Traffic Light Control Using Reinforcement Learning

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***Abstract*—Nowadays, one of the biggest issues in urban areas is traffic. This problem wastes important time and contributes to air and sound pollution. This affects people's general quality of life in addition to posing health dangers. Our study attempts to mitigate these problems, effectively cutting down on wait times and delays. Our Reinforcement Learning method creates intelligent agents that can adjust traffic lights at crossings instantly. Our objective is to minimize delays, reduce congestion, reduce travel times, improve safety, and improve traffic flow. We implemented the Deep Q Learning algorithm which activities yield the greatest benefits under various traffic scenarios. Our model can the sequence time since the Green signal (GS) lasts 10 seconds and the Red signal (RS) lasts 5 seconds. The waiting period is shortened by 50% as a result. This study suggests reinforcement learning may improve traffic signal controller synchronization and urban traffic congestion. This novel method may improve transport efficiency and sustainability.**

***Index Terms*—vehicles, Model, Rewards, State, Action, Deep Q Learning, Waiting Time, Q Value, Traffic signal, RS, GS.**

I. Introduction

The increase in urban traffic congestion in recent years has grown to be a serious and difficult problem, particularly in densely populated places. Because of the rising number of travel delays and fuel usage worldwide, traffic congestion results in significant economic losses [1] [2]. It contributes [3] to delays in emergency services, air, and sound pollution, and nervous disorders brought on by stress. Congestion reduction [4] usually involves the deployment of Urban Traffic Control (UTC) systems for effective intersection management. Modern Intelligent Transportation Systems (ITS), which emphasize the use of technology to efficiently control traffic, are built around UTC systems. According to reports [5] [6], the traffic light network in place today is unable to adjust to changes in the traffic situation in real time. Existing traffic light control either deploys fixed-time mode without considering real-time traffic or considers the traffic to a very limited degree [7]. which cause vehicle accumulation at intersections and degrade traffic efficiency [8]. As a result, creating a traffic signal control method [9] [10] that works well is crucial for metropolitan networks. Deep reinforcement learning (RL) has been used in Intelligent Transportation Systems (ITS) recently, and its performance has shown promise.

The use of intelligent transportation systems (ITS) for traffic management is growing, particularly during peak hours when priority lanes can ease congestion. Since urbanization increases the complexity of road networks, Deep Q-Learning is crucial for effective traffic management. Urban mobility might become more efficient by lowering traffic, cutting down on delays, and optimizing incentives with the aid of this innovative approach. Because Deep Q-learning can learn from past events and make well-informed decisions, it can create transportation systems that are more efficient, safe, and ecologically friendly. A precise traffic signal control system that reduces wait times and traffic congestion is our main goal. We can enhance traffic management and create more efficient transportation networks by using reinforcement learning. An overview of the study's main findings and contribution is provided below:

- To reduce traffic and wait times, we create a set of standard trials using Reinforcement Learning.
- To determine the Q value needed to assess the best possible result, we put the Deep Q Learning model into practice.
- By merging the Reinforcement learning methodology with the Deep Q Learning algorithm, we achieved the best outcomes in comparison to previous studies.

The following parts comprise the remainder of this essay. The linked works are shown in Section II. Section III presents the techniques. Section IV presents the analyses that were conducted. The job is finally concluded in section V.

II. Related Works

Nowadays machine learning [11] is applied in various fields such as Banking systems [12] [13], Healthcare [14] [15] [16] [17], Business management [11], and many more [18] [19] [20]. In our study, the goal of traffic signal control in metropolitan areas is to minimize delays, and waiting times, and a functional congestion system. Numerous researchers use various techniques to mitigate traffic congestion. In particular,

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we may see several cutting-edge approaches now in use for traffic signal regulation in metropolitan areas.
For Finding the optimal signal timing in Large-scale Traffic Xiaoqiang et al. [21] suggested Cooperative double Q-learning (Co-DQL), a novel MARL with several noteworthy characteristics. The authors used a highly scalable independent double Q-learning technique that ensured exploration while resolving the over-estimation issue seen in conventional independent Q-learning. This technique was based on double estimators and the upper confidence bound (UCB) strategy. The Researchers modeled the interaction between agents using the mean field approximation, which helped the agents acquire more effective cooperative techniques. The authors included a novel incentive distribution system and a local state-sharing technique to increase the learning process stability and robustness. They examined the suggested algorithm's convergence characteristics. Co-DQL was implemented for TSC and evaluated using several TSC simulator traffic flow situations. According to their findings, Co-DQL performed better in terms of some traffic indicators than the most advanced decentralized MARL algorithms. Considered TSC System Qiang et al. [22] implemented New traffic signal control (TSC) systems, Nash-A2C and Nash-A3C, based on game theory and Nash Equilibrium, were introduced to manage complex urban traffic networks. A distributed computing architecture for IoT traffic simulation was designed to use Nash-A3C effectively. Both Nash-A2C and Nash-A3C led to a significant 22.1% reduction in congestion time and a 9.7% decrease in network delay compared to traditional TSC methods, demonstrating their effectiveness. Development of Connected Autonomous Vehicles (CAV) control Guillen et al. [23] expressed a new approach, advanced Reinforced AIM (adv.RAIM), utilizes Multi-Agent Deep Reinforcement Learning (MADRL) trained through Curriculum Self-Play to enable Collaborative Autonomous Vehicles (CAVs) to navigate intersections without traffic signals. It can autonomously adapt and learn complex traffic dynamics. adv.RAIM demonstrates significant improvements over traditional traffic light control, reducing travel time by 59%, congestion time by 95%, and waiting time by 56%. This highlights the advantages of using MADRL for smarter and more proactive Autonomous Intersection Management (AIM).
A fusion-based intelligent traffic congestion control system for VNs (FITCCS-VN) designed by Muhammad et al. [24] utilized ML techniques to collect traffic data and reroute traffic on available routes to alleviate traffic congestion in smart cities. The authors provided innovative services to drivers, allowing them to remotely monitor traffic flow and vehicle volume on the roads to prevent traffic jams. The proposed model had improved traffic flow and reduced congestion. Their system had achieved an impressive accuracy of 95% with a miss rate of only 5%, surpassing the performance of previous approaches. For Smart Traffic Lights and Traffic Flow Prediction Alfonso et al. [25] aimed to enhance traffic control with machine learning and deep learning, using two public datasets to predict traffic flow at four out of six intersections. The Multilayer Perceptron Neural Network (MLP-NN) had outshone others with an impressive R-squared and EV score of 0.93 and rapid training. While Gradient Boosting and Recurrent Neural Networks (RNNs) had also performed well, they required longer training times. Additional methods like Random Forest, Linear Regression, and Stochastic Gradient had delivered good results. In a nutshell, all models demonstrated strong performance, indicating their suitability for implementing an intelligent traffic light controller.
For unknown traffic-system uncertainties and reduced delays in vehicle travel time, Wanshiet et al. [26] used Multiple-Model Neural Networks to accurately identify traffic system models. They employed an online learning scheme to switch between candidate NNs based on estimation errors, facilitating the design of optimal signal-timing controllers. Simulation studies validated these strategies, showcasing reduced vehicle travel delays and enhanced traffic system robustness compared to traditional actuated traffic signal control schemes.
The main problem is that traffic cannot be properly reduced. Furthermore, Current Approaches also don't work well enough. To address this difficulty, we developed a reinforcement learning technique employing the deep Q learning algorithm, which has attracted a lot of historical attention and regularly draws academics to this field of study.

III. Proposed Method

The use of deep Q-learning in reinforcement learning in this research This work's learning constitutes a significant advancement in traffic management. Deep Q-Learning has the potential to transform traffic management by boosting flow and reducing congestion if it can adapt to changing circumstances. This illustrates how crucial AI and ML are to enhancing transportation, enabling quicker travel, and lowering gridlock. Figure 3 expresses the system Architecture with our Proposed Model.

A. Dataset Analysis and Discussion

We utilize a GitHub dataset [27] consisting of two XML files to create a representation of a dynamic environment with around 150 lanes. Each lane is defined by fundamental attributes including lane ID, index, speed, length, form, edge, and junction connection data. Simultaneously, our secondary file has extensive vehicle data, including vehicle ID, kind, route, departure time, departure lane, and departure speed. This file contains 1000 records of vehicle data.
By using these XML data files, we create an advanced agent environment specifically designed for training reasons. The training method focuses on improving the agent's capacity to make decisions in the complex lane network, making it more adaptable and sensitive to changing situations. Afterward, we thoroughly evaluate the trained agent by subjecting it to the given data and evaluating its performance in real-world simulations. By employing this thorough technique, we can verify the effectiveness and strength of our agent in various traffic situations, offering significant insights into its possible uses and enhancements.

B. Reinforcement learning

Traffic light systems may become more intelligent and flexible with the help of reinforcement learning. To maximize traffic, these data-driven algorithms use negative reinforcement to discourage congestion and positive reinforcement to encourage smooth movement. This constant learning process makes urban transit networks smarter and more flexible. By illustrating how the state engages with the environment and the decision-making process, Figure 1 illustrates the dynamic nature of this revolutionary approach to traffic management.

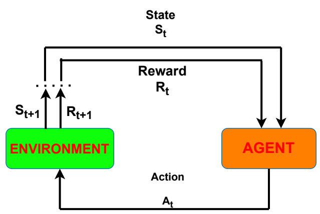

Fig. 1. Reinforcement Life Cycle

1) State: A snapshot of the environment, the state contains information about objects, agent status, and location, and it has a major impact on the actions that are accessible and the anticipated rewards.
In reinforcement learning, a state is expressed mathematically as follows:

$$s = (x, y, z, ..., v) \tag{1}$$

When the agent is located at position x in the surroundings, Things are situated at position y in the surroundings. Z is the agent's internal state. Value (v) represents the agent's internal state, and z is its state. Consider some lanes where the Green is 1 and the red signal is 0.

$$\begin{bmatrix} R & R & R \\ R & G & R \\ R & R & G \end{bmatrix} \tag{2}$$

$$\begin{bmatrix} 0 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix} \tag{3}$$

Consider a Phase:

$$\begin{bmatrix} 0 & 0 & 1 \end{bmatrix} \tag{4}$$

Here the last index is open. So, For the last state, this is workable.

2) Action: Options like timing adjustment and synchronized green light lane design choices are offered by traffic light control systems. These choices give traffic cops additional authority to manage crossings and enhance traffic flow. In Figure 2 the action set for the traffic light system is Shown
A = NSA, NSLA, EWA, EWLA

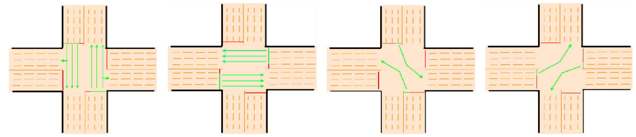

Fig. 2. Environment Based Action

3) Rewards: Rewards for traffic signal management show improved traffic flow and reduced congestion, the reinforcement learning framework determines how these expressions are expressed.

$$R(s, a, \acute{s}) \tag{5}$$

- s: This is an accurate representation of the environment right now. States explain the circumstances or setup in which the agent is operating. The prize may be unique to the situation at hand.
- a: This represents the action that the agent has done so far. The agent's choice of action determines the reward.
- s': This is the state into which the environment changes after an agent action a. The outcome state may also have an impact on the award.

The reward signal might be a scalar value, a positive or negative integer, or even a more intricate function, among other formats. In reinforcement learning, the main goal is for the agent to learn a strategy that maximizes the predicted cumulative reward over time also called the return.

C. Proposed Deep Q Learning Mode

Using neural networks, deep Q-learning (DQL) improves decision-making, such as traffic signal management. Stability is ensured by the use of strategies like experience replay and target networks. Showing off AI's flexibility, DQL optimizes incentives by adjusting traffic signals dynamically in real-time. Figure 4 depicts the lifetime of Deep Q learning and illustrates how the Q value is returned. According to the chosen action, the updated Q-value is:

$$Q(s, a) = Q(s, a) + (r + max(Q(\acute{s}, \acute{a}))Q(s, a)) \tag{6}$$

In the current state-action Q-value, Q(s, a) represents the value of the observed action, reward, next state, next action, and discount factor, respectively, represented by a, r, s', a', and . The workings of deep Q learning are shown in Figure 3. A deep neural network is used in first-state interaction, and a Q value is returned. This completes the model once the Q value has been updated. To estimate Q-values for many possible actions in a state, Deep Q-Learning makes use of a deep neural network. differently from conventional Q-Learning, which modifies a state-action pair's Q-value directly during training. Since $Q_i\left(S_t, A_t\right)$ includes fresh Q value estimation, it serves as our primary Deep Q learning function.

$$Q\left(S_t, A_t\right) + \alpha\left[R_{t+1} + \gamma max_a Q\left(S_{t+1}, \alpha\right) - Q\left(S_t, A_t\right)\right] \tag{7}$$

- Q(S_t, A_t) contains an estimate of the previous Q value.

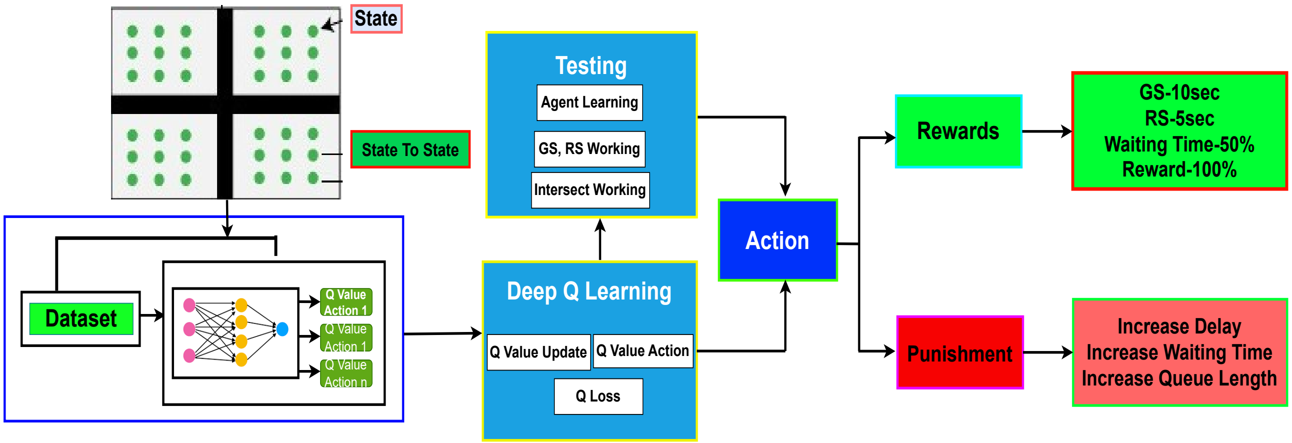

Fig. 3. Reinforcement Learning Traffic Signal Management Architecture

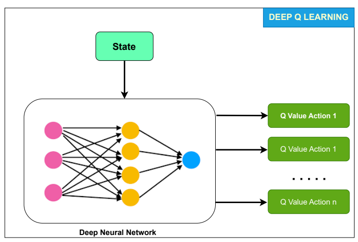

Fig. 4. Deep Q Learning Life Cycle

- $\alpha\,[R_{t+1}$ includes the Learning Instant Rate Reward.
- $\gamma max_a Q\,(S_{t+1}, \alpha)$ contains the optional Discounted Estimate Q-value for the next state.
- Q(S_t, A_t) x contains the estimated former Q-value.

Deep Q-Learning uses gradient descent to modify the Deep Q-Network weights to reduce the difference between the expected and actual Q-values.

$$y_j = r_j + \gamma max_{\acute{a}} \hat{Q}\left(\phi_{j+1}, \acute{\alpha}; \theta^{-}\right) \quad (8)$$

$$R_{t+1} + \gamma max_a Q\,(S_{t+1}, \alpha) \quad (9)$$

- R$_{t+1}$ provide instant rewards.
- $\gamma max_a Q\,(S_{t+1}, \alpha)$ includes Discounted Calculate the following state's ideal Q value.

When the model calculates the value of Q, this whole equation expresses the goal of Q.

$$[R_{t+1} + \gamma max_a Q\,(S_{t+1}, \alpha) - Q\,(S_t, A_t)] \quad (10)$$

- $[R_{t+1}$ provide instant rewards.
- $\gamma max_a Q\,(S_{t+1}, \alpha)$ includes Discounted Calculate the following state's ideal Q value.
- Q(S_t, A_t) contains the estimated previous Q value.

When the model calculates the Q value, this whole equation expresses the value of Q loss.
This paper clarifies the Deep Q Learning algorithmic framework, which is essential to the training and evaluation of our model. It also advances the area of intelligent systems and reinforcement learning approaches by offering a thorough understanding of our methodology.

D. Agent Training with Environment

To train a Deep Q Learning agent, you set up the environment, initialize DQN, configure replay memory, define parameters, use a loss function to adjust DQN weights, and have the agent make informed decisions in the real world based on updated Q-values. The research aims to improve our understanding of a complex road network with four main directions to enhance urban traffic management. This will lead to improved traffic flow, reduced congestion, and more sustainable urban mobility.
An illustration of the environmental scenario is shown in Figure 5. It shows a grid of intersections with four lanes at each, giving a good overview of the surrounding area.

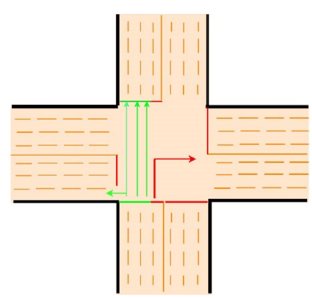

Fig. 5. Environment Direction of traffic intersection

E. System Implementation

In the system architecture, a state is first defined by the environment, and then crucial state-to-state links are precisely established by integrating datasets. In terms of math-

$$s = (x, y, z, ..., v) \quad (11)$$

$$Y = w * x + b \quad (12)$$

where X is the node's input, B is its bias, W is the weight of the connection, and Y is the node's output. Neural networks employ weights and biases without inputs, while deep learning obtains Q-values via dataset training. Choosing behaviors via reinforcement learning while accounting for incentives and penalties is what testing entails. Applications like traffic light management, which optimizes traffic using action Q-values, benefit greatly from the use of deep Q-learning, which estimates Q-values from dataset interactions. Figure 4 shows the whole deployment process and a reinforcement learning-based traffic light control system.

IV. Results and Discussion

This paper explores our methods using a dataset of 1091 cars and 300 junctions using a Deep Q Learning system. By measuring congestion reduction and reduced vehicle waiting times, it evaluates traffic reduction, reward maximization, and queue length reduction. This successfully illustrates the efficacy of the technique by increasing incentives.

We have pioneered a groundbreaking traffic management system by introducing a novel model known as Deep Q Learning. This innovative approach has enabled us to successfully optimize traffic signal timings, reducing the Red Signal (RS) duration to a mere 5 seconds and doubling the Green Signal (GS) duration to 10 seconds. This historic development marks a significant milestone in the field of traffic management. A graphical depiction of the Red Signal (RS) and Green Signal (GS) timing concerning the number of lanes in our research is shown in Figure 6.

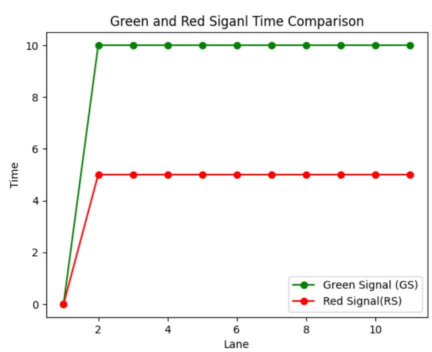

Fig. 6. Red and Green signal Timing showase

By setting the Red Signal (RS) timing to just 5 seconds and the Green Signal (GS) timing to 10 seconds thereby doubling the GS duration—we have accomplished a noteworthy success in our implementation. Congestion now lasts just 5 seconds during the RS phase, a major reduction from its previous state. This allows us to compute that the waiting time is just half of the overall signal cycle time, which results in an astounding 50% decrease in waiting time. This revolutionary result in traffic control shows that a system may reduce wait times at a junction by an additional 50%. The waiting periods that are seen in our system are shown graphically in Figure 7.

A. Rewards Of Traffic Signal Control

Reinforcement learning in traffic signal management offers rewards like reduced traffic jams, fewer delays, improved traffic flow, enhanced fuel economy, lower pollutants, increased safety, and overall transportation system enhancement. It adapts dynamically to changing traffic conditions, leading to more efficient urban mobility.

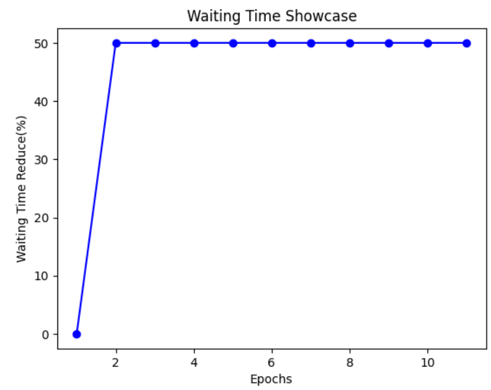

Fig. 7. Waiting Time measurement with several Epochs

The significant impact of signal timing on overall efficiency is a remarkable discovery in traffic signal management. Traditionally, when red and green lights share equal time, each gets 50% of the allocation. However, a breakthrough occurs when the timing shifts to 10 seconds for green and 5 seconds for red, giving green a full 100% share, doubling its duration. This showcases how dynamic signal management can greatly enhance traffic flow and the driving experience, illustrating the potential for traffic control systems to reach new heights. The overall rewards obtained in our research are presented in a simple and informative manner in Figure 8.

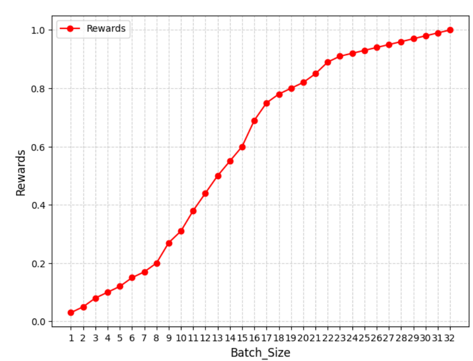

Fig. 8. Rewards Shows with Batch size of system

B. Performance Ratings of Different model that we Examined

We have created and assessed a collection of innovative models, such as Q-learning, policy gradient, RCNN, Bi-LSTM, VST, Transformer, VIT, EGNet, and CRT, to measure their effectiveness in the field of traffic signal management. Our deep Q-learning model has exhibited exceptional performance in comparison to alternative models, as evidenced by extensive testing. Based on these findings, we strongly recommend using and enhancing our deep Q-learning model as a viable approach to improve the efficiency of traffic signal management systems. The remarkable effectiveness of this system in negotiating intricate traffic situations makes it a strong and efficient option for improving traffic flow efficiency and reducing congestion. We are certain that the use of this model has substantial potential to enhance traffic management methods and contribute to the advancement of more intelligent and adaptive traffic signal control systems. In Table 1 we show the implemented model result where we show the proposed model improvement.

TABLE I
DIFFERENT MODEL OF IMPLEMENT FOR EFFICIENT OUR SYSTEM

Model	Improvement
Q Learning	GS-3sec, RS-5sec, Waiting Time 20%
Policy Gradient	GS-5sec, RS-7sec, Waiting Time 32%
RCNN Bi-LSTM	Waiting Time 40% GS-2sec, RS-4sec, Waiting Time 250%
VST	GS-3sec, RS-3sec, Waiting Time 30%
Transformer	GS-2sec, RS-5sec, Waiting Time 20%
EGNet	Waiting Time 32%
Transformer	GS-2 sec, RS-5 sec, Waiting Time 30%
CRT	Waiting Time 42%
Proposed Deep Q Learning	**GS-10sec, RS-5sec, Waiting Time 50%**

C. Comparison Of proposed and existing system

We are performing a comparison analysis between our model and many innovative ways in the field of traffic. This comparison seeks to highlight the effectiveness of our system while assessing the attainable enhancements. We assess a variety of models and algorithms used in various studies linked to traffic management. This encompasses a range of approaches such as Reinforcement Learning (RL), Deep Learning (DL), Hierarchical Reinforcement Learning (HRL), and a variety of algorithms including Deep Q-Learning (DQL), Convolutional Neural Networks (CNN), and Neural Networks (NN). Table II shows a comparison of existing systems for Traffic signal control in terms of model and their improvement.

TABLE II
A COMPARISON OF EXISTING SYSTEMS FOR TRAFFIC SIGNAL CONTROL IN TERMS OF MODEL AND IMPROVEMENT

Ref.	Model and Algorithm	Improvement
[28]	RL and DQL	Reduce Fuel consumption (7.8%)
[29]	DL+RCNN	Accurately 91%
[30]	SPSA and NN	Delay (7.8%) Waiting Time(8.5%)
[31]	RL and NN	Waiting Time(6.95%)
[32]	HRL	Travel time(11.75%) Energy consumption (12.70%)
Proposed	**RL and DQL**	**GS-10sec, RS-5sec Waiting Time (50%) Rewards Increase (100%)**

D. Discussion

The Traffic Light Control system we have developed aims to minimize delays, alleviate congestion, promote safety, and optimize traffic flow. This is achieved by utilizing a complete dataset that includes environmental factors and vehicle-specific information for training and testing the system's agents. To construct this system, we utilized the Anaconda IDE and wrote the code using the Spider tool. Our solution relies heavily on the integration of an advanced and innovative model called Deep Q Learning (DQL). This innovative methodology surpasses current models and brings a notable improvement to traffic management tactics. The DQL model notably reduces waiting times by optimizing the sequence time of traffic lights. The Green Signal (GS) length is set to 10 seconds in this novel design, while the Red Signal (RS) duration remains constant at 5 seconds. Consequently, the waiting duration is reduced by 50%. The duration of the red signal is 5 seconds, whereas the duration of the green signal is 10 seconds, resulting in a significant enhancement in traffic efficiency. The significant decrease in waiting times highlights the tangible advantages of our DQL concept, especially in the context of enhancing traffic conditions. Our strategy effectively incorporates sophisticated machine learning techniques to tackle crucial issues in traffic management and significantly contributes to the continuous development of intelligent transportation systems.

V. CONCLUSION

The research is commended for its trustworthy and practical approach to traffic management. To ensure real-world relevance, it employs a validated traffic simulator, looks into different reward metrics for effective reinforcement learning, emphasizes accurate problem context modeling, and recognizes the value of knowing both machine learning and the application domain.

Future research will optimize junction traffic flow while considering vehicle behavior, traffic flow, and driver experience to inform practical self-adaptive traffic management system implementation. Traffic management will be improved using synchronized reinforcement learning bots and powerful algorithms.

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