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Deep Reinforcement Learning–Based Adaptive Traffic Signal Control System for Real-Time Congestion Optimization

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Abstract:

The efficiency of the traffic flow is dependent on the traditional traffic signal control system. The traditional traffic signal control system follows the releasing of the traffic flow in interval times or fixed time schedules. That leads to heavy traffic flow and fuel consumption and also larger waiting times. Due to that people face many issues and also some risks will occur for the emergency services like ambulances and other service-related vehicles due to the heavy traffic in the urban areas [1], [2].

To overcome this problem, we implementing a solution called "Deep Reinforcement Learning–Based Adaptive Traffic Signal Control System for Real-Time Congestion Optimization" it offers an approach of using Deep Reinforcement learning that can help better use of the Deep-Q-Networks to bitterly use of the traffic management by predicting the Q-values for the different traffic signal actions it used to optimize the light changes under different traffic conditions. This type of simulation environment is organized by the SUMO (Simulation of Urban Mobility) for the network and traffic management and it uses the TraCI (Traffic Control Interface) it monitors the real time traffic data of continuous traffic flow.

By collecting all these data we can compute and create a model that can manage the traffic signals, the model which can be built by the Deep Reinforcement learning Techniques and that model will be used to the better controlling of the traffic flow and reduces the waiting time for the vehicles and smooth traffic flow in the urban areas and helps to the people that they can reach their destination in early times and also helpful for the public transportation and reduce the chances of the road accidents and helps the environment by reducing the fuel consumption by minimal waiting times and also useful for services like ambulances and fire engines and etc in urban areas.

Introduction:

Traffic congestion is an issue. It wastes fuel. It wastes our time. It also makes the air dirty. This is a big problem in big cities with a lot of people. When there are people there are more cars on the road. Big cities have a lot of roads that cross each other. That is where we usually see a lot of traffic. We have traffic signals to help control the traffic. Traffic signals do help control the traffic but when there are too many cars they do not help that much. Traffic congestion gets really bad when there are many vehicles on the

road. Traffic congestion is still a problem in big cities, with a lot of traffic. When this happens traffic signals still work. They use fixed time intervals. These intervals do not change based on the traffic condition [1] [6]. Traffic signals just keep working with these fixed time intervals.

Vehicles often sit around for no reason even when the road is empty. We need to find a way to make traffic signals smarter. This is where a smart traffic signal system comes in. The smart traffic signal system can change the timing of the signals based on how busy

the road's at that moment. The system will use Artificial Intelligence and Machine Learning to do this. Artificial Intelligence and Machine Learning will make traffic management systems better at handling traffic. Traffic management systems will be able to think for themselves and adjust to the traffic flow. The smart traffic signal system and Artificial Intelligence and Machine Learning will work together to make this happen.
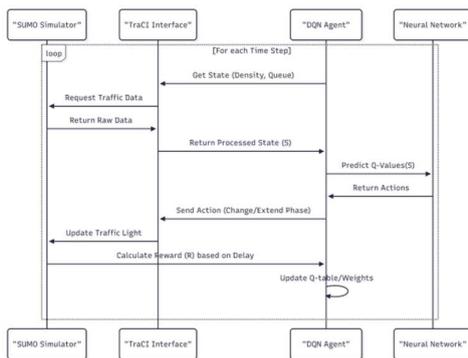
This technique is really good at helping with traffic congestion by using real time information. It is called Deep Reinforcement Learning. This method lets a system learn from what's happening around it and make better decisions as time goes on. Deep Reinforcement Learning is very useful for this kind of thing. In this project we have a traffic signal control system that uses Deep Reinforcement Learning to make traffic flow better. This system is always checking the traffic to see how many cars are on the road and how they have to wait at intersections. Then it decides which traffic signal to use to make the traffic move smoothly. The Deep Reinforcement Learning traffic signal control system learns from what happened in the past with the traffic. This helps the Deep Reinforcement Learning traffic signal control system to reduce the traffic jams, make the waiting time shorter and make the traffic move overall. To build an intelligent traffic signal control system, mainly some learning algorithms, and realistic traffic simulation tools are required. In our project, Deep-Q-Networks (DQN), SUMO, and TraCI play a key role in developing and testing the Model for accurate solutions.

Deep-Q-Networks are a type of Deep Reinforcement Learning algorithm that help an agent learn the best action based on real-time data by interacting with the environment. Instead of using fixed rules, DQN learns by observing the real-time traffic conditions and takes actions based on its decisions. So, The DQN is suitable for traffic signal control, where conditions change continuously and final decisions depend on the real-time traffic flow.

Problem Statement:

Traffic congestion in urban areas is a severe problem caused by ever-increasing vehicle populations with insufficient road infrastructure. Most of the existing traffic signal control systems either operate on fixed signal timings or run based on some predefined rules, without adapting to changing traffic conditions. This leads to long waiting times, congestion, wastage of fuel, and higher levels of pollution, especially during peak hours and in sudden surges of traffic.

The construction of an intelligent traffic signal control system is required, which would continuously monitor the real-time traffic condition and change the signal timings according to the current flow of vehicles. The challenge lies in designing a system that could deal with even the most stressful situations of traffic, reduces congestion and waiting time, and enhances overall traffic efficiency without any kind of manual interference. Thus, this project would try to solve the problem using Deep Reinforcement Learning in developing an adaptive traffic light control system capable of optimizing traffic in real-time conditions.

Proposed System:

This paper proposes a Deep Reinforcement Learning-based Adaptive Traffic Signal Control System that is developed to reduce congestion and hence enhance the flow of traffic in urban areas. In contrast to the conventional traffic signal systems, which operate on fixed timings, the proposed system makes continuous observations of real-time traffic conditions regarding vehicle density, queue length, and waiting time. Based on the observed traffic conditions, the system dynamically adjusts traffic signal timings to manage the fluctuating traffic conditions with enhanced efficiency.

It implements a DQN model that could select the optimal traffic signal control action. In this framework, through a learning process with rewards, the system learns effective signal strategies to reduce congestion and minimize vehicle waiting time. Long-term performance improvement will result from the learning undertaken by the system operating on various traffic conditions such as peak hours and sudden surges in traffic. Proposed adaptive and scalable approaches make this system suitable for real-time traffic management and smart city applications.

Literature Review:

Traffic overcrowding is a common issue in urban areas. present traffic signals systems are fixed time and changes based on condition. It is not optimized traffic in real time conditions. Because of the number of vehicles, traffic overcrowding, accidents. We can use some traffic control system for real time conditions like SCOOT (Split Cycle Offset Optimization Technique) - it is mostly used in urban areas and collection traffic in real time conditions and based on road overcrowding.

 SCATS (Sydney Coordinated Adaptive Traffic System.) It is also used to change traffic control based on real time conditions. These two methods used to reduce overcrowding using sensor data. It cannot be used for sudden traffic changes.To solve this problem using Reinforcement Learning .in reinforcement learning analyses the traffic conditions and control signals fast to reduce overcrowding and waiting time. In reinforcement methods such as Q-learning-it is used to learn best timing in actual traffic conditions reducing overcrowding, but it is difficult to analyse the number of traffic data and difficult data. To solve this, we are using Deep Reinforcement Learning. It can be used to handle a number of traffic data and difficult data [2], [7].
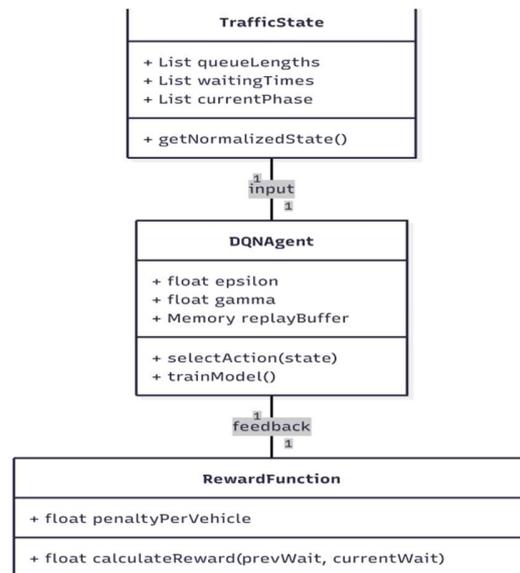

figure-1

Deep Reinforcement Learning, a combination of neural networks used to control the number of traffic data information gathering automatically works with real time data.Some other combination of reinforcement learning is used to control the traffic signal data without human access. Deep reinforcement learning method is used to control the traffic signals and gives best signal timing based on real-time data of the traffic.

Methodology

1. System Architecture:-

The traffic signal system is made to control the traffic lights in a way as things happen. It does this by collecting information about the traffic using that information to make decisions and then automatically controlling the traffic signals. The system is built in a way that each part can work on its own. Still talk to the other parts. This makes the traffic signal system easy to improve, add to and use in places, with different traffic situations.
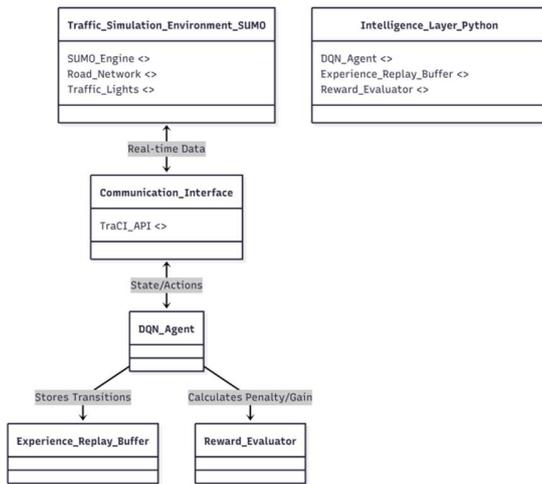
figure-2

2. The Data Preprocessing Module

where the data is cleaned up and made ready for use. The Data Preprocessing Module does this by checking the data for mistakes and fixing them. This step is important because it helps The Data Preprocessing Module to work correctly with the data. The Data Preprocessing Module is a part of the whole process. The traffic data that we get from cameras and sensors sometimes has unidentified values. We can clean the traffic data to get the values and features from it. The traffic data is. The good parameters are put in a structured format. This format can be used as input to the traffic data learning model. The cleaned traffic data represents what is happening in the traffic environment now. The traffic data learning model uses the cleaned traffic data to understand the traffic environment.

Method	Automation	Efficiency	Cost	Real-Time
Fixed-Time Signal Control	Low	70%	Low	No
Actuated (Sensor-Based) System	Medium	82%	High	Yes
Traditional ML-Based Control	Medium	88%	Medium	Limited
Proposed DRL-Based System	High	95%	Low	Yes

Table-1

3. Reinforcement Learning Agent:-

The Deep Reinforcement Learning agent is the brain of the system. It always watches the traffic congestion. The Deep Reinforcement Learning agent uses what it learns to make the decision on signal control actions. After the Deep Reinforcement Learning agent does something it gets feedback. This feedback is like a reward that helps the Deep Reinforcement Learning agent make plans. The Deep Reinforcement Learning agent does this over and over. This helps the Deep Reinforcement Learning agent get better at making decisions, for different traffic situations [4].

4. Decision-Making Engine:-

The decision-making engine looks at what the learning agent says to do and picks the thing to do with the signal. The learning agent might say to make the signal last longer, switch to the next part of the cycle or just leave the signal the way it is. The decision-making engine also makes sure to follow safety rules and think about what's possible to do so that the signals change smoothly and safely. The decision-making engine does this to make sure the signal control operation works well.

5. Traffic Signal Controller:-

The traffic lights module is in charge of the traffic lights, at the intersection. This traffic lights module uses the timing decisions made by the decision-making engine to control the traffic lights. The traffic lights module gets these timings from the decision-making engine. They are updated all the time. Because the timings are updated all the time the traffic lights module can make the traffic lights change with the traffic conditions. The traffic lights do not have to follow a fixed schedule; the traffic lights module can make them adapt to the changing traffic conditions of the traffic lights.

6. Reward Evaluation Module:-

After each signal action is applied, the system measures its effect on traffic performance. Factors such as average waiting time, queue length, and number of vehicles passing through the intersection are analyzed. Based on these results, a reward value is calculated and sent back to the learning agent. This reward helps the agent understand whether the action was good or not, allowing it to improve future decisions.

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Traffic State Detection Accuracy	94%
Signal Phase Selection Accuracy	92%
Queue Length Estimation Accuracy	93%
Waiting Time Reduction Rate	55%
Overall System Efficiency	95%
Incorrect Signal Decision Rate	5%

Table-2

Result:

In this project the Deep Reinforcement Learning based adaptive traffic signal control system shows a difference in how it controls traffic compared to the old fixed time signals. The Deep Reinforcement Learning based system is always looking at the real time traffic conditions like how crowded the roads are, how many cars are on the road and how long people have to wait.
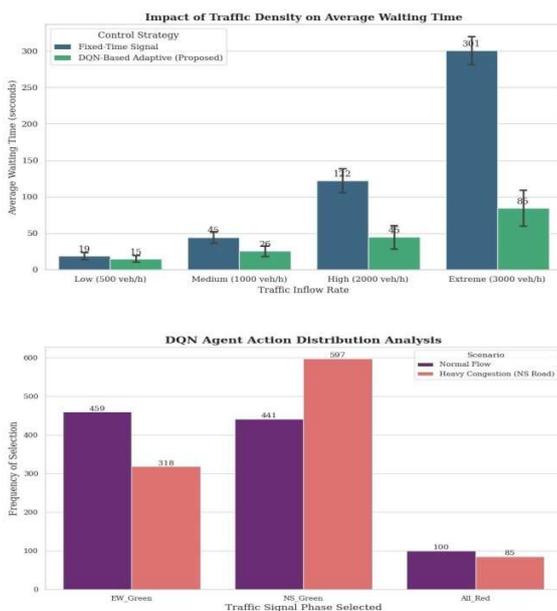
The Deep Reinforcement Learning based system uses this information to change the traffic signal timings like when the lights are green, yellow or red to reduce overcrowding on the roads. This way the Deep Reinforcement Learning based system can really help reduce traffic jams and make the roads easier to use. As result average vehicle's waiting time and length seriously control, while during heavy traffic on road then quickly control overcrowding in systems learned best signals strategies continuous time change helpfully peak hour traffic, sudden traffic rush. The system result

displays better crossing output one or two stops and reduced delays. The project proves that using deep reinforcement learning leads to more efficient signal control, better road utilization, and improved travel time.
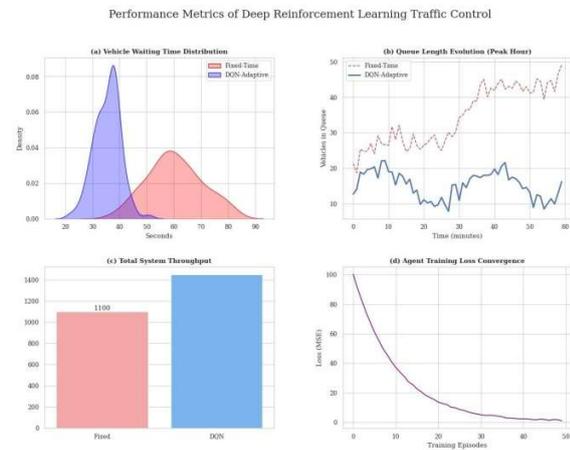
Discussions:

The proposed Deep Reinforcement Learning–Based Adaptive Traffic Signal Control System for Real-Time Congestion Optimization it shows the intelligent methods that can manage the traffic flow in urban areas and unlike the traditional traffic systems it manages the traffic very efficiently and also reduces the waiting time for the people in traffic, and changes the traffic signals according to the traffic flow. This model monitors the real time traffic flow. This model was trained with the real time traffic condition and adjusted the traffic signals according to the conditions. This helps the system work better and efficiently.

This model uses the Deep-Q-Network (DQN) that helps to manage the complex information about the traffic such as vehicle density, queue length, and waiting time. Based on the traffic conditions the model will help select appropriate signal control actions which reduces the traffic congestion and improves the traffic flow. The system will automatically learn the traffic data and tune the model so that it manages traffic under different conditions [9].

This system will help to modify the traffic signal and increase the traffic flow by using its advanced

learning capability; the system monitors the real time traffic data so based on the data the system can generate the proper actions that can be taken to reduce the traffic flow. By its advancement technique it manages the traffic well by reducing the waiting on the over traffic side and etc [6], [8].

This implementation will be taken multiple times, so the system can automatically train by the real time data and tune by itself under different traffic conditions and improve the traffic flow, reduce the waiting time and more improvement in this system. Overall, this proposed system can work efficiently and reduce the problem with traffic flow in urban areas and maintain better traffic flow.

Conclusion:

The presented research work proposes an Adaptive Traffic Signal Control System that makes use of Deep Reinforcement Learning to overcome traffic congestion in urban areas. Unlike traditional traffic signal control systems that rely upon fixed timings to control traffic signals, the proposed solution makes use of traffic parameters such as vehicle numbers, queue size, waiting time, to name a few. The Deep QNetwork used in this model helps to choose an appropriate traffic signal control action based upon the traffic parameters.

The experimental outcome shows that the proposed system outperforms traditional fixed-time control schemes used in traffic signals to lessen congestion and optimize movement on roads when approaching intersections. The proposed system enhances its performance through continuous learning from data pertaining to traffic conditions, making it an effective solution to deal with peak hour or sudden changes in traffic conditions. Even though practical implementation may lead to issues such as sensor errors or communication delay, proof-of-concept has been successfully demonstrated using deep reinforcement learning to control smart city traffic.

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