

DQN-Based Adaptive Traffic Signal Control Using Directional Vehicle Count Data

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Abstract: Urban traffic congestion has become a significant challenge, highlighting the need for intelligent and adaptive traffic signal control systems. This paper presents a Deep Q-Network (DQN)-based approach for intelligent traffic signal optimization using real-world traffic observations from Pune, India. The proposed methodology involves traffic data preprocessing, directional vehicle volume estimation, reinforcement learning environment design, and DQN model training. Vehicle observations are categorized into four directions, namely UP, DOWN, LEFT, and RIGHT, with two discrete signal phases considered for control. The trained model is evaluated against a fixed-time signal strategy using an average reward-based metric. Preliminary experimental results show an average reward of 372.21 for DQN compared with 412.84 for the fixed-time baseline. These findings indicate potential benefits, although further realistic traffic simulation and validation are required to establish practical effectiveness.

Keywords: Deep Reinforcement Learning, Deep Q-Network, Traffic Signal Optimization, Intelligent Transportation Systems, Adaptive Traffic Control.

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I. INTRODUCTION

Urban traffic congestion has become a major challenge in modern cities due to rapid urbanization, increasing vehicle ownership, and limited road infrastructure. Traffic congestion leads to longer travel times, higher fuel consumption, increased emissions, and reduced transportation efficiency [2]. Conventional traffic signal control systems generally operate using fixed timing schedules, which may not respond effectively to variations in traffic demand across different directions. Therefore, intelligent traffic signal control systems are required to adapt signal phases according to observed traffic conditions and improve the utilization of existing road infrastructure. Artificial Intelligence (AI) and Machine Learning (ML) have emerged as promising technologies for developing intelligent transportation systems. Among these techniques, Reinforcement Learning (RL) enables an agent to learn

an effective decision-making policy through interactions with an environment and feedback in the form of rewards. Unlike conventional fixed-time approaches, RL-based methods can potentially adapt traffic signal decisions to changing traffic conditions. Deep Reinforcement Learning (DRL) combines reinforcement learning with deep neural networks, enabling the learning of policies from complex state representations. Deep Q-Network (DQN), a widely used DRL algorithm, approximates action-value functions and selects actions based on estimated cumulative rewards [3]. This paper presents a preliminary DQN-based framework for intelligent traffic signal optimization using directional vehicle observations from traffic data collected in Pune, India. The dataset contains vehicle-count information for cars, motorbikes, buses, and trucks across four directions: UP, DOWN, LEFT, and RIGHT. During

pre-processing, repeated observations are aggregated using the median to obtain representative directional vehicle counts. These counts are used to construct the state representation for a simplified reinforcement learning environment. The agent selects between two signal phases: North–South and East–West. A reward function based on traffic volume in the non-prioritized direction is employed to guide the agent's decisions.

The proposed approach is evaluated against a simple fixed-time baseline using average reward as the evaluation metric. Preliminary results indicate an average reward of 372.21 for DQN, compared with 412.84 for the fixed-time strategy. Although these results suggest improved performance under the defined reward formulation, they do not directly demonstrate reductions in real-world waiting time or congestion. The present study provides an initial experimental framework for applying DQN to directional traffic observations and highlights the need for realistic traffic simulation, additional performance metrics, and broader validation in future work.

II. LITERATURE REVIEW

Intelligent traffic signal control has emerged as an effective solution for mitigating urban traffic congestion and improving transportation efficiency. Recently, reinforcement learning techniques have gained significant attention due to their ability to learn adaptive control policies directly from traffic environments.

[1] Proposed a deep reinforcement learning-based traffic signal control framework for connected vehicle (CV) environments. The study utilized real-time traffic information and a compressed traffic state representation to optimize signal phases more efficiently. The proposed approach eliminated the need for prior traffic model knowledge while improving the flexibility of signal control. Experimental results demonstrated superior performance over existing methods by reducing queue length and waiting time while increasing average vehicle speed and improving overall traffic density management.

[2] Presented a novel adaptive traffic signal control (TSC) approach based on Deep Reinforcement Learning (DRL) instead of conventional optimization and rule-based methods. The study introduced an improved feature-based state representation and reward mechanism to enhance the generalization and

scalability of the learning process. The proposed model was evaluated using a high-fidelity microscopic traffic simulator, and the results demonstrated that the DRL-based approach is a promising solution for real-time traffic signal control with improved adaptability and performance.

Author's [3] a comprehensive review of reinforcement learning (RL)-based traffic signal control techniques for intelligent transportation systems. The study analyzed recent RL approaches based on methodology, multi-agent architectures, reward design, simulation platforms, network scale, and practical applicability. The review highlighted the growing importance of RL in developing adaptive and sustainable traffic management systems while identifying key challenges and future research directions for next-generation urban mobility.

Authors [4] proposed an enhanced Deep Reinforcement Learning (DRL)-based traffic signal control method to improve convergence speed and robustness under varying traffic conditions. The approach integrated Double DQN, Dueling Networks, prioritized experience replay, and noise parameters to enhance learning efficiency and reduce overestimation. Experimental results showed faster convergence and significant improvements in queue length and vehicle waiting time, demonstrating the model's effectiveness across diverse traffic scenarios.

Authors [5] proposed SHLight, a hierarchical deep reinforcement learning framework for traffic signal control that consists of a manager and multiple worker agents to jointly optimize global and local traffic objectives. The model incorporated importance sampling to address non-stationarity and auxiliary actions to improve state observability. Experimental evaluations on both synthetic and real-world traffic networks demonstrated that SHLight outperformed existing methods by reducing queue lengths, vehicle waiting times, and overall traffic delays.

Author [6] proposed a cross-domain intelligent traffic signal control framework based on Federated Proximal Policy Optimization (Fed-PPO) to improve the generalization and convergence of deep reinforcement learning models across multiple intersections. The approach employed distributed collaborative training while preserving data privacy and enhancing inter-agent communication through an improved state interaction mechanism and reward function.

Experimental results demonstrated that the proposed method reduced average vehicle waiting time by up to 27.34% and achieved significantly faster convergence than conventional PPO-based approaches, highlighting its effectiveness and robustness for large-scale traffic signal optimization.

III. PROPOSED METHODOLOGY

This research work proposes an intelligent traffic signal optimization approach using Deep Reinforcement Learning (DRL), specifically Deep Q-Network (DQN), to select appropriate traffic signal phases based on observed traffic demand. The methodology comprises dataset acquisition, pre-processing, reinforcement learning environment design, model training, and performance evaluation. A Pune traffic dataset covering Alankar Chowk, Jehangir Chowk, and RTO Chowk was explored. The initial experiment used the a3_15.csv file from Alankar Chowk, containing 883,100 rows and six attributes: timestamp, direction, cars, motorbikes, buses, and trucks. Numeric conversion and missing-value handling were performed, and repeated observations were aggregated using median values. This process produced 35,320 timestamp-direction records.

The traffic control problem was formulated as a Markov Decision Process (MDP). The state consists of vehicle volumes in four directions: UP, DOWN, LEFT, and RIGHT. Two discrete actions represent North-South and East-West green phases. The reward function penalizes traffic demand in the directions not served by the selected phase. A DQN model with a multilayer perceptron policy was implemented using Stable-Baselines3 in Python on Google Colab. The model was trained for 5,000 time steps, with learning commencing after 100 steps. Its performance was compared with a conventional fixed-time signal strategy using average reward. The proposed approach provides an initial learning-based prototype for traffic signal control. However, the current evaluation uses a simplified reward function and does not explicitly simulate vehicle queues, waiting times, or signal clearance intervals. These limitations are considered in interpreting the experimental results.

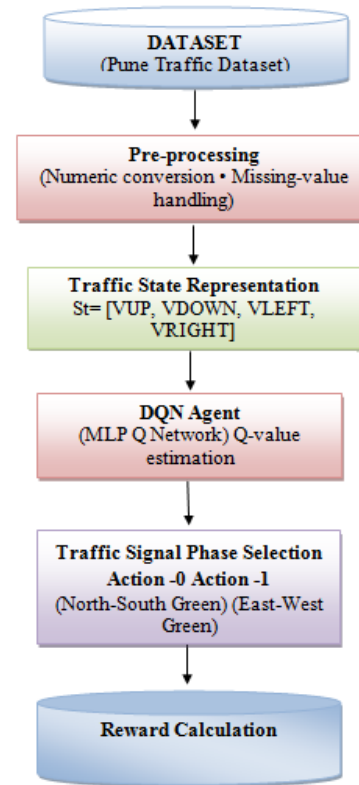


Figure 1: Proposed Framework

IV. RESULT ANALYSIS

The selected Alankar Chowk traffic dataset initially contained 883,100 records. After numeric conversion, missing-value handling, and median-based aggregation by timestamp and direction, the dataset was reduced to 35,320 records. This represents an approximate 96% reduction in the number of records. The preprocessing procedure generated a more manageable representation of directional traffic demand for the proposed Deep Reinforcement Learning (DRL) framework. Median-based aggregation also helped mitigate the potential overestimation of traffic volume caused by repeated observations. However, the aggregation strategy requires further validation against the original data collection methodology to ensure that the processed observations accurately represent traffic conditions.

The proposed Deep Q-Network (DQN) model was trained for 5,000 time steps using the Stable-Baselines3 library. The trained model was subsequently tested on ten consecutive traffic observations to examine its action-selection capability. During this preliminary test, the agent selected Action 0 for all ten observations, with rewards ranging from 0 to -12.

These results demonstrate that the trained model can generate traffic signal phase decisions from the observed state representations. However, selecting the same action throughout a short test sequence does not necessarily demonstrate an optimal or adaptive control policy. The behavior may be influenced by the limited training duration, observed traffic patterns, reward formulation, or characteristics of the training environment. Therefore, further testing across multiple episodes and varying traffic conditions is necessary to determine whether the learned policy can respond effectively to changing directional traffic demand. The experimental results demonstrate the feasibility of implementing a DQN-based traffic signal control prototype using real traffic observations and Python-based reinforcement learning tools. The proposed framework integrates traffic data preprocessing, directional state representation, discrete signal phase selection, reward calculation, and comparative evaluation within a unified methodology.

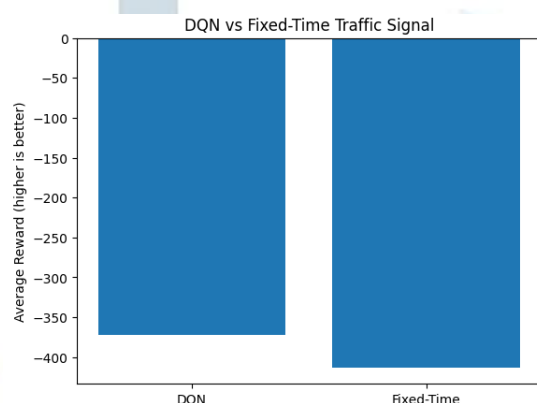


Figure 2: Comparative Average Reward of DQN-Based and Fixed-Time Traffic Signal Control Strategies

The higher average reward obtained by the DQN controller suggests that reinforcement learning may provide benefits over a fixed-time strategy under the current experimental assumptions. However, this conclusion remains preliminary. The environment does not explicitly simulate vehicle queue accumulation, vehicle departures, signal transition intervals, or waiting times. Furthermore, the experiment uses a single selected traffic data file, a training duration of 5,000 time steps, and a limited preliminary action-selection test.

Another important consideration is that the observed reward difference alone does not establish statistical

significance or generalization to other intersections. A more comprehensive evaluation should employ repeated test episodes, multiple random seeds, and representative traffic conditions. The study should also compare the DQN controller with a clearly specified fixed-time policy and, where possible, a queue-based adaptive controller. For a realistic assessment, future experiments should incorporate a validated traffic simulation environment and evaluate metrics such as average vehicle waiting time, mean queue length, throughput, and travel delay. These additional experiments would help determine whether the observed reward improvement translates into measurable operational benefits for intelligent traffic signal control. The present results provide an initial indication that a DQN-based controller can be implemented and can achieve a more favorable average reward than the selected fixed-time baseline. Further simulation-based validation and comprehensive performance testing are required before drawing conclusions regarding real-world traffic efficiency.

V. CONCLUSION

This research work presented a DQN-based approach for intelligent traffic signal optimization using real traffic observations from Alankar Chowk, Pune. After preprocessing, the dataset was reduced from 883,100 to 35,320 records through median-based aggregation. The trained DQN controller achieved an average reward of 372.21, outperforming the fixed-time baseline reward of 412.84 by 40.63 points, or approximately 9.84% in negative-reward magnitude. These preliminary findings demonstrate the feasibility of applying deep reinforcement learning to traffic signal phase selection. However, the simplified environment limits real-world conclusions. Future work will further integrate traffic simulation, evaluate multiple scenarios, and measure waiting time, queue length, throughput, and delay.

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