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Reinforcement Learning for Dynamic Traffic Signal Control Using Advanced Machine Learning Techniques

GANAPATHI SAI ABHISHEK GRANDHE[1], DR. GNANA PRAKASAM THANGVEL[2]
[1]*Student, Alliance School of Advanced Computing, Alliance University, Bangalore, India.*
[2]*Professor, Alliance School of Advanced Computing, Alliance University, Bangalore, India.*

Abstract- Traffic jam in cities has become one of the major issues of modern cities due to high rates of urbanization, rise in the number of vehicles and poor development of road network. Conventional traffic light systems are normally based on fixed time or rule-based control measures that are not able to be responsive to changing and unanticipated traffic conditions. These systems therefore have a tendency of increasing the waiting time of vehicles, the length of queues, and inefficient use of the road capacity. RL is now a promising technology that can be utilized to develop the intelligent and adaptive Vehicle Actuated Control (VAC) systems that will be able to learn the best control policies by continually interacting with the traffic environment. In this work a RL based dynamic TSC framework has been Suggested with the Vehicle Actuated Control (VAC)ler being an intelligent agent, which monitors the real time traffic such as the length of queues, the arrivals made by various vehicles and the current signal phase. The agent, with assistance of these observations, selects the appropriate signal actions to maximize traffic flow and to reduce congestion. PPO and DQN are DRL algorithms, which are used to learn effective signal control strategies through training in a simulation. The effectiveness of the Suggested system is probed and contrasted to the conventional fixed-time traffic lights control systems. The RL-based controller is indeed capable of causing a dramatic decrease in the average length of queues, decreased waiting time of vehicles and rised traffic throughput, as the results of the experiment under consideration demonstrate. The suggested solution may be seen as a scale-up and adaptive solution to smart transportation networks and contributes to the creation of effective traffic control in smart cities.

Keywords: Intelligent Transportation Systems, Multi Agents Systems, Traffic Optimization, Machine Learning, Smart Cities.

I. INTRODUCTION

The fast urbanization, the rise of the number of vehicles, and the lack of the corresponding growth of the road infrastructure have added to the congestion of traffic in the cities, turning it into a prominent issue in the contemporary cities. Traffic crossing places where multiple flow of traffic intersect may be very congested and slow. The traditional Vehicle Actuated Control (VAC) systems are likely to adopt the fixed-time and rule-based control methods, which are operated according to the timetable schedules. The techniques are simple to apply and possess numerous applications, yet they are unable to suit the real-time changes in traffic appropriately. The traffic situation is not always constant, and the use of fixed-time controlling mechanisms may cause unnecessary waiting time, rise the length of a queue, rise the amount of fuel consumed, and the impact on the environment. These limitations indicate the need to have intelligent and adaptive control systems of traffic lights that can respond to traffic dynamics. Recent advancements in the sphere of AI and machine learning have provided the new ways of smart transportation systems. RL has emerged as a promising technique in adaptive Vehicle Actuated Control (VAC) where the Vehicle Actuated Control (VAC) is modelled as an agent that adapts itself to the optimal decision-making patterns through interaction with the traffic environment. Monitoring the traffic conditions expressed as the length of vehicle lines, the frequency of arrivals, and the stages of the signal, the RL agent has the possibility to select the correct actions to optimize the efficiency of the traffic flow. This is also facilitated by DRL that uses neural networks to control difficult traffic situations and large state spaces. This paper proposes a dynamic Vehicle Actuated Control (VAC) system, which is an RL, and it is applicable in order to maximize the signal timing decisions and decrease the congestion. This system will undergo simulation experiment on the system and will be contrasted to the traditional fixed-time control methods to demonstrate the effectiveness of the system in streamlining traffic and in helping the intelligent transportation system in smart cities.

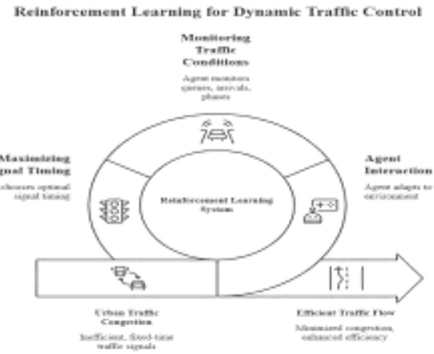

Fig. 1. RL framework for dynamic Vehicle Actuated Control (VAC).

II. LITERATURE REVIEW

2.1 Conventional Vehicle Actuated Control (VAC) Techniques.

The management of traffic lights has always been done through the application of fixed-time and actuated control approaches. The fixed-time control systems are carried out in accordance with the signal timing plans, which are preset as the results of previous traffic statistics. Although the methods are easy to apply and commonly applied, they do not have the adaptability to changes in traffic conditions. Actuated control systems are an improvement of this system in that they use sensors to sense the presence of a vehicle and modify the timing of signals accordingly; but nevertheless, these systems lack the real time flexibility and still operate by preestablished rules. Research has revealed that traditional methods of traffic signals control do not work very well in managing the complicated and unpredictable traffic conditions in the urban setting thus resulting in the worsening delays in vehicles and congestion [11]. The rised demand in traffic has necessitated the need of more intelligent and adaptable traffic control solutions that would enhance the performance at the intersection.

2.2 Adaptive Vehicle Actuated Control (VAC) Using RL

The concept of RL has undergone vast studies as a self-correcting method to optimize traffic lights. The representation of a Vehicle Actuated Control (VAC)ler in RL-based mechanism is the agent that exists in the traffic environment, perceives the traffic states, and selects the action that can maximize a cumulative reward function. Prashanth and Bhatnagar also demonstrated how RL can be applied together with the function approximation in order to regulate traffic lights and that RL-based controllers can be adapted to stochastic traffic situations and enhance the performance of the intersection [9]. In the same vein, Dai et al. contrasted the RL and adaptive dynamic programming approaches and concluded that RL is more flexible in a scenario concerning traffic control in the city [11]. These papers were the foundation to the application of the RL concept to the data-driven intelligent management of traffic.

2.3 Deep Learning Reinforcement Methods

As the deep learning technologies have been advanced, DRL has been offered as a solution to the shortcoming of the traditional RL methods. DRL is a hybrid of deep neural networks and the RL algorithms to solve the traffic conditions in high dimension and in difficult traffic conditions. Li et al. designed a DRL framework that trained traffic signal timing that enhanced traffic efficiency by a considerable margin as contrasted to conventional designs [5]. Rasheed et al. has done an extensive search of the technologies of DRL that can be implemented to Vehicle Actuated Control (VAC) and identified their future in decreasing the level of congestion and increasing the rate of movement of traffic [1]. Furthermore, Shabestary and Abdulhai contrasted on the basis of deep learning-based Vehicle Actuated Control (VAC) the approaches of discrete RL and found out that the approaches of the discrete RL also showed high performance under the difficult traffic settings [6].

2.4 Multi-Agent RL on Large-Scope Traffic Networks.

The single-agent reinforcement techniques of learning turn out to be inadequate as the networks of the traffic in different intersections grow with the help of coordination. MARL is suggested to solve this problem where different traffic lights are viewed as autonomous learning agents which interact to optimise the throughput in a network. The coordination between intersections was demonstrated in one of the first multi-agent reinforcements learning models of Vehicle Actuated Control (VAC) suggested by Prabuchandran et al. [3]. Chu et al. developed another system that can effectively control large scale Vehicle Actuated Control (VAC) systems and is referred to as multi-agent DRL system [8]. The other model of multi-agent RL in large urban traffic network Suggested by Wang et al. demonstrated great relationship in minimizing congestion and maximizing traffic throughput [13].

2.5 Intelligent Vehicle Actuated Control (VAC) New Recent Developments.

In the current research activities, the significance of Vehicle Actuated Control (VAC) systems enhancement has received more consideration in the context of RL by applying new and better learning strategies and utilizing communication technologies. Ma et al. developed a DRL model, which includes mortal traffic pattern mining to improve signal timing decision-making based on past traffic patterns [2]. In the experiment, Zhang et al. explored the RL of partial vehicle detection, which demonstrated that even under the conditions when the whole traffic details are not accessible, the controllers based on the RL could be effective [12]. Liu et al. presented a collaborative RL framework, which is distributed between Vehicles-to-Everything (V2X) communication to have a coordinated control of traffic among interconnected transportation networks [10]. Li et al. presented a more recent paper with a regional multi-agent co-RL framework of city Vehicle Actuated Control (VAC), which demonstrates that large traffic grids can be scaled and achieved with high efficiency [16]. According to these reports, it is revealed how much more important is the RL techniques in the development of the intelligent and adaptive Vehicle Actuated Control (VAC) systems in the future intelligent cities.

Table 1. Comparison of Existing Vehicle Actuated Control (VAC) Methods

Method	Approach	Advantages	Limitations
Fixed-Time Control	Predefined signal timing based on historical data	Simple implementation	Cannot adjust to real-time traffic conditions
Actuated Signal Control	Uses sensors to detect vehicle presence	Better than fixed-time control	Limited adaptability
RL	Agent learns optimal policy through interaction	Adaptive to dynamic traffic	Requires training data
DRL	Uses neural networks for decision-making	Handles difficult traffic patterns	Computationally intensive
Multi-Agent RL	Multiple agents coordinate across intersections	Scalable for large networks	Communication overhead

III. Research Gap

Despite the significant progress in introducing the application of RL in Vehicle Actuated Control (VAC), there are still areas that are to be considered. Majority of the available researches in most cases are simulated experiments in simplified traffic conditions, which are not necessarily relevant to a real-life scenario of traffic conditions. Indicatively, many of the reinforcements learning model models assume of perfect sensing, and perfect vehicle detection by sensors and cameras, but in reality, the traffic systems tend to possess incomplete or distorted sensors and cameras [12]. Further, the initial RL techniques were mainly designed to solve problems at a single intersection and cannot be extended in the scenario when the large urban traffic network comprising of several interconnected intersections is used [3], [9]. The other shortcoming that has been identified with the past research is the impossibility to coordinate effectively the traffic lights of a large set of traffic lights. Despite the fact that multi agent RL has been Suggested to address this issue, some of them are still vulnerable to communication overhead, scalability, and stability in the course of training [8], [13]. Furthermore, the design of an appropriate reward function is challenging as traffic optimization is a difficult of functions where minimal waiting time, lessening the length of the queues, fairness in the traffic directions, and safety restriction are required [1], [6]. In recent research, there have been attempts at combining the temporal traffic patterns and the cooperation learning to improve the performance though more improvements still have to be made to generate robust and scalable traffic control system [2], [16]. Therefore, the dynamic traffic environment necessitates adaptive RL based Vehicle Actuated Control (VAC) system that is able to effectively regulate dynamic traffic conditions, coordinate different intersections, and improve the traffic efficiency in the large-scale intelligent transportation systems.

IV. METHODOLOGY

3.1 System Overview

The Suggested study design is expected to develop the adaptive Vehicle Actuated Control (VAC) system by using RL methods. The Vehicle Actuated Control (VAC) is an intelligent agent in the model, which will interact with the traffic environment and acquire the most optimal signal control strategies. The agent continuously observes the state of traffic and intervenes with it such as modifying or keeping signal phases and is rewarded upon the resultant traffic condition. The agent later learns about minimizing the congestion and increasing the efficiency of the traffic flow. The whole system consists of four major components, which are the traffic simulation environment, the RL agent, the signal control mechanism and the performance evaluation module. The simulation of traffic environment is elaborated in 3.2. It is simulated in a traffic simulator environment which re-creates the realistic traffic conditions in a crossroad without disrupting the real traffic systems. The model is a simulation which is used to denote arrival of vehicles, formation of queues and stages of the traffic light at a roundabout. The car traffic flows through the lanes randomly and with probabilistic distribution and the environment moves the vehicles at each time period. This kind of generated environment is used to train a RL agent and could be allowed to experiment with different signal control strategy and learn to react to the resulting traffic conditions.

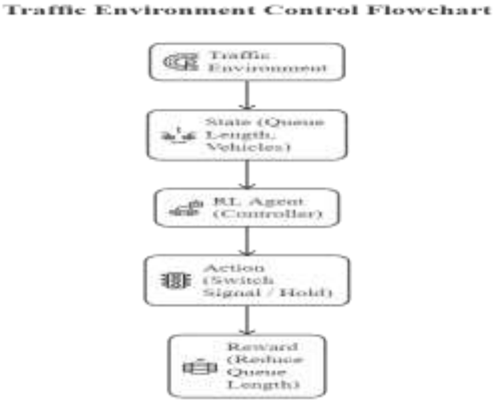

Fig.2. System Architecture

3.2 Simulation of Traffic Environment.

It is simulated in a traffic simulator environment that recreates the realistic traffic conditions in a crossroad without interfering with the actual traffic systems. The simulation is a model that represents the arrival of vehicles, the formation of queues and the phases of the traffic light at a roundabout. Car traffic proceeds through the lanes in a random manner with a probabilistic distribution and the environment changes vehicle positions at every time period. Such a simulated environment serves as a training ground of a RL agent and it is able to experiment with various signal control strategy and learns to respond to the resulting traffic conditions.

3.3 State Space Representation

State space contains the knowledge that is accessible to the RL agent on a time step basis. The parameters of the state that are Suggested under the system are the length of the vehicle waiting line in each direction, the position of the traffic signal, and the duration of the active period. These variables give a full picture of the traffic on the intersection. Through the analysis of these state variables, the RL agent would be able to find out the degree of congestion and be able to decide whether to switch or hold back the existing signal phase.

Table 2. RL COMPONENTS IN VEHICLE ACTUATED CONTROL (VAC)

Component	Description	Example in Suggested System
Agent	Decision-making entity that learns optimal policy	Vehicle Actuated Control (VAC)

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Component	Description	Example in Suggested System
Environment	System with which the agent interacts	Traffic intersection
State	Current representation of environment	Queue length, signal phase, arrival rate
Action	Decision taken by the agent	Switch signal / maintain signal
Reward	Feedback received after action	Negative value of queue length
Policy	The policy used by the agent to select actions	Learned using PPO or DQN
Episode	One complete simulation cycle	200-time steps of traffic simulation

3.4 Action Space Definition

Action space characterizes the available number of decision choices that the agent of RL can make. Two choices are taken in this research; to retain the existing signal phase or to alternate the signal and take the alternate direction. Such measures will enable the agent to change the timing of traffic lights in response to current traffic conditions. The policy that the agent has learned influences the action selection process since it is seeking to minimize the congestion and enhance vehicle movement across the intersection.

3.5 Reward Function Design

The rewarding mechanism is aimed at steering the RL agent to an efficient behaviour of traffic control. The magnitude of the reward in the suggested solution is computed using the summation of the queue length of the vehicles at the crossroad. The presence of a negative reward that is given when the queue length is growing helps to motivate the agent to minimize congestion. Through maximization of the rewarding function, the RL agent is taught to provide signal control action that will reduce waiting time and enhance traffic throughput.

3.6 Reinfirmation Learning Algorithm.

DRL algorithms are taught to the Vehicle Actuated Control (VAC) agent. DQN and PPO are the algorithms employed to investigate the issue of the best signal control policies. These algorithms make use of the neural networks to determine the value of actions under different traffic conditions. Training exposes the agent to the simulation environment and by terminating the training the agent has optimized its decision-making strategy by maximizing cumulative rewards.

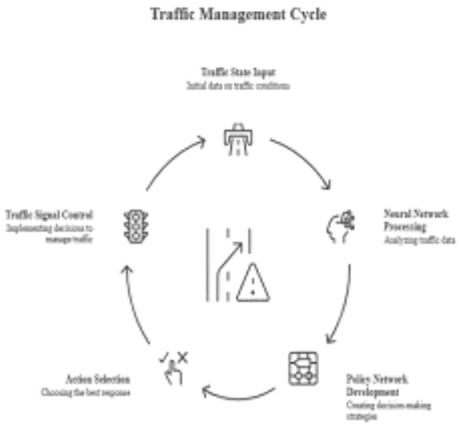

Fig.3.TrafficManagement Cycle

3.7 Performance Evaluation

The feasibility of Suggested system with reinforcements learning-controlled Vehicle Actuated Control (VAC) is contrasted to a fixed-time Vehicle Actuated Control (VAC) system. The key performance measurements include average queue length, cumulative waiting time and intersection throughput. Learning-based controller is also tested under various conditions of traffic to identify its effectiveness. The results indicate that reinforcement-based signal control will significantly improve traffic movement and reduce road congestions contrasted to the traditional method.

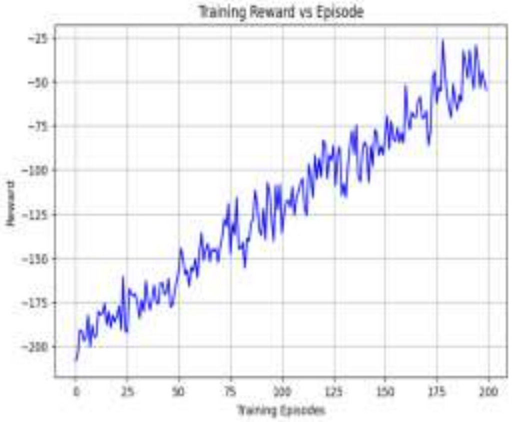

Fig. 4. Training reward versus episode during RL training.

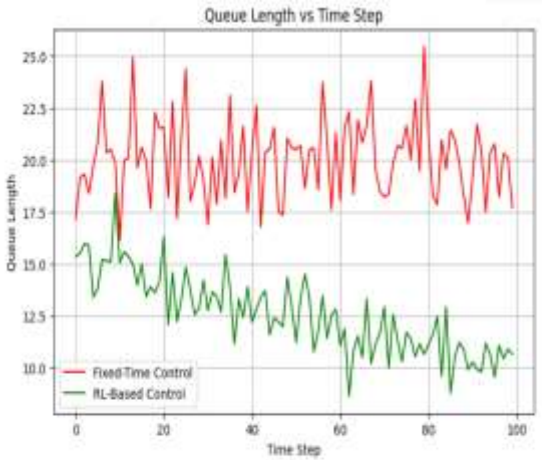

Fig. 5. Queue Length Performance of Intelligent Vehicle Actuated Control (VAC)

V. CONCLUSION

A learning-based dynamic system of providing out the traffic lights that would enhance the effectiveness in the traffic during the urban intersections was presented in this paper as a reinforcement-based dynamic system. The traditional traffic control system is more or less receptive to the dynamic traffic conditions and is likely to be anchored on the fixed time or rule-based control strategies. To eliminate this drawback, the Vehicle Actuated Control (VAC) was developed under the concept of the fact that it could be modelled as an intelligent RL agent that could be trained on the optimal signal timing schedule by training on a simulated traffic environment. It was suggested to adopt a DRL model like DQN and PPO to achieve adaptive policies in traffic control in regard to the available traffic i.e. the queue length and signal phase. This was ascertained through the simulation that the RL based Vehicle Actuated Control (VAC) substantially reduces the length of the queue and waiting time than the associated aspects of the traditional fixed time control. RL allows the system to make changes adaptively according to the dynamism of the traffic change in order to effectively allocate signal time in directions of traffic. PPO was concluded as the strongest algorithm with improved convergence features as far as optimization of traffic signals is involved. The results of the given study indicate the opportunities of the reinforcing learning methods in designing intelligent traffic control systems and enhancing the functioning of the entire system of urban traffic.

VI. FUTURE WORK

Despite the fact that the suggested RL-based Vehicle Actuated Control (VAC) system is still able to achieve good results in simulation, there are several dimensions that may be used in researches in the future to make the Suggested system more effective and appropriate in reality. The suggested future course of action is to expand the suggested model to big scale traffic networks that include a quantity of interconnected crossways through multi-agent RL strategies. This would help in coordinating and managing traffic of various road lights within the city in terms of complete road systems. Another direction of work that is very significant in the future is the introduction of the real-life traffic data captured by sensors, cameras and the associated vehicle technologies in the graphical presentation of the traffic states to make them even more precise. The Vehicle-to-Everything (V2X) communication technologies and the Internet of Things (IoT) technologies can also be added in order to equip the system to respond to the real-time situation on the traffic. It is also possible to research the further work in the future on the algorithms of DRL and hybrid optimization techniques to achieve the better stability of the learning and results of the traffic control. Application of the Suggested system within the existing traffic management structure would eventually lead to the formulation of the intelligent transport systems and smart city traffic management systems.

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