic coordination and mobility in smart cities. By utilizing real-time information from connected autonomous vehicles, the proposed system optimized traffic signal decisions, reduced travel time, minimized congestion, and improved road safety. The study highlighted the potential of integrating reinforcement learning with next-generation intelligent transportation technologies.

Gregurić et al. [21] presented a comprehensive overview of Deep Reinforcement Learning (DRL) applications in traffic signal control and emphasized the importance of open traffic datasets for developing reliable intelligent transportation systems. The study reviewed various DRL algorithms, simulation platforms, state representations, and reward functions adopted in previous research. The authors concluded that DRL significantly improves traffic efficiency compared with conventional control methods; however, challenges related to data availability, computational complexity, scalability, and real-world deployment remain major research concerns.

Haydari et al. [22] conducted an extensive survey on the application of Deep Reinforcement Learning in Intelligent Transportation Systems (ITS). The study systematically reviewed major DRL algorithms, including Deep Q-Networks, Policy Gradient methods, Actor-Critic models, and Multi-Agent Reinforcement Learning for traffic management applications. The authors highlighted the advantages of DRL in handling dynamic traffic environments while identifying limitations associated with training complexity, safety constraints, transfer learning, and computational requirements for real-world intelligent transportation systems.

Noaeen et al. [23] presented a systematic literature review on reinforcement learning for urban traffic signal control by analyzing existing methodologies, simulation platforms, state representations, reward functions, and evaluation metrics. The study categorized reinforcement learning approaches into value-based, policy-based, and multi-agent learning techniques while discussing their advantages and limitations. The authors concluded that although DRL has demonstrated remarkable improvements in traffic optimization, issues related to scalability, coordination, reward engineering, and practical implementation still require significant research attention.

Shakya et al. [24] provided a comprehensive survey of reinforcement learning algorithms and their applications across various engineering domains, including intelligent transportation systems. The review discussed the evolution of reinforcement learning from conventional Q-learning to advanced Deep Reinforcement Learning techniques and compared different value-based and policy-based algorithms. The authors highlighted that algorithm selection depends on the complexity of the application environment and emphasized the growing importance of DRL for solving large-scale optimization problems.

Matsuo et al. [25] reviewed recent advances in deep learning, reinforcement learning, and world models with particular emphasis on autonomous decision-making systems. The study discussed how reinforcement learning has evolved through the integration of deep neural networks and model-based learning techniques. The authors emphasized that future intelligent systems should combine prediction, planning, and learning capabilities to improve adaptability and generalization. Their findings provide valuable insights for developing next-generation intelligent traffic signal control systems.

Huang [26] proposed an adaptive reinforcement learning-based traffic signal control method for intelligent transportation systems. The developed framework dynamically adjusted traffic signal timings according to continuously changing traffic conditions to minimize vehicle delay and improve intersection performance. The proposed adaptive learning strategy demonstrated faster convergence and better robustness than conventional traffic control approaches. Experimental results confirmed significant improvements in traffic efficiency, making the framework suitable for real-time smart city traffic management.

Li et al. [27] proposed an adaptive traffic signal control framework that integrated Deep Reinforcement Learning with Connected Autonomous Vehicle (CAV) coordination for mixed traffic environments. The proposed model simultaneously optimized traffic signal timing and vehicle movement by utilizing real-time vehicle-to-infrastructure communication. Simulation results demonstrated reductions in queue length, travel time, and traffic congestion while improving intersection throughput. The study highlighted the benefits of integrating intelligent infrastructure with connected vehicle technology for future urban transportation systems.

Zhang et al. [28] introduced a dual-objective reinforcement learning framework that simultaneously optimized traffic efficiency and carbon emission reduction. Unlike conventional traffic signal controllers focusing only on congestion minimization, the proposed model incorporated environmental sustainability into the reward function. Experimental analysis demonstrated that the developed controller effectively reduced vehicle delay, fuel consumption, and carbon emissions while maintaining efficient traffic flow. The study supports the development of environmentally sustainable intelligent transportation systems.

Saadi et al. [29] presented a comprehensive survey of reinforcement learning and Deep Reinforcement Learning techniques for intelligent traffic signal control. The review critically analyzed recent developments in value-based, policy-based, and multi-agent reinforcement learning algorithms while comparing their applications, strengths, and limitations. The authors identified scalability, explainability, transfer learning, and computational efficiency as major challenges for future research and emphasized the importance of integrating emerging technologies such as connected vehicles, edge computing, and digital twins.

Michailidis et al. [30] reviewed recent innovations in reinforcement learning-based traffic signal control with emphasis on practical implementation and intelligent urban mobility. The study compared various reinforcement learning algorithms, communication architectures, and optimization strategies used in modern traffic management systems. The authors concluded that future research should focus on explainable artificial intelligence, cooperative multi-agent learning, Graph Neural Networks, and real-world deployment to improve the reliability and scalability of intelligent traffic signal control systems.

Alanazi et al. [31] proposed the DR-AGON framework, which combines Dueling Deep Reinforcement Learning with Graph Optimization Networks for adaptive traffic signal control. The proposed model effectively captured spatial relationships among neighboring intersections and improved coordination across complex urban road networks. By integrating graph-based feature learning with reinforcement learning, the framework achieved higher traffic throughput, lower vehicle delay, and faster convergence than conventional DRL models. The study represents one of the latest advancements in graph-based intelligent traffic management for smart cities.

Alanazi et al. [32] proposed the DR-AGON framework for adaptive traffic signal control in complex urban transportation networks. The proposed model integrates Graph Neural Networks (GNNs) with Dueling Deep Reinforcement Learning to capture both spatial dependencies among neighboring intersections and temporal traffic variations. Unlike conventional DQN-based approaches, DR-AGON effectively learns coordinated signal control policies by utilizing graph-based traffic representations. Experimental results demonstrated significant improvements in traffic throughput, reduced average vehicle delay, faster convergence, and enhanced scalability, indicating its strong potential for next-generation intelligent transportation systems and smart city traffic management.

3. CONCLUSION

Deep Reinforcement Learning (DRL) has emerged as an effective and intelligent approach for adaptive traffic signal control, overcoming many limitations associated with conventional fixed-time and actuated traffic management systems. The reviewed literature demonstrates that DRL-based algorithms, particularly Deep Q-Network (DQN) and its advanced variants, can significantly improve traffic signal performance by minimizing vehicle delay, reducing queue length, increasing traffic throughput, and enhancing overall intersection efficiency.

Over the years, research has evolved from single-intersection control to advanced multi-agent, graph-based, and model-driven reinforcement learning frameworks capable of managing large-scale urban traffic networks. The literature also highlights the growing integration of emerging technologies such as Graph Neural Networks (GNNs), Connected Autonomous Vehicles (CAVs), Internet of Things (IoT), and Vehicle-to-Everything (V2X) communication with DRL, enabling more intelligent, adaptive, and coordinated traffic management. These advancements have improved scalability, decision-making capability, and real-time responsiveness under dynamic traffic conditions. However, several challenges remain, including computational complexity, reward function design, training stability, transferability, safety assurance, and limited real-world implementation. Most existing studies are still validated primarily through simulation environments, indicating the need for practical deployment and standardized evaluation frameworks.

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