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Collaborative Traffic Signal Automation using Deep Q-Learning

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Abstract

Every metropolitan trip is punctuated by traffic signals, which have an immediate effect on drivers, the environment, and the economy whether the route is crowded or not. Traffic signal automation to reduce traffic delay is a major issue all over the world. Nevertheless, the current solutions to reduce exponentially rising traffic issues are not completely dealing with the problem. Companies, traffic engineers and researchers have suggested several Traffic Signal control systems. The main function of the traffic signal management system is to coordinate individual traffic signals to accomplish operational goals for the entire network. The single junction-based systems are unable to reduce the waiting time of exponentially increasing traffic load on the roads. To deal with this, we propose collaborative signal automation on a traffic simulator based on reinforcement learning techniques. The model utilized a q-learning technique that depicts composing units of addressed issues: agents, surrounding and response. The collaborative network takes advantage of traffic flow prediction with signal automation. Multi-junction road environments and vehicles are fed to the network as input. The proposed system suggests optimal signal automation to alleviate delay time and sequence length of traffic. Q-learning-based model decreases the wait time and leads to a steady flow of vehicles with several significances in composite traffic areas.

KEYWORDS:
Reinforcement Learning; Deep Q-learning; Traffic Signal Automation; Traffic Flow Prediction

1 | INTRODUCTION

Life quality has risen throughout the globe, resulting in the expansion of commercial automobile companies. Automobile companies are producing a higher number of cars and other vehicles on the road every year. In the large cities of developing countries, traffic congestion has increased day by day. People are facing this problem everywhere, especially in metropolitan cities. The Ministry of Road communication in China released traffic-related statistics that indicate numerous issues. According to them, the damage of the financial amount is 20% of metropolitan inhabitants' expendable cash or a 5%–8% of GDP loss. The Chinese Citizens of 15 major states invest 2.88 billion seconds extra to get to the workplace than citizens of advanced Nations like the European region [1]. Furthermore, indirect costs increased due to road vehicle delays (including those related to vehicle crashes, social welfare, and air degradation) are very hard to calculate. When it comes to traffic congestion, time wasted, and smoke emitted by traffic, two sorts of remedies are widely used. The first approach entails boosting throughput by widening roadways, which can be costly and ineffective in dealing with rapidly changing vehicle situations. The next effective form of remedy entails improving the effectiveness of the highway network. One of the most critical measures for increasing the performance of road junctions and accident prevention is the collaborative management of road signals [2]. Several experts have anticipated the development of linked and autonomous transport that will significantly alter traditional road signal operations, such as different types of transport cooperative driving through signal-free junctions [3]. Nevertheless, it is predicted that road or traffic signal regulation will continue to be important in the coming years since autonomous cars and conventional transport coexist in every type of field for an extended period of time[4]. Several transportation systems worldwide currently employ preset duty cycles of the traffic signal, which means they regularly modify the traffic signal on the road in a round-robin fashion. While such a technique is simple to adopt, it ignores current road vehicle patterns and possibly leads to a higher number of traffic jams. As a result, smart and dynamic traffic or road signal management is required. Many proposed techniques that optimize the particular parameters of road vehicle controller systems depend on numerous statistical equations in commercial sectors for road signal management. The famous United Kingdom-based technique "Split Cycle Offset Optimization Technique"[4] and Australia-based "Sydney CoVOLUME 4, 2016 1 Author et al.: Preparation ordinated Adaptive Traffic System"[5] are two conceivably best implementations of such technologies that have worked to enhance road traffic pattern in different cities. Furthermore, due to a lack of instantaneous workability and elasticity, they have inadequate management of unforeseen road circumstances[6], particularly when unwanted anthropocentric influences like disasters or exceptional events happen. Particular reliable technologies that handle compelling optimization issues, like the "Real-time Hierarchical Optimizing Distributed Effective System (RHODES)" proposed in[7], suffer from high complexity, making them unsuitable for large-scale deployment[8]. The largest queued first (LQF) technique has been established as trustworthy that decides to turn on the green light on the route with the highest number of vehicles[9]. The LQF, on the other hand, may be inequitable for cars waiting in a narrow lane that cannot be allocated sufficient duration[10]. In the last few decades, numerous machine learning-based studies have been proposed for controlling urban traffic signals by utilizing fuzzy logic, dynamic programming, evolutionary algorithm, and neural networks for traffic lights at a remote intersections with varying traffic densities. Yang et al.[11] proposed a fuzzy logic-based two-stage adaptive technique. Fuzzy logic-based signal controllers' systems typically create a set of principles based on professional knowledge and then choose the right actions for the traffic light according to inputs. However, the formulation of rules relies mainly on professional experience. Moreover, when there are more phases at various crossings, it is challenging to come up with a set of efficient rules. A study[12] also proposed a model with the combination of fuzzy logic and neural networks for automatic traffic signal networks of roads with bus priority. The use of the neural network is very sensitive to data and the training process. In[13], a genetic algorithm was used to optimize traffic flow through an urban traffic junction. Due to the high cost of computing required to converge to the best solution, such a method is inappropriate for online issues like junction signal control. Additionally, traffic signal control frequently makes use of dynamic programming. A task heuristic dynamic programming method was suggested in[14] to regulate traffic signals at two junctions. Dynamic programming needs efficient ways to overcome high computation costs and the difficulty of determining the transition probability for the operational environment as the problem's size grows. Reinforcement Learning (RL) has been extensively used by the specific community to solve problems in the intellectual world. The two essential differentiating properties that make RL appropriate for traffic signal management are investigative exploration and trial and error search. The components of the traffic control system can be accurately represented using RL: the road signal represents the operator, the traffic represents the condition, and the execution of the traffic signal represents as act. Balaji et al.[15] introduced the model-free RL-oriented road signal management architecture. The purpose was to improve the traffic passage duration of the signal in a metropolitan arterial road system in order to minimize traffic delay time. The state space is expanded using intersection features created by humans in the traditional RL method. State representation is typically made simpler to minimize the excessive volume of state space. However, this tactic will lead to the loss of some crucial data. For instance, the approach of describing the state space by the length of the vehicle queue[16 17] excluded the information about the passing traffic as well as their position and speed. The average vehicle delay[18] method only considered historical traffic data and cannot meet the demand for traffic in the present. These tactics are based on incomplete intersectional knowledge, so they cannot always be relied upon to produce the best possible outcomes. Given the popularity of deep Q-networks, deep RL has recently received a lot of attention (DQN). This method is used in several other works[19 20 21 22 23 24], producing satisfactory outcomes. However, if the scenario becomes more complicated, the machine's memory can also be packed and look at a specific condition on a huge table, which takes a lot of time. Deep neural networks are used to rescue this problem in Q networks. Wan and Hwang[25] used a dense Q network to minimize the average system-generated delay in an 8 steps road signal management system. A dense-q-network is a method of sorting in RL which has some advantages of quality learning and ANN in a single approach. Numerous research studies for traffic signal management were published[26],[27],[28],[29],[30] and provided significant outcomes. However, a comparison study contains several flaws that need to be addressed. Initially, all of these studies[19 21 26 27] rely on a single particular enhancement, which will not be sufficient in real-time traffic-based scenarios. They may not increase current effectiveness because they only concentrate on a restricted range and reduce traffic on the roads going somewhere in a city. Additionally, despite initiatives at a broader range of networks, including[19 20 24 31], they make use of a static statistical model. As the traffic flow rate fluctuates in various time frames and road conditions, most of the prediction models discussed up to this level expect the same flow rate in different time frames and road conditions. The proposed research is helpful in managing and controlling the traffic flow between the junctions and making the average waiting time of every vehicle at different road junctions. The traffic signal can decide the signal patterns by analyzing its adjacent traffic signals' status and the traffic flow.The main contributions of the proposed work can be summarized in the following points:

- Proposed novel reward function by utilizing the traffic intensity, delay time, waiting time and environmental conditions to overcome the average waiting time of the vehicles at the road signals.

- Consider novel features like the state of the signal on the previous junction, the distance between two junctions and the average speed between the junction for the collaborative control of traffic signals.
- Optimize the performance of MDP (Markov decision processor) to efficiently analyze the traffic density and queue length of the vehicle for traffic signal controls.

The rest of the paper is structured as follows: Section 2 provides the related work and section 3 presents the methodology of the paper. Experiments and results are explained in section 4. At the end, section 5 gives the conclusion and future directions of this paper.

2 | RELATED WORK

Deep RL and RL-based methods have several appealing characteristics. Firstly, RL is an environment-based learning strategy that focuses on the environment's interactions and is goal-oriented. In contrast, deep learning has significant nonlinear estimation and hierarchical feature extraction capabilities. This section first goes through the RL and deep RL-based traffic signal control methods. Then we examine the current issues and discuss the driving factors for this article. Most of the studies that proposed RL-based traffic signal control systems are focused on the single traffic intersection [32 33 34 35 36]. The state space of intersection grows potentially with the increase of intersection, and the representation of all possible actions for each state is not feasible. As a result, it is challenging to expand conventional tabular-based reinforcement classifiers to many intersections. In order to solve this issue, multi-agent RL-based methods for adaptive signal control in regional traffic scenarios have been developed [37]—the control technique of these algorithms into two different categories: independent and integrated control mode. Every junction in the independent method has an RL agent operating separately from other agents. A significantly larger traffic system is represented as a multi-agent network by Abdoos et al. [17]. Each agent is in charge of managing the traffic light at a single junction. It merely estimates the states using local data from the junction, such as the typical queue length. This strategy did not consider the impact of nearby junctions based on an independent approach. In the integrated mode, the agents used various methods to communicate signal control activities with their companions. In a proposed study [38], the author designed two agents: centralized and outgoing. The longest-queue-first approach is used by the outward agents to manage traffic signals, and they support the centralized agent by supplying proportionate traffic flow. The central agent picked up value functions based on the traffic patterns in its immediate surroundings. In this manner, coordination is limited to the central agent, while the outgoing agents operate autonomously. A synchronized traffic signal management strategy based on collaboration models is proposed by Kuyer et al. [39]. To learn about the local state, the nearby agents communicate with one another. However, the computationally demanding and prone to the local optimum max-plus technique is used to identify the best joint movement. In other words, implementing these kinds of algorithms in multi-junction signal control is constrained by the inadequate exploitation of local traffic monitoring systems and low scalability. In recent studies, the RL algorithm has been used for collaborative traffic signals control after the significant performance of deep Q networks [40 41]. An autoencoder method [26] based on deep stacked is introduced in RL to predict the optimal Q-value at the single junction. In this encoder method, the number of cars in a line and the reward are used to indicate the traffic status and the queue variance across roads travelling in orthogonal directions, respectively. Deep Convolutional Neural Networks (CNN) are used by Genders et al. [42] to extract aspects of vehicle position and speed as well as to approximate the ideal Q-value. The created deep RL agent is then trained for single junction traffic control using Q-learning and experience replication. Despite the algorithm's improved performance, it was unstable because of possible correlations between the possible action states and the target values. Gao et al. adopted a target network technique to overcome the instability issue [43]. In addition, Jeon et al. [44] claimed that most earlier RL studies related to traffic characteristics couldn't accurately capture the diversity of an actual traffic situation. Instead, they used video footage of a junction to do so. Recently a study proposed by the Van der Pol et al. [28] used a multi-agent deep RL technique to regulate the signals of numerous straightforward junctions without left turnings. According to [28], a Q-function is learned for small resource situations involving only two agents and is applied to other challenges. The best synchronized collaborative action is eventually learned using the max-plus algorithm at various junctions. The max-plus approach is used in supportive multi-agent systems; however, it is not guaranteed to converge to the best outcome. Additionally, the state space size and the number of phases at each junction must be the same in order to transfer the Q function between various smaller problems; hence the structure of junctions must be constrained or approximated. Numerous state-of-the-art studies using the RL technique for traffic control systems are presented in table (1). All the studies in table (1) used a stimulating environment for the learning of the agent for signal control management. Although, few studies used the real-world environment dataset for the better performance of the agent that resultantly controls the traffic signal more efficiently. But the collaboration of the traffic signals at different intersections still required further investigation to reduce the vehicles' average delay and wait time. In traditional traffic signal management systems, RL agents only consider the current intersection and take the best possible action by investigating the environment, like the vehicle's queue length and delay time, etc. Moreover, in real-world scenarios, the time of the vehicle to cover the area between two adjacent signals varies with the effect of different environmental factors like high temperature, rain, and fog. Collectively, the latest traffic signal management system requires more efficient RL agents that collaboratively control the signals and reduce the vehicle's average delay time and wait time during the complete journey rather than on a single intersection. The proposed study implemented the RL-based

Table 1 Overview and comparison of published studies.

Study	Synthesized Dataset	Real World Dataset	Environmental Variable Consideration	Multiple Intersection Management	Collaborative Signal Management
Chen et al., 2020 [45]	Yes	Yes	No	Yes	No
Wei et al., 2021 [46]	Yes	Yes	No	Yes	No
Boukerche et al., 2022 [47]	Yes	No	No	Yes	Yes
Qiao et al., 2021 [48]	Yes	Yes	No	Yes	Yes
M. Wang et al., 2022 [49]	Yes	Yes	No	Yes	No
T. Wang et al., 2021 [50]	Yes	Yes	No	Yes	No
Zhang et al., 2021 [51]	Yes	Yes	No	Yes	No
Antonio & Maria-Dolores, 2022 [52]	Yes	No	No	Yes	No
Proposed	Yes	Yes	Yes	Yes	Yes

framework for collaborative traffic signal management to reduce the average delay time, average wait time, and sequence length of vehicles in the intersection. Moreover, the proposed framework considered the environmental factors to robust the proposed framework. Resultantly, the proposed framework will control the traffic signals collaboratively to reduce the vehicle's average delay time in different weather conditions.

3 | METHODOLOGY

It is necessary to formulate the traffic control challenge in the RL terminology, mainly by establishing a state space S, an action space A, and a reward function R, before trying to find solutions using RL. The approach of RL is based on behavioral psychology, in which an agent performs actions to reach different states, with a positive or negative reward for each state. The agent aims to capitalize on the reward after consecutive series of actions. With the experience in the surrounding, the agent observes to behave in a peculiar situation, and this process is called policy. In order to understand the concept of RL, takes an example of a human completing a goal of moving from A to B.

- The human is representing an agent here
- Here the surroundings are the environment
- The whole episode is to reach the point B

The action can be walking, running, right, left, etc. The result of each action describes the reward, either addition or removal to the score. The reward will be positive if an action reduces the distance from the target point. In contrast to this, an increased distance yields a negative reward. Hence, compared to other intelligent methods, RL algorithms are not fed with information about how to behave. Instead, these techniques learn to execute based on surroundings. RL's most remarkable and perplexing part is that an immediate maximum reward might lead to consistent and continuous minimal rewards. In order to decrease the average delay time, wait time, and sequence length, the architecture of the proposed study is presented in figure (1).

3.1 | State Space

The proposed study used Discrete Traffic State Encoding (DTSE), which is motivated by a widely used method for estimating the discretization and quantization of continuous objects. The DTSE divides the length l of each lane segment reaching towards the intersection into the different cells of length c. The division of the lane segment into cell c starts from the stop line. The change in the size of cell c will change the total behavior of the model. The particular characteristics of every vehicle will be eliminated if c exceeds the average vehicle length, but the computational load will be decreased. The individual characteristics of each vehicle will still be present if c is substantially less than the average vehicle length, but the computation complexity may rise excessively. The proposed study pointed out that choosing c is crucial. However, in this study, we do it in a streamlined approach to assess the suggested method.

The DTSE method received the three vectors as input that represent the vehicle density or presence of a vehicle in the cell, the vehicle's speed, and the traffic signal's current state, respectively. The used DTSE enables the agent to consider the valuable information rather than only focusing on vehicle presence. The first vector of DTSE representing the vehicle presence contains the Boolean values. The one means in the first vector represents the vehicle's presence, and zero represents the absence of the vehicle. The second vector contained the number representing the speed of the vehicles. The third vector that represents the state of the traffic light contains the zero value except the current traffic value. The complete state space function can be represented as equation (1). In equation (1), T represents the state of the current traffic light, and the RL agent will observe the environment state $s_t \epsilon$ S in time t.

$$S \epsilon (B * R)^{(l/c)*n} * T \tag{1}$$

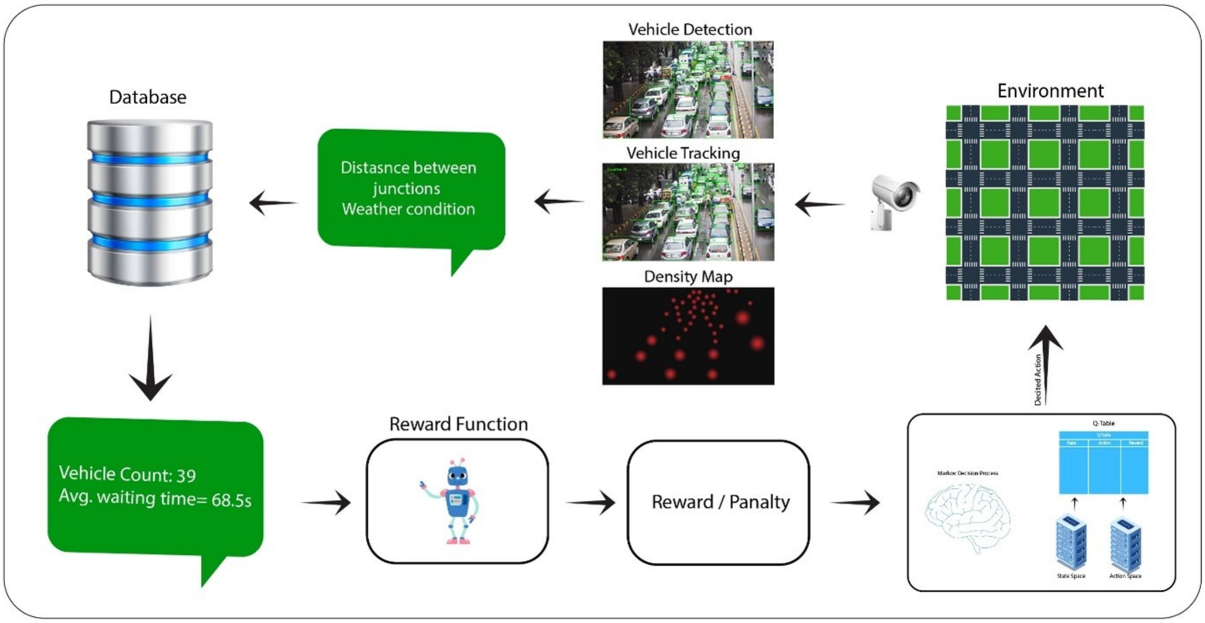


Figure 1 Proposed System Architecture.

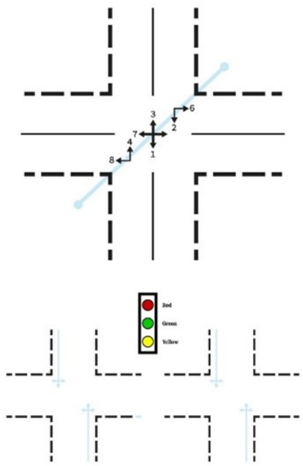
3.2 | Action Space

The next step of the RL agent is to take the feasible action from the possible action set after observing the environment at the current time. The possible action of the agent is the configuration of traffic signals for traffic control. Each possible action is defined with the help of vehicle direction and the traffic signal state in front of that vehicle. For a better understanding of the readers, the directions were labelled with compass directions, and the traffic signal state with different colors. The green state of the traffic signal represents that the traffic will pass through the intersection, the yellow light will slow down the vehicles, and the red represents that the vehicle will stop and should not pass through the intersection. For instance, the few possible states with the combination of vehicle direction and traffic signal state are East-West Green (EWG), West-East Green (WEG), North-South Red (NSR), and North-South Advance Left Green (NSLG). For the green signal of the current state, it is considered that the omitted signals are red.

Formally, A = $\{EWG, NSG, EWLG, NSLG\}$ defines the set of all possible actions, and all the possible states of the signal are presented in figure (2). As a result, the agent picks action at time t where at ϵ A. When an agent decides on a course of action, it cannot be carried out right away. Massive traffic signal control configurations may come before the selected action in order to ensure the proper management of the junction. A series of intermediary actions are selected based on the current traffic signal phase and chosen action that may be required rather than switching directly from the current state to the final state (desired state). Figure (2) represents the possible action state for the agent, but there are some phases that cannot be chosen as an action by the RL agent, like North-South Yellow (NSY) and East-West Yellow (EWY). But these actions or phases are implicit in traffic signal control systems.

3.3 | Reward Function

Following the observation of the environment and choosing an action to carry out, the last step is the criteria to reward or penalty the action based on the result. The reward function in RL is the criteria for awarding the chosen action. The main agenda of the reward function is to create a policy between states and actions to maximize the cumulative reward. The reward is a factor that sets RL apart from other sorts of machine learning. RL allows the agent to assess behaviors through interaction with the environment, in contrast to other methods of machine learning that rely on instructions to perform the right actions. A challenge in conventional RL is how to choose the best reward for a particular task. Several incentives have been put forth in the context of traffic signal regulation, including changes in the volume of backed-up traffic, cumulative vehicle delays, and vehicle throughput. The result of performing a chosen action from a particular state is the reward $r_t + 1\epsilon$ R. The reward is defined in the proposed study as a shift in the overall vehicle delay between actions. As a result, the agent may receive a reward or a punishment depending on whether the delay is increased or decreased ($r_t + 1$ > 0 for the reduction in delay). The subscript t + 1 is used on purpose to highlight the causal relationship



Signal	First Phase	Second Phase
1 - 2	G - Y - R	R - R - R
3 - 4	G - Y - R	R - R - R
5 - 6	R - R - R	G - Y - R
7 - 8	R - R - R	G - Y - R

Figure 2 This diagram shows the two phases of signals. We can see all the possibilities of signals at signals 1-2. it can be green, yellow, or red in the first phase, and it can be read in three directions in the second phase.

between action at in state st and receiving the reward because the former occurs before the latter. The agent has the chance to examine the updated state of the environment s_t+1, which was affected by its most recent activity and obtain compensation from the environment. A new action can be chosen and then rewarded with this new state observation. Depending on the RL task at hand, this loop can go on forever or cease when certain conditions are met.

3.4 | RL Agent

The agent is the object that trains by observing the environment in RL. For traffic signal controlling, the proposed study used the deep convolutional Q Network as an agent. The curse of dimensionality, which occurs when the number of dimensions of the data increases and the amount of training and processing resources needed rises exponentially, can cause several machine learning problems. The ability of artificial neural networks lessens the issues caused by the dimensionality curse. The proposed study used Q-Learning [20] as an RL algorithm to create the best action-selection strategy. The Markov Decision Processor (MDP) was used to estimate the action-value function in order to establish the best possible policy. The action-value function converts states into action utilities, or what each action from a given state is worth. Values stand for long-term gain. Taking an activity that has a high value involves reaping the rewards in the future, possibly not right away. The agent obtains the state from the environment for each time step t. Simultaneously, the agent sends the current and previous junction state with the environmental condition and average delay time to the traffic flow prediction model. They use realistic variables to estimate upcoming traffic flow. The state t+1 should then be returned to the agent. After that, to choose the action, the agent calculates the reward value using equation (2). In equation (2), s is the current state, a is the action taken in the current state, s' is the next state, $P\left(s'|s,a\right)$ is the probability of transitioning to state s' given that the current state is s and the action taken is a. $R\left(s,a,s'\right)$ is the reward received for transitioning from state s to s' by taking action a and y is the discount factor, which determines the importance of future rewards relative to immediate rewards. The reward is granted for specific states and actions. Our model's main purpose is to determine the best policy that maximizes future reward. The algorithmic learning approach for the proposed system is shown in 1.

$$V\left(s\right) = max\left(\sum s'P\left(s'|s,a\right)\left[R\left(s,a,s'\right)+yV\left(s'\right)\right]\right) \tag{2}$$

3.5 | Multiple Junctions

A traffic signal control model is presented for a multi-intersection environment along with traffic flow prediction based on transfer planning [42]. The multi-intersection scenario is modelled as a multi-agent where each agent is used to estimate the local optimized Q-value. After that, the global Q-value is optimized by transferring messages with each agent's local optimal value. For cooperative traffic signal control, the Q-value of adjoining intersections and its value is essential.

3.6 | Environmental Setup

A well-known simulated environment SUMO (Simulation of Urban Mobility) is used to perform the experiment of the proposed study. A multi-junction environment of 5*5 is established in the simulated environment, and the single RL agent used a subpart of environment 2*2. ITS is evaluated on 25 junction scenarios, and each intersection point operates as an intelligent RL agent. Each vehicle in the junction scenario has a unique index, representing its occurrence in a particular region. Furthermore, to implement the concept of collaborative ITS, the information regarding the state of each agent is shared on the network. The automobiles are synthesized using simulation and perceived at particular road segments. Each automobile is then examined by an agent of the zone. SUM generates automobiles on road scenarios based on predefined software functions followed by agent assignment at each junction.

Algorithm 1 Agent Learning Process

```
Input: Hyper Parameters (HPs), Action Space (A), State Space(S), Current-junction-State (S_c ), previous-junction-state (S_p ), distance -between-junctions (d), Environment-condition (env)
Output:Q-Table
Initialize HP:Q-Table {batch − size, learning − rate, reply − memory(RM)}
Observe S_c and S_p
Observe d and env
Random (A_t ϵ A for S_t)
for each epoch in epochs do
    Perform A_t in Environment
    reward=calculate-reward (delay − time, density, sequence − length)
    if reply-memory ≥ size(memory) then
        Q-Table ≥ pop(0)
    end if
    Q-Table[S_c][S_p][d][env][A_t]=reward
    Observe Next S_c as (Sn): S_n ϵ S
    S_t=S_n
    Observe Next S_p as S_p ϵ S
    Next A_t=Q-Table[S_c][S_p][d][env]
    if reply-memory==batch-size then
        loss=Calculate-loss()
        optimize-Weights
        if Avg(reward) ≥ Target then
            Stop
        end if
    end if
end for
Return Q-Table
```

4 | EXPERIMENTS AND RESULTS

To evaluate the proposed intelligent traffic signal (ITS), a junction of 5 X 5 is chosen, as shown in figure (3). In order to experiment, we have chosen a sub-part of the junction region, i.e., 2 X 2. The figure illustrates that the later junction layout is a part of the complete area under examination. ITS is evaluated on 25 junction scenarios, and each intersection point operates as an intelligent RL agent. Each vehicle in the junction scenario has a unique index, representing its occurrence in a particular region. Furthermore, to implement the concept of collaborative ITS, the information regarding the state of each agent is shared on the network. We took advantage of simulation urban mobility (SUM)[32], a software utilized for research experimentation in transportation. The complete framework for experimentation is shown in figure (3). The automobiles are synthesized

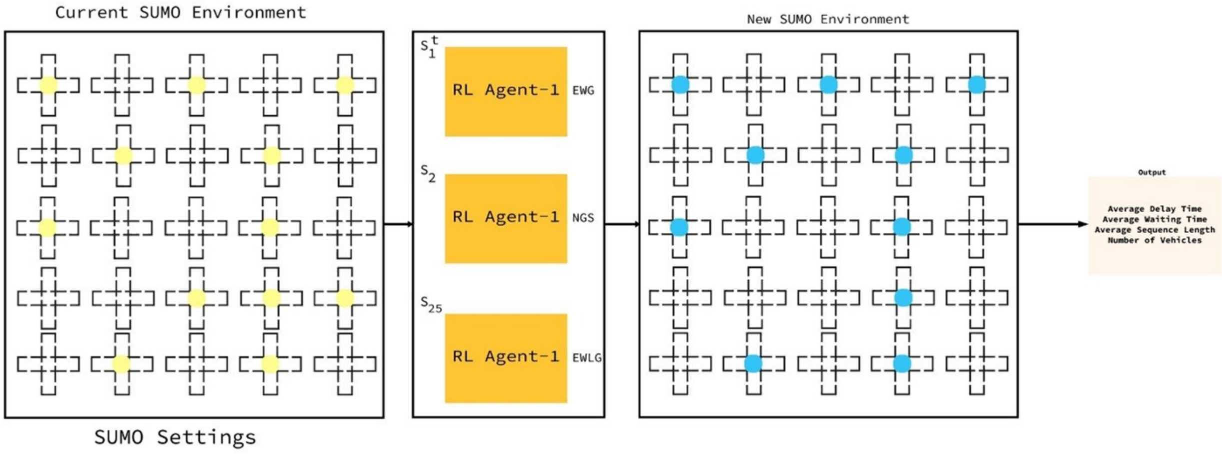


Figure 3 This diagram shows the output with respect to SUMO present scenario and the new SUMO scenario. There are total 25 agents are used.

Table 2 Hyperparameters of the MDP and their values.

Sr No.	Hyperparameter	Value
1	Learning Rate	0.0001
2	Decay	0
3	Weight Initialization	Kaiming
4	Optimizer	Adam
5	Momentum	0.9
6	Epochs	1000
7	Dropout	0.25

Table 3 Average delay and wait time for different learnings.

Input Previous States	Average Delay (Minutes)		Average wait (Minutes)	
	Q- Learning	Proposed ITS	Q-Learning	Proposed ITS
1	2.05	0.69	2.11	0.67
3	3.48	1.97	3.74	1.95
5	4.52	2.23	4.65	2.26

using simulation and perceived at a particular road segment. Each of the automobiles is then examined by the agent of the zone. SUM generates automobiles on road scenarios based on predefined software functions followed by agent assignment at each junction.

All agents observe the maximum reward for traffic signals and shift the control to other signals based on the density, average delay, and average wait time of automobiles on the road. Road traffic scenarios are observed comprehensively in terms of delay time and sequence length. The deep network training is performed for 1000 epochs by tuning the different hyperparameters. The proposed model showed the optimized results on the hyperparameters: learning-rate:0.0001, dropout:0.25, and Adam as optimizer. The complete details of the tunned parameters for agent learning are presented in table (2). The optimized weights of the model during the model's training were saved for the evaluation of the proposed model.

Further, different input strategies were considered for learning the deep network. For instance, the state of the current junction with the previous 1, 2, and 5 junctions states is passed to the model. Resultantly, the model is trained with 2, 3, and 6 input states for collaborative traffic control. The training of a deep network with 2 input states reflects that the model will get the current junction's state with the previous junction's state. The training results of the proposed model are shown in table (3).

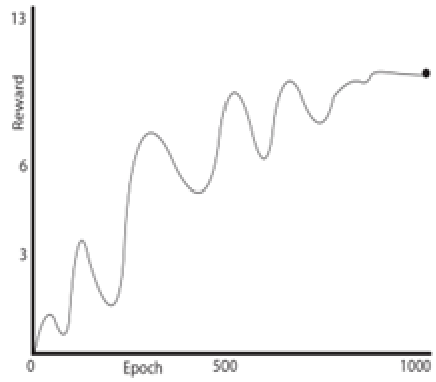


Figure 4 The reward of the Deep network during 1000 epochs.

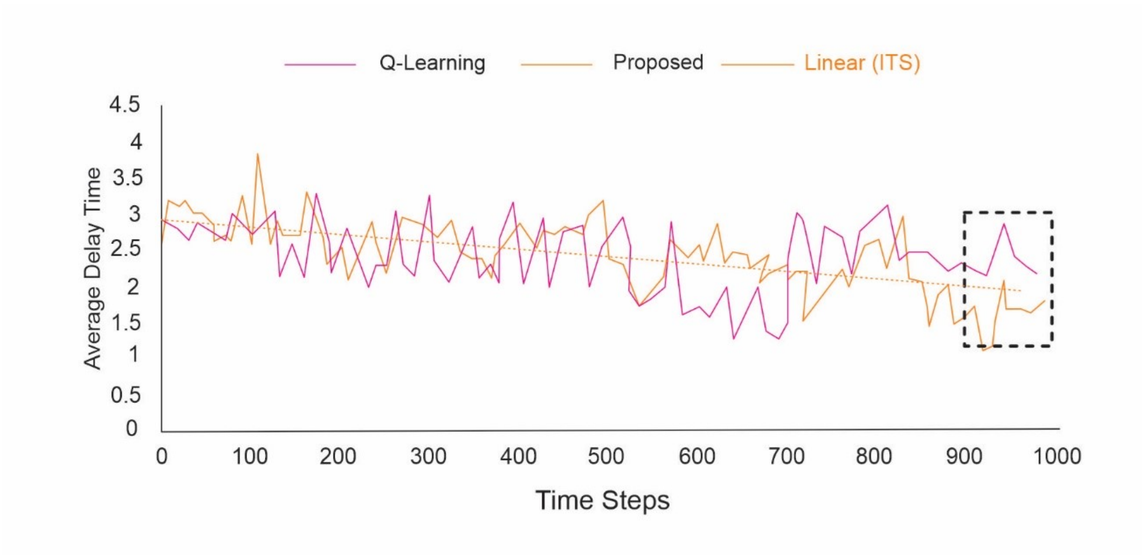


Figure 5 Graph represents average delay time comparison of baseline systems with Q-learning approach.

Table (3) shows that the deep network showed the optimal results with the one previous junction state. For the 3 and 5 previous junction states, the model did not show the outer performance relative to the result of one previous state. It is assumed that the consideration of more previous states raised the complexity of learning that ultimately decreasing the targeted results. By considering the result of table (3), the results with one previous junction state are proposed as contributions to collaborative traffic signal control systems. The reward graphs during the training of the deep network for 1000 epochs is shown in figure (4).

The above graphs showed the gradual increase in reward and achieve the highest reward of 11.3 after 900 epochs. After 900 epochs the reward graph becomes straight and curved downside. So, we stop the training at 1000 epochs and save the model parameters as a trained model because the learning of the model is stopped. The graphs (5), (6) and (7) illustrate that the proposed ITS model outperforms the baseline model. The comparison is drawn based on the reward parameter.

5 | CONCLUSION

This research study proposes a collaborative autonomous signal control with traffic density forecast at multiple junctions. The proposed intelligent traffic system comprises a variant of Deep Q-Networks for accelerated and fast feature learning. Moreover, the study takes advantage of collaborative signal automation to fill the gap of multiple junction scenarios in traffic signal automation. Every junction of the environment is operating as an agent for collaborative signal automation with a prediction for a local Q-value. The information about local q values is exchanged to

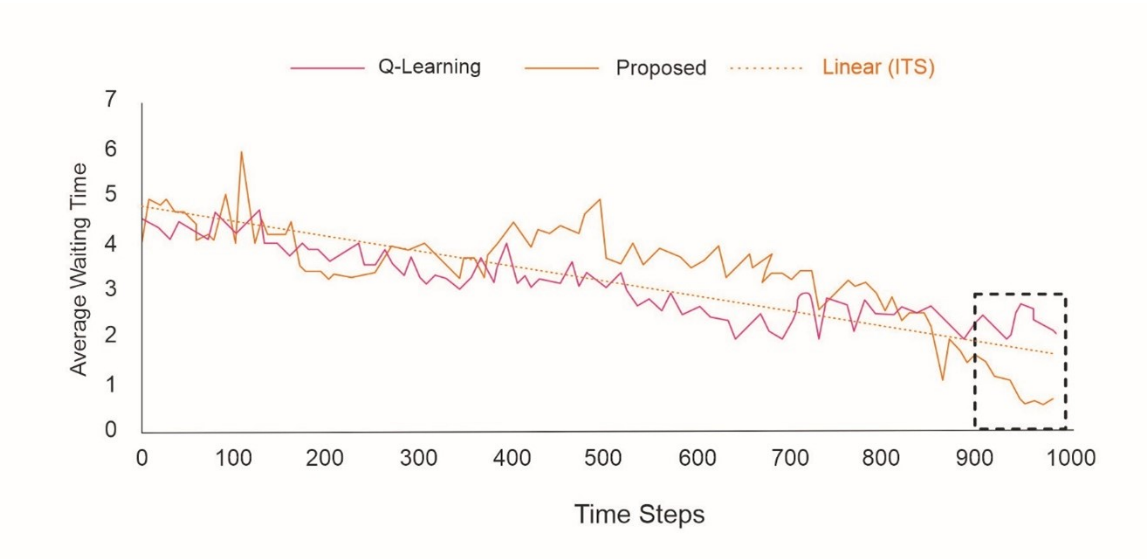


Figure 6 Graph shows average wait time comparison of baseline systems with Q-learning approach.

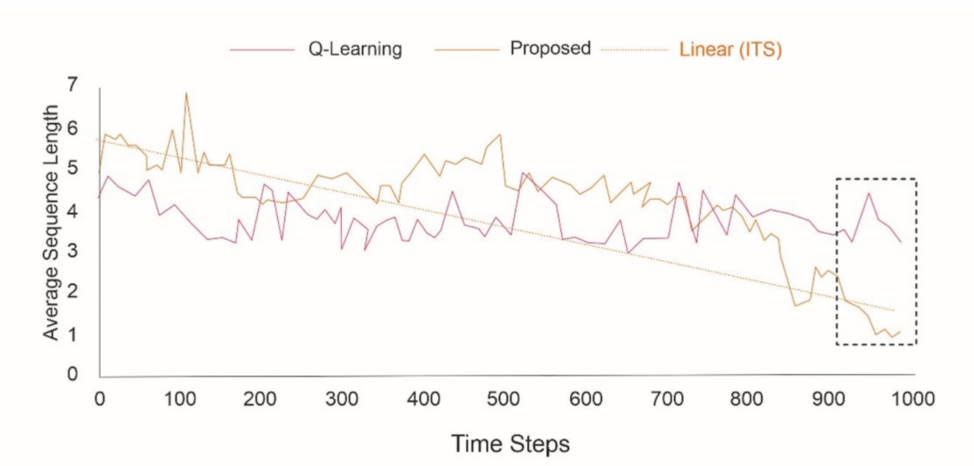


Figure 7 Graph shows the average sequence length comparison of baseline systems with the Q-learning approach.

approximate an overall Q-value. Furthermore, considering the non-trivial parameters influencing the actual traffic, an independent traffic density prediction model is designed. The predicted traffic density for the future assists to gain maximum reward by searching the optimal policy for reinforcement learning. The evaluation results based on multiple parameters show the proposed model outperforms existing approaches. In addition to this, to validate the potency of the collaborative model, a comparative analysis is conducted with collaboration-free models. Hence, the study effectively proposes collaborative traffic signal automation to reduce traffic blockage at junctions. The work can be extended to cover the area of an entire city for application. The use of Radio Frequencies Identification (RFID) devices in sectors of industrial technologies for example the sector of health, agriculture sector, transportation sector, and many other disciplines of life have increased dramatically in current time. In addition, the Internet of Things is exploding at the same time. As a result, an attempt was made to tackle the system of attendance and its monitoring issues using these technologies. The environmental features like the rush hours that affect the traffic flow can be considered in the future studies. The average speed of the vehicle between two junctions will ultimately be affected due to rush hours which needs to be addressed in future studies. Lastly, the up-gradation of Q-Table by considering these features and the lightweight traffic analyzing models are essential in future studies to deploy in the real-world environment.

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