DynLight: Realize dynamic phase duration with multi-level traffic signal control

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Abstract

Adopting reinforcement learning (RL) for traffic signal control (TSC) is increasingly popular, and RL has become a promising solution for traffic signal control. However, several challenges still need to be overcome. Firstly, most RL methods use fixed action duration and select the green phase for the next state, which makes the phase duration less dynamic and flexible. Secondly, the phase sequence of RL methods can be arbitrary, affecting the real-world deployment which may require a cyclical phase structure. Lastly, the average travel time and throughput are not fair metrics to evaluate TSC performance. To address these challenges, we propose a multi-level traffic signal control framework, DynLight, which uses an optimization method Max-QueueLength (M-QL) to determine the phase and uses a deep Q-network to determine the duration of the corresponding phase. Based on DynLight, we further propose DynLight-C which adopts a well-trained deep Q-network of DynLight and replace M-QL with a cyclical control policy that actsuates a set of phases in fixed cyclical order to realize cyclical phase structure. Comprehensive experiments on multiple real-world datasets demonstrate that DynLight achieves a new state-of-the-art. Furthermore, the deep Q-network of DynLight can learn well on determining the phase duration and DynLight-C demonstrates high performance for deployment.

Keywords: traffic signal control, reinforcement learning, multi-level control, cyclical phase structure, real-world deployment

1 Introduction

Signalized intersections are one of the most common types in urban environments, and traffic signal control (TSC) plays an important role in urban traffic management. Nowadays, using reinforcement learning (RL) (Sutton and Barto 2018) for traffic control is increasingly popular. RL-based methods can learn directly through trial-and-errors without the strict assumptions in traditional methods. MPLight (Chen et al. 2020) and CoLight (Wei et al. 2019) have demonstrated superior performance and capacity for large-scale TSC. Efficient-XLight (Wu et al. 2021), and QL-XLight (Zhang, Wu, and Deng 2021) adopt more effective state representations to further improve the control performance. AttendLight (Oroojlooy et al. 2020) develops a universal model to handle different topologies of intersections.

RL-based methods have become a promising solution for adapting traffic signal control. Considering the control logic, most RL-based TSC methods (such as MPLight (Chen et al. 2020), CoLight (Wei et al. 2019), Efficient-XLight (Wu et al. 2021), and AttendLight (Oroojlooy et al. 2020)) use fixed action duration and select the green phase for the next state. Such a control logic is the same as in most games (such as Atari games (Mnih et al. 2013)), which are designed for people to play with. Under this control logic, the duration of each phase cannot adapt to dynamic traffic conditions, and the capability of RL methods is strongly limited. Moreover, Efficient-XLight (Wu et al. 2021) and QL-Light (Zhang, Wu, and Deng 2021) have demonstrated that the action duration can significantly influence the model performance.

In several studies, the RL agent can change the duration of green lights to adapt to the changing traffic flow. Liang et al. (2019), Chenguang, Xiaorong, and Gang (2021), Zhao et al. (2022), but they are not flexible enough as expected. In Liang et al. (2019), the duration of one and only one phase in the next cycle is the current duration added or subtracted by 5 seconds. In the multi-intersection scenario, PRGLight (Chenguang, Xiaorong, and Gang 2021) and IP-DALight (Zhao et al. 2022) change the phase duration for all the intersections rather than set different phase duration for each intersection. Realizing dynamic phase duration according to real-time traffic for different intersections is needed.

Although RL-based TSC methods develop rapidly, most have limited capacity for deployment in the real world. A major obstacle to implementation in practice is the non-cyclical phase actuation, which can actuate any phase in any sequence. Specifically, drivers prefer a cyclical phase structure for traffic signals. This arbitrary phase selection can be confusing for travelers expecting regular signal patterns and is therefore unacceptable for some city traffic engineers. Although a non-cyclical phase selection may improve throughput, its limitations include potentially unbounded waiting times and the appearance of phases being “skipped” for waiting drivers. Also, some intersections require additional conditional phase orders such as go-straight must follow turn left with the existence of a waiting area (Ma et al. 2017). Few RL methods support cyclical phase structure.

Considering the evaluation metric, average travel time and throughput are the most used to evaluate TSC perfor-
2.2 RL based methods

RL methods improve the TSC performance mainly in three ways: (1) design an effective state and reward; (2) develop a new network structure; (3) introduce advanced RL techniques. LIT (Zheng et al. 2019b) introduces a very simple state and reward design and gets significant performance improvement from IntelliLight (Wei et al. 2018). PressLight (Wei et al. 2019a) introduces pressure into state and reward design and gets significant improvement from LIT and IntelliLight. Efficient-XLight (Wu et al. 2021) rethinks the calculation of pressure and introduce efficient pressure as an effective state representation, improving the control performance of MPLight (Chen et al. 2020) and CoLight (Wei et al. 2019b). QL-XLight (Zhang, Wu, and Deng 2021) rethinks queue length and uses it both as state and reward, getting improvement from CoLight (Wei et al. 2019b). FRAP (Zheng et al. 2019a) develops a special network structure to construct phase features and capture phase competition relations. CoLight (Wei et al. 2019b) adopts a graph attention network (Velickovic et al. 2017) to realize intersection cooperation. AttendLight (Oroojlooy et al. 2020) adopts the attention network to handle the different topologies of intersections. DemoLight (Xiong et al. 2019) introduces imitation learning (Ho and Ermon 2016), HiLight (Xu et al. 2021) adopts hierarchical RL (Kulkarni et al. 2016), and MetaLight (Zang et al. 2020) introduces meta-learning ( Finn, Abbeel, and Levine 2017).

2.3 Dynamic phase duration and cycle traffic control

Most RL methods use fixed action duration (denoted as $t_{\text{duration}}$) and select the green phase for the next state. Under this circumstance, the duration of each phase can only be multiple of the fixed $t_{\text{duration}}$ and can’t realize dynamic duration. Several studies can realize dynamic traffic light duration but are not adaptive and flexible enough. Liang et al. (Liang et al. 2019) develop a model that can change the duration of a traffic light in a cycle control, but the duration of one and only one phase in the next cycle is the current duration added or subtracted by 5 seconds. IPDALight (Zhao et al. 2022) dynamically adjusts the phase duration according to the real-time traffic condition. PRGLight (Chenguang, Xiaorong, and Gang 2021) uses dynamic phase duration according to real-time traffic state and predicted traffic state. However, both IPDALight and PRGLight apply the same duration for all the intersections in the multi-intersection scenario which ignores the difference in intersections and lacks flexibility. Moreover, the reported performance of IPDALight and PRGLight cannot outperform AttentionLight (Zhang, Wu, and Deng 2021).

There are several studies that concentrate on cycle traffic signal control in the traditional TSC field (Le et al. 2015, Levin, Hu, and Odell 2020). However, in RL based TSC field, few studies concentrated on cycle traffic control (Liang et al. 2019) due to the performance limitation.
3 Preliminary

In this paper, we consider multi-intersection TSC, in which each intersection is controlled by an RL agent. Agent \( i \) views the environment as its observation and takes an action to control the signal of intersection \( i \). The goal of the agent \( i \) is to take an optimal action to maximize its cumulative reward. To illustrate the definitions clearly, we use the intersection of four approaches as an example.

![Traffic network](image)

**Traffic network** The traffic network is described as a directed graph in which nodes represent intersections and edges represent roads. Each road consists of several lanes, which are the basic unit of vehicle movement and determines the way each vehicle passes through an intersection, such as turning left, going straight, and turning right. An incoming lane is where vehicles enter the intersection, and an outgoing lane is where vehicles leave the intersection. We denote the set of incoming lanes and outgoing lanes of intersection \( i \) as \( \mathcal{L}_{in}^i \) and \( \mathcal{L}_{out}^i \) respectively.

**Traffic movements** Each traffic movement is defined as traffic traveling across an intersection towards a certain direction, i.e., left, straight, and right. According to the traffic rules of some countries, vehicles that turn right can pass regardless of the signal but must stop at a red light. As shown in Figure 1, each intersection has twelve traffic movements and eight of which are used to construct signal phases.

**Signal phase** Each signal phase is a set of permitted traffic movements, denoted by \( d \), and \( \mathcal{D}_i \) denotes the set of all the phases at intersection \( i \). As shown in Figure 1, twelve traffic movements can be organized into four phases(d) or eight phases (e). We use a four-tuple \( < A, B, C, D > \) to denote 4-phase, and a eight-tuple \( < A, B, C, D, E, F, G, H > \) to denote 8-phase.

![Traffic movements](image)

![Four phases](image)

![Eight phases](image)

Figure 1: Illustration of a traffic network.

| Notation Meaning |
|------------------|
| \( \mathcal{L}_{in}^i \) | set of incoming lanes of intersection \( i \) |
| \( \mathcal{L}_{out}^i \) | set of exiting lanes of intersection \( i \) |
| \( l, m, k \) | lanes |
| \( d \) | a signal phase |
| \( \mathcal{D}_i \) | set of all phases at intersection \( i \) |
| \( x(l) \) | number of vehicles on lane \( l \) |
| \( q(l) \) | queue length on lane \( l \) |

4 Method

In this section, we first propose a multi-level traffic signal control framework DynLight which divides the TSC into two levels: phase selection and duration selection. The state, action, reward, and network design of DynLight are further described in detail. Next, we develop a model with a cyclical phase structure that is suitable for deployment based on DynLight. Finally, we develop the adjusted average time as a fair evaluation metric.

4.1 Multi-level traffic signal control

We divided the progress of traffic signal control into two levels: phase selection and duration selection. Phase selection and duration selection are also called phase action and duration action of each agent. In the stage of phase selection, a phase \( d \) is determined to be actuated according to the traffic condition. In the stage of duration selection, a phase duration \( t \) is further determined for phase \( t_{duration} \) according to the traffic condition. We refer to the multi-level traffic signal control framework as DynLight. The DynLight is formally summarized in Algorithm 1.

4.2 Network design of DynLight

DynLight consists of two complete control approaches: phase selection and duration selection. The phase selection is realized with an optimization method: Max-QueueLength (M-QL) \cite{Mnih2015}, which selects the phase with the maximum queue length. The duration selection is realized with a deep Q-network \cite{Mnih2015}, which outputs the Q-values of each duration action. Before designing the network of DynLight, we first fully describe the state, action, and reward.

- **State.** The queue length on each entering lane is used for M-QL to determine the phase. The number of vehicles on each segment of incoming lanes \( x(l) \), \( k = 1, 2, 3, 4 \)
Algorithm 1: DynLight

Parameters: Intersection number $n$; current phase at intersection $i$ $\hat{d}_i$; duration of phase $\hat{d}_i^{duration}$; current phase time at intersection $i$ $h_{alt}^i$.

1: for (time step) do
2: for $i = 1 : n$ do
3: Select phase $\hat{d}_i$ for intersection $i$;
4: Select duration $\hat{d}_i^{duration}$ for phase $\hat{d}_i$;
5: end for
6: for $i = 1 : n$ do
7: $t^i = t^i + 1$
8: if $t^i = \hat{d}_i^{duration}$ then
9: Select phase $\hat{d}_i$ for intersection $i$;
10: Select duration $\hat{d}_i^{duration}$ for phase $\hat{d}_i$;
11: $t^i = 0$
12: end if
13: end for
14: end for

is used for duration selection. In this paper, each lane is divided into 100-meter long segments, and we denote the segment on lane $l$ nearest to the intersection as the first segment $x(l)$.1

• Action. At time $t$, each agent first chooses a phase $\hat{d}$ as its phase action from action set $A$, indicating the traffic signal should be set to phase $\hat{d}$. Next, each agent chooses a duration $\hat{t}$ as the duration of $\hat{d}$, indicating the traffic signal of phase $\hat{d}$ will last $\hat{t}$. In this paper, each agent has four permissible phase actions, correspondingly four phases in Figure 1 and each agent has seven permissible duration actions, denoted as $\{10, 15, 20, 25, 30, 35, 40\}$.

• Reward. Negative intersection queue length is used as the reward. The reward for the agent that is controlling intersection $i$ is denoted by:

$$r_i = -\sum_{l \in L_i^{in}} q(l)$$ (1)

in which $q(l)$ is the queue length at lane $l$. Intuitively, by maximizing the reward, the agent is trying to minimize the average travel time in the system. In addition, M-QL can optimize the reward.

Network design The network of DynLight mainly consists of three stages (see Figure 2):

• Phase feature selection. After the phase $\hat{d}$ is determined by M-QL, the feature of phase $\hat{d}$ will be extracted from the feature of all the phases according to the phase composition (see Figure 1(c) and (d)).

• Feature fusion. The features of phase $\hat{d}$ are embedded and fused. In this paper, we use addition to fuse the features.

• Predict Q-values. The feature of phase $\hat{d}$ is further embedded to get Q-values. Dueling block is used to accelerate learning efficiency.

The illustration of DynLight is shown in Figure 2.

4.3 Cyclical phase selection

In real-world deployment, the phase is usually required in a fixed cyclical order. To describe the cyclical phase selection, we define fixed cyclical control.

Definition 1 (Fixed Cyclical control). A policy that cyclically actsuates a set of phases in order.

Due to the property of DynLight that determines the phase and duration at a different level, we can replace the M-QL with a fixed cyclical control policy that actsuates the phase with a fixed cyclical order. Because the fixed phase order cannot support the optimization of reward, we cannot directly learn the RL model with the fixed cyclical phase order. Under fixed phase order, the duration action is required and highly influences the control performance.

To solve this problem, we first well train DynLight, next replacing M-QL with fixed cyclical control. We refer to DynLight with cyclical phase selection as DynLight-C.

4.4 Adjusted average travel time

With the problem of average travel time and throughput, we propose adjusted average travel time that extends the testing time of each episode to enable all the vehicles can pass through the traffic network. In this way, with the same throughput, the adjusted average travel time can fully evaluate the model performance.

5 Experiments

We conduct comprehensive experiments on CityFlow which is open-source and supports large-scale traffic signal control (Zhang et al. 2019). CityFlow has been widely used by multiple RL methods such as MPLight (Chen et al. 2020), CoLight (Wei et al. 2019b), and HiLight (Xu et al. 2021). The simulator provides the environments observations to the TSC methods and executes the actions from the control methods.

http://cityflow-project.github.io
5.1 Datasets
Each traffic dataset consists of two parts: traffic network dataset and traffic flow dataset. The traffic network dataset describes the lanes, roads, intersections, and signal phases. The traffic flow dataset describes how vehicles travel across the network, denoted as \((t, u)\), in which \(t\) is the time when the vehicle enters the traffic network, and \(u\) is the pre-defined route from its original location to its destination. After the traffic data is fed into the simulator, each vehicle starts moving according to the pre-defined route at time \(t\).

We use two groups (JiNan and HangZhou) of datasets consisting of seven (three from JiNan, two from HangZhou) real-world traffic flow datasets from China. The average arrival rate of the five datasets are different from each other as shown in Table 2.

- **JiNan datasets** The traffic network has 12\((3 \times 4)\) intersections. Each intersection is four-way, with two 400-meter road segments (East-West) and two 800-meter road segments (South-North).
- **HangZhou datasets** The traffic network has 16\((4 \times 4)\) intersections. Each intersection is four-way, with two 800-meter road segments (East-West) and two 600-meter road segments (South-North).

Table 2: Average arrival rate of the two datasets.

| Dataset       | Arrival rate (vehicles/s) |
|---------------|---------------------------|
| \(D_{JiNan1}\) | 1.75                      |
| \(D_{JiNan2}\) | 1.21                      |
| \(D_{JiNan3}\) | 1.53                      |
| \(D_{HangZhou}\) | 0.83                      |
| \(D_{HangZhou2}\) | 1.94                      |

5.2 Evaluation metric
Instead of using average travel time and throughput as evaluation metrics in most studies (Zheng et al. 2019a, Wei et al. 2019b, Chen et al. 2020), we adopt adjusted average travel time in this article which is proposed to evaluate model performance.

5.3 Compared methods
We compare our proposed methods with the following baseline methods, including traditional and RL TSC methods. For a fair comparison, the phase number is set as four, the action interval is set as 15-second for all the baseline methods. Each episode is a 60-minutes simulation, and we adopt one result as the average of the last ten episodes of testing. Each reported result is the average of three independent experiments.

**Traditional Methods**
- **FixedTime** (Koonce and Rodegerdts 2008): a policy uses a fixed cycle length with pre-defined phase split among all the phases.
- **Max-QueueLength** (Zhang, Wu, and Deng 2021): a policy selects the phase with maximum queue length.
- **Efficient-MaxPressure** (Wu et al. 2021): a policy selects the phase with maximum efficient pressure.

**RL Methods**
- **FRAP** (Zheng et al. 2019a): uses a modified network to construct phase features and capture phase competition relations among all the traffic movements.
- **CoLight** (Wei et al. 2019b): uses a graph attention network (Velićković et al. 2017) to realize intersection cooperation and has shown superior performance in large-scale TSC.
- **Efficient-MPLight** (Wu et al. 2021): uses FRAP (Zheng et al. 2019a) as the base model and introduces efficient pressure as an effective state representation. It has shown superior performance than FRAP (Zheng et al. 2019a) and MPLight (Chen et al. 2020).
- **AttentionLight** (Zhang, Wu, and Deng 2021): uses self-attention (Vaswani et al. 2017) to learn phase correlation and adopts queue length as the state and reward.

**Our Proposed Methods**
- **DynLight**: a multi-level traffic signal control method that uses M-QL for phase selection and a deep RL network for duration selection.
- **DynLight-C**: with well pre-trained DynLight, the M-QL is replaced with a fixed cyclical control policy to realize cyclical phase structure for real-world deployment.

5.4 Overall performance
Table 3 and Figure 3 demonstrate the overall performance under JiNan and HangZhou real-world datasets with respect to the adjusted average travel time.

DynLight consistently outperforms all other previous methods among JiNan and HangZhou real-world datasets. The performance difference is significant. DynLight achieves a new state-of-the-art performance for traffic signal control.

Cyclical phase structure significantly influences the model performance. The comparison of DynLight and DynLight-C indicates that phase selection is essential for traffic signal control. In addition, DynLight-C demonstrates high performance and is a promising solution for traffic signal control.

The performance of DynLight and DynLight-C demonstrates that the network of DynLight can well learn a policy to determine the phase duration. The importance of phase duration is further emphasized for traffic signal control.

5.5 Action study
How DynLight performs under different phase action sets and duration action sets is further studied. With the phase action set as 4-phase, the duration action sets are configured with different range and resolution:
- **Config1**: The duration actions are configured as \(set\{10, 20, 30, 40\}\).
- **Config2**: The duration actions are configured as \(set\{10, 15, 20, 25, 30, 35, 40\}\).
Table 3: Overall performance comparison with respect to adjusted average travel time, the smaller the better.

| Method        | JiNan 1 | JiNan 2 | JiNan 3 | HangZhou 1 | HangZhou 2 |
|---------------|---------|---------|---------|------------|------------|
| FixeTime      | 585.76  | 411.63  | 465.64  | 611.65     | 834.99     |
| M-QL          | 288.84  | 248.36  | 254.74  | 300.54     | 468.28     |
| Efficient-MP  | 286.37  | 247.75  | 252.47  | 299.73     | 459.81     |
| FRAP          | 331.97  | 272.23  | 282.67  | 326.12     | 524.32     |
| CoLight       | 283.14  | 257.44  | 261.23  | 311.54     | 477.77     |
| Efficient-MPLight | 279.42 | 250.59  | 253.53  | 301.26     | 417.60     |
| AttentionLight| 270.14  | 247.16  | 250.61  | 300.22     | 417.62     |
| DynLight      | 255.16  | 237.44  | 238.82  | 286.69     | 399.04     |
| DynLight-C    | 293.62  | 258.06  | 269.12  | 343.99     | 465.05     |

Figure 3: Overall performance comparison.

- Config3. The duration actions are configured as set \{10, 13, 16, 19, 22, 25, 28, 31, 34, 37, 40\}.
- Config4. The duration actions are configured as set \{10, 15, 20\}.
- Config5. The duration actions are configured as set \{10, 15, 20, 25, 30, 35, 40, 45, 50, 55, 60\}.

Experiments are conducted on JiNan and HangZhou datasets, and Figure 4 demonstrates the performance of DynLight under different duration action sets. The configuration of duration action significantly influences the performance of DynLight. We select set \{10, 15, 20, 25, 30, 35, 40\} as the default duration action set.

![Figure 4: Model performance under different duration action sets.](image)

With the duration action as set \{10, 15, 20, 25, 30, 35, 40\}, the phase action sets are configured as 4-phase and 8-phase. Figure 5 demonstrates the model performance under 4-phase and 8-phase. DynLight has better performance under 8-phase than 4-phase. For fair comparison in baseline, the default phase action of DynLight is set as 4-phase.

![Figure 5: Model performance under different phase action sets.](image)

Figure 5: Model performance under different phase action sets.

5.6 State representation study

The performance of DynLight under different state representations is further studied. We choose some typically used state representations for comparison:

- Number of vehicles (NV): total number of vehicles on each entering lanes of the intersection.
- Traffic movement pressure (TMP): we adopt the traffic movement pressure from Efficient-MPLight [Wu et al.]
which is the difference of average queue length between upstream and downstream.

- Queue length (QL): queuing vehicle number on each entering lanes of the intersection.
- Number of vehicles under segmented roads (NV-S): the number of vehicles on each segment of incoming lanes $x(l)_k$, $k = 1, 2, 3, 4$, under which each road is divided into 100-meter long segments, and we denote the segment on lane $l$ nearest to the intersection as the first segment $x(l)_1$.

Figure 6 demonstrates the model performance under four state representations. DynLight performs best under NV-S. Under the framework of DynLight, the model performs better under NV than TMP and QL although TMP and QL have been considered more effective in Efficient-XLight (Wu et al., 2021) and QL-XLight (Zhang, Wu, and Deng, 2021). In addition, even under NV, DynLight consistently outperforms previous methods under JiNan and HangZhou datasets. NV-S is more effective than NV under DynLight to determine an optimal phase duration. We choose NV-S as one of the default state representations.

Figure 6: Model performance under different state representations.

5.7 Phase control study

As an optimization method, Efficient-MP can also be used by DynLight to determine the phase. When Efficient-MP is used, the reward is set as pressure to be consistent with Efficient-MP. With only change phase selection policy and reward, Figure 7 demonstrates the model performance under JiNan and HangZhou real-world datasets. DynLight has better performance under M-QL than Efficient-MP. We finally choose M-QL as the default phase selection policy for DynLight.

Figure 7: DynLight performance under different phase selection policies.

5.8 Model generalization

Model generalization is an essential property of RL models. An idea RL model should be resilient to different traffic conditions after training in a traffic situation. In addition, the over-fitting problem is addressed by model generalization. We train DynLight on each dataset and transfer them to other datasets. Same to the training process of baseline models, each transfer result reports the average of three independent experiments, and each experiment shows the average result of the final 10 episodes. Experiments are conducted under JiNan and HangZhou real-world datasets. The transferability of each mode that trained on dataset $i$ and transferred on dataset $j$ is calculated as follows:

$$E^j_i = \frac{t^j_{\text{transfer}}}{t^i_{\text{train}}} - 1$$

in which $t^i_{\text{train}}$ represents the training result (average travel time) on datasets $i$, $t^j_{\text{transfer}}$ represents the transfer result on dataset $j$.

Figure 8 demonstrates the transferability of DynLight. DynLight can learn better at JiNan datasets than HangZhou datasets, and they all show high transferability.

Figure 8: The transfer performance comparison, the smaller the better.

5.9 Model deployment

DynLight and DynLight-C fully consider deployment issues. If the phase is allowed in arbitrary order, DynLight shows state-of-the-art performance and high transferability. If the phases are required in cyclical order, DynLight-C supports cyclical phase structure and demonstrates superior performance than FRAP (Zheng et al., 2019a).

The demonstrated performance of DynLight and DynLight-C indicates they are promising solutions for real-world traffic signal control. The comparison of DynLight-C and FixedTime further addresses the importance of dynamic duration. As shown in Figure 9, DynLight-C significantly outperforms FixedTime among JiNan and HangZhou datasets.

Figure 9: The transfer performance comparison, the smaller the better.

6 Conclusion

In this paper, we rethink the logic of traffic signal control and propose multi-level traffic signal control which first select
phase next select duration. The phase selection is realized by an optimization method: M-QL and the duration selection is realized by a DQN. In addition, we propose a more fair evaluation metric as adjusted average travel time and use it for model comparison. Comprehensive experiments under real-world datasets demonstrate that DynLight outperforms all the previous methods. With well pre-trained DynLight, the phase selection is replaced with a cyclical phase selection that can also demonstrate high performance. Our proposed DynLight not only achieves state-of-the-art performance but is also flexible enough for deployment. The phase duration is essential for traffic signal control.

In future research, we will consider more complex network and RL techniques for traffic signal control. More efficient state representation is also under consideration.

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