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Traffic Control System using Deep Q-Network with Replay Memory

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***Abstract*— Urban road congestion presents significant challenges, causing economic losses, environmental damage, and a lower quality of life. Conventional traffic management systems often struggle to handle unpredictable traffic patterns, leading to delays and inefficient road use. This paper introduces an adaptive traffic management system that leverages real-time data analysis through advanced image processing and artificial intelligence (AI). The system adapts traffic signals in real-time based on how traffic is flowing, helping vehicles move more smoothly and giving priority to the busiest lanes. By integrating machine learning (ML), the system learns from historical and live data, making proactive signal adjustments to prevent congestion. This intelligent coordination reduces wait times, enhances intersection throughput, and ensures balanced vehicle distribution across lanes. In addition to improving traffic flow, the system lowers fuel consumption and greenhouse gas emissions by reducing vehicle idling, supporting environmental sustainability. The adaptive model is highly scalable, making it suitable for cities of different sizes and complexities. It can also integrate with other smart city technologies, such as connected vehicles and public transit systems, to enhance urban mobility. The proposed system offers a sustainable and efficient solution for addressing the growing challenges of urban transportation networks.**

I. INTRODUCTION

The increasing number of motor vehicles in urban areas, especially during peak commuting hours, has led to severe traffic congestion. This congestion not only disrupts the daily movement of commuters but also contributes to excessive fuel consumption and heightened emissions, which significantly impact air quality. Poor air quality, in turn, poses serious health risks to urban residents and creates challenges for environmental sustainability efforts.

Conventional traffic light systems operate on predetermined schedules that do not consider current traffic conditions, which worsens the problem of congestion. As a result, road users experience delays, and road efficiency is compromised. One of the most common inefficiencies is the occurrence of "empty green lights"—green lights that appear at intersections despite the absence of vehicles. This results in the waste of valuable green light time, increasing road congestion and decreasing overall intersection efficiency.

The problem of inefficient traffic management becomes even more critical when it affects emergency vehicles. Ambulances, fire trucks, and other emergency responders often face significant delays due to rigid traffic light sequences, preventing them from reaching their destinations promptly. Some traffic authorities address these issues manually by adjusting traffic light timings, but these interventions are reactive, time-consuming, and often ineffective in managing the dynamic nature of urban traffic.

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With the advent of big data, artificial intelligence (AI), and advanced algorithms, Traffic management systems can now utilize real-time data to dynamically enhance traffic flow efficiency. These technologies offer the potential to replace traditional, rigid traffic control systems with more adaptive, efficient, and reliable solutions. One promising approach involves dynamic traffic signal scheduling, where the length of traffic light phases is adjusted based on real-time conditions at intersections.

This paper proposes a dynamic traffic signal scheduling system using an advanced greedy algorithm and image recognition technology to capture and analyze real-time traffic conditions. The system prioritizes the smooth movement of vehicles and ensures that emergency vehicles are given priority passage through intersections. The optimization framework divides the scheduling process into multiple time intervals, with reward, cost, and constraint functions guiding the adjustment of signal phases.

To understand how well the proposed system works, Simulation of Urban Mobility (SUMO) software was used, integrated with the Traffic Control Interface (TraCI) for real-time signal management. Through simulations, we demonstrate the ability of the dynamic system to reduce congestion, enhance road efficiency, minimize waiting times, and ensure timely emergency response. This research seeks to offer a flexible and scalable approach to urban traffic management, contributing to the development of smarter and more sustainable cities.

II. Literature Review

Urban traffic congestion has been widely studied because of its negative impact on mobility. fuel consumption, and environmental sustainability in modern cities. Traditional traffic management systems are often unable to address the complexities of dynamic and unpredictable urban traffic patterns, leading to inefficiencies such as increased travel times, fuel wastage, and higher emissions. To tackle these challenges, recent research has explored using advanced machine learning models, graph-based frameworks, and real-time data analysis to make traffic forecasting more accurate, detect congestion faster, and manage traffic more efficiently. This literature review summarizes key contributions in these areas.[1] Graph-based frameworks have shown significant potential in accurately forecasting traffic and detecting congestion. Liu et al. (2024) proposed a system that uses graph-based methods to predict traffic patterns and quickly spot congestion systems that process real-time images from multiple cameras to assess traffic conditions. Their model represents traffic networks as graphs, with intersections and road segments modeled as nodes and edges. This framework enables real-time monitoring and offers enhanced accuracy in predicting congestion by leveraging graph theory alongside visual data. Such an approach is well-suited for complex urban environments where traffic patterns can fluctuate rapidly.[2] Li et al. (2023) proposed the Dynamic Graph Convolutional Recurrent Network, which is an integration of graph convolutional networks with recurrent neural networks to predict traffic flow patterns efficiently. The DGCRN addresses spatial and temporal dependencies while making predictions and dynamically updates its predictions according to the incoming traffic data. This approach improves traditional static methods on forecasting by providing greater accurate real-time predictions with improved precision, especially with high complexity in traffic conditions when conditions change frequently.[3] GNNs have significantly promoted the modeling of traffic flow and congestion. In the year 2022, Shao et al proposed a Decoupled Dynamic Spatial-Temporal Graph Neural Network for traffic prediction, which differentiated the process of spatial and temporal data processing for the improvement of the accuracy of prediction. With these differences, the model would be efficient in representing spatial relationships- for example, road connectivity-as well as temporal factors, including the difference of traffic pattern during the day, independent of each other. So far, DST-GNN has proven that it can impressively predict both short-term and long-term traffic patterns and thus be well applied in real-time urban traffic management systems.[4] Jiang and Luo conducted an in-depth survey on the application of Graph Neural Networks in the field of traffic forecasting, where these networks are used to illustrate the complex interdependencies at the road segment level and on the flow of vehicles. Their review highlighted the special effectiveness of GNNs in capturing both the static spatial configuration of urban networks and the dynamic features in traffic flow. Besides, hybrid models that incorporate the data sources include supplementary sources, such as weather information and accident reports.[5] Graph-based methodologies aside, advanced machine learning techniques include Generative Adversarial Networks, or GANs for short. Jin et al. developed a GAN-based approach to predict the short-term traffic condition of a certain region. Thus, this model could learn from a parallel framework and determine the nonlinear associations within the traffic data and, when historical records are only available in certain areas, produce simulated traffic patterns. This ability of learning from partially available data makes GANs highly helpful for forecasting in rapidly changing traffic scenarios.[6] An innovative real-time traffic congestion detection system that Liu et al. have proposed is on the basis of online images taken by cameras. The computation in such a model may decrease due to auto-cropped images used to

focus on just the pertinent parts of the traffic scene. This may make it possible for updating the information of traffic in real-time, and then the responses to the traffic congestion are faster.[7]
Another study to develop a multi-vehicle tracking system was done by Wang et al. in 2021, where the intention is to monitor and track real-time conditions of traffic. The system employed deep learning techniques, in this case, CNN, which evaluates traffic images against different luminosity and different weather conditions. This feature will enhance the detection of traffic patterns with more precision. This again helps better manage congestion.[8]
Deep learning methods have also been extensively utilized for detecting traffic congestion. Lam et al. (2019) introduced a real-time traffic status detection system that employs deep learning-based object detection to monitor and classify vehicles within traffic images. Their system highlights the effectiveness of deep learning for real-time congestion management, significantly minimizing the need for manual intervention in traffic control.[9] Similarly, Ke et al. (2019) presented a multi-dimensional traffic congestion detection method that combines visual traffic features with convolutional neural networks (CNNs). By merging visual data with spatial and temporal traffic patterns, their system improves the detection of congestion in complex traffic conditions. This method proves particularly effective at intersections and other areas where traffic flows from multiple directions, offering more comprehensive congestion analysis.[10]
The literature suggests that advanced techniques of artificial intelligence and machine learning have to be brought into play in the area of management of urban traffic. The systems, under such applications, would carry out real-time analysis and enhance predictive accuracy while at the same time permitting adaptive decisions to be enacted for improved efficiency in solutions under traffic management. The given adaptive traffic control system develops ideas based on the above insight but utilizes YOLO as well as MobileNet techniques for the real-time classification and detection of vehicles integrating with other smart city technology for urban mobility improvement.

III. METHODOLOGY

This section outlines the methodology employed in the development of the Deep Q-Learning agent for traffic signal management, including the system architecture, agent design, and learning algorithm implementation.

A. Systems Architecture

The system architecture for managing traffic signals is designed to efficiently control the flow at a four-way intersection.

Intersection Setup

- Intersection consists of four arms, each with four lanes:
  - The two middle lanes are reserved for straight movements.
  - The left-most lane is dedicated to left turns.
  - The right-most lane supports both right turns and straight movements.
- Each arm extends 750 meters, with unique traffic signals managing lane operations. The left-most lane has its own traffic signal, while the other three lanes share a single signal.

B. Traffic Simulation

Traffic simulations are crucial for modeling realistic vehicle behavior and traffic conditions.

Traffic Generation

- Each simulation episode generates 1,000 vehicles using a Weibull distribution with a shape parameter of 2, indicating a peak traffic volume mid-episode followed by a gradual decline.
- Vehicles enter randomly from any of the four arms, with a 75% probability of proceeding straight and a 25% probability of turning left or right. This random generation ensures variability across different simulation runs.

C. Agent Design: Traffic Light Control System (TLCS)

The agent design consists of state representation, action selection, and reward mechanisms.

State Representation

- The incoming lanes are divided into 80 discrete cells to determine vehicle occupancy:
  - Each arm has 20 cells: 10 for the left-turn lane and 10 for the remaining lanes.
- The presence of vehicles in any cell is marked as occupied, forming the input state for the agent.

Actions

➢ The agent selects from four predefined traffic phases, each running for 10 seconds, followed by a 4-second yellow light:
- North-South Advance: Green for north-south lanes moving straight or right.
- North-South Left Advance: Green for left-turn lanes on the north-south axis.
- East-West Advance: Green for east-west lanes moving straight or right.
- East-West Left Advance: Green for left-turn lanes on the east-west axis.

Reward Mechanism

➢ Reward system is based on cumulative waiting time, calculated as the sum of waiting times for all stationary vehicles:
- A positive reward is granted when the total waiting time decreases.
- Once a vehicle exits the intersection, its waiting time no longer contributes to the total.

D. Learning Algorithm: Deep Q-Learning Implementation

The agent employs a Deep Q-Learning algorithm to predict optimal actions and enhance traffic light control.

Neural Network Architecture

➢ Input Layer: 80 neurons representing the intersection state.
➢ Hidden Layers: 5 layers, each containing 400 neurons.
➢ Output Layer: 4 neurons corresponding to each traffic phase.

Experience Replay

➢ The agent uses a memory buffer to store previous states and actions, allowing for random sampling of experiences to improve learning efficiency and prevent overfitting.

Target Q-Network

➢ A target network is maintained to stabilize learning, with periodic updates to avoid rapid changes in Q-values, ensuring more reliable learning.

E. Training and Testing Configurations

The training and testing of the traffic signal management system are conducted using SUMO (Simulation of Urban Mobility) with real-time communication enabled via the TraCI API.

Training Parameters

➢ Episodes: Total number of simulation episodes.
➢ Steps per Episode: Duration of each episode (1 second per step).
➢ Batch Size: Number of samples used for training after each episode.
➢ Learning Rate: Controls the weight updates of the neural network.
➢ Memory Size: Specifies the minimum and maximum number of stored experiences.
➢ Gamma: Discount factor for future rewards in the Q-learning equation.

Testing Parameters

➢ Model to Test: Specifies the version of the trained model to be loaded.
➢ Seed: Random seed for reproducibility during testing.
➢ SUMO Interface: Option to enable or disable SUMO's GUI for visualizing traffic flow.

IV. RESULT

For testing purposes, three distinct scenarios were designed, incorporating 800, 1300, and 1800 vehicles to simulate different traffic conditions: low, medium, and peak loads. The results for each case are displayed in the tables below, showing metrics for queue length and cumulative waiting time.

TABLE I - LOW TRAFFIC LOAD (800 CARS)

Metric	**CNN-DQN**	**FC-DQN**	**90 sec**
Queue Length (mean, std)	(1.99, 2.27)	(47.25, 18.04)	(87.34, 58.42)
Cumulative Waiting Time s)	(4.26e04, 2.76e04)	(1.23e06, 1.42e06)	(1.09e07, 1.11e07)

TABLE II - MEDIUM TRAFFIC LOAD (1300 CARS)

Metric	CNN-DQ N	FC-DQN	90 sec
Queue Length (mean, std)	(5.7, 9.1)	(100.66, 34.3)	(144.44, 91.7)
Cumulative Waiting Time (s)	(3.56e05, 1.89e05)	(6.38e07, 7.02e07)	(1.87e07, 1.91e07)

TABLE III - PEAK TRAFFIC LOAD (1800 CARS)

Metric	CNN-DQN	FC-DQN	90 sec
Queue Length (mean, std)	(26.41, 42.58)	(174.89, 68.83)	(235.51, 159.42)
Cumulative Waiting Time (s)	(3.98e06, .29e06)	(1.21e08, 1. 33e08)	(2.78e07, 3.01e07)

In road traffic management, CNN-DQN demonstrates its efficiency under peak load conditions by maintaining an average vehicle wait time of approximately 117 seconds, achieving a 20% reduction compared to a fixed 90-second traffic signal cycle. This highlights CNN-DQN's capability to dynamically adjust under heavy traffic, enhancing overall flow. In contrast, FC-DQN faces challenges managing medium traffic loads, resulting in less effective traffic handling. Thus, CNN-DQN emerges as a more adaptive model, effectively minimizing wait times in congested situations.

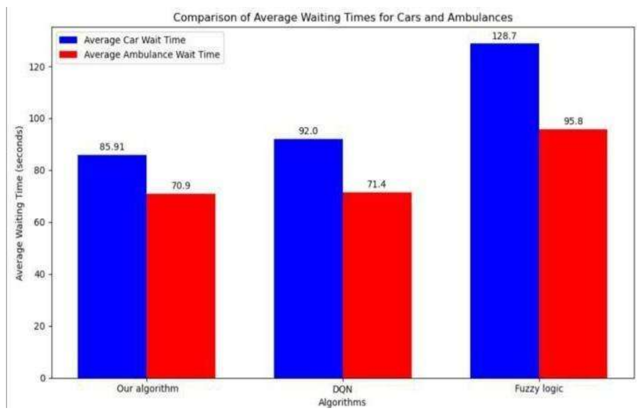

Figure 1 - Comparison of Traffic Control Models: CNN, FC-DQN, and Fixed 90-Second Cycles

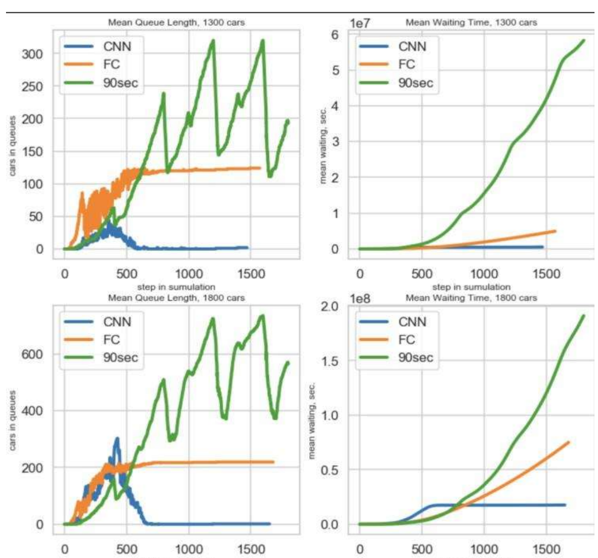

Figure 2 - Comparison of Average Waiting Times for Different Algorithms (20% chance of ambulance and 80% chance of normal vehicle in any lane.)

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