Efficiency and Equity are Both Essential: A Generalized Traffic Signal Controller with Deep Reinforcement Learning

Shengchao Yan, Jingwei Zhang, Daniel Buescher, Wolfram Burgard

Abstract—Traffic signal controllers play an essential role in the traffic system, while the current majority of them are not sufficiently flexible or adaptive to make optimal traffic schedules. In this paper we present an approach to learn policies for the signal controllers using deep reinforcement learning. Our method uses a novel formulation of the reward function that simultaneously considers efficiency and equity. We furthermore present a general approach to find the bound for the proposed equity factor. Moreover, we introduce the adaptive discounting approach that greatly stabilizes learning, which helps to keep high flexibility of green light duration. The experimental evaluations on both simulated and real-world data demonstrate that our proposed algorithm achieves state-of-the-art performance (previously held by traditional non-learning methods) on a wide range of traffic situations. A video of our experimental results can be found at: https://youtu.be/3rc5-ac3XX0

I. INTRODUCTION

Traffic congestions are enormously expensive in terms of fuel and time and many cities all over the world suffer from them [1]. Moreover, the emissions of road transport have been considered as the main cause for air pollution [2], [3]. To alleviate traffic congestion and the associated problems, people have been investigating smarter and cleaner vehicles [4], [5]. However, another way to improve the effectiveness of road traffic is to optimize the scheduling of traffic lights.

In this paper, we focus on reducing congestions by improving automated traffic controllers. More specifically, we focus on traffic signal controllers (TSCs) for isolated intersections [6], i.e., signalized intersections whose traffic is unaffected by any other controllers or supervisory devices.

The performance of conventional fixed-time TSCs or actuated TSCs is limited by the restricted setup and the relative primitive sensor information available. Recently, adaptive TSCs [7] are attracting more attention due to their high degree of flexibility. Advances in perception and vehicle-to-everything (V2X) communication [8] could make such controllers even better by providing more traffic information, such as real-time locations and velocities of the vehicles. With more detailed information available, adaptive TSCs have the potential to provide optimal control according to real-time traffic situations. One approach to achieve this is by considering traffic signal optimization as a scheduling problem [7], [9], which treats the junction as a production line and the input vehicles as different products to be processed. However, this line of methods suffers from the curse of dimensionality when dealing with a large amount of vehicles [10]. In turn, these methods can only satisfy real-time requirements for either oversimplified intersections or under small traffic flow rates.

A recent line of research proposes to design adaptive TSCs based on deep reinforcement learning (DRL). DRL has been shown to reach state-of-the-art performance in various domains [11], [12]. However, the performance of DRL approaches in the traffic domain could be pushed further, in particular with regards to the following limitations:

- Most previous approaches have focused on improving efficiency, which is calculated according to the average travel time of vehicles in intersection. However, we argue that the equity of the travel time of individual vehicles is also of vital importance. Previous works have been mostly evaluating in scenarios with relatively low traffic flow, in which case the trade-off between efficiency and equity might not have a great influence on the performance of the controller. However, in dense traffic with nearly- or even over-saturated intersections and unbalanced traffic density on incoming lanes, the efficiency-equity trade-off can be an important factor.
- The flexibility of adaptive TSCs has not been sufficiently explored. Instead, most approaches employ fixed green traffic light duration or fixed traffic light cycles.
- Previously proposed DRL agents are trained and evaluated in relatively simplified traffic scenarios: very few traffic cycles with limited variation or evenly distributed flow for each incoming lane [13]. Thus, their experimental results might not be sufficient indicators of their performance in real traffic scenarios.
- Current DRL-based approaches have shown performance improvement mainly against fixed-time or actuated TSCs. They either have not compared with state-of-the-art adaptive TSCs, such as the Max-Pressure controller [14], or do not surpass state-of-the-art performance [15], [13].

To overcome these limitations, we present a novel method that is comprised of the following contributions:

- An equity factor to trade off efficiency (average travel time) against equity (variance of individual travel times) as well as a solution to calculate a rough bound for it.
- An adaptive discounting method to account for the issues brought by transitional phases in traffic cycles, which is shown to substantially stabilize learning.
• A learning strategy that surpasses state-of-the-art baselines. It is generic with regards to different traffic flow rates, traffic distributions among incoming lanes and intersection topologies.

In line with the aforementioned DRL approaches, we conduct experimental studies in the traffic simulation environment SUMO [16]. We show that our method achieves state-of-the-art performance, which had been held by traditional non-learning methods, on a wide range of traffic flow rates with varying traffic distributions on the incoming lanes.

II. RELATED WORKS

In traditional fixed-time TSC designs [6], the traffic flow rates at intersections are treated as constants, and the green-red phases for each route are scheduled in a cyclic manner. Then the duration for each green phase is optimized using history flow rates. The Uniform TSC with the same fixed duration for all green phases and the Webster’s method [17] with pre-timed duration according to latest traffic history are usually used as baselines in TSC works [13]. As in the real world the traffic flow rates generally vary across lanes and across time, the performance of such TSCs could be very restricted in real traffic.

Actuated TSCs [6] make use of loop detectors, which are electromagnetic sensors mounted within the road pavement. Such sensors can detect the incoming vehicles and estimate their velocity when they pass by, so that actuated TSCs can dynamically react to the vehicles driving into the intersection. Yet, their performance are still restricted due to the limited information provided by the sensor.

Since decades researchers have been investigated on developing adaptive TSCs, which can schedule traffic lights acyclic and with flexible green phase duration according to the real-time traffic situation of the whole intersection. Some early works like [18], [19] have been largely applied in real traffic designs. Yet it is still believed that the performance of TSC can be further improved. In recent years, analytical [20], [8], heuristic [14], [21] and learning-based [22], [13], [15], [23] approaches have been proposed. Among these, the heuristic Max-Pressure method [14] is reported to be holding state-of-the-art performance [13]. DRL-based methods hold great promise with the possibility to learn generalized and flexible controller policies by interacting with traffic simulators, as well as that they could provide scheduling decisions in real-time, as opposed to some non-learning methods that need optimization iterations before giving out each decision.

Only a few works have deployed DRL for isolated intersection TSCs [24], [15], [25], [13], however, none of them were able to surpass state-of-the-art performance achieved by the Max-pressure method. Each of these method proposes its own reward functions for training the agent, but the connection between them has not been clear. In this work we attempt to give such an analysis of those different reward functions that have been proposed (Sec.III-D).

While efficiency has been the main objective for most of these works, some previous algorithms actually had considered equity implicitly. They [26], [23], [24] design the reward as a weighted sum of several different quantities about the intersection. However, finding the optimal weighting is non-trivial. In this paper we instead propose an equity factor along with a method to calculate its rough bound.

III. METHODS

A. Background

We consider the task of traffic signal control in standard reinforcement learning settings. At each step, from its current state \( s \in S \) the agent selects an action \( a \in A \) according to the policy \( \pi(\cdot|s) \). It then transits to the next state \( s' \in S \) and receives a scalar reward \( r \in \mathbb{R} \). The state, action spaces as well as the reward function in our method are discussed in the next subsections.

For learning the optimal policy that maximizes the discounted (by \( \gamma \)) cumulative expected rewards, we use proximal policy optimization (PPO) [12] as the backbone DRL algorithm. For a policy \( \pi_\theta \) parameterized by \( \theta \), PPO maximizes the following objective:

\[
J_\theta = \mathbb{E}_t \left[ \min \left( \rho_t(\theta) A_t, \text{clip} \left( \rho_t(\theta), 1 - \epsilon, 1 + \epsilon \right) A_t \right) + \beta_{\text{entropy}} \cdot H \left( \pi_\theta(s_t) \right) \right],
\]

where the expectation is taken over samples collected by following \( \pi_{\theta_{\text{old}}} \), and \( \rho_t(\theta) = \frac{\pi_{\theta_{\text{old}}}(a_t|s_t)}{\pi_\theta(a_t|s_t)} \) is the importance sampling ratio. \( H \) represents the entropy of the current policy, \( \beta_{\text{entropy}} \) adjusts the strength of entropy regularization. \( A_t \) is a truncated version (on trajectory segments of length up to \( K \)) of the generalized advantage estimator [27], which is an exponentially-weighted average (controlled by \( \lambda \)):

\[
A_t = \delta_t + (\gamma \lambda) \delta_{t+1} + \cdots + (\gamma \lambda)^{K-1-t} \delta_{K-1},
\]

where \( \delta_t = r_t + \gamma V_{\phi_{\text{old}}}(s_{t+1}) - V_{\phi_{\text{old}}}(s_t) \). The value function \( V_{\phi_{\text{old}}} \), parameterized by \( \phi_{\text{old}} \), is learned by minimizing the following loss (with coefficient \( \beta_{\text{value}} \)):

\[
\mathcal{L}_{\phi} = \beta_{\text{value}} \cdot \mathbb{E}_t \left[ \left\| V_{\phi}(s_t) - \left( V_{\phi_{\text{old}}}(s_t) + A_t \right) \right\|^2 \right].
\]

B. Action Space

We carry out our method on four-road intersections where each road contains three incoming lanes (one forward-only, one forward+right-turning, one left-turning. Fig.14). We note that our approach can easily generalize to other types of intersections.

The agent has an action space of size \( 4 \times 4 \times 4 \): the two sets of the two facing directions (north and south, east and west) can schedule at the same time either of the following two signal combinations (Fig.15): • Green light for the forward-only and forward+right-turning lanes and red light for the left-turning lanes; • Green light for the left-turning lanes and red light for the rest. In order to give the agent more flexibility, we set the duration for each of the 4 actions as 1 second.

We note that choosing any of the four actions means scheduling a distinct green phase. While during the transition between different green phases, yellow or all-red phases must be scheduled. In our work, a 3s-yellow and a 2s-all-red phase
will be automatically scheduled before activating a new green phase. We denote this constant $T_{yr} = 5s$ as the duration for this yellow-red phase.

Due to this setting, if two different actions (green phases) are scheduled consecutively, the effective duration of the second action is 6s instead of 1s; while if the same action (green phase) is scheduled for two times in a row, then the effective duration for the second action is still 1s. During the learning process, the aforementioned two scenarios should not be treated equally. To cope with this we propose the method of *adaptive discounting* which will be presented when discussing the reward function (Sec III-D).

**C. State Space**

At each process step, the state $s_t$ the agent receives is comprised of the following components: ▪ The distance along the lane to the traffic light and the velocity of each vehicle that is within 150m range (each lane has a maximum capacity of 19 vehicles) to the center of the intersection. Since there are in total 12 incoming lanes (3 for each of the four roads), this component results in a vector of size $12 \times 19 \times 2$. The values are normalized to be within $[-1, 1]$. If any lane does not reach its maximum capacity, the corresponding position and velocity values will be set to 1 and $-1$. ▪ The action of the last step $a_{t-1}$ (in one hot encoding so a 4-dimensional vector). ▪ A traffic signal counter that contains for each action the number of steps since its last execution. This 4-dimensional vector is normalized by the maximum length $T$ of an episode. This component along with the last action $a_{t-1}$ helps to avoid state-aliasing.

**D. Reward Function**

Several different reward functions have been proposed in previous works to train DRL agents for controlling traffic signals. However, the reasoning behind different designs have not been clearly presented, also the connection between those different choices and the different effects they are causing have not been thoroughly analyzed. We attempt for such an analysis below, which indicates that the vanilla versions of different choices and the different effects they are causing have not been thoroughly analyzed. We attempt for such an analysis below, which indicates that the vanilla versions of those rewards tend to result in policies that only consider time efficiency (average travel time in an intersection). We then propose solutions that also take equity (variance of individual travel time) into consideration.

1) Definitions: We first give the definitions of several important concepts in traffic intersections systems. We visualize the important ones in Fig 2.

- Total number of vehicles in the intersection ($N$): At $t$, the number of vehicles in the intersection system $N_t$ is the total number of vehicles that are within a certain range to the intersection center (e.g. 150m) but have not yet passed through the traffic lights on their corresponding incoming lane.
- Throughput ($N^{TP}$): The number of vehicles that pass through the traffic lights of their corresponding incoming lane within $[t-1, t]$ is denoted $N^{TP}_t$.
- Travel time ($T_{travel}$): For a single vehicle, its travel time is counted as the time period starting from when it enters the intersection and ending when it passes through its corresponding traffic light. The total travel time of the intersection is the summation of the individual travel times of all vehicles in the intersection. We note an equivalent way of calculating the total travel time is to count $N_t$ and sum this value over a given time period.
- Delay time ($T_{delay}$): Similar to travel time, except that a constant is subtracted from each individual travel time: $T_{delay} = T_{travel} - T_{free}$, where $T_{free}$ is the constant time length for a vehicle to pass through the intersection system with no cars ahead and green lights always on.
- Traffic flow rate ($F$): The number of vehicles that pass through an intersection in unit time. A commonly used unit is the number of vehicles per hour $/h$.
- Saturation flow rate ($F_s$): This is a constant representing the traffic flow rate for one lane under the condition that the traffic light stays green during unit time and that the flow of traffic is as dense as it could be [28].

2) Reward Function Categories: Given the above definitions, the majority of the different reward functions proposed in the TSC domain can be categorized into the following two:

- Throughput-based reward functions $R^{TP}$ [23]. The vanilla form of this category uses the throughput $N^{TP}_t$ as the reward for step $t$. Learning on this reward function means maximizing the cumulative throughput of the intersection. The change in throughput $N^{TP}_t - N^{TP}_{t-1}$ has also been used as a reward function [29].
- Travel-time-based reward functions $R^{TT}$ [15], [13], [22], [24], [23]. As mentioned before, the total travel time of an intersection for a given period of time $[t_{start}, t_{end}]$ can be calculated as the summation of $N_t$ for a given period of time: $\sum_{t_{start}}^{t_{end}} N_t$. The vanilla reward function of this type thus uses $-N_t$ as the reward for step $t$. We note that $N_t = N_{t-1} - N^{TP}_t + N^{TP}_{t+N}$ where $N^{TP}_{t+N}$ denotes the number of new vehicles input into the system from $t-1$ to $t$, which is commonly assumed to be determined solely by the traffic flow distribution thus is out of the control of TSC. Learning on this reward function would result in policies that minimize cumulative delay time. Many variants of this form of reward function have been investigated, e.g., the change of cumulative delay time between actions, the total
3) Adaptive Discounting: When calculating rewards of either of the two reward categories, the two scenarios discussed in Sec. III-D should not be discounted in the same way. We propose the method of adaptive discounting that properly discount for those scenarios and is shown to be critical for convergence in our experiments.

We illustrate this method under the throughput based reward $R_t^{TP}$ in Fig. 2. At system elapsed time 10 the reinforcement learning process is at step $t$. The action $a_t$ is chosen that schedules green lights for the left-turning lanes for the north-south roads. Transitioning from $t$ to $t + 1$, the throughput reward obtained is $r_{t+1} = 2$. This is a normal RL iteration and no special adjustments need to be done. But at step $t + 1$ when the system elapsed time is at 11, the action $a_{t+1}$ is chosen to schedule green lights for the forward-right turning lanes of the north-south roads, which is a different green phase than the one chosen by $a_t$. With the traffic system implementation this means a 3s-yellow and a 2s-all-red phase will be automatically scheduled before the chosen new green phase, where the 5s intermediate phase and the chosen 1s green phase are all within step $t + 2$ of the learning process. In the scenario shown in Fig. 2 the throughput obtained at elapsed times $\{12, 13, 14, 15, 16, 17\}$ are $\{1, 0, 0, 0, 2\}$. With no special treatment when counting the reward for step $t + 2$ this would be $r_{t+2} = 3$. But this could lead to undesired properties since this the agent gets those yellow and all-red phases “for free” for collecting extra rewards whenever it chooses to schedule a different green phase, and that its subsequent states are not sufficiently discounted as well. Furthermore, if the throughput of two episodes happen to match at every system elapsed time, they should obtain exactly the same return. While the transitional yellow and all-red phases mean that it is not anymore a one-to-one mapping between the system time and the process step. So when discounting according to the process step, those two episodes of interest could lead to different returns. This issue has been overlooked in the current literature of DRL methods for TSC designs [13], [22]. Thus we propose the method of adaptive discounting to account for the mismatch between the two timing paradigms, in which we discount the reward for $t + 2$ as:

$$r_{t+2} = 1 + \gamma \cdot 0 + \gamma^2 \cdot 0 + \gamma^3 \cdot 0 + \gamma^4 \cdot 0 + \gamma^5 \cdot 2,$$

and a discount factor of $\gamma^6$ instead of $\gamma$ will be used for the subsequent reward or value.

4) The Equity Factor: Having presented the adaptive discounting technique, now we present the equity factor for reward functions for training TSC.

The aforementioned two types of reward functions (throughput-based and travel-time based) both treats effi-
ciency, i.e. average travel time of the intersection as the major concern. Equity, the variance of individual travel times, is at least not explicitly considered. Take the following scenario as an example: Assuming the north-south roads are saturated with dense traffic flows, while the east-west roads have lighter traffic. Then the policy to maximize the cumulative throughput should always keep the north-south traffic lights green, while keeping the east-west lights red. However, this means that the vehicles on the east-west roads might have to wait for an intolerable long time to pass through the intersection. This is due to that in the vanilla reward definitions (Sec.III-D.2), every vehicle contributes equally to the throughput or to the travel time, independent of how long it has been (waiting) in the intersection.

Following the above analysis, we propose to use an equity factor $\eta$ in the reward function. The basic idea is to adapt the contribution of each vehicle to the reward according to its travel time in the intersection system. We consider three ways to incorporate $\eta$ into the reward calculation: linear ($\eta \cdot T_{\text{travel}}$), power ($T_{\text{travel}}^{\eta}$) and exponential ($\eta T_{\text{travel}}$). Since simply scaling the rewards does not change the value function landscape, we mainly consider the power and exponential forms. During research our experiment results show that the power form equity factor leads to convergence to better policies than the exponential form. Therefore, we focus on the analysis of the power function in the following.

To define the proper range of the equity factor $\eta$ for the power function form of reward $T_{\text{travel}}^{\eta}$, two special scenarios are considered. 

- Scenario 1: Only one vehicle is waiting at the intersection at step $t$, and its travel time at this step is $\tau$. With the equity factor $\eta$ and the discount factor $\gamma$, the return contributed by this vehicle would be $\gamma \cdot (\tau + 1)^{\eta}$ if it passed through the traffic light at $t$, and $\gamma \cdot (\tau + 1)^{\eta}$ so that releasing this vehicle sooner is more desirable. With this we get $\eta < \frac{\ln(\gamma)}{\ln(\tau + 1)}$.

- Scenario 2: One lane with green light is over-saturated, while a single car is waiting at red light on another lane. In the case where the over-saturated lane always has green light on and the single vehicle is never released, the return for any state $s_t$ is $G^e = T_{\text{free}} \gamma (1 + \gamma^2 + (\gamma^2)^2 + \cdots) = \frac{T_{\text{free}}}{1 - \gamma^2}$ (denoted as $G^e$ as in this case efficiency is the top priority). If the waiting vehicle is released at step $t$ then the upper limit of the return the system can obtain at state $s_t$ is (we use $G^{\text{free}}$ since this strategy cares about efficiency and equity):

$$\sup(G^{\text{free}}) = T_{\text{free}} + \gamma \cdot T_{\text{travel}} \cdot (T_{\text{free}} + 2 T_{\text{travel}} + 1) = \frac{T_{\text{free}}}{1 - \gamma^2}.$$ (5)

The three terms in the summation are all calculated out of the best case scenario (the traffic light on the saturated lane turns yellow then red for a total of $T_{\text{travel}}$ elapsed time, then the light on the single vehicle lane turns green then turns yellow as soon as this single vehicle passes through) to admit to the upper limit: the first term is the reward obtained by the vehicles on the saturated lane that manage to pass through the intersection at the beginning of the yellow-red phase; the second term is contributed by the single vehicle which passes through the traffic light at the beginning of its green phase; the last term is the summation of the reward obtained by the vehicles on the saturated lane after the green phase switches back to this lane. We require that $G^e < \sup(G^{\text{free}})$ to release the single vehicle after certain travel time $\tau$. With these analysis a rough range of $\eta$ can be found.

We note that this is a rough calculation under our system settings as for example $T_{\text{free}}$ could be different as vehicles might have different driving models. Nevertheless the analysis gives a general solution to calculate a rough bound for $\eta$. The experimental evaluations also show that the desirable TSC policies could be learned within this rough bound.

IV. EXPERIMENTS

A. Experimental Setup

We conduct experiments using the urban traffic simulator SUMO [16] and evaluate the trained agents in both simulated one-hour traffic cycles (with the intersection type described above) and a real-world whole-day traffic cycle (with another type of intersection in Freiburg, Germany). Both intersections have a speed limit of $50\text{km/h}$. We compare with the following common baselines in the TSC domain:

- Uniform: This controller circulates green phases around each road in the intersection. Each green phase is scheduled for a same fixed period, the duration of which is a hyper-parameter of this algorithm.

- Webster’s [17]: Same as the Uniform controller, the Webster’s controller schedules traffic phases in a cyclic manner. But instead of scheduling each green phase for a fixed duration, each phase is adjusted in accordance with the latest traffic flow history. It has three hyper-parameters: the length $T_{\text{history}}$ of how long the traffic flow history to take into account for deciding the phase duration for the next $T_{\text{history}}$ period, and the minimum and maximum duration for one complete cycle.

- Max-pressure [14]: Regarding vehicles in lanes as substances in pipes, this algorithm favors control schedules that maximizes the release of pressure between incoming and outgoing lanes. More specifically, with incoming lanes containing all lanes with green traffic light in a certain phase, and outgoing lanes being those lanes where the traffic from the incoming lanes exit the intersection system, the Max-pressure controller tends to minimizes the difference in the number of vehicles between the incoming and outgoing lanes. The minimum green phase duration is a hyper-parameter.

We note the previous learning methods were not able to surpass the state-of-the-art performance held by the non-learning method Max-pressure TSC [13].

Regarding network architecture, the input size for both the policy network $\theta$ and the value network $\phi$ is $4+4+2=19+12=464$. Then $\theta$ consists of fully connected layers of sizes $2048$ (ReLU), $1024$ (ReLU) and $4$ (SoftMax), where 4 is the size of the action space. For $\phi$ the fully connected layers are of sizes $2048$ (ReLU), $1024$ (ReLU) and 1. We perform a grid
search to find the hyperparameters. We use $2.5e^{-5}$ as the learning rate for the Adam optimizer, $1e^{-3}$ as the coefficient for weight decay. For PPO, we use 32 actors, $0.2$ for the clipping $\epsilon$. In each learning step a total number of around 20 mini-batches of size 1000 is learned for 8 epochs.

B. Training

Previous methods have been focusing on relatively limited traffic situations, for example only a single one hour cycles [22] and traffic input less than $3000\text{veh/h}$ [13], [15]. In this paper we challenge our method to experience a wider range of traffic input. For the four-way junction we consider, the upper bound of the traffic capacity can be calculated as $4 \cdot F_s$, where $F_s$ is the saturation flow rate for one incoming lane. This maximum capacity is reached when all forward-going lanes of either the north-south or the east-west roads have green traffic lights and all 4 incoming lanes are in full capacity. However, this extreme scenario rarely happens in real traffic. In our experiments we found that the intersection already starts to saturate from around $3000\text{veh/h}$ of total traffic flow rate. In our training we set the range of traffic flow rate to be $[F_{\min}, F_{\max}] = [0, 6000\text{veh/h}]$ which is already much wider than that used in previous works.

With this traffic flow rate range, we sample a traffic cycle for each episode during training. Each traffic cycle is defined by these randomly sampled parameters: the total traffic flow at the beginning and end of this cycle $F_{\text{start}}$ and $F_{\text{end}}$, and for each incoming lane its traffic flow ratio of the total traffic flow at the beginning and end this cycle. $F_{\text{start}}$ is randomly sampled from $[F_{\min}, F_{\max}]$. This empirically leads to better convergence and performance than other sampling strategies. Then $F_{\text{end}}$ is sampled uniformly within $[\max(F_{\min}, F_{\begin{align*}\text{begin} - 1500}), \min(F_{\max}, F_{\begin{align*}\text{begin} + 1500})]$. The flow ratios for the 12 incoming traffic lanes are decided by sampling 12 uniform random numbers then normalize by their sum. The traffic flow in between the cycle is then linearly interpolated. The sampled traffic cycles with possibly big change of traffic flow and unbalanced traffic distribution should be enough to cover real traffic scenarios.

C. Evaluation during Training

During training, we conduct evaluation to monitor the learning progress every 20 learning steps, which corresponds to 640 episodes of experience collected by 32 actors. A total number of 5 evaluators are deployed for each evaluation phase, corresponds to traffic flow ranges of $[500,1500]$, $[1500,2500]$, $[2500,3500]$, $[3500,4500]$ and $[4500,5500]$ respectively. Each evaluator samples evaluation cycles for the corresponding range similar as how training cycles are sampled.

Ablation study is conducted to analyze the individual contributions of the different components in our proposed algorithm. The points are shown in Fig. [3] where the following agent configurations are compared: $[x] + [\eta = 0]$, $[\text{ad}] + [\eta = 0]$, $[\text{ad}] + [\eta = 1]$, $[x] + [\eta = 0.25]$, $[\text{ad}] + [\eta = 0.25]$. $[\text{ad}]$ means the corresponding configuration utilizes adaptive discounting while $[x]$ means not; $[\eta = \cdot]$ denotes the value of the equity factor used by the corresponding agent, where the $[\eta = 0]$ agents effectively care only about efficiency and not consider equity at all while the $[\eta = 1]$ ones favors equity.

Interestingly, from Fig. [3] we can observe that the the two agents without the technique of adaptive discounting struggles to learn successful policies in both low and high flow rates. We can also observe the influence of the equity factor $\eta$: the $[\text{ad}] + [\eta = 0]$ agent who does not care about equity converges to a better policy than the $[\text{ad}] + [\eta = 1]$ agent in the lower traffic density, while the latter agent outperforms the former one in higher traffic flow rates. This makes sense, since with lower traffic density the equity problem is not critical, while with higher traffic flow the intersection could be over-saturated with continuously growing queues even under optimal policies. The efficiency-first policies favor releasing more vehicles in over-saturated traffic thus vehicles on other lanes could have long waiting times.

![Fig. 3: Average waiting time obtained in evaluation during training for all agent configurations under ablation study. Each plot shows the mean with $\pm \text{1/s standard deviation over 3 non-tuned random seeds (we show 1/s of the standard deviation for clearer visualization). The upper figure shows the logs of the evaluator for traffic flow range } [500,1500], \text{while the lower one shows that of } [4500,5500]. \text{The vehicles exit the cycle are not considered for the waiting time. The waiting time for a vehicle is calculated with } 1h - T_{\text{in}}, \text{where } T_{\text{in}} \text{is the time when it enters the intersection. As the generation time of the last vehicle is after one hour, the waiting time of low traffic flow could be negative if only few vehicles do not exit the intersection.}]


Fig. 4: Performance comparison of our work with baselines on 30 one-hour simulated traffic cycles. We note that the baselines are optimized for each of the 150 test cycle (30 from each of the 5 ranges) before they are tested on it.

We observe that the \([ad] + [g] = 0.25\) configuration obtains the best performance across different traffic flow rates, thus this is the configuration we use for the agent \textit{Ours} in the following experiments.

Having compared the plots of travel time (for released vehicles) and waiting time (for not released vehicles), we notice that the average waiting time always decreases during training when the policy gets better, while the average travel time may vary in different ways. This is because the travel time only considers the released vehicles. Some initial poor policies may choose one action all the time, which leads to fast throughput for vehicles on the lanes with green light while extremely long waiting time of other vehicles. The waiting time, however, considers only the vehicles not pass the intersection during the cycle. As the policy gets better, the number of vehicles staying in the intersection at the end becomes smaller. In order to show the training process clearly, we choose to use plot of waiting time.

D. Evaluation on Simulated Traffic Cycles

To test the performance of our trained agent we first evaluate on simulated traffic cycles that each lasts one hour. For each of the five traffic flow rate ranges as used for the evaluators during training, we randomly sample a set of 30 1-hour cycles; this exact set of 5 · 30 cycles are used to test all compared algorithms. These test cycles are sampled following the same procedure as the cycles used for evaluation during training.

To ensure a fair comparison, for each test cycle, we use the exact same generation time for each vehicle when evaluating different methods. Via the sampling process described above, our test set covers a very wide range of traffic scenarios and could in turn provide a more thorough evaluation.

The evaluation results are shown in Fig. We observe that our method reaches state-of-the-art performance on all considered traffic flow ranges. It is worth noting that for each non-learning baseline that we compare with, we find its optimized hyperparameters for each of the 150 testing cycles; while our agent is trained only once and a single agent is used to evaluate on all 150 testing cycles (we rerun our method 3 times with different random seeds to estimate its variance in learning). This means that the overall performance of our one trained model outperforms that of the 150 individually optimized models. The performance improvement at about 1000\(v/h\) and 5000\(v/h\) is not very obvious, because when in light traffic many vehicles do not have to wait in queue and in saturated traffic, where there is a queue in every incoming lane, the best policy is to schedule the green phases cyclically. The capability of our agent to react to real time traffic situation can be fully utilized for the traffic flow ranges in the middle, where the improvement against the Max-Pressure controller and the fixed-time controllers could be over 20% and 40%. The Webster’s method performs worse than the Uniform controller due to the quick change and short duration of the test cycle, which is most of the time not the case in real traffic (Fig. 5).

As mentioned, the travel time only indicates how fast the released vehicles drive through. In order to show that our agent can also benefit more drivers than baselines, we present the testing statistics for throughput in Table I. The percentage values are the ratio of the released vehicles in the total vehicle number generated in cycles. With traffic flow lower than about 3000\(v/h\), all TSCs can properly release vehicles input. Not 100 percent of the generated vehicles can be released, because the test is stopped directly after one hour. Some vehicles generated at the end do not have enough time to travel through. From about 3000\(v/h\) the throughput of the baselines start to drop, which means the TSC can not fully release the input traffic flow and traffic jam starts to form, while our agent can avoid traffic jams in much denser traffic. With the increased efficiency, our agent can still guarantee equity, which is shown by the low standard deviation of all vehicles travel time and the high throughput.

E. Evaluation on Real-world Traffic Cycles

To further measure the generalization performance of our agent in more realistic traffic scenarios, we conduct additional tests with a whole-day traffic cycle of a real-world intersection of Loerracherstrasse and Wiesentalstrasse located in Freiburg, Germany. This intersection has different layout than the 12-incoming lane intersection evaluated before. Here each road has 1 incoming lanes with one additional short lane for protected left turn. This is a common design to increase the capacity of intersections. So the size of the state changes to 224. Here we regard the short left-turning lane.

| Traffic Flow Rate | Uniform | Websters | Max-pressure | Ours |
|-------------------|--------|----------|--------------|------|
| 500 ~ 1500        | 97.38  | 97.47    | 97.59        | 97.76|
| 1500 ~ 2500       | 97.09  | 97.52    | 97.54        | 97.95|
| 2500 ~ 3500       | 93.77  | 95.34    | 95.91        | 97.76|
| 3500 ~ 4500       | 87.16  | 86.65    | 88.84        | 92.88|
| 4500 ~ 5500       | 77.62  | 74.90    | 81.75        | 86.27|
the forward-right-turning lane and the lane segment before the branching as separate lanes when we construct the state.

Since the size of the input is different from the experiments above, we need to train another agent with this changed input size. As we want to test the generalization capabilities of our method, we still train on the simulated cycles as the before (only the maximum limit of the traffic flow is reduced to \(1/2\) of before to reflect the change in the intersection layout) and test on the real-world traffic cycle, which is a normal workday cycle with typical traffic flow picks at rush hour. The input traffic flow is in the range \([0, 1740]\)/h.

The results of this real-world experiment is shown in Fig. 5. All the TSCs can properly release all vehicles, because the traffic flow is nearly zero in the night when the test cycle ends. We can observe that our method is again outperforming all baseline methods, even though the baselines are firstly optimized with exactly the same test cycle and our model is only trained on the simulated training cycles with 1200s duration. The substantial improvement of nearly 30% on average travel time is even greater than the performance gain in the simulated evaluations, this validates that our proposed method has great generalization capabilities and can adapt to a wide range of traffic scenarios due to its flexibility design.

V. CONCLUSION

In this paper we developed a novel approach to learn traffic signal controllers using deep reinforcement learning. Our approach extends existing reward functions by a dedicated equity factor. We furthermore proposed a method that utilizes adaptive discounting to comply with the learning principles of deep reinforcement learning agents and to stabilize training. We validated the effectiveness of our approach using simulated and real-world data. Besides substantially outperforming the state-of-the-art methods, our approach is a general method, which can be easily adopted for different intersection topologies.

REFERENCES

[1] INRIX, “INRIX 2018 Global Traffic Scorecard,” https://inrix.com/scorecard/2005. [Online; accessed 16-Jan-2020].

[2] R. A. Silva, Z. Adelman, M. M. Fry, and J. J. West, “The impact of individual anthropogenic emissions sectors on the global burden of human mortality due to ambient air pollution,” Environmental health perspectives, vol. 124, no. 11, pp. 1776–1784, 2016.

[3] R. W. Denney Jr, E. Curtis, and P. Olson, “The national traffic signal report card,” ITE Journal, vol. 82, no. 6, pp. 22–26, 2012.

[4] S. Thrun, W. Burgard, and D. Fox, Probabilistic Robotics. MIT Press, 2005.

[5] H. Lipson and M. Kurman, Driverless: intelligent cars and the road ahead. Mit Press, 2016.

[6] M. Papageorgiou, C. Diakaki, V. Dinopoulou, A. Kotsialos, and Y. Wang, “Review of road traffic control strategies,” Proceedings of the IEEE, vol. 91, no. 12, pp. 2043–2067, 2003.

[7] L. Li, D. Wen, and D. Yao, “A survey of traffic control with vehicular communications,” IEEE Transactions on Intelligent Transportation Systems, vol. 15, no. 1, pp. 425–432, 2013.

[8] S. I. Guler, M. Menendez, and L. Meier, “Using connected vehicle technology to improve the efficiency of intersections,” Transportation Research Part C: Emerging Technologies, vol. 46, pp. 121–131, 2014.

[9] X.-F. Xie, S. F. Smith, L. Lu, and G. J. Barlow, “Schedule-driven intersection control,” Transportation Research Part C: Emerging Technologies, vol. 24, pp. 168–189, 2012.

[10] B. Abdulhai and L. Kattan, “Reinforcement learning: Introduction to theory and potential for transport applications,” Canadian Journal of Civil Engineering, vol. 30, no. 6, pp. 981–991, 2003.

[11] V. Mihd, K. Kavukcuoglu, D. Silver, A. A. Rusu, J. Veness, M. G. Bellemare, A. Graves, M. Riedmiller, A. K. Fidjeland, G. Ostrovski, et al., “Human-level control through deep reinforcement learning,” Nature, vol. 518, no. 7540, pp. 529–533, 2015.

[12] J. Schulman, F. Wolski, P. Dhariwal, A. Radford, and O. Klimov, “Proximal policy optimization algorithms,” arXiv preprint arXiv:1707.06347, 2017.

[13] W. Genders and S. Razavi, “An open-source framework for adaptive traffic signal control,” arXiv preprint arXiv:1909.00395, 2019.

[14] P. Varaiya, “The max-pressure controller for arbitrary networks of signalized intersections,” in Advances in Dynamic Network Modeling in Complex Transportation Systems. Springer, 2015, pp. 27–66.

[15] W. Genders and S. Razavi, “Using a deep reinforcement learning agent for traffic signal control,” arXiv preprint arXiv:1611.01142, 2016.

[16] P. A. Lopez, M. Behrisch, L. Bieker-Walz, J. Erdmann, Y.-P. Flötteröd, R. Hilbrich, L. Lücken, J. Rummel, P. Wagner, and E. Wieländer, “Microscopic traffic simulation using sumo,” in The 21st IEEE International Conference on Intelligent Transportation Systems. IEEE, 2018. [Online]. Available: [https://elib.dlr.de/124092]

[17] F. V. Webster, “Traffic signal settings,” Tech. Rep., 1958.

[18] N. H. Gartner, OPAC: A demand-responsive strategy for traffic signal control, 1983, no. 906.

[19] P. Lower, “Scats, sydney co-ordinated adaptive traffic system: A traffic responsive method of controlling urban traffic,” 1990.

[20] K. Yang, S. I. Guler, and M. Menendez, “Isolated intersection control for various levels of vehicle technology: Conventional, connected, and automated vehicles,” Transportation Research Part C: Emerging Technologies, vol. 72, pp. 109–129, 2016.

[21] J. Gregoire, X. Qian, E. Frazzoli, A. De La Fortelle, and T. Wongpiromsarn, “Capacity-aware backpressure traffic signal control,” IEEE Transactions on Control of Network Systems, vol. 2, no. 2, pp. 164–173, 2014.

[22] S. El-Tantawy, B. Abdulhai, and H. Abdelgawad, “Design of reinforcement learning parameters for seamless application of adaptive traffic signal control,” Journal of Intelligent Transportation Systems, vol. 18, no. 3, pp. 227–245, 2014.

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

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

[25] X. Liang, X. Du, G. Wang, and Z. Han, “A deep reinforcement learning network for traffic light cycle control,” IEEE Transactions on Vehicular Technology, vol. 68, no. 2, pp. 1243–1253, 2019.

[26] H. Wei, G. Zheng, V. Gayah, and Z. Li, “A survey on traffic signal control methods,” arXiv preprint arXiv:1904.08117, 2019.

[27] J. Schulman, P. Moritz, S. Levine, M. I. Jordan, and P. Abbeel, “High-dimensional continuous control using generalized advantage estimation,” arXiv preprint arXiv:1506.02438, 2015.

[28] C. Bester and W. Meyers, “Saturation flow rates,” SATC 2007, 2007.

[29] A. a. Salkham, R. Cunningham, A. Garg, and V. Cahill, “A collaborative reinforcement learning approach to urban traffic control optimization,” in 2008 IEEE/WIC/ACM International Conference on
