# Adaptive Traffic Light System of Four-Phase Intersection using Reinforcement Learning

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***Abstract*—This paper proposes an adaptive traffic light system for four-phase intersection using reinforcement learning. The existing adaptive traffic light system using two-phase order so far. While the four-phase order in the intersection can avoid vehicle conflict and decrease the vehicle waiting time. Therefore, the reinforcement learning algorithm is used to optimize the reward of reducing waiting time in the intersection through real-time traffic information and traffic light control formulation. The simulation results show the validation of reward can decrease the waiting time of the training system of deep neural networks (DNN).**

***Index Terms*—Adaptive traffic light system, reinforcement learning, urban area.**

## I. Introduction

Advanced traffic management system (ATMS) is a primary sub-field with an intelligent transportation system (ITS), which support to improve the smart city. The recent road infrastructure corporates with information and communication technology to stream the real-time transport data in transportation management center (TMC). By using the real-time data, ATMS takes obligation in the monitoring, controlling, and optimizing the traffic. Particularly, the traffic light system in the intersection [1]. Which in, the intersection is gathering area of vehicle that connect the three or more roads. Thus, optimization of signal timing is a focus in this paper.

Nowadays, the adaptive traffic control system is popular to be implemented in the urban area that everyday increases the number of vehicles. Adaptive traffic control system can increase transport efficiency and reduce traffic congestion. However, the system two phase order has drawbacks that can lead the collision of two or more vehicles in the intersection and not safety [2] [3]. Afterward, the four-phase order of traffic signal control is efficient to be implemented in the urban area. Safety and contribute to the pedestrian area should be considered while using the reinforcement learning algorithm [4].

This paper proposes an adaptive traffic light system using reinforcement learning for preserving the vehicle. First, the reinforcement learning model with four-phase order is designed. Then, optimize the policy in turning green light through deep neural network (DNN) structure and training. In the optimization, a formula to choose the optimal action is given. Therefore, the traffic signal control can decrease the waiting time in the intersection.

The remainder of this paper is organized as follows. System overview in Section II; and simulation result in Section III. Sections IV presents the conclusion and future work.

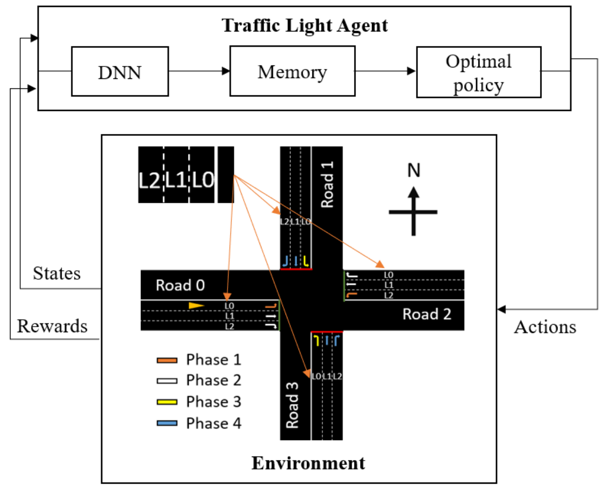


Fig. 1. Road model of urban traffic in the intersection

## II. Proposed System

The intersection model is illustrated in Fig. 1 with four road segments and each road segment has three directions ($L_1$, $L_2$, and $L_3$). The traffic light manages the vehicles to pass the intersection through green, yellow, and red signals. Then, the four-phase of vehicle direction is used to avoid the vehicles conflict. The phases order are showed in four different color. If phase 1 is allowed to pass its vehicles, the other pass is not allowed it. The vehicle is assumed in the stable speed and the pedestrian is allowed in the phase 2 and 4. The pedestrian has higher priority than vehicle that will turn left or right.

In the traffic light system, an agent interacts with the intersection at discrete time steps $t = 0, 1, 2, ...$ to elevate the traffic congestion. Start from agent investigates the intersection state $S_t$ by vehicle occupancy and signal status of each phase at the beginning of step $t$. The state $S_t$ denotes the characteristics of each lane that signed by red and green signals to sequence the phases. Then, the agent selects and actuates traffic signal $A_t$ (i.e., the sequence of traffic signals in each phase). While, the reward $R_t$ consists of adding time or cutting the time for the next action that will be given at the end of time step $t$. In the time sequence as showed in Fig. 2, the agent that interact with the intersection is showed as $..., S_t, A_t, S_{t+1}, A_{t+1}, ..., S_{t+n}, A_{t+n}$. For reducing vehicle staying time, the taken action is according to the policy $\pi$ that further optimized $\pi^*$ by Q-values through total future rewards.

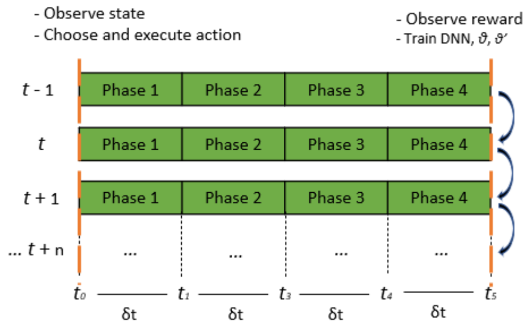


Fig. 2. Traffic signal timing by agent


Fig. 3. Training and test

Fig. 1 is the reinforcement learning model that follows the structure and training of deep neural network (DNN) by [4], the $S$ is input of the network layer and $Q(S_t, a : \theta)$ is the output for action in each time step $t$. In the DNN architecture, the input $S$ consists of 8 matrices with size 36 x 20 that collected by 4 phases and 2 directions. The rectifier non-linearity activation function (ReLU) is composed in the first layer with 16 filters and second layer with 32 filters. Furthermore, the DNN training is schemed to learns the parameter $\theta$ and optimize the target network with $\theta'$. It through observed system at time step $t$ is stored into the replay memory. If the capacity is full, the old data is removed and new data is stored.

The effective trade-off method, greedy algorithm, is used to select the action with the current greatest estimated Q-value with the probability $\epsilon$ and randomly select one action with probability $1 - \epsilon$ at each time step of the traffic signal.

## III. Simulation Results

The intersection and traffic signal system is simulated using open source simulator, simulation of urban mobility (SUMO). The road segments 0 and 2 is set to be busy and road segments 1 and 3 is set not busy. Moreover, the vehicles randomly choose the destination road.

Fig. 3 shows the DNN training and test of traffic light systems that manage the vehicles to passes the intersection. In the training, the system attempts to store the output network that will be optimized to reduce the vehicle staying time. While the test shows the result of the total waiting time of vehicles in the intersection. The figure shows that adopting the training process of DNN, the waiting time of the vehicle can be reduced and the traffic light system learns the data from the replay memory.

The average total waiting time of vehicles in the test line is stable reducing after 37 episodes. Due to the randomly generating vehicle in the SUMO simulation, the vehicles move based on the traffic phase order. The Fig. 4 shows the comparison of adaptive TLC and static TLC to take an action of traffic signal timing. In the static TLC, the total waiting time is the same from each episode, while the adaptive TLC works based on the number of vehicles in the road segments. Although the system has increased the total waiting time in

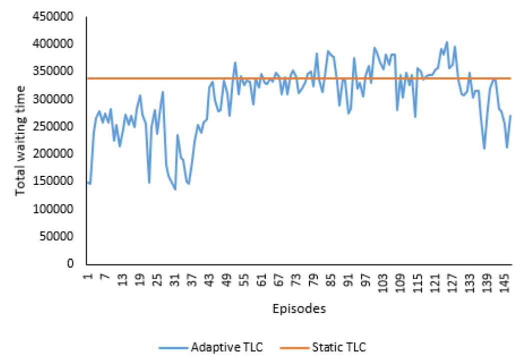


Fig. 4. Comparison of total waiting time Adaptive and Static TLC

some episodes, the adaptive TLC with reinforcement learning can learn according to needs.

## IV. Conclusion

Reinforcement learning algorithm for adaptive traffic signal control to reduce traffic congestion. The four-phase order of intersection shows an efficient way with the sequence of traffic signals that optimized using reinforcement learning. The real-time traffic data can learn the optimal traffic signal control policy. Then in the future, the stability in the sense that our algorithm converges to good traffic signal control policy.

## Acknowledgment

This work was supported by Priority Research Centers Program through the National Research Foundation of Korea(NRF) funded by the Ministry of Education, Science and Technology(2018R1A6A1A03024003).

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