Artificial Intelligence Based Traffic Control System Using Reinforcement Learning

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***Abstract*—Recently significant achievements have been taken place with latest technologies in the field of transportation. Traffic is increasing day by day and huge data is accumulating on the other side. To utilize this data for future prediction and to control increasing traffic problems, we need a system to handle efficiently. This paper uses Artificial Intelligence technology along with machine learning algorithms to manage the traffic based on its previous situations (experiences). Reinforcement learning algorithms is used to take intelligent action at intersection point. The system is implemented in SUMO simulation environment with three performance parameters. The results are show in the form of graph.**

Index TermsClass: Reinforcement learning, Artificial Intelligence, Q-learning, traffic control.

I. Introduction

Revolution of smart and intelligent transport systems communication technologies taking the world to a big challenge. Emerging technologies penetrating to different parts of day-to-day life including transportation problems. There has been a noticeable increase in the number of vehicles utilizing road infrastructure. Everyday growing quantity has put lot of strain on the government or provision of services. Due to this, several problems are being faced by people, such as congestion, air and noise pollution, traffic offence, power deficiency and many more. To solve such issues researcher along with government are working hard to get efficient solution [1].

Artificial Intelligence (AI) is cutting edge technology and wide area which include machine learning and it related algorithms [2][3]. AI is the top technology to manage traffic control system automatically. Figure 1 shows the relation between AI and ML and learning algorithms of ML. Under the big umbrella of Emerging technologies AI is the most popular technique which can learn and mimic like humans. Mean while, ML is subset of AI, has ability to learn without being explicitly programmed to improve a task with experience.

Reinforcement learning (RL) is the one of the learning methods in ML and is combination of an action, environment, reward, and state [1], [4]. AI helps to identify the traffic issues, guides the system especially traffic lights and helps to improve safety too. In traffic management system AI works by collecting raw data from the road environment which is the huge input data for historical traffic behavior. In order to handle this huge unstructured data, system uses ML techniques to process and analyze. This is known as learning about traffic infrastructure. The AI uses these inputs to solve traffic issues.

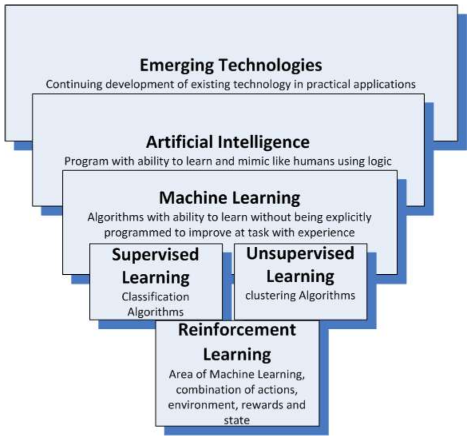

Fig. 1. Relation between Emerging Technologies, AI, ML, and RL

There is a requirement of superhuman performance which able to find solutions not thought before. When no prior knowledge is given and only the present environment is given to the system. System should adaptively learn the scenarios not encountered before. Only AI with ML has the ability to provide the solution for above said issues. RL is agent-based method which takes the best action to control the situation based on the history or experience. The paper is structured as follows. Section one introduces the technical part and the latest technologies used in the work, where as Section two formulates the problem with reinforcement learning and some mathematical equations. Section three describes the theory behind this work and Section four is given with system model. Results are discussed in Section five and the work is concluded in Section six and future work of the research is mentioned in the same section.

II. Problem Formulation

There has been a noticeable increase in the number of vehicles utilizing traffic infrastructure all over the world. This has put a strain on the provision of service, and issues already being faced by urban areas. AI applications and machine learning concepts contribute much more to traffic control

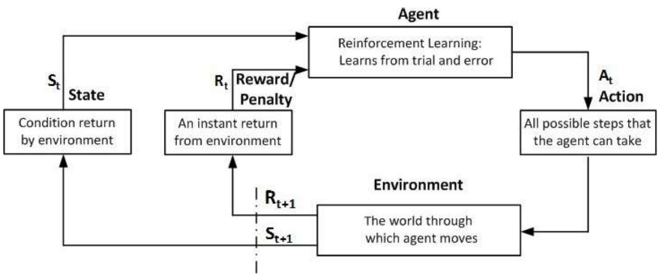

Fig. 2. Reinforcement Learning Model for Traffic Control System

system. AI enables to collect data from various sensors or Internet of Things (IoT) devices. The combined technology analyzes traffic data and generates efficient solutions.

The ongoing research work using cutting edge technologies is still in experimental stage to improve traffic flow and its data analysis. The aim is to find reliable and stable traffic control system. The two categories of traffic control system are used; one is primetime control and actuation control systems. The pretimed control system presets the timings of green lights. During peak hours, they set longer time duration during peak hours. However, the system fails to handle dynamic traffic condition. On the other hand, actuation control system handles dynamic traffic. Yet, fails to serve efficiently during long term scenarios.

During peak hours at certain intersection, traffic inflow is more than outflow. And sometimes downstream is full, no vehicles can cross despite green signal. There may be a situation, no vehicles at intersection and green signal is activated. All the above issues point towards congestion, cross blocking, and green signal idling. The challenges include inappropriate traffic phase, traffic offences, accidents, air pollution and noise pollution. This may spread over nearby intersection points too. The current system optimizes the traffic signal scheduling by extending green lights at right movement. All the system works in cycle. Taking note of all above missioned issues we should have an algorithm which takes care of all this. However, RL handles the situation by shortening, lengthening, or by skipping based on the situation. RL provides online adaptive approach and is dynamic to current long-term traffic [2], [5].

In the Figure 2, environment describes the situation in certain intersection. Here traffic light is the agent and current situation at the intersection is the environment. Agent learns from the previous experience without any pre-program or human interaction. The agents learn themselves with three components take action, remain in the same state or change the state and get feedback, and same time agents explore the environment. Along with this, they store in memory that what actions perform reward and what actions perform penalty. Each time agent will make a decision on whether to change action $A_{t=1}$ or continue with the same action $A_{t=0}$. When the action A_t is executed at environment, current state is now new state that is A_{t+1}. The agents are rewarded by the environment R_t. The equation for the same is defined as:

$R(S_t, A_t)$

Reward R at state St with action A_t. Then we can formulate simple problem as we need to minimize the queue length, average queuing time and queue time with very less speed at given state set S_t, action set A_t and reward function $R(S_t, A_t)$. The agent needs to learn a best action A at state S

$$\text{Best strategy } = \sum_{i=0}^{\infty} \gamma_i R_{t+i+1}$$

Where the reward Rt is defined as,

$$R_t = \sum_{j=1}^{m} q_{t,j}$$

Where $q_{t,j}$ is queue length at j^{th} lane

III. THEORY OF REINFORCEMENT LEARNING

Reinforcement learning is type of machine learning where an agent learns to behave in an environment by performing actions and seeing the results. It learns from itself by two components, agent and environment and get rewards (either negative or positive). RL reduces the whole work of data collection and preprocessing or data cleaning. In this work RL algorithm is used to reduce queue length experimentally, average waiting time and queue length of the vehicle. Here we considered an intersection of four roads and each road having four lanes, two lanes for incoming and two for outgoing

Here we can elaborate the situation with the pseudocode

Step1: The RL agent, traffic light collects the state S_t, from the road environment 1.
Step2: Based on the state S_t, the traffic light takes an action A_t.
Step3: Environment now increments to next state, S_t.
Step4: Traffic light gets a reward R_t from the environment.
Step5: The loop executes till traffic light learns all the policies.

List of parameters with definitions

- Agent: Traffic lights are the agent in our work which learns from each iteration.
- Environment: Environment is the situation at intersection. The place through which agent travels.
- Action: All the possible steps that the traffic light can take to make its best.
- State: Present situation updated by the environment.
- Reward: Return from the environment either negative or positive to appraise the last action.
- Policy: The method or rule that agent uses to determine next action based on present situation or state
- Value: The expected return with discount. Long-term return is value and short-term return is reward.
- Action value: Similar to value by taking an extra parameter, current action.

Primary goal of the RL algorithm is to maximize the reward. In other words, minimize the queue length and average waiting time of the vehicle by minimizing the queue length. So, traffic lights must be trained in such a way that, it takes the best action to minimize the above said performance metrics.

IV. SYSTEM MODEL

The objective of the research is to design a traffic control system which manages the traffic in efficient way. The work should minimize total queue length, average waiting time and queue length with less speed using RL algorithm. Q-learning is model free RL algorithm based on Bellman theory [19]. This is the appropriate algorithm used in AI to manage the heavy traffic. Aim of Q-learning is to learn a policy, or it can be defined as value-based learning algorithm. This instructs the agent to take best action to maximize the reward in given environment. In other words, we can redefine it as maximize the Q-values based on the action and state in given environment [9, 10].

This paper uses Q-learning and the symbols used are given in table 1.

TABLE I. SYMBOLS USED IN THE WORK

Symbol	Description
A	Set of actions
S	The Set of States
R	The Reward
π	Policy
v	Value

The values of Q-learning are represented by $Q(S, A)$. and computed by the formula,

$$Q(S, A) = R(S, A) + \gamma * max\ [Q\ (nextstate, allactions)] \quad (1)$$

Where γ is the discount factor, the value of γ is between

$$(0 <= \gamma > 1)$$

If value of γ is closer to 0, the agent will get short-term reward. If value of γ is closer to 1, the agent will get long-term reward. All the computed Q values and R values stored in the form of tables or in the form of matrix. Commonly known as Q-matrix. Row values represent state and column values represent agent. So, it is action state pair S, A

Q Represents the quality in Q-learning, quality of action A at State S.

The algorithm is given as follows,

Algorithm 1 Reinforcement Learning Algorithm

Input: Set $\gamma = 0.8$
Q [ ] =0, R [ ] = 0
Method: Initial state $=S_t$
S_t = current state
Action for current state = S_t
If A_t is completed?
$S_t = S_t+1$
Q_m=max[Q(next state,all actions)]
Update R matrix
Q(S,A)= R(S,A) +Y *Q_m
Repeat until S_t=Goal State
Output: Updated Q table Updated R table

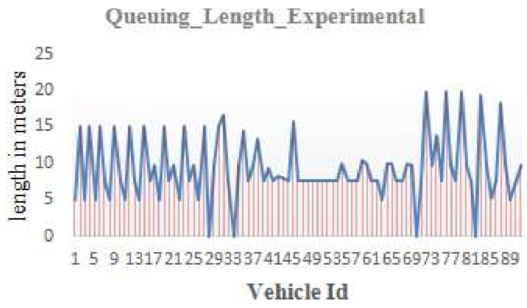

Fig. 3. Queue Length Including Speed less than 5 km/h

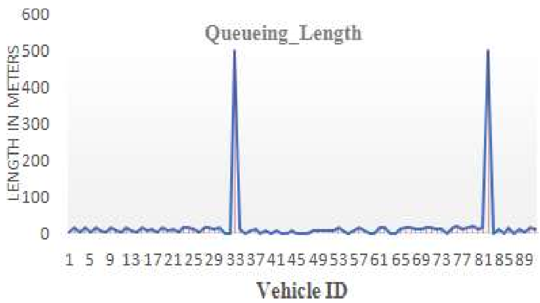

Fig. 4. Queue Length in Meters

V. RESULTS AND DISCUSSION

This section elaborates on simulation environment and results from the obtained simulation. The work is performed with Simulation of Urban Mobility (SUMO), a microscopic traffic simulator. It is an open source package used to build a road traffic network by assigning routes with an environment [6], [7], [3], [8]. SUMO provides manual creation of network with edge, route, node, and network files. It also allows to import road network from external source. It provides the GUI to check the performance of the agent handling in heavy traffic intelligently [9], [10], [11].

Figure 3 explains the queue length of the vehicles which are standing in the queue. This is measured in meters. Here the vehicles with less than 5 km/h are also included because those are also considered as standing vehicles, or which contribute for queuing.

Figure 4 describes the queue length of the vehicles, measured in meters. Length of the first vehicle from the intersection till the last vehicle standing in the queue. Here only zero speed vehicles are considered.

Figure 5 explains the queuing time of the vehicles. The time is measured in seconds. This is given by total time of the vehicle standing in the queue due to heavy traffic.

VI. CONCLUSION AND FUTURE WORK

This paper proposed AI based reinforcement learning for traffic control system. Firstly, we analyzed the existing difficulties which directly impact on road traffic performance. Then we give some analysis about reinforcement learning and Q-learning. The work is implemented using SUMO with three performance metrics and the results are produced in the form

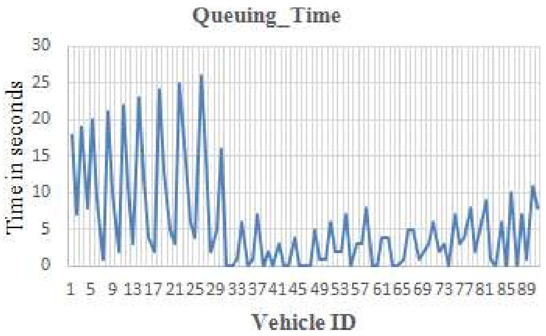

Fig. 5. Waiting Time at the Intersection

of graph. Although, the proposed work can be improved by comparing the results with already proposed models. We propose future plans for the same work.

- Though the simulation works well with the traffic environment produced by SUMO, we can consider real world road scenarios and real traffic.
- The same method can be connected to transportation theory from Operational Research to prove the concept more mathematically.
- The results are available with three major metrics but those can be compared with other models to show the efficiency.

Since applying AI techniques in Road traffic is still ongoing research work, we can also implement the above said shortcomings in our future paper.

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