Knowledge intensive state design for traffic signal control

Liang Zhang¹, Qiang Wu², Jianming Deng¹*

¹ School of Life Sciences, Lanzhou University, Lanzhou 730000, China
² Institute of Fundamental and Frontier Sciences, University of Electronic Science and Technology of China, Chengdu 611731, China

Abstract

There is a general trend of applying reinforcement learning (RL) techniques for traffic signal control (TSC). Recently, most studies pay attention to the neural network design and rarely concentrate on the state representation. Does the design of state representation have a good impact on TSC? In this paper, we (1) propose an effective state representation as queue length of vehicles with intensive knowledge; (2) present a TSC method called MaxQueue based on our state representation approach; (3) develop a general RL-based TSC template called QL-XLight with queue length as state and reward and generate QL-FRAP, QL-CoLight, and QL-DQN by our QL-XLight template based on traditional and latest RL models. Through comprehensive experiments on multiple real-world datasets, we demonstrate that: (1) our MaxQueue method outperforms the latest RL based methods; (2) QL-FRAP and QL-CoLight achieves a new state-of-the-art (SOTA). In general, state representation with intensive knowledge is also essential for TSC methods. Our code is released on Github

Keywords: intensive knowledge, traffic signal control, reinforcement learning, state design, effective state

1 Introduction

With population and economic growth, automobiles increase rapidly, and traffic congestion has become an emergent problem. Traffic congestion causes fuel waste, environmental pollution, economic losses, and waste of time. Mitigating traffic congestion and improving transportation efficiency is of great urgency.

In many modern cities, FixedTime[5], GreenWave[12], SCOOT[4], and SCATS[7] are the most common traffic signal control systems, which relys on pre-designed traffic signal plans. These methods can’t adapt to dynamic traffic flows. In addition, some traditional traffic signal control (TSC) methods such as MaxPressure[14] and SOTL[2] have good performance but takes much efforts to deploy.

Recently, reinforcement learning (RL) has drawn increasing attention, and people have begun to use RL to solve TSC problems. RL models can directly learn from the environment through trial-and-error without requiring assumptions like traditional TSC methods. Furthermore, RL models can handle complex and dynamic environments with a deep neural network[8]. RL-based TSC methods[16][1][16] become a promising solution for realizing intelligent transportation systems. PressLight[16] can realize large-scale traffic signal control. Furthermore, MPLight[1] and CoLight[17] have demonstrate the ability to handle city-level TSC. In addition, MPLight uses a decentralized RL paradigm and is easier for large-scale deployment. PressLight[16] and MPLight all demonstrate the essential role of the state and reward design.

In RL-based approach, the state representations vary in terms of queue length[9][18], number of vehicles[18][23][20][16][22][20][17][19], traffic image[13][18], the reward representations vary in terms of queue length[22][16][17][19], pressure[11], total wait time[18][9][13][19], and delay[18][13][19]. Some methods can perform better with simple state and reward. However, some methods with complex state and reward designs get limited results. However, most studies concentrate on developing novel network structures to improve TSC performance. Few of the studies have deeply explored why some methods have great performance with simple state and reward design. More attention should be paid to the state design for TSC.

In summary, the main contribution of this article as follows:

1. Propose an effective state representation as queue length with intensive-knowledge;
2. Propose one transportation method, namely MaxQueue, which has superior performance than previous state-of-the-art RL methods;
3. With effective state design, we develop an RL-based TSC template: QL-XLight with queue length as state and reward;
4. Based on QL-XLight, we generate three RL-based methods: QL-DQN, QL-FRAP, QL-MPLight, which all have superior performance than the latest methods;
5. Demonstrate that state design with intensive knowledge is as essential as network structure design.

The remainder of this paper is organized as follows: Section 2 introduces the related works, including typical transportation and RL-based approaches for TSC; Section 3 depicts the definitions of TSC; Section 4 systematically analyzes the typical used state representation with
intensive-knowledge, and develop the MaxQueue algorithm and QL-XLight template. Section 5 conducts experiments and demonstrates the results. Section 6 concludes the paper and discusses future work.

2 Related work

2.1 Conventional transportation methods

Conventional transportation methods can be mainly categorized into the four categories: fixed-time control\[5,12\], actuated control\[3,8\], adaptive control\[4,7\], and optimization-based control\[14,6,10\]. All the methods mentioned above highly rely on expert knowledge. Fixed-time and adaptive control rely on predefined signal plans (i.e., cycle length, phase split, and offset). Actuated control relies on the predefined threshold, which highly influences the control performance; optimization-based control also relies on the predefined signal plan (i.e., cycle length), turn ratios, and saturation flow rates. Therefore, these conventional transportation methods have limited capacity to adapt to dynamic traffic.

2.2 RL based methods

RL models can learn their policy directly from environments through trial-and-error, and deep neural networks make them adapt to various conditions. The RL-based method is a promising solution for traffic signal control. PressLight\[16\] can achieve multi-intersection traffic signal control. MPLight and CoLight can realize city-level TSC. HiLight also achieves superior performance than MPLight and CoLight with hierarchical RL models. The state, reward, and neural network design play an essential role in RL models. We summarize some typical RL-based methods and category them into the following classes:

- The methods that introduce effective state and reward design. MPLight\[1\] incorporates pressure into state design and finds the improvement than queue length as a reward representation. MPLight introduces pressure into state design and finds the improvement in the model. However, none of them systematically explain why some state and reward is better. The state representation for TSC needs to be further discussed.

3 Preliminary

In this section, we summarize the definition for recent TSC methods\[1,17\].

**Definition 1** (Traffic network). Each traffic network is described as a directed graph, in which each node represents the intersection, and each edge represents the road. Each road consists of several lanes. An incoming lane for an intersection is where the vehicles enter the intersection. An outgoing lane for an intersection is where the vehicles leave the intersection. We denote the set of incoming lanes and outgoing lanes of intersection \(i\) as \(L_{in}^i\) and \(L_{out}^i\) respectively. We use \(l, m, k\) to denote the lanes.

**Definition 2** (Traffic movement). A traffic movement is defined as the traffic traveling across an intersection towards a certain direction, i.e., left turn, go straight, and right turn. Following the traffic rules in most cities, right turn traffic can pass regardless of the signal, but it needs to yield on a red light. In Figure 1(a), there are 12 traffic movements.

**Definition 3** (Signal phase). Each signal phase is a set of permissible traffic movements, denoted by \(d\), and \(D_i\) denotes the set of all the phases at intersection \(i\). As shown in Figure 1, the intersection has 4 phases with phase #2 activated.

**Definition 4** (Phase queue length). The queue length of each phase is the sum queue length of the incoming lanes of the phase, denoted by

\[
q(d) = \sum q(l), l \in d
\]

in which \(q(l)\) is the queue length of lane \(l\).

**Definition 5** (Intersection queue length). The queue length of each intersection is defined as the total queue length of the incoming lanes of the intersection, denoted by

\[
Q(i) = \sum q(d), d \in D_i
\]
length of the incoming lanes of the intersection, denoted by

\[ Q_i = \sum q(l), l \in L_i^{in} \tag{2} \]

in which \( q(l) \) represents the queue length of lane \( l \).

**Definition 6** (Phase duration). The minimum duration for each phase is denoted by \( t_{duration} \). It can also represent the action interval of RL-based models.

**Problem** (Multi-intersection traffic signal control). Each intersection is controlled by a RL agent. At time step \( t \), agent \( i \) views the environment as its observation \( o_i^t \). Every \( t_{duration} \), the action \( a_i^t \) is taken to control the signal of intersection \( i \). The goal of the agent is to take an optimal action \( a_i^t \) (i.e. which phase to set) to maximize the throughput of the systems and minimize the average travel time.

| Table 1: Summary of notation. |
|-----------------------------|
| Notation       | Meaning                                      |
| \( L_i^{in} \)     | set of incoming lanes of intersection \( i \) |
| \( L_i^{out} \)    | set of outgoing lanes of intersection \( i \) |
| \( l, m, k \)      | lanes                                        |
| \( q(l) \)         | queue length of lane \( l \)                 |
| \( d \)            | signal phase which is set of traffic movements|
| \( D_i \)          | set of all phases at intersection \( i \)     |
| \( Q_i \)          | total queue length of intersection \( i \)    |
| \( t_{duration} \) | minimal phase duration or said action interval|

### 4 Method

In this section, we first propose an effective state representation as queue length with intensive knowledge. Next, we discuss why queue length is more effective than some typical used state representation. Then, we propose a transportation method MaxQueue based on intensive knowledge inspired by MaxPressure. Finally, we develop an RL-based TSC template: QL-XLight and generate QL-DQN, QL-FRAP, and QL-COLight.

#### 4.1 Queue length as the state

For TSC, each vehicle in the traffic network has two states: running and queuing. Queueing vehicles can directly result in congestion while running vehicles potentially result in congestion. Almost all the queueing vehicles stop near the intersection and have the demand for a green signal. MP\[14\] maximizes the throughput of the traffic by balancing the queue length in the network. The queueing vehicles play an essential role in the traffic condition representation. From empirical knowledge, the queue length is considered adequate.

In the traffic network, the phase signal can only directly change the state of the queuing vehicles. Any consequent changes such as the number of vehicles, vehicle position, speed score are full of uncertainty. Therefore, we choose to use queue length as the traffic state representation.

**Discussion** According to the existing studies, various state representations are used in TSC, while some state representation is more effective than others. We will summarize the typically used state representations and give a systematical analysis to answer which state is an effective traffic state representation.

The RL agents learn from the environment through trial-and-error and learn the state-action value through exploration. Suppose the state representation does not include critical contents of traffic movement. In that case, the agent will be confused about the state and can’t learn an appropriate policy.

If one phase is activated, the queue length of the phase changes to zero, while the queue length for other phases may grow gradually, depending on the arrival from upstream. There is a deterministic change when each phase is activated, and is considered effective.

Then, we analyze the following traffic state representation and explain why they are as effective as queue length.

- **Number of vehicles:** it is described as the total vehicle number of the incoming lanes. If one phase is activated, the vehicles near the intersection pass through gradually, but vehicles also arrive from upstream. The total number of the corresponding lanes probably becomes larger if the number of entering is larger than exiting; (2) do not change if the number of entering is equal to exit; (3) become smaller if a number of entering is smaller than exiting. In addition, if there is no vehicle near the intersection, the traffic state can’t change even if the phase changes. Therefore, the change of state is vague and can’t be explicitly captured, which makes the agent “confusing.”
- **Vehicle position.** The position of vehicles is usually integrated as an image representation, which is defined as a matrix, with “1” indicating the presence of vehicles on a location, and “0” the absence of vehicles on that location. Each lane is usually divided into small segments, and some use the total vehicle number to replace “1” and “0”. This is similar to a number of vehicles that do not have explicit changes after one phase be activated.
- **Speed score.** The speed score is calculated by the average speed divided by the speed limit. If one phase is activated, the speed score change degree relies on the acceleration. In addition, if there are only queueing vehicles, the speed score grows proportional to the acceleration; if there are lots of running vehicles and few queueing vehicles, the speed score may change, not obvious. It is also confusing for the RL agents.
- **Traffic movement pressure calculated by a number of vehicles.** It is calculated by a number of vehicles and has similar properties to it.

#### 4.2 MaxQueue control

Based on MaxPressure\[14\] and the property of queue length, we propose a TSC method called MaxQueue. Like MaxPressure, MaxQueue control selects the phase with maximum queue length in a greedy manner. At intersection \( i \), the phase
queue length is calculated (by equation(1)), then activate the phase with maximum pressure every \( t_{\text{duration}} \), denoted by
\[
\hat{d} = \text{argmax } (q(d)) | d \in D_t 
\] (3)
The MaxQueue method is formally summarized in Algorithm 1.

Algorithm 1: MaxQueue Control

**Parameter:** Current phase time \( t \), minimum phase duration \( t_{\text{duration}} \)

for (time step) do
  \[
t = t + 1; 
  \]
  if \( t = t_{\text{duration}} \), then
  For each intersection, get \( q(d) \) by equation (1);
  Activate the phase according to equation (3);
  \[
t = 0 
  \]
  end if
end for

**Comparison of MaxQueue and MaxPressure** MaxPressure control selects the phase with maximum pressure, which is the difference of queue length between upstream and downstream, indicating the balance of the queue length. Only consider the control logic, MaxQueue(MQ) and MaxPressure(MP) are highly similar, and both use a greedy manner to select the phase. For the case of single intersection control, MP and MQ are the same. There are no queuing vehicles on the outgoing lanes of the single intersection because it is assumed that the outgoing is infinite. Thus, the calculated pressure is exactly the queue length.

MP considers the neighbor influence, stabilizes the queue length, and maximizes the throughput by selecting the phase with maximum pressure. The key idea of MP is that ensure the vehicles can’t be stopped by the queue vehicle of the upstream. Therefore, if a phase has a large pressure, the queue length can only be larger. The MP method is really effective when the traffic road length is small because the neighbor vehicles can fast influence the current intersection.

However, when the traffic road length is longer, the influence may come after several \( t_{\text{duration}} \), and the pressure is not effective. For example, set \( t_{\text{duration}} = 15s \) and vehicles’ maximum velocity is \( 10m/s \); if the road is 100m, then it takes 10s to the neighbor, and the neighbor condition influences the policy; if the road is 300m, then it takes at least 30s to the neighbor, and the policy can’t be influenced by the neighbor condition.

In summary, if the traffic road is relatively long, the MQ will perform better; if the traffic road is relatively short, the MP will perform better.

**4.3 QL-XLight**

We develop an RL-based TSC methods template with queue length as the traffic state and reward, QL-XLight. Based on QL-XLight, DQN, FRAP, and CoLight are introduced as the based model, and we get QL-DQN, QL-FRAP, and QL-CoLight.

- **State** The current phase and queue length are used as the state representation (agent observations).
- **Action** At time \( t \), each agent choose a phase \( \hat{d} \) according to the state, and the traffic signal will be changed to \( \hat{d} \).
- **Reward** Negative intersection queue length is used as the reward. The reward for the agent controlling intersection \( i \) is denoted by
\[
r_i = -Q_i = -\sum q(l), l \in L^i_{\text{in}} 
\] (4)
in which \( q(l) \) is the queue length at lane \( l \). By maximizing the reward, the agent is trying to maximize the throughput in the system.

**Deep Q-learning** The DQN agents are updated by the Bellman Equation:
\[
Q(s_t, a_t) = R(s_t, a_t) + \gamma \max_{a_{t+1}} Q(s_{t+1}, a_{t+1})
\] (5)
in which \( s_t \) and \( s_{t+1} \) are the state, \( a_t \) and \( a_{t+1} \) are the action.

**Base model** The following base models are introduced to get QL-DQN, QL-FRAP, QL-CoLight:

- **DQN based model.** A simple DQN[8] with only two fully connected layers. The neural network structure is straightforward and basic. Besides, we also adopt the decentralized approach from MPLight to train the model. We refer to a simple DQN based approach as QL-DQN.
- **FRAP-based model.** FRAP[22] is adopted as one of the base models. FRAP can learn the phase competition in TSC with a specially designed architecture. It has a fast training process compared with other TSC methods. FRAP has been used as the base model by MPLight. We refer to FRAP based approach as QL-FRAP.
- **CoLight based model.** CoLight[17] is graph attention network[15] based method, and learns intersection communication and cooperation for TSC. CoLight is capable of large-scale TSC. We will adopt CoLight as one of the base models. We refer to CoLight based model in this article as QL-CoLight.

Theoretically, we could build QL-LIT and QL-HiLight. However, because the code of HiLight is not available, we implement QL-FRAP, QL-CoLight, and QL-DQN first, without the loss of validity of our conclusion.

**Parameter Sharing** Parameters of the network are shared among all the agents. It is essential to improve model performance[1]. Besides, the replay memory is also shared so that all the intersections can benefit from the experiences of others. Note that the CoLight based model does not need parameter sharing. Some baseline models are also trained under parameter sharing for fair model comparison.

**Discussion** We are not the first that introduce queue length into both state and reward, but we are the first to propose queue length as an effective state representation. IntelliLight[18] uses complex state and reward representation apart from queue length. GCN[9] uses queue length and average velocity as state, total wait time as a reward. Tan et al. [11] uses queue length as state, queue length and a number of running vehicles as a reward. Although these studies have used queue length as state representation, they do not emphasize queue length property.
The results of FRAP\textsuperscript{22} and CoLight\textsuperscript{17} demonstrates the poor performance of IntelliLight and GCN. In addition, the reward in \textsuperscript{11} indicates the smaller queue length and running number, the better results, which is unreasonable because for the number of running vehicles, the larger, the better. Therefore, the reward is also essential for RL-based TSC, and only queue length is more reliable than that used in IntelliLight, GCN, and \textsuperscript{11}.

5 Experiment

5.1 Settings

Simulator We conduct the experiments on an open-source simulator called CityFlow\textsuperscript{21}, which supports large-scale traffic signal control and has faster speed than SUMO. The simulator provides the environment observations to the agent and receives the command from the agent. In the experiments, each green signal is followed by three-second yellow time and two-second all red time to prepare the transition.

Table 3: Average arrival rate of the two datasets

| Dataset     | Arrival rate (vehicles/s) |
|-------------|---------------------------|
| $D_{JiNan_1}$ | 1.75                      |
| $D_{JiNan_2}$ | 1.21                      |
| $D_{JiNan_3}$ | 1.53                      |
| $D_{HangZhou_1}$ | 0.83                   |
| $D_{HangZhou_2}$ | 1.94                   |

Datasets We use five real-world dataset\textsuperscript{1} in the experiment, three from Jinan and two from Hangzhou. These datasets have been wildly used by various methods such as MPLight, CoLight, and HiLight.

Each traffic dataset consists of two parts: (1) traffic road-net dataset; (2) traffic flow dataset. The traffic road-net dataset describes the traffic network, including lanes, roads, and intersections. The traffic flow dataset contains vehicles travel information, which is described as $(t, u)$, where $t$ is the time that each vehicle starts entering the traffic network, $u$ is the pre-planned route from its original location to destination.

- **Jinan datasets**: The road network has 12 intersections $(3 \times 4)$. Each intersection is four-way, with two 400-meter road segments (East-West) and two 800-meter road segments (South-North). There are three traffic flow datasets, and they have different average arrival rates (Table 3).
- **Hangzhou datasets**: The road network has 16 intersections $(4 \times 4)$. Each intersection is four-way, with two 800-meter road segments (East-West) and two 600-meter road segments (South-North). There are two traffic flow datasets, and they also have different average arrival rates (Table 3).

\textsuperscript{2}https://cityflow-project.github.io

\textsuperscript{3}https://traffic-signal-control.github.io

Evaluation metric Based on existing studies in traffic signal control\textsuperscript{17}, we choose average travel time as the evaluation metric, which is the mostly used metric to evaluate control performance in the TSC. The travel time of each vehicle is the time speed between entering and leaving the traffic network. We use all the vehicles’ average travel time to evaluate the model performance.

Compared methods We compare our methods with the following baseline methods, including both transportation and RL methods. For a fair comparison, the phase number is set as four, and the action interval (phase duration) is set as 15 seconds. All the RL methods are learned with the same hyper-parameters. 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 results.

- **Transportation Methods**:  
  - Fixed-Time\textsuperscript{5}: a policy uses fixed cycle length with predefined phase split among all the phases.  
  - Max-Pressure\textsuperscript{14}: the max-pressure control selects the phase with maximum pressure.

- **RL Methods**:  
  - FRAP\textsuperscript{22}: uses a novel network structure to capture phase competition relation between different traffic movements. FRAP is trained with parameter sharing for fairly comparison.  
  - PressLight\textsuperscript{16}: incorporates pressure in the state and reward design for the RL model and has shown superior performance in multi-intersection control problems. PressLight is trained with parameter sharing for fairly comparison.  
  - MPLight\textsuperscript{1}: a FRAP\textsuperscript{22} based decentralized model, incorporates pressure in the state and reward design and has shown superior performance in city-level TSC. It is one state-of-the-art RL-based TSC method.  
  - CoLight\textsuperscript{17}: another state-of-the-art method uses a graph attention network to realize intersection cooperation and has shown superior performance in large-scale TSC.

Our Proposed Methods:  
- **MaxQueue**: the MaxQueue control selects the phase with maximum queue length.  
- **QL-DQN**: adopts a two-layer network as the base model, uses queue length and current phase as state, intersection queue length as a reward.  
- **QL-FRAP**: a FRAP-based model, uses queue length and current phase as state, intersection queue length as a reward.  
- **QL-CoLight**: a CoLight based model, uses queue length and current phase as state, intersection queue length as a reward.

5.2 Overall Performance

Table 2 reports our experimental results under JiNan and HangZhou real-world datasets with respect to the average travel time. We have the following findings:
5.3 State representation is also essential

Both the neural network structure and the state representation play an important role in the performance improvement. However, most studies pay attention to the network design. We will demonstrate that the state representation is also essential.

QL-DQN uses a simple neural network structure, but effective state representation. FRAP and CoLight use advanced neural network structure, but the state representation is not effective. In addition, FRAP, CoLight, and QL-DQN use the same reward. Compare the performance of QL-DQN with FRAP and CoLight, QL-DQN is consistently better over all the datasets.

Therefore, we can conclude that state representation is also essential as neural network structure for TSC. The state representation should be paid more attention in TSC.

| Method    | JiNan 1  | JiNan 2  | JiNan 3  | HangZhou 1 | HangZhou 2 |
|-----------|---------|---------|---------|------------|------------|
| FixedTime | 428.11% (+56.29%) | 368.77% (+50.29%) | 383.01% (+55.82%) | 495.57% (+71.75%) | 406.65% (+16.53%) |
| MaxPressure | 254.96 | 245.38 | 245.81 | 288.54 | 348.98 |
| PressLight | 314.63% (+14.85%) | 264.62% (+7.84%) | 258.12% (+5.01%) | 385.71% (+33.68%) | 458.12% (+31.27%) |
| FRAP       | 296.46% (+8.21%) | 266.93% (+8.78%) | 269.64% (+9.69%) | 309.60% (+7.30%) | 356.47% (+2.15%) |
| MPLight    | 297.46% (+8.58%) | 270.05% (+10.05%) | 276.15% (+12.34%) | 314.60% (+9.03%) | 357.61% (+2.47%) |
| CoLight    | 272.06% (+0.69%) | 252.44% (+2.88%) | 249.56% (+1.53%) | 297.02% (+2.94%) | 347.27% (-0.49%) |
| MaxQueue   | 268.21% (-2.10%) | 238.91% (-2.64%) | 237.8% (-3.26%) | 283.12% (-1.88%) | 324.38% (-7.05%) |
| QL-DQN     | 260.74% (-4.83%) | 245.32% (0.02%) | 239.33% (-2.64%) | 284.74% (-1.32%) | 333.44% (-4.45%) |
| QL-FRAP    | 255.53% (-6.73%) | 238.74% (-2.71%) | 236.04% (-3.97%) | 282.28% (-2.17%) | 315.03% (-9.73%) |
| QL-CoLight | 254.94% (-6.94%) | 239.05% (-2.58%) | 236.25% (-3.89%) | 282.17% (-2.21%) | 322.75% (-7.52%) |

(1) Our proposed MaxQueue consistently outperforms all other previous methods. MaxQueue has a significant improvement as a conventional transportation method compared to MaxPressure. In addition, MaxQueue has superior performance than MPLight and CoLight. The conventional transportation methods are still powerful.

(2) Our proposed QL-DQN, QL-FRAP, and QL-CoLight outperform all other previous methods. With only changing the state and reward compared to MPLight and CoLight, the improvement of QL-FRAP and QL-CoLight is significant, proving the importance of state representation for RL-based TSC.

(3) QL-FRAP and QL-CoLight are state-of-the-art among traditional and RL-based TSC methods. CoLight and MPLight are the previous state-of-the-art methods, and QL-FRAP and QL-CoLight have a better performance. Besides, QL-XLight only uses queue length information of a particular intersection, which has the advantage of deployment than CoLight and MPLight.

(4) Parameter sharing is essential for RL-based models. MPLight[1] has shown better performance than FRAP and addresses the importance of parameter sharing. However, when FRAP is trained with parameter sharing same to MPLight, it has slightly better performance than MPLight.

5.4 Performance under different phase duration

Experiments are also conducted under different phase duration for further model comparison. Figure 2 reports the model performance under different phase duration. QL-DQN, QL-FRAP, and QL-CoLight consistently perform better than CoLight and MPLight over all the datasets and phase duration. MaxQueue performs better than MPLight and CoLight in most cases, except at JiNan 1 and JiNan 3 when $t_{duration} = 10s$. MaxQueue also perform better than QL-DQN in most cases. The performance of MaxQueue addresses that the transportation method is still powerful and essential.

5.5 Reward comparison

PressLight and MPLight have demonstrated that RL approaches perform better under pressure than queue length. We will re-test the impact of reward settings with queue length as the state representation. The FRAP and CoLight are used as the base model; experiments are conducted under the following configurations:

- Config1: queue length and current phase are used as the state, intersection queue length as the reward. This is exactly QL-XLight.
- Config2: queue length and current phase are used as the state, intersection pressure as the reward.

Experiments are conducted over all the datasets, and Figure 3 reports the model performance with a different reward.
Figure 3: Model performance under different reward w.r.t average travel time, the smaller the better.

QL-FRAP performs better under queue length than pressure. The performance difference is not promising. QL-CoLight has significantly better performance under queue length than pressure. The CoLight based model has poor performance under pressure, maybe the property of GAT that already considers the neighbor influence and optimizes the global queue length in the network.

Considering the calculation of state and reward, the queue length is easier to get because pressure requires complex calculation and neighbor information. Queue length can directly get from the traffic environment. In summary, using the queue length as state and reward is a better choice.

6 Conclusion

In this paper, we propose an effective state representation as queue length. Based on queue length, we developed a transportation method: MaxQueue and an RL template: QL-XLight. Our proposed methods have demonstrated superior performance than the previous state-of-the-art method, and QL-CoLight achieves state-of-the-art performance. The importance of transportation methods is also addressed by MaxQueue. The comparison of QL-DQN with FRAP and CoLight demonstrates that state representation is as essential as a neural network structure. In a word, we should pay more attention to the state design apart from the neural network design.

However, only queue length as the state representation is not enough for the complex traffic conditions, and more information about the traffic conditions should be added to the state representation. In future research, we will try to add more information about the traffic conditions to the RL agent observations. In addition, a more complex reward and novel network structure are also taken into consideration to improve the performance of TSC.

7 Acknowledgments

References

[1] Chen, C.; Wei, H.; Xu, N.; Zheng, G.; Yang, M.; Xiong, Y.; Xu, K.; and Li, Z. 2020. Toward a thousand lights: Decentralized deep reinforcement learning for large-scale traffic signal control. In Proceedings of the AAAI Conference on Artificial Intelligence, volume 34, 3414–3421.

[2] Cools, S.-B.; Gershenson, C.; and D’Hooghe, B. 2013. Self-organizing traffic lights: A realistic simulation. In Advances in applied self-organizing systems, 45–55. Springer.

[3] Gershenson, C. 2004. Self-organizing traffic lights. arXiv preprint nlin/0411066.

[4] Hunt, P.; Robertson, D.; Bretherton, R.; and Royle, M. C. 1982. The SCOOT on-line traffic signal optimisation technique. Traffic Engineering & Control, 23(4).

[5] Koone, P.; and Rodengerdts, L. 2008. Traffic signal timing manual. Technical report, United States. Federal Highway Administration.

[6] Le, T.; Kovács, P.; Walton, N.; Vu, H. L.; Andrew, L. L.; and Hoogendoorn, S. S. 2015. Decentralized signal control for urban road networks. Transportation Research Part C: Emerging Technologies, 58: 431–450.

[7] Lowrie, P. 1992. SCATS: A traffic responsive method of controlling urban traffic control. Roads and Traffic Authority.

[8] Mnih, V.; Kavukcuoglu, K.; Silver, D.; Rusu, A. A.; Veness, J.; Bellemare, M. G.; Graves, A.; Riedmiller, M.; Fidjeland, A. K.; Ostrovski, G.; et al. 2015. Human-level control through deep reinforcement learning. nature, 518(7540): 529–533.

[9] Nishi, T.; Otaki, K.; Hayakawa, K.; and Yoshimura, T. 2018. Traffic signal control based on reinforcement learning with graph convolutional neural nets. In 2018 21st International conference on intelligent transportation systems (ITSC), 877–883. IEEE.

[10] Sun, X.; and Yin, Y. 2018. A simulation study on max pressure control of signalized intersections. Transportation research record, 2672(18): 117–127.

[11] Tan, T.; Bao, F.; Deng, Y.; Jin, A.; Dai, Q.; and Wang, J. 2019. Cooperative deep reinforcement learning for large-scale traffic grid signal control. IEEE transactions on cybernetics, 50(6): 2687–2700.

[12] Török, J.; and Kertész, J. 1996. The green wave model of two-dimensional traffic: Transitions in the flow properties and in the geometry of the traffic jam. Physica A: Statistical Mechanics and its Applications, 231(4): 515–533.

[13] Van der Pol, E.; and Oliehoek, F. A. 2016. Coordinated deep reinforcement learners for traffic light control. Proceedings of Learning, Inference and Control of Multi-Agent Systems (at NIPS 2016).

[14] Varaiya, P. 2013. Max pressure control of a network of signalized intersections. Transportation Research Part C: Emerging Technologies, 36: 177–195.

[15] Velicković, P.; Cucurull, G.; Casanova, A.; Romero, A.; Lio, P.; and Bengio, Y. 2017. Graph attention networks. arXiv preprint arXiv:1710.10903.
[16] Wei, H.; Chen, C.; Zheng, G.; Wu, K.; Gayah, V.; Xu, K.; and Li, Z. 2019. Presslight: Learning max pressure control to coordinate traffic signals in arterial network. In Proceedings of the 25th ACM SIGKDD International Conference on Knowledge Discovery & Data Mining, 1290–1298.

[17] Wei, H.; Xu, N.; Zhang, H.; Zheng, G.; Zang, X.; Chen, C.; Zhang, W.; Zhu, Y.; Xu, K.; and Li, Z. 2019. Co-light: Learning network-level cooperation for traffic signal control. In Proceedings of the 28th ACM International Conference on Information and Knowledge Management, 1913–1922.

[18] Wei, H.; Zheng, G.; Yao, H.; and Li, Z. 2018. Intellilight: A reinforcement learning approach for intelligent traffic light control. In Proceedings of the 24th ACM SIGKDD International Conference on Knowledge Discovery & Data Mining, 2496–2505.

[19] Xu, B.; Wang, Y.; Wang, Z.; Jia, H.; and Lu, Z. 2021. Hierarchically and Cooperatively Learning Traffic Signal Control. In Proceedings of the AAAI Conference on Artificial Intelligence, volume 35, 669–677.

[20] Zang, X.; Yao, H.; Zheng, G.; Xu, N.; Xu, K.; and Li, Z. 2020. Metalight: Value-based meta-reinforcement learning for traffic signal control. In Proceedings of the AAAI Conference on Artificial Intelligence, volume 34, 1153–1160.

[21] Zhang, H.; Feng, S.; Liu, C.; Ding, Y.; Zhu, Y.; Zhou, Z.; Zhang, W.; Yu, Y.; Jin, H.; and Li, Z. 2019. Cityflow: A multi-agent reinforcement learning environment for large scale city traffic scenario. In The World Wide Web Conference, 3620–3624.

[22] Zheng, G.; Xiong, Y.; Zang, X.; Feng, J.; Wei, H.; Zhang, H.; Li, Y.; Xu, K.; and Li, Z. 2019. Learning phase competition for traffic signal control. In Proceedings of the 28th ACM International Conference on Information and Knowledge Management, 1963–1972.

[23] Zheng, G.; Zang, X.; Xu, N.; Wei, H.; Yu, Z.; Gayah, V.; Xu, K.; and Li, Z. 2019. Diagnosing reinforcement learning for traffic signal control. arXiv preprint arXiv:1905.04716.