Real Time Intelligent Traffic Signalling System

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1 Introduction

Introduction Increased urbanization has led to growing congestion in the urban transportation system. Because of the rigidity of the systems employed for traffic monitoring, we must reconstruct the available methods to provide better efficiencies. This is especially true in the case of developed cities. This project aims to develop a traffic light signaling system based on real-time data collected from traffic cameras. The target of the generated machine learning algorithm will be to increase the intersection capacity, decrease the delays that the car drivers face, guarantee the safety of people while crossing the road, ensure the safety of the vehicles during the crossover, and reduce the crossing time for people.

Generally, two standard methods are used contemporarily for traffic control. [1]

1. conventional traffic lights with static timers are the most used technique for traffic lights. A constant numerical value is loaded in the timer end the lights automatically switch accordingly. These predetermine times could be based on historical figures or could be constant but they are never real-time.
2. Real-time traffic control- data is collected which determines the density of the traffic in the area. The traffic system acts accordingly. This data can be managed in multiple ways- using proximity sensors, cameras, loop detectors, etc. in this project; we will assume that cameras are detecting the traffic density in real-time and will simulate this very assumption.

This paper will use reinforcement learning in artificially created environments to optimize the traffic flow. The domain will be carefully created while considering the characteristics of normal traffic flow while also modeling the unusual behaviors. Occasionally we also have to introduce challenging scenarios for the machine learning algorithm.

We will implement reinforcement learning using different machine learning algorithms and compare their performances with the current version of the static-time method of traffic light signaling.

2 Background Review

There have been multiple attempts to solve the proposed problem.

Prasoon et al.[10] proposes a simulation-based framework that facilitates smart traffic light adoption under budget constraints. This paper defines a model city and its various variables, which would be used to make an artificial road environment in our project. They prioritize the location on which intelligent traffic lights system should be placed based on constraints and the potential to improve traffic speeds. Their solution is reached using graph theory and Optimization.

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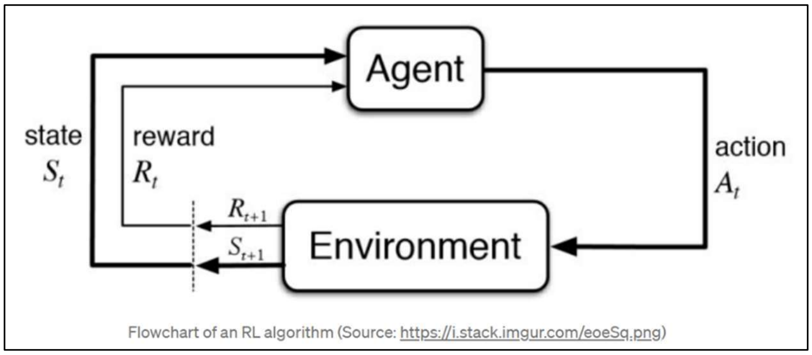


Fig(1). Logic Flow of Reinforcement Learning.

El Hassan Imad et al.[9] talk about the three elements to optimize - time cycle, green light time, and phase. They listed the current technology used in traffic light systems. They proposed a new system that combines the SOTL(self-organization traffic light) phase and SOTL request suitable for high traffic and low traffic situations, respectively. The authors have taken advantage of the synergies of both of these approaches and have come up with a new method. They have used NetLogo software for modeling the road network. The signaling depends upon the real-time traffic density to turn the traffic signals green or red.

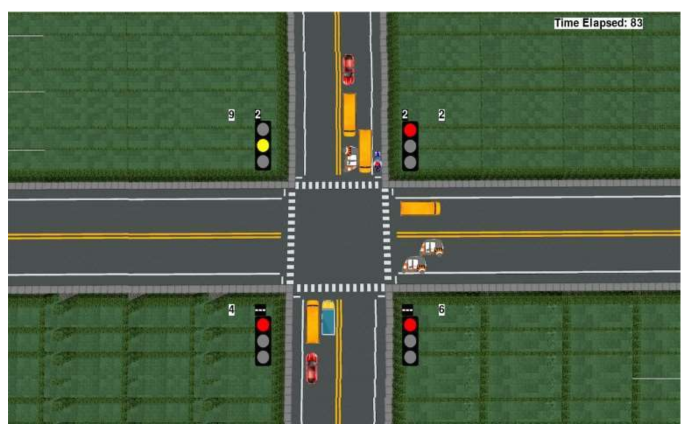
Mihir et al.[1] proposes an intelligent control system using CCTV cameras. The paper discusses object identification accuracy obtained using CCTV camera images. They have used a CNN to generate an accuracy of about 90% in image classification to get vehicle density in real-time. The paper has also used the pygame software module to visualize the traffic system. The traffic light system does not use any form of artificial intelligence to run. They have proposed a new plan that takes vehicle density as input and decides the green light Start time and duration.

Mohamad Belal Natafgi et al.[3] proposes a traffic control system based on reinforcement learning where they have taken shorter queue lengths as a reward. They've also presented a limitation in extreme cases where the proposed model stops one car for a disproportionately long time. They have solved it by taking the rewards for different lanes and averaging them. However, they have not accounted for people crossing roads at these traffic junctions. In this paper, we'll focus on adding them too. After training the reinforcement learning model, they compared their model's performance with the static traffic management system. And have shown improvements of 62.82% in Q lengths and 56.37% in delay time.

Apart from this, Monireh Abdoos et al.[2] and Deepeka Garg et al.[8] have also used Reinforcement learning to get better efficiencies. Sydney Coordinated Adaptive Traffic System is another technology in use that relies upon sensors to get data regarding the queues of cars and then responds in real-time [5]. Intelligent Traffic Light Scheduling(ITLS) algorithm has been proposed in [6]. This work introduces an ITLS algorithm based on a Genetic Algorithm (GA) merging with Machine Learning (ML) algorithms. Other similar proposed solutions are fuzzy logic, neural network, and Q-learning [7].

3 Design of Experiment

In this paper, we will use reinforcement learning to model a traffic light in city settings; we will use the stochastic methods to model the movement of vehicles on the streets and let them interact with the traffic lights. Initially, traffic lights will be running the static algorithm, which will use the time intervals to show green and red signals. With time as the traffic light learns, it will itself change its timings. This system can also be used on real data as soon as it is available. But for the purpose of practicality, we will use the stochastic movement of vehicles. We will then report the result of reinforcement learning and static performer, report the improvements in combating traffic congestion. A learning curve will be presented about how much time it takes for reinforcement learning to reach



Fig(2). The Environment

Simulation Run	Total Vehicle Passed	Vehicle Weight Time (s)	Average Weight time per vehicle
T = 100s, Static Model	41	22892	558.34
T = 100s, Formula-Based Model	65	17111	263.24
T = 1000s Static Model	902	855109	948.0
T = 1000s Formula-Based Model	933	593867	636.51
T=1000s, RL	948	682595	720.03

Table(1). Results of Experiment

optimal performance. A discussion of how fast the learned model can change to accommodate the unexpected traffic changes shall be presented. This will be done by suddenly changing the stochastic variables that determine the route and the number of vehicles and pedestrians.

The variables that will decide the movement of vehicles will be –

1. Density of vehicles
2. Direction of movement of vehicles.
3. Speed of movement of Vehicles.

The environment will look like as described below-

1. One Traffic Light in a square.
2. Different vehicle types with different speeds
3. Cars will be generated at the boundary and reach another boundary before they diminish.
4. Vehicles will be generated at four boundaries and they can take turns; whether the vehicle will turn or not shall be decided at its inception.

The variables that the reinforcement learning model will optimize –

1. Green Signal Timing for the next signal.

The improvement in traffic congestion resulting from reinforcement learning will be interesting to watch.

3 Results

To test the performance of different algorithms, we will require a strong matric; the author of [1] have used the number of the vehicle passed per unit time as the matric. I'm afraid I have to disagree that It will lead to the right inference because if the vehicle is generated, then it will eventually diminish, but what matters is the wait time. So, A new matrix has been extracted for success. We will use this matrix for reinforcement learning as well as check the accuracy of our model.
The simulation environment has been taken from [1]. I have made several changes to it.
I ran the simulation for different times t =1000s, and t = 100s and recorded the accuracy of the three algorithms – (i). Static, (ii). Formula-Based (iii). Reinforcement Learning. The formula was derived by considering the following variables – (i). No. of Vehicles waiting. (ii) Velocity of all the different Vehicles (iii). Their intended destination after the signal is crossed (meaning turn). Based on these parameters, a greenTime is found for the next signal which is going to turn green. There are upper bounds and lower bounds to this value. In our case, we kept the lower bound at 10s and the upper bound at 60s.
For the static model, we kept the value of greenTime as 30s, non-changing, and ran the simulation.
For reinforcement learning, I use the same parameters as the

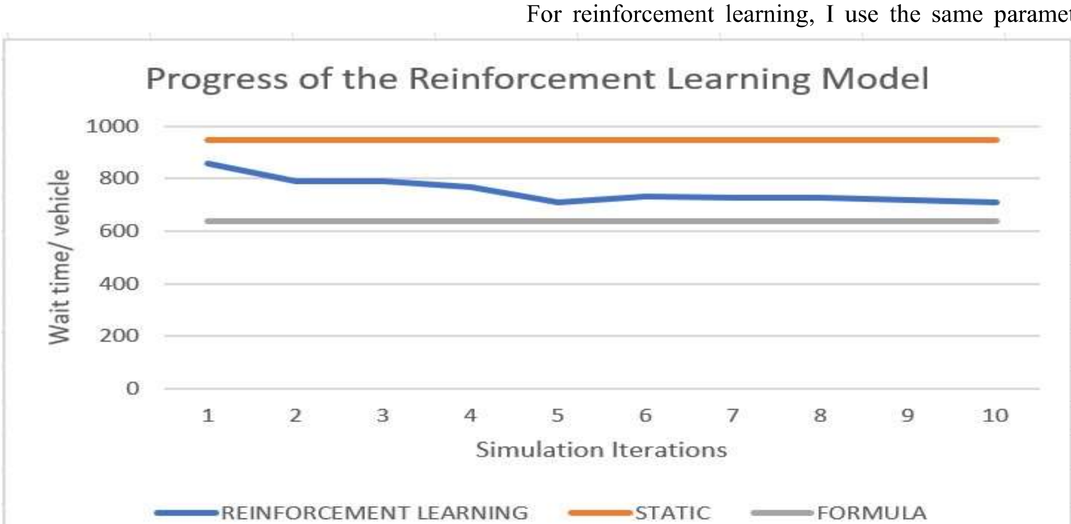


Fig (3). Gradual Increment in the performance of the Reinforcement learning model.

formula-based model but will try to converge to the best formula. An image of the environment is as shown in the Fig(2).

The vehicle generation method is same as in [1], however, I have tweaked the model to change its initial probabilities of vehicle generation from different boundaries at an interval of 100s. This is done to make sure that the models are tested on a wide variety of challenges and scenarios. On top of this randomization, I have also randomized the time that it takes for next vehicle to be generated, this brings the real scenario quiet close to the road scenario.

The results are as shown in Table(1).

An appropriate vehicle generation rate was determined at which the we can run the simulation. Then the reinforcement learning model was run on it. With every run, the best performance was chosen. As discussed above, the reward for the reinforcement learning model was the wait time per vehicle and the objective was to minimize it (maximize reward = 1/wait_time_per_vehicle). The following graph was observed during the training (Fig (2)).

4 Discussion

1. The first thing that is to be observed is that the simulation is not the real environment, and therefore whatever we simulate cannot be implemented directly in the real world. So if we want to apply reinforcement learning in a traffic light signaling system, then we will have to take the data real-time from the road. This was the plan from the beginning. The problem with this kind of approach is that if the system makes an incorrect decision, the life of vehicle drivers passengers, and the pedestrians is in danger. this fragility of the system will it be one major challenge that have to be overcome.
2. this simulation had many assumptions, for example, the time taken by a vehicle to cross the intersection is constant however in real life we know that it is not constant. only five kinds of vehicle as there whereas in real life there can be more. all the vehicles are driven at a constant speed we might want from the vehicles to be having randomized speeds. that will allow us to have a reinforcement learning model that will be able to perform well in the real world situation.
3. On top of it the reinforcement learning model does not perform as well as the formula-based model, the reason for this is that because the simulation is so simplistic with constant velocities and constant time to cross the intersection, that you can actually assign a formula that will be perfect for the simulation however in real life the situation varies a lot and there could be numerous situation too which could be complex also. In those circumstances collecting data continuously and applying reinforcement learning seems like the best method to come up with. therefore while in our experiments reinforcement learning model does not perform as well, it still has application in the real world, where the data is enormous.
4. It is also to be observed that the enforcement learning model very quickly achieved better accuracy then the static model. this is an assurance that if we implement reinforcement learning model anywhere where there is static learning model in application then we are expected to get a better performance as soon as we implement it.
5. Another challenge that can be observed is that we still need to have the cameras and the image recognition technology needed to map the exact number of cars that are waiting on the intersection signal to turn green. Until we have that with good accuracy, we will not be able to accurately model the reinforcement learning. This goes the same even for the formula-based model. research has been done in this regard and good outputs have been produced which could be implemented in conjunction with the current work.
6. I wanted to talk about the implementation of robust AI. since we can see that this system if used incorrectly could pose a serious threat to the life of pedestrians as well as the drivers, it is worthwhile to discuss the robustness of AI. It has been a recent development in the field of AI which mixes human expertise with machine intelligence to come up with better results and safer operations. I believe that for such a system, a robust AI would be applicable

5 Conclusion

In this paper, we presented the advantages that the reinforcement learning models have always static models and formula-based models in traffic light monitoring systems. we discussed the limitations of the current simulation and how it cannot be an actual representation or even near representation of that real scenario and therefore it could be dangerous to apply it to the actual world. on the simulated world, the accuracy of the reinforcement learning model was not as good as the performance of the formula-based model however it still has applications because in the real world the data is highly varied. and accuracy that was closer to the formula-based model than the static model but between them both were observed.

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