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Intelligent Traffic Signal Control Using Reinforcement Learning for Adaptive Urban Traffic Management

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Abstract- Traffic congestion has become one of the most important problems in modern cities due to a rise in population, the number of vehicles owned, and the ineffective traffic management systems. Conventional traffic signal control mechanisms generally function under fixed time intervals, which do not take real time traffic conditions into account. As a result, there is often unnecessary waiting time for the vehicles, and traffic is severely congested, and the fuel consumption is high and the environmental pollution is intense. In order to overcome these challenges, intelligent traffic management solutions based on Artificial Intelligence (AI) and Machine Learning (ML) have emerged as promising solutions to improve urban transportation systems. This research presents an intelligent traffic signal control research proposal that uses Reinforcement Learning (RL) algorithm to dynamically adjust the traffic signal timing based on the real-time traffic condition. Reinforcement Learning lets the system learn the best strategy for controlling the traffic through its continuous interaction with the traffic environment. The proposed model analyses the important traffic factors such as the queue length of vehicles, the density of the traffic, and the waiting time of vehicles to make experienced decisions for the adaptive traffic signals. The effectiveness of the suggested reinforcement learning based traffic signal system control is tested by comparing the system performance with the traditional traffic signal control system based on the fixed time. Performance indicators such as average waiting time for vehicles, long queues are used to measure the system's efficiency and traffic throughput. The expected results on the reinforcement learning approach are that it would be able to greatly improve the efficiency of traffic flow, eliminate congestion, and overall improvement of urban traffic flow management. This study supports the promotion of intelligent transportation systems and also helps in the progress of smarter and more sustainable traffic management solutions to cities.

I. INTRODUCTION

rapid urbanisation and population growth rate have increased substantially that the number of vehicles on road network and so major problem for urban traffic management Traffic congestion has become a permanent problem in many cities which leads to longer travel time, higher fuel consumption, pollution, and also a decrease in transportation efficiency. Efficient traffic signal control is an important task to regulate the traffic and minimise congestion in the urban intersections.

Traditional traffic signal control systems generally work on fixed time signal schedules that are predefined by using historical traffic data. While these sorts of systems are easy to implement, they cannot respond well to real-time fluctuations in traffic. As the traffic conditions change over the course of the day, fixed-time signals often contribute to unnecessary delays for vehicles as well as inefficient use of road infrastructure. This limitation points out the need for smarter and adaptive traffic management solutions.

Recent developments of Artificial Intelligence (AI) and Machine Learning (ML) has paved the way for new opportunities in improving traffic signal control systems. Intelligent Transportation Systems (ITS) leverage advanced computational techniques to introduce the processing of traffic data and optimization of the operations in the transportation. Among various approaches of machine learning, Reinforcement Learning (RL) has attracted much attention in the field of traffic signal optimization as it helps systems to learn how to control traffic optimally through interaction with their environment.

Reinforcement Learning enables the traffic signal controller to continuously observe what the traffic, make control action, and get feedback in the form of reward based on traffic performance. Through learning from the above interactions, the system can slowly figure out the optimal signal timing policies which can minimise the waiting time of vehicles, avoid congestion and also improve the overall traffic flow efficiency.

In this research, an intelligent control of traffic signals based on Reinforcement Learning, where dynamic performance optimization of traffic signal timing based on the real-time traffic conditions, is proposed. The proposed system uses the analysis of key traffic parameters such as the vehicle queue length, the traffic density, and waiting time to take the adaptive signal control decisions. By incorporating reinforcement learning algorithms with the management of traffic signals, the proposed approach is focused on increasing the efficiency of traffic flow and assisting the development of smart city transportation infrastructure.

II. RESEARCH PROBLEM

Urban traffic congestion has become a major issue for transportation system in a modern city. The ongoing increase in vehicle ownership as well as the lack of road infrastructure has put a lot of pressure on urban traffic networks. One of the main causes of this issue is the inefficient operation of traditional traffic signal control systems based on signal scheduling for a set time.

III. LITERATURE REVIEW

[1]Winata et al. (2025) – Optimization of Traffic Signal Control in City X Using a Deep Reinforcement Learning Approach
The researchers chose to design a simulation-based traffic environment based upon real-world traffic data from an important intersection. A Deep Reinforcement Learning model was implemented based on Deep Q-Network (DQN) algorithm applied the model where the agent learned to time signals optimally by observing traffic states namely queue length and waiting time. The performance of DRL model was compared with traditional fixed-time traffic signals system.

The model based on DRL showed a significant improvement compared to the fixed time system. It saved all kinds of vehicle delay from 115.0 seconds to 82.8 seconds and maximum queue length from 55.0 vehicles to about 35.75 vehicles and increased traffic throughput from 1,550 to 1,829 vehicles per hour.

The study has come up with the conclusion that Deep Reinforcement Learning approach is extremely advantageous in optimizing the traffic signal. The proposed system can greatly alleviate the congestion and enhance the efficiency of traffic flow, and it can also offer a scalable solution that can be implemented in other cities with similar traffic conditions.

[2] Fereidooni et al. (2025) – Multi-Agent Optimizing Traffic Light Signals Using Deep Reinforcement Learning
This study sought to attempt to create the advanced system of traffic signal optimisation by Deep Reinforcement Learning (DRL) emphasis was placed on creating an improved coordination across multiple intersections and integration of public transportation system such as trams and Bus Rapid Transit Systems (BRTS).

The researchers proposed three ways to implement DRL-based: Single-Agent Deep Reinforcement Learning (SADRL); Multi-Agent Deep Reinforcement Learning (MADRL) and an actuated control system (SMART). These models were implemented using SUMO traffic simulator with real-life traffic data. The system took into account the traffic parameters such as density, flow and waiting time of vehicles and the number of stopped vehicles. The performance of the proposed methods was compared with the traditional methods such as Webster method, genetic algorithm and SUMO based actuated control method.

The DRL-based approaches significantly improved performance of traffic by reducing the waiting time of vehicles and the congestion level. Multi-agent systems showed improved coordination between intersections over that for single agents. The performance of the SMART model was so successful to handle dynamic traffic condition while the multi agent models improved the scalability and fairness in traffic management.

The study concluded that "multi-agent deep reinforcement learning presents a good and scalable solution to traffic signal optimization in complex urban environments." It increases the coordination between many intersections as well as for integration with public transportation systems.

[3] Gowri et al. (2024) – Adaptive Traffic Control Using Machine Learning Algorithm

This study aimed at developing an adaptive traffic control system based on machine learning techniques, in order to adjust the timing of the traffic signals, dynamically in response to real-time of traffic conditions and vehicle density.

The researchers came up with a system using image processing and a (YOLO - You only look once) algorithm to identify, classify and count vehicles from the data in traffic cameras. The real-time data is processed at the edge of the network by machine learning models by predicting the best signal timing. It also uses sensors, IoT devices and real-time analytics to continually monitor traffic and adjust traffic signals.

The proposed system achieves successful detection and classification of vehicles both in real time and dynamic signal timing control according to the traffic density. The usage of YOLO based object detection improved the accuracy of vehicle identification and counting and resulted in the better flow of traffic and relief in congestion.

The study concluded that adaptive traffic control systems based on machine learning can go a long way in improving the efficiency of traffic by utilizing real-time data and intelligent decision-making. The method improves traffic monitoring, alleviates congestion and aids in the smart city traffic management.

[4] Sattarzadeh et al. (2024) – Enhancing Adaptive Traffic Control Systems with Deep Reinforcement Learning and Graphical Models

This study was aimed at designing an advanced traffic signal control system based on Deep Reinforcement Learning (DRL) combined with probabilistic graphical models to make the traffic more efficient and less congested in multi-intersection urban areas.

The researchers developed a hybrid model of Deep Reinforcement Learning with the probabilistic graphical models or PGMs in order to improve decision-making and interpretability. The implementation of this system was done in a simulated environment using SUMO that used traffic parameters such as queue length, delay and traffic flow as input states. The model used actor-critic reinforcement learning algorithms and the optimization technology based on entropy to learn the optimal policies for the traffic signals.

The proposed model brought significant improvements as compared to traditional and baseline methods of DRL. It was able to reduce average queue length by more than 50%, intersection delay by up to 80%, and have a success rate of about 95%. As can be seen from the graphs on page 5, the model was always more efficient and stable than algorithms such as IPPO, TD3 and SAC.

The study said that combining Deep Reinforcement Learning with probabilistic graphical models is a scalable, efficient, and interpretable solution for traffic signal control. The approach has wide benefits in improving traffic flow and enabling real-time adaptive traffic management at smart city environment.

[5] Sasirekha et al. (2025) – EcoDriveAI: Real-Time Smart Traffic Signal Control Using V2I and Deep Reinforcement Learning

This study was to develop a real-time intelligent traffic signal control system using deep reinforcement learning combined with the Vehicle to Infrastructure communication (V2I) to improve the efficiency of traffic flow, help in reducing environmental damage and prioritization of the emergency vehicles.

The researchers proposed EcoDriveAI which is a reinforcement learning system based on Deep Q-Network (DQN), deployed in end devices (Raspberry Pi). The system uses real-time V2I data such as vehicles speed, position, queue length and emergency signals to provide the best traffic signal control. A multi-objective reward function was developed based on the traffic flow, fuel consumption, CO2 emission, and emergency response time. A model of the system to be developed was trained and tested with the SUMO traffic simulator and was compared with fixed-time and adaptive traffic systems.

The proposed system greatly enhanced the performance of traffic. With respect to fixed-time and adaptive systems, it reduced average vehicle delay by about 37% and 21%, respectively. Attending the emergency response time was improved by 42%, CO2 reduced by 28% and fuel consumption reduced by 19%. As demonstrated in the graphs in page 5, EcoDriveAI was able to consistently outperform traditional traffic control systems in several ways.

The study concluded with the advantage of the Deep Reinforcement Learning integrated V2I communication and edge computing provides an efficient, scalable, and environmentally sustainable solution for traffic signal control. The system improves the decision-making in real time and aids in smart cities managing the traffic.

IV. RESEARCH GAP

Although great progress has been taken in the research of intelligent traffic signal control systems, there are several limitations in current research. Many traditional traffic signal control systems can be based on fixed time signal scheduling, which cannot be adjusted according to the actual traffic conditions. This leads to inefficient traffic flow, longer wait times and congestion at intersections in the urban environment.

A. Absence of Adaptive Real-time Traffic Signal Control

Most traditional traffic signal systems operate by using fixed time schedules which are not responsive to changing traffic conditions. As a result, there are often times when vehicles experience unnecessary waiting time and inefficient traffic flow during times of peak traffic hours.

B. Lack of Coordination Between Several Intersections

Many existing research studies are dedicated to optimally controlling a single traffic signal. However, urban traffic networks contain a number of spatially connected intersections, in which the lack of coordination between signals can lead to traffic bottlenecks propagation; and maybe more generally, traffic congestion.

C. Scalability Issues in Intelligent Traffic System

Several reinforcement learning trafficking control models have only been tested in limited simulation environments. Possible limitations of such a model are scalability problems when working for large urban traffic networks with a number of intersections.

D. Lack of Use of Reinforcement Learning in Continuous Learning

Some approaches of traffic control do not make full usage of reinforcement learning capabilities for continuous adaptation and learning of changing traffic patterns. This puts intelligent traffic signals systems in dynamic environments at an efficiency limit.

E. Comparative Analysis

Method	Waiting Time	Queue Length	Throughput
Fixed-Time Signal	High	High	Low
RL-Based Signal	Lower	Lower	Higher

V. METHODOLOGY

The proposed system presents an intelligent control of the traffic signal system (reinforcement learning (RL) to optimize the signal timing in urban traffic network. Unlike the traditional fixed-time traffic signal systems, the traffic signal system proposed in this paper dynamically adjusts the signal phases based on the real-time traffic signals. The system continuously observes the states of traffic such as the vehicle density, the queue length, and the waiting

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time, and learns the optimal traffic signal control policies via interacting with the traffic environment.

The proposed framework comprises a few important components such as traffic sensors, traffic state representation module, reinforcement learning agent, and traffic signal controller. Traffic information obtained from sensors or simulation environment is processed to identify the current traffic state. The reinforcement learning agent then chooses the best action for the traffic signal to take in order to reduce congestion and maximize traffic flow effectiveness.

A. System Architecture
The system architecture shows the data flow of the traffic in the intelligent traffic control system. Traffic information is gathered from the sensors or sensors that track the traffic and is then fed to the reinforcement learning agent that decides which traffic signal phase is the best.

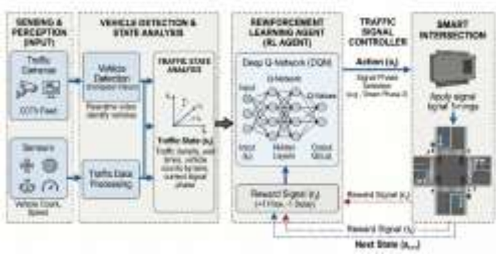


Figure 1: Architecture of the Intelligent Traffic Signal Control System

B. Reinforcement Learning Framework
Reinforcement Learning is used to make the traffic signal controller learn the best way of control by interacting with the traffic environment. The RL agent receives the current state of traffic, and selects an action (change of signal phase), and receives a reward related to the traffic conditions that have been created.

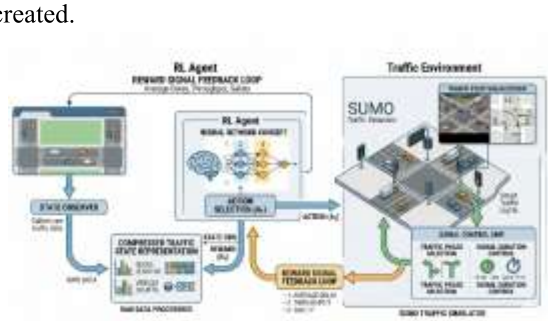
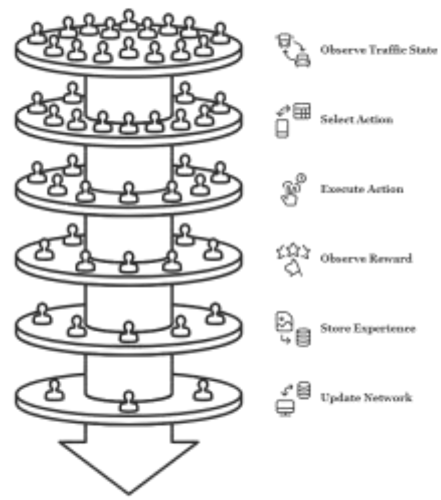


Figure 2: Reinforcement Learning Interaction Model

C. Deep Q-Network Algorithm
The proposed traffic signal control system is based on the Deep Q-Network (DQN) algorithm, a reinforcement learning algorithm, which is an ensemble of Q-learning and neural network. The neural network estimates Q-values for every possible traffic signal action, and assists the system in selecting the action with the maximum traffic efficiency.



Algorithm 1: Deep Q Network for Traffic Signal Optimization

D. Algorithm Workflow
The workflow of the algorithm explains how the reinforcement learning algorithm agent is continuously improving the traffic signal control through various interactions with the environment of traffic.

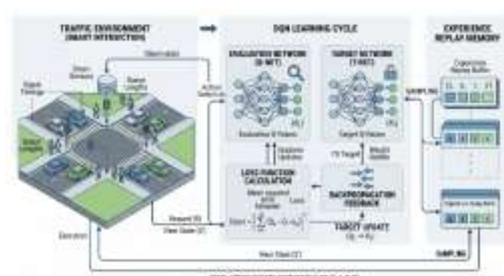


Figure 3: Workflow of the Reinforcement Learning Traffic Signal Control Algorithm

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VI. EXPERIMENTAL SETUP

In order to test the performance of the specified reinforcement learning-based traffic signal control system, simulation experiments are performed using Simulation of Urban Mobility (SUMO) traffic simulator. SUMO is an open-source traffic simulation tool which is widely used for modeling and analyzing of an urban traffic system. It helps researchers to model traffic flow, road networks, and vehicle behavior under various traffic conditions.

In this research a simulation urban intersection environment is developed representing one common traffic environment of multiple incoming and outgoing lanes. Vehicles come for various directions into the intersection of different traffic densities. The reinforcement learning is used in this example for controlling the traffic signal phases at the intersection, depending on observed traffic conditions.

The experimental environment is involved in collecting the traffic parameters such as queue length of vehicles, waiting time of vehicles and density of traffic. These parameters are passed as the input states for the reinforcement learning model. Based on these inputs, the RL agent takes the optimal signal actions in order to minimize the traffic congestion and enhance the overall traffic flow.

The proposed reinforcement learning model is compared with traditional fixed time traffic signal control systems in order to test its effectiveness. Several performance metrics of traffic are used to measure the efficiency of the system such as average vehicle waiting time, queue length at intersections, and traffic throughput.

VII. RESULT AND DISCUSSION

The effectiveness of the proposed reinforcement learning-based traffic signal control system is verified by simulating the traffic signal control with the SUMO traffic simulation environment. The results that the model proposed to develop get compared with that of a traditional system of traffic signal control with a fixed time. The purpose of this evaluation is to find out if the reinforcement learning approach can be used to improve the efficiency and reduce the congestion of traffic at urban intersections.

There are several traffic performance metrics that are used to analyze the system performance. These metrics include average waiting time of vehicles, queue length and traffic throughput. These indicators give some significant insight into effectiveness of the traffic signal control strategy.

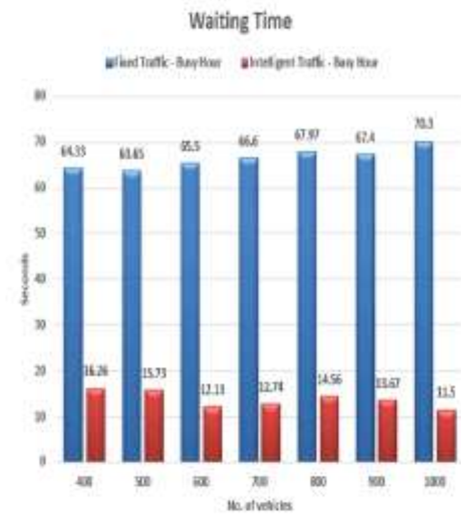

Figure 5: Comparison of Average Vehicle Waiting Time

According to the experimental results, the reinforcement learning-based traffic signal control system is better than the technology of fixed-time traffic signal system. The problem with the idea of reinforcement learning is that it provides a way for the traffic signal controller to dynamically modify the signal phases used for the intersection based on the real-time traffic conditions. As a result, there are shorter waiting times and improved traffic flow across intersection for vehicles.

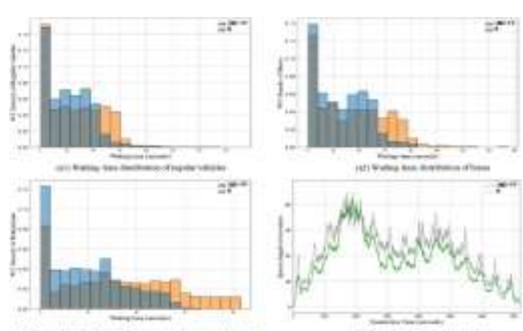

Figure 6: Queue Length Comparison

In the fixed time traffic signal systems, the signal timing is the same for all traffic density in each lane. This often leads to unnecessary delays where some lanes will have little traffic and others will have traffic congestion. On the contrary, the reinforcement learning model continuously monitors the traffic situation and determines the best signal action that results in the least congestion.

The simulation results show that the proposed RL-based model reduces a large difference between the waiting time, and the queue length of the vehicles with traditional signal control methods. Furthermore, traffic throughput is improved with vehicles being able to pass through more efficiently.

Overall, the experimental results show that reinforcement learning can be an effective and intelligent solution to optimise the traffic signals. By dynamically adjusting traffic signal phases based on traffic conditions, the proposed system helps to improve the flow efficiency of the traffic and promotes the development of smart city transportation systems.

VIII. CONCLUSION

Traffic congestion has been a severe problem with urban areas in modern society because of population boom and increased vehicle use. Traditional traffic signal control systems are based on fixed-time schedules which are not capable of adapting with real-time traffic conditions that can cause efficient traffic flow, high vehicle waiting time and excessive level of congestion.

This research presented an intelligent traffic signal control system which is based on Reinforcement Learning (RL) to dynamically optimise traffic signal timings. The proposed system analyses the parameters of traffic such as the length of the queue of vehicles, the density of traffic, and waiting time for vehicles to traffic signals for deciding the optimal action to be taken by the traffic signal. By continuously interacting with the traffic environment, the reinforcement learning model learns the efficient signal control policies to improve the overall performance of the traffic environment.

Simulation experiments performed with SUMO traffic simulator show that the proposed reinforcement learning based traffic signal control system performs better than the traditional fixed time traffic signal systems. The results show that the RL based approach results in reduced waiting time of vehicles, minimises waiting queue length at the intersections and increases the overall traffic throughput.

The results of this study show the potential of reinforcement learning techniques in building intelligent traffic management systems in the smart city. By facilitating adaptive and data-driven management of traffic signals, the proposed system can play a role in the enhanced efficiency of transportation, as well as in the decreased urban traffic congestion.

Future work could be to enhance the proposed model to multi-intersection traffic networks, connect real-time traffic data from the IoT and apply multi-agent reinforcement learning methods to enhance the coordination between multiple traffic signals in large-scale urban environments.

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