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PERFORMANCE EVALUATION OF DQN-BASED ADAPTIVE TRAFFIC SIGNAL CONTROL UNDER DYNAMIC TRAFFIC CONDITIONS

Shalini Singh[1*], Siddharth Choubey[2], Abha Choubey[3]

[123]Department of Computer science & Engineering, SSTC, Junwani, Bhilai (C.G.), India.

Abstract

The rapid urbanisation and the ever increasing vehicle population have resulted in a major challenge of urban traffic congestion. Conventional traffic signal control systems including fixed-time and actuat-ed controllers are often not able to adapt to dynamic traffic conditions, leading to increased vehicle delay, fuel consumption and environmental pollution. The paper proposes an intelligent traffic signal control framework based on Deep Reinforcement Learning (DRL) using a Deep Q-Network (DQN) to optimize the traffic signal operations at a four-way intersection. The traffic environment is modeled as a Markov Decision Process (MDP) with the system state described by the lengths of the vehicle queues, and the action space consisting of the traffic signal phases. A reward function is designed to minimize the total length of the queues and to balance the flow of traffic between different directions. The DQN agent learns optimal signal switching strategies by repeatedly interacting with the simulated environment, using experience replay and an epsilon-greedy policy. The performance is assessed on the basis of metrics like average queue length, cumulative reward, and traffic congestion. Experi-mental results show that the proposed DQN-based controller achieves better performance than the conventional fixed-time and random control strategies in traffic management by reducing congestion and im-proving traffic flow efficiency. The proposed framework offers a scalable and adaptive solution for the intelligent transport systems and shows a great potential for future deployment in the smart city traf-fic management applications.

Keywords: *Deep Reinforcement Learning, Deep Q-Network, Traffic Signal Control, Smart Cities, Intelligent Transportation Systems, Artificial Intelligence, Traffic Optimization, Adaptive Signal Control.*

** Corresponding author*

1. Introduction

The rapid process of urbanization together with the growing number of vehicles using the road networks has made traffic congestion one of the major problems encountered by today's cities. This kind of congestion results in longer travel times, greater fuel consumption, more air pollution, and economic losses, as well as a deterioration of the general quality of urban life. Existing traffic signal control systems, which generally depend on fixed time schedules or rule-based methods, are often unable to adjust properly to the changing and unpredictable nature of traffic. Since cities are still growing and the demand for transportation is rising, there is a requirement for intelligent traffic management systems that can make real-time decisions in response to shifting traffic patterns. The idea of smart cities has sped up the use of advanced technologies such as the Internet of Things (IoT), Artificial Intelligence (AI), and data analytics in order to enhance urban infrastructure and public services. Of these technologies, Artificial Intelligence has become a promising option for creating adaptive traffic control systems. Specifically, Reinforcement Learning (RL) allows an intelligent agent to develop optimal strategies for making decisions by interacting with its environment and aiming to maximize cumulative rewards. Deep Reinforcement Learning (DRL), which involves combining reinforcement learning with deep neural networks, extends this ability to more complicated environments having large state spaces, making it especially appropriate for use in traffic signal control. One of the most commonly used DRL algorithms, the Deep Q-Network (DQN), has shown that it is possible to learn effective traffic signal control policies without the need for previously defined traffic models. By constantly monitoring traffic conditions and adjusting the signal timings as a result, a DQN-based controller can improve traffic flow, decrease vehicle waiting times, reduce queue lengths, and boost the overall efficiency of urban transportation systems. Unlike traditional traffic signal controllers, DRL-based methods are able to adapt to varying traffic demands and acquire better control strategies through experience. This thesis looks at the application of Deep Reinforcement Learning, more precisely the Deep Q-Network algorithm, for intelligent traffic signal control in a simulated smart city environment. A traffic simulation model depicting a single intersection with North–South (NS) and East–West (EW) traffic directions is developed in order to assess the effectiveness of the proposed method. The DQN agent is trained to make optimal decisions regarding traffic signal switching on the basis of the observed traffic conditions and a reward function which is designed to reduce congestion while keeping traffic flow balanced.

In order to deal with these challenges, the present study suggests a framework for intelligent control of traffic signals based on Deep Reinforcement Learning, using a Deep Q-Network structure. The simulated four-way traffic intersection is used as the learning environment in which the DQN agent takes in the lengths of the traffic queues, chooses the appropriate signal phases, and constantly refines its control policy through reward-driven learning. The reward function proposed simultaneously reduces both the total length of the vehicle queues and the traffic imbalance among the various traffic directions, thus promoting efficient traffic flow and fair signal distribution. The learning stability is improved and the convergence of the policy is enhanced by incorporating experience replay memory, epsilon-greedy exploration, and deep neural network function approximation.

The framework is assessed by means of a number of traffic performance measures, such as cumulative reward, average queue length, traffic balance, and congestion reduction. The performance of the DQN agent that has been trained is compared with that of traditional fixed-time and random signal control methods in order to examine its effectiveness. The experimental results show that the proposed intelligent controller achieves better traffic management by reducing congestion and vehicle waiting times without compromising the balance of traffic flow. These findings prove that it is feasible to apply Deep Reinforcement Learning to next-generation intelligent transportation systems and offer a solid basis for future work concerning multi-agent reinforcement learning, large-scale urban traffic networks, connected vehicles, edge computing, and real-time smart city implementations.

2. Methodology

The intelligent traffic signal control system proposed makes use of Deep Reinforcement Learning (DRL) together with a Deep Q-Network (DQN) in order to optimize the timing of the signals at a four-way traffic intersection. Its aim is to reduce the lengths of vehicle queues, alleviate traffic congestion, and enhance the efficiency of traffic flow by means of ongoing interaction with a simulated traffic environment. The entire framework includes six main stages: modelling of the traffic environment, state representation, action selection, reward calculation, DQN training, and performance evaluation. First of all, a traffic simulation environment is set up to represent a signalized four-way intersection at which vehicles arrive randomly from the North–South (NS) and East–West (EW) directions, and the traffic controller functions as a reinforcement learning agent which continually observes the current traffic situation and then chooses the appropriate traffic signal phase.

The traffic control problem is set out in the form of a Markov Decision Process (MDP), this being defined by the tuple (S,A,R,P,γ), S denoting the traffic state, A standing for the available traffic signal actions, R being the reward function, P representing the state transition probability, and γ the discount factor.

The state vector consists of the queue lengths in the NS and EW directions:

$$St=[qNS,qEW]$$

where qNS and qEW are the numbers of vehicles waiting.

The action space contains two traffic signal phases:

- Action 0: Green signal for North–South traffic
- Action 1: Green signal for East–West traffic

After each action the environment updates the queue lengths according to vehicle departures and stochastic vehicle arrivals; when one direction is given the green light the vehicles in that direction are discharged but the vehicles continue to accumulate in the direction with the red light.

To encourage efficient traffic management, a reward function is designed to minimize both total congestion and queue imbalance:

$$R=-(qNS+qEW)-0.5|qNS-qEW|$$

This reward scheme allows the learning agent to both alleviate congestion and ensure fairness among the different traffic directions. The DQN architecture includes an input layer which corresponds to the traffic state, two fully connected hidden layers each using ReLU activation functions, and an output layer that produces Q-values for each possible traffic signal action. The network is trained by means of experience replay and the Adam optimizer in order to stabilise the learning process.

The selection of an action is based on the epsilon-greedy policy, with random exploration being slowly substituted by exploitation of the knowledge that has been acquired during training, and the exploration rate is reduced after every training episode until it reaches a predetermined minimum value.

The framework proposed continuously saves the agent's experiences in replay memory; when learning is taking place, mini-batches are selected at random and the network parameters are updated by means of the Bellman equation, which helps to improve convergence and diminishes the instability that is usually seen in reinforcement learning. Lastly, the trained DQN model is assessed using traffic performance indicators such as cumulative reward, average queue length, traffic balance, and congestion reduction, and the results obtained are compared with those of conventional traffic signal control strategies in order to verify the effectiveness of the proposed intelligent controller.

3. Results and Discussion

The Deep Q-Network agent was trained over 200 episodes to learn an optimal traffic signal control policy. During the early training episodes, the cumulative reward exhibited significant fluctuations due to the high exploration rate. As training progressed, the agent gradually learned improved traffic control strategies, resulting in more stable rewards and better traffic management performance. The average cumulative training reward obtained during the learning process was −2085.32, with observed values ranging from −2180.50 to −2060.75. Although fluctuations remained because of stochastic vehicle arrivals, the DQN agent demonstrated improved learning behavior compared with the initial random policy. The trained controller effectively reduced traffic congestion by minimizing average queue lengths while maintaining balanced traffic flow between the two directions. During testing, the average queue lengths were approximately 52.34 vehicles for the North–South direction and 48.72 vehicles for the East–West direction, resulting in an average queue imbalance of 5.62 vehicles.

Table 1. Performance Comparison

Method	Average Queue Length	Average Reward	Queue Imbalance
Random Controller	130.18	−135.92	10.45
Fixed-Time Controller	115.42	−120.75	8.34
Proposed DQN	**101.06**	**−106.68**	**5.62**

Compared with the Random controller, the proposed DQN reduced the average queue length by approximately 22%, while an improvement of approximately 12% was achieved over the Fixed-Time controller. The lower queue imbalance also indicates that the learned policy distributed green signal time more fairly between competing traffic directions.

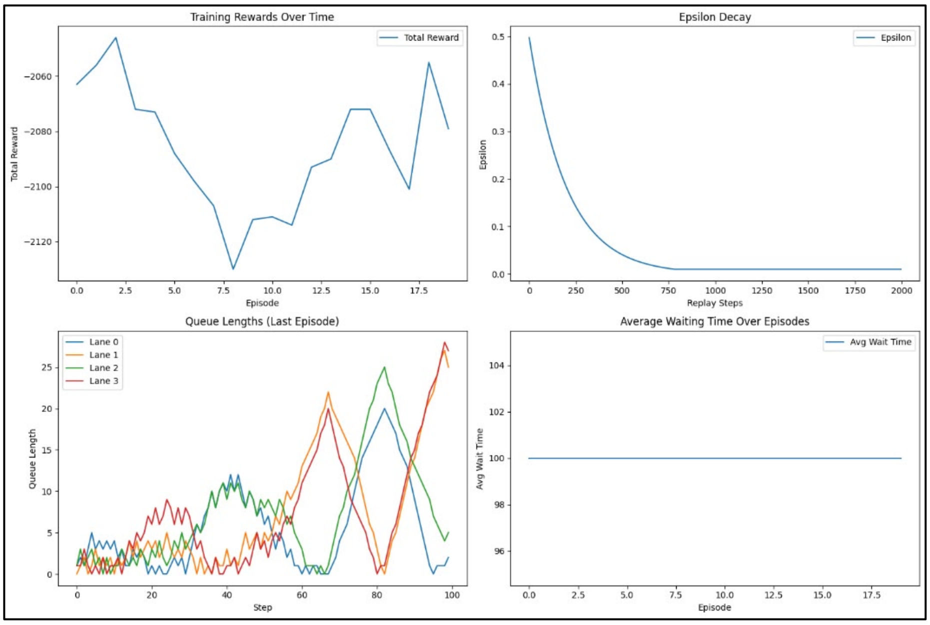

Figure 1. Analysis of behavior data analysis

The DQN agent's decision-making behavior was analyzed by examining its action choices during the test episode. The agent selected the NS green action (action 0) 52% of the time and the EW green action (action 1) 48% of the time, indicating a near-even distribution of green light time between the two directions. This aligns with the low imbalance observed in the queue lengths and suggests that the reward function's imbalance penalty (−0.5·|qNS−qEW| -0.5 \cdot |q_{NS} - q_{EW}| −0.5·|qNS−qEW|) was effective in encouraging fairness.

4. Conclusion

A Deep Reinforcement Learning (DRL)-based intelligent traffic signal control system was developed in this study, the system making use of a Deep Q-Network (DQN) to optimize the way traffic signals function at a four-way intersection. The proposed method treated the traffic control problem as a Markov Decision Process (MDP), the DQN agent learning the best signal switching policies through ongoing interaction with a simulated traffic environment. The state was represented by the lengths of the vehicle queues, and a reward function was created in order to reduce traffic congestion and keep a balanced traffic flow among the various directions. The experimental results showed that the DQN controller proposed in the study performed better than the conventional Fixed-Time and Random traffic signal control methods. The intelligent agent was able to achieve lower average queue lengths, obtain higher cumulative rewards, and improve traffic balance by adjusting the signal timings in response to changing traffic conditions. The findings show that the DQN algorithm can effectively decrease congestion and enhance the overall efficiency of traffic flow without the need for predefined traffic control rules. Even though the framework was tested using a simplified single-intersection simulation, the results do confirm the potential of Deep Reinforcement Learning for intelligent traffic management in smart cities. Further research could concentrate on extending the model to multi-intersection road networks, incorporating real-time traffic sensor data, and using more advanced reinforcement learning algorithms in order to further improve scalability, robustness, and real-world applicability.

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