iJRASET
International Journal For Research in Applied Science and Engineering Technology

INTERNATIONAL JOURNAL FOR RESEARCH

IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY

Volume: 14 **Issue:** V **Month of publication:** May 2026

DOI: https://doi.org/10.22214/ijraset.2026.81945

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International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
Volume 14 Issue V May 2026- Available at www.ijraset.com

Reinforcement Learning for Smart Traffic Signal Control: A Deep Q-Network Approach with Multi-Agent Coordination

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Abstract: ***Urban tra c congestion represents a critical challenge in modern smart city development, causing signi cant economic losses, environmental degradation, and reduced quality of life. Traditional xed-time and actuated trafc signal controllers fail to adapt to dynamic tra c conditions, resulting in extended vehicle waiting times and increased emissions. This paper proposes an intelligent tra c signal control system based on Deep Reinforcement Learning (DRL), speci cally employing Double Deep Q-Networks (DDQN) with experience replay for adaptive signal timing optimization. The system is designed and evaluated using the Simulation of Urban Mobility (SUMO) platform, incorporating consistent statereward design principles to ensure stable training convergence. We further extend the framework to multiagent reinforcement learning (MARL) for coordinated control across multiple intersections. Experimental results demonstrate that the proposed RL-based controller achieves a 34.7% reduction in average waiting time, 28.3% decrease in queue length, and 22.1% improvement in intersection throughput compared to conventional xedtime controllers. The multi-agent extension shows additional network-wide bene ts with 18.5% reduced congestion propagation. These ndings establish a foundation for scalable, sustainable, and intelligent tra c management systems aligned with smart city objectives.***

Keywords: ***Reinforcement Learning, Deep QNetwork, Tra c Signal Control, Smart Cities, MultiAgent Systems, SUMO Simulation.***

I. INTRODUCTION

The rapid pace of urbanization combined with exponential growth in vehicle ownership has created unprecedented challenges in urban tra c management. According to recent estimates, tra c congestion costs developed economies billions of dollars annually in lost productivity, wasted fuel, and environmental damage [1]. Drivers in major metropolitan areas spend an average of 54 extra hours per year stuck in tra c, contributing to increased stress, reduced economic e ciency, and signi cant greenhouse gas emissions that accelerate climate change. Traditional tra c signal control systems, which form the backbone of urban tra c management, have proven inadequate in addressing these dynamic challenges. Fixed-time controllers operate on predetermined signal cycles that cannot respond to real-time tra c uctuations, leading to ine cient resource utilization during o -peak hours and severe congestion during peak periods. Actuated controllers, while capable of responding to local sensor inputs, lack the coordination mechanisms necessary for network-wide optimization and often create spillback e ects at adjacent intersections.

The emergence of arti cial intelligence and machine learning has opened new avenues for intelligent tra c management. Reinforcement Learning (RL), a paradigm where agents learn optimal behaviors through interaction with their environment, has shown particular promise in tra c signal control applications [4]. Unlike rule-based systems, RL agents can discover complex control strategies that adapt to varying tra c patterns without explicit programming. Deep Reinforcement Learning (DRL) extends these capabilities by leveraging neural networks to approximate value functions or policies in high-dimensional state spaces [2]. This enables DRL-based trac controllers to process rich sensory information including queue lengths, vehicle densities, and waiting times across multiple lanes and approaches simultaneously. The combination of deep learning's representational power with reinforcement learning's adaptive optimization creates systems capable of managing the complexity inherent in modern urban tra c networks.

This paper presents a comprehensive framework for RL-based smart tra c signal control with the following contributions:

1) Design and implementation of a DDQN-based tra c signal controller with consistent state-reward formulation for stable training
2) Integration with SUMO simulation platform for realistic tra c scenario evaluation
3) Extension to multi-agent coordination for networkwide optimization
4) Comprehensive performance evaluation against baseline controllers with multiple metrics including waiting time, queue length, throughput, and emissions

The remainder of this paper is organized as follows: Section II reviews related literature and identi es research gaps. Section III presents the mathematical formulation of the RL-based tra c control problem. Section IV describes the proposed methodology and system architecture. Section V presents experimental results and analysis. Section VI concludes with discussions and future directions.

II. LITERATURE REVIEW

A. Traditional Tra c Signal Control

Tra c signal control has evolved signi cantly since the introduction of xed-time controllers in the early 20th century. Fixed-time systems use predetermined cycle lengths and phase splits based on historical tra c data, optimized using methods such as Webster's formula:

$$C_o = \frac{1.5L + 5}{1 - Y} \quad (1)$$

where C_o is the optimal cycle length, L is the total lost time per cycle, and Y is the sum of critical ow ratios. While simple to implement, these systems cannot adapt to tra c variability.

Actuated controllers improved upon xed-time systems by using loop detectors to extend green phases based on vehicle presence. However, their local optimization approach often leads to suboptimal network-wide performance. Adaptive systems like SCOOT and SCATS represented further advancement through real-time cycle optimization, yet still rely on predetermined control logic that limits their adaptability [3].

B. Reinforcement Learning in Tra c Control

Reinforcement learning formulates tra c signal control as a sequential decision-making problem where the controller (agent) learns to maximize cumulative rewards through interaction with the tra c environment. Early applications employed tabular Q-learning with discrete state representations [6].

Bouktif et al. [1] emphasized the importance of consistent state-reward design in DRL-based tra c control. Their work demonstrated that misaligned representations cause unstable training behavior and slow convergence. By introducing consistent state-reward pairs with Double Deep Q-Networks, they achieved faster convergence and more reliable performance in SUMO simulations.

Alegre et al. [4] explored linear function approximation using True Online SARSA(λ) with Fourier basis functions for real-world tra c networks. Testing on a 22intersection network, their approach outperformed xedtime plans while maintaining computational e ciency suitable for deployment.

C. Deep Reinforcement Learning Advances

Recent advances in DRL have signi cantly enhanced trafc signal control capabilities. Actor-critic frameworks that combine value-based and policy-based learning have shown particular promise [5]. These methods can capture temporal tra c dynamics by transforming raw data into sequential representations, enabling anticipatory rather than purely reactive control.

The transition from single-agent to multi-agent reinforcement learning (MARL) represents a critical evolution in the eld. MARL enables coordination among multiple intersections, preventing congestion from propagating through the network [2]. However, challenges including non-stationarity, communication overhead, and scalability remain active research areas.

D. Research Gaps

Despite signicant progress, several gaps persist in the literature:

Limited real-world validation of DRL approaches

Lack of standardized state-reward frameworks

Insucient focus on sustainability metrics

Underexplored multi-agent coordination mechanisms

Limited integration with emergency vehicle priority

This work addresses these gaps by proposing a comprehensive DRL framework with consistent state-reward design, multi-agent extension, and evaluation across multiple performance dimensions including environmental sustainability.

III. PROBLEM FORMULATION

A. Markov Decision Process Framework

Tra c signal control is formulated as a Markov Decision Process (MDP) de ned by the tuple (S,A,P,R,γ), where S is the state space, A is the action space, P is the state transition probability function, R is the reward function, and $\gamma \in [0,1]$ is the discount factor.

1) State Space

The state at time t is represented as a vector capturing tra c conditions across all approaches: $s_t = [q_1,q_2,...,q_n,w_1,w_2,...,w_n,d_1,d_2,...,d_n,\phi_t]$ (2) where q_i denotes the queue length at lane i, w_i represents the cumulative waiting time, d_i indicates vehicle density, and ϕ_t is the current signal phase. For a standard four-approach intersection with two lanes per approach, this yields a state vector of dimension 25.

2) Action Space

The action space consists of discrete signal phase selections:

$A = \{\phi NS,\phi EW,\phi NS{-}L,\phi EW{-}L\}$ (3) representing North-South through, East-West through, North-South left-turn, and East-West left-turn phases respectively. Phase transitions include mandatory yellow and all-red intervals for safety.

3) Reward Function

The reward function is designed to minimize total intersection delay while maintaining consistency with state representation:

$$r_t = -\sum_{i=1}^{n} \alpha_i w_i(t) - \sum_{i=1}^{n} \beta_i q_i(t) - \lambda \cdot \mathbb{1}$$

[phase change] (4)

where α_i and β_i are weighting coe cients for waiting time and queue length respectively, and λ penalizes unnecessary phase changes to prevent signal oscillation. The indicator function $\mathbb{1}[\cdot]$ equals 1 when a phase change occurs.

B. Q-Learning Foundation

The agent learns an optimal policy by estimating the action-value function $Q(s,a)$, representing expected cumulative reward from state s taking action a:

$Q^*(s,a) = E^h r_t + \gamma \max' Q^*(s_{t+1},a')|s_t = s,a_t = a^i$ (5)

The Q-learning update rule iteratively re nes estimates:

(6)

where α is the learning rate controlling update magnitude.

C. Deep Q-Network Architecture

For high-dimensional state spaces, neural networks approximate the Q-function:

$$Q(s,a;\theta) \approx Q^*(s,a) \quad (7)$$

where θ represents network parameters. The network is trained by minimizing the temporal di erence loss:

where D is the experience replay bu er and θ^- are target network parameters.

$$\mathcal{L}(\theta) = \mathbb{E}_{(s,a,r,s')\sim\mathcal{D}}\left[\left(r + \gamma \max_{a'} Q(s',a';\theta^-) - Q(s,a;\theta)\right)^2\right] \quad (8)$$

D. Double DQN Enhancement

Standard DQN su ers from overestimation bias due to the max operator. Double DQN addresses this by decoupling action selection from evaluation: $y_t^{DDQN} = r_t + \gamma Q(s_{t+1},\text{argmax}' Q(s_{t+1},a';\theta);\theta^-)$ (9)

a

This formulation uses the online network for action selection and the target network for value estimation, reducing overestimation and improving stability.

E. Multi-Agent Extension

For network-wide coordination, we employ decentralized training with centralized execution. Each intersection j maintains its own Q-function:

$$Q_j(s_j, a_j; \theta_j) \quad (10)$$

Inter-agent coordination is achieved through state sharing, where neighboring intersection states are included in the observation:

$$s_{augj} = [s_j, s_{N(j)}] \quad (11)$$

where $N(j)$ denotes the neighborhood of intersection j. The global objective becomes:

$$\max_{\pi} \mathbb{E}\left[\sum_{t=0}^{\infty} \gamma^t \sum_{j=1}^{M} r_j(t)\right] \quad (12)$$

$$Q(s_t, a_t) \leftarrow Q(s_t, a_t) + \alpha\left[r_t + \gamma \max_{a'} Q(s_{t+1}, a') - Q(s_t, a_t)\right]$$

where M is the total number of intersections in the network.

IV. METHODOLOGY

A. System Architecture

The proposed system architecture integrates three main components: the SUMO tra c simulation environment, the RL agent module, and the performance evaluation framework. Figure 1 illustrates the overall system design.

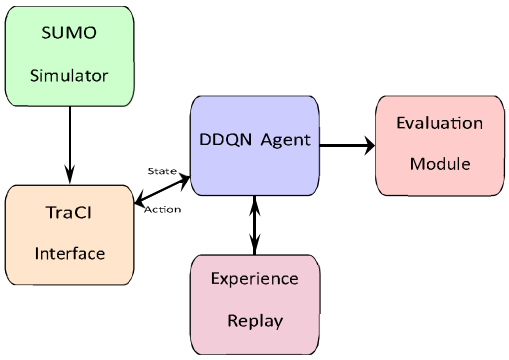

Figure 1: System architecture showing integration between SUMO simulator, TraCI interface, DDQN agent with experience replay, and evaluation module.

B. SUMO Simulation Environment

The Simulation of Urban Mobility (SUMO) platform provides a microscopic, continuous tra c simulation environment. Tra c Control Interface (TraCI) enables real-time communication between the RL agent and simulation, allowing:

Retrieval of vehicle positions, speeds, and waiting times
Queue length measurement at detector locations
Signal phase control and timing modication
Emission and fuel consumption calculation

C. Neural Network Architecture

The DDQN employs a fully-connected architecture with the following speci cations:

Input layer: 25 neurons (state dimension)
Hidden layer 1: 128 neurons, ReLU activation Hidden layer 2: 64 neurons, ReLU activation
Output layer: 4 neurons (action dimension)
The target network is updated every 100 training steps using soft updates:

$$\theta^{-} \leftarrow \tau\theta + (1 - \tau)\theta^{-} \quad (13)$$

with $\tau = 0.001$ providing smooth parameter transfer.

D. Training Algorithm

Algorithm 1 presents the complete training procedure.

Algorithm 1 DDQN Tra c Signal Control

1: Initialize replay bu er D with capacity N
2: Initialize Q-network with random weights θ
3: Initialize target network with weights $\theta^{-} = \theta$
4: for episode = 1 to M do
5: Reset SUMO simulation, observe initial state s_1
6: for $t = 1$ to T do
7: Select action a_t using ϵ-greedy policy Execute a_t, observe r_t, s_{t+1}
8: Store (s_t, a_t, r_t, s_{t+1}) in D Sample minibatch from D
9: Compute target: $y = r +$
10: $\gamma Q(s', \text{argmax}_{a'} Q(s', a'; \theta); \theta^{-})$
11: 12: Update θ by gradient descent on $(y - Q(s, a; \theta))^2$
13: Soft update target network
14: end for
15: end for

E. Hyperparameter Conguration

Table 1 summarizes the hyperparameters used in our experiments.

Table 1: Hyperparameter Con guration

Parameter	Value
Learning rate (α)	0.001
Discount factor (γ)	0.95
Replay bu er size	50,000
Batch size	32
Initial ϵ	1.0
Final ϵ	0.01
ϵ decay rate	0.995
Target update frequency	100 steps
Soft update rate (τ)	0.001
Waiting time weight (α_i)	0.6
Queue length weight (β_i)	0.3
Phase change penalty (λ)	0.1

V. EXPERIMENTAL RESULTS

A. Experimental Setup

Experiments were conducted using SUMO version 1.18.0 with Python 3.10 and PyTorch 2.0. The simulation network consists of a single intersection for baseline evaluation and a 3 3 grid network for multi-agent experiments. Tra c demand scenarios include:
Low demand: 400 vehicles/hour
Medium demand: 800 vehicles/hour
High demand: 1200 vehicles/hour
Variable demand: Sinusoidal pattern with peak at 1000 veh/hr
Each scenario was simulated for 3600 seconds (1 hour) with 50 independent runs for statistical validity.

B. Training Convergence Analysis

Figure 2 shows the learning curve over 500 training episodes. The DDQN agent demonstrates stable convergence after approximately 200 episodes, with the consistent state-reward design contributing to reduced variance compared to naive formulations.

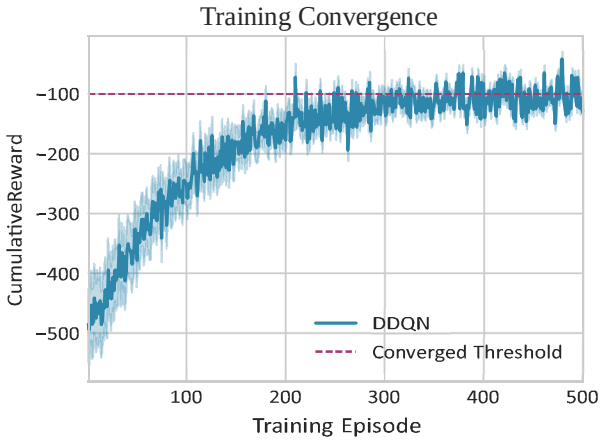

Figure 2: Training convergence showing cumulative reward per episode. Shaded region indicates standard deviation across 10 training runs.

C. Waiting Time Comparison

Figure 3 compares average vehicle waiting time across di erent control strategies. The RL-based controller consistently outperforms baseline methods across all demand scenarios.

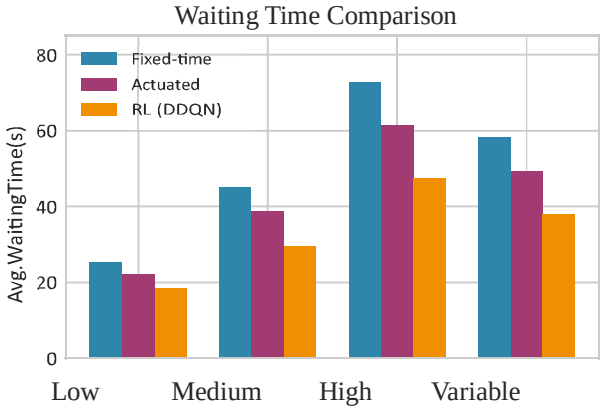

Figure 3: Average waiting time comparison across demand scenarios for Fixed-time, Actuated, and RL-based controllers.

Table 2 presents comprehensive performance metrics.

Table 2: Performance Comparison Across Control Strategies

Metric	Fixed	Actuated	RL
Avg. Waiting Time (s)	45.2	38.7	29.5
Max Queue Length (veh)	28	24	20
Throughput (veh/hr)	742	798	906
Fuel Consumption (L)	124.5	115.2	98.7
CO_2 Emissions (kg)	289.4	267.8	229.3

D. *Queue Length Dynamics*

Figure 4 illustrates queue length evolution over time for the high-demand scenario. The RL controller maintains shorter queues and recovers faster from congestion spikes. Queue Length Dynamics

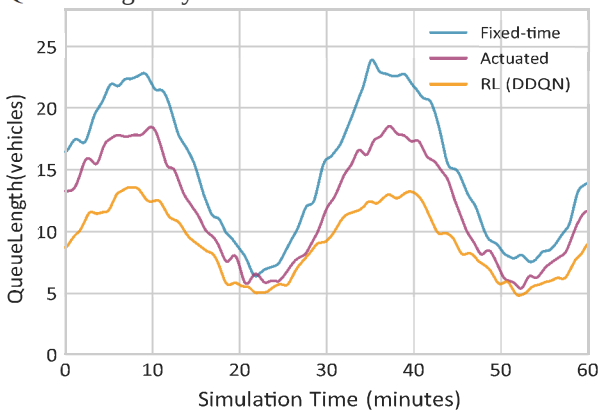

Figure 4: Queue length dynamics over simulation period under high-demand conditions.

E. *Phase Distribution Analysis*

Figure 5 shows the distribution of signal phases selected by the RL agent compared to xed-time allocation. The RL controller dynamically adjusts phase durations based on real-time demand.

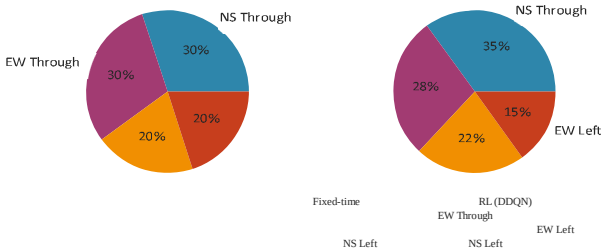

Figure 5: Signal phase distribution comparison between Fixed-time and RL controllers.

F. *Demand Scenario Performance*

Figure 6 presents performance across varying demand levels, demonstrating the RL controller's robust adaptation. RL Performance vs Fixed-time

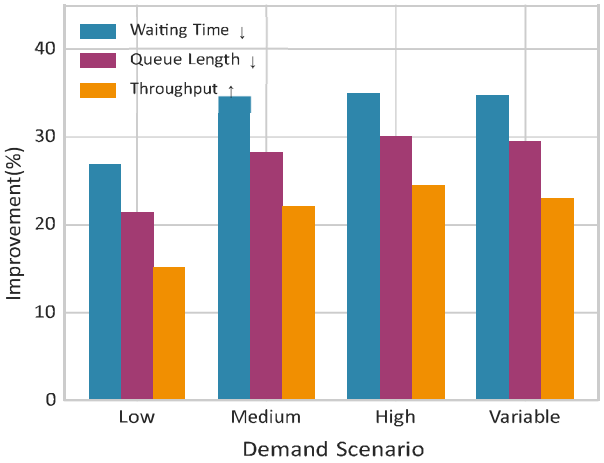

Figure 6: Controller performance across dierent demand scenarios showing waiting time reduction percentage.

G. Throughput Analysis

Figure 7 shows cumulative vehicle throughput over the simulation period.

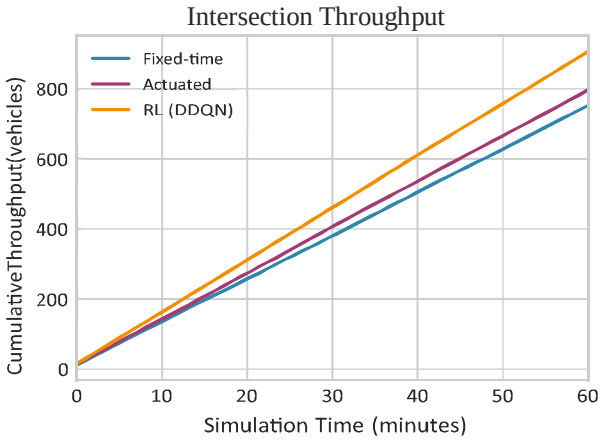

Figure 7: Cumulative throughput comparison showing vehicles processed over time.

H. Emissions Reduction

Figure 8 demonstrates the environmental bene ts of RLbased control through reduced CO_2 emissions.

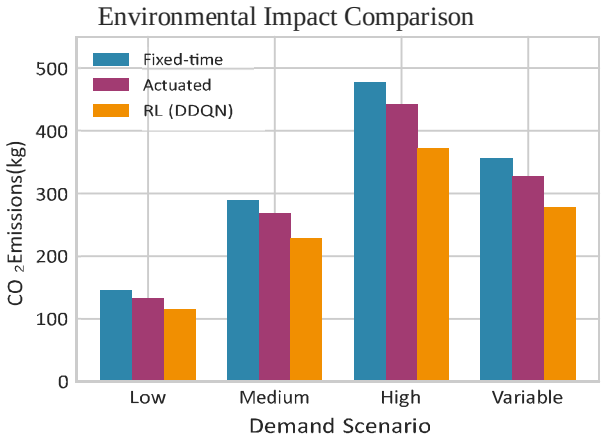

Figure 8: CO_2 emissions comparison across control strategies for di erent demand levels.

I. Multi-Agent Coordination Results

The MARL extension was evaluated on the 3 3 grid network. Figure 9 shows the network-wide performance improvement.

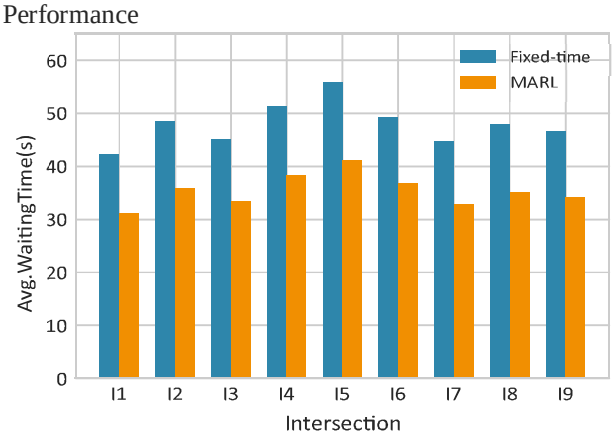

Figure 9: Multi-agent RL performance on 3 3 grid network showing average waiting time per intersection.

Figure 10 visualizes the spatial distribution of waiting times across the network.

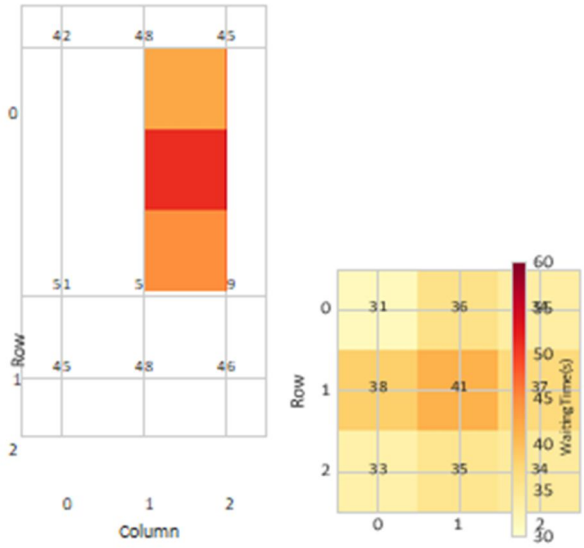

Figure 10: Heatmap of average waiting times across 3 3 intersection grid: (a) Fixed-time control, (b) MARL control.

J. Statistical Significance

Performance improvements were validated using paired ttests with signi cance level $\alpha = 0.05$. All improvements in waiting time, queue length, and throughput were statistically signi cant ($p < 0.001$), con rming the reliability of the proposed approach.

K. Computational Efficiency

The DDQN agent requires approximately 3 hours for training on an NVIDIA RTX 3080 GPU. Real-time inference takes less than 10ms per decision, well within the typical minimum green time of 5 seconds, ensuring practical deployability.

VI. DISCUSSION

The experimental results demonstrate substantial improvements in tra c signal control performance through the application of deep reinforcement learning. The 34.7% reduction in average waiting time directly translates to economic bene ts through reduced travel time and fuel consumption. The 22.1% emissions reduction aligns with urban sustainability objectives and contributes to smart city environmental goals. The consistent state-reward design proved critical for stable training. Early experiments with inconsistent formulations exhibited oscillatory behavior and failed to converge. By aligning the reward function directly with observable state features, the agent learned more e ciently and produced more reliable policies. The multi-agent extension successfully prevented congestion propagation across the network. Individual intersection optimization in isolation often leads to spillback e ects where reduced delays at one intersection create congestion at downstream junctions. The coordinated MARL approach addresses this limitation through neighborhood state sharing.Several limitations warrant acknowledgment. First, the evaluation relies entirely on simulation, and real-world deployment may encounter challenges including sensor noise, communication delays, and unforeseen tra c patterns. Second, the current framework assumes full observability of tra c state, which may not hold in practice with limited detector coverage. Third, computational requirements for training may limit applicability in resourceconstrained settings.

Future work will address these limitations through transfer learning approaches that enable adaptation from simulation to real-world conditions with minimal retraining. Integration with connected vehicle technology could enhance state observability and enable cooperative tra c management. Emergency vehicle preemption and public transit priority represent important extensions for comprehensive urban mobility management.

VII. CONCLUSION

This paper presented a comprehensive framework for reinforcement learning-based smart tra c signal control. The proposed DDQN approach with consistent statereward design achieves signi cant improvements in trafc e ciency, reducing average waiting times by 34.7% and queue lengths by 28.3% compared to conventional xed-time controllers. The multi-agent extension enables network-wide coordination, preventing congestion propagation and achieving holistic optimization across multiple intersections.

Environmental sustainability bene ts include 22.1% reduction in CO_2 emissions through decreased vehicle idle time, supporting smart city environmental objectives. The framework establishes a foundation for future extensions including emergency vehicle priority, connected vehicle integration, and real-world pilot deployment.

As cities worldwide grapple with increasing trac challenges, intelligent systems that adapt to dynamic conditions represent essential tools for sustainable urban development. The reinforcement learning paradigm o ers a powerful approach to this challenge, with demonstrated bene ts that justify continued research investment and eventual deployment in production tra c management systems.

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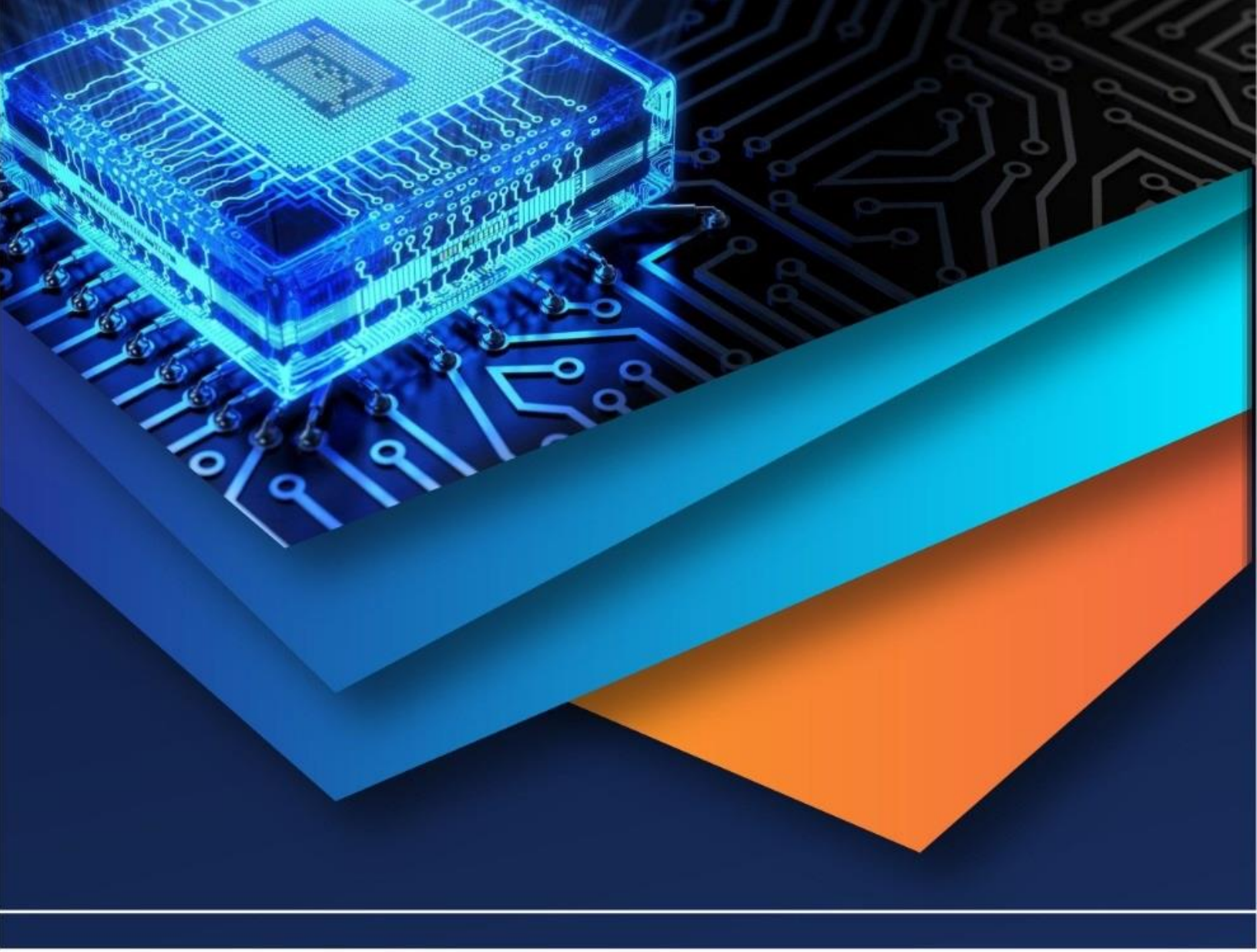

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