

# Game-theoretic reinforcement learning for multi-intersection control with oversaturated traffic

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## APPENDIX A

We summarize the key notations in the following table.

TABLE A.1: List of key notations.

Notation	Definition
$s_i(t)$	Traffic states of intersection $i$ at time $t$
$a_i(t)$	Action of intersection $i$ at time $t$
$r_i(t)$	Reward of intersection $i$ at time $t$
$f_{ij,c}(t)$	Traffic flow of cell $c$ at time $t$
$k_{ij,c}(t)$	Traffic density of cell $c$ at time $t$
$v_{ij,c}(t)$	Speed of cell $c$ at time $t$
$y_{ij,c}(t)$	Exogenous demand of cell $c$ at time $t$
$h_{ij,c}$	Length of cell $c$
$d_{ij}(t)$	Delay of lane $j$ at time $t$
$\theta$	Neural network parameters
$\phi$	Potential functions
$Q_i$	$Q$ -function of intersection $i$
$\delta_i$	TD error of intersection $i$
$L(\theta)$	Loss function of neural networks
$\gamma$	Discount rate
$\kappa$	Index of training epoch
$\psi$	Batch size
$\xi$	Learning rate

## APPENDIX B

This section provides the proof of Proposition 2 in the main text as follows.

**Proof.**

$$\begin{aligned} & \sum_{t \in \mathbb{T}} \sum_{i \in \mathbb{I}} -r'_i(t) \\ &= \sum_{t \in \mathbb{T}} \sum_{i \in \mathbb{I}} \sum_{j \in \mathbb{L}_i^{in}} (d_{ij}(t) - \lambda_1 f_{ij}(t) \Delta t) \end{aligned} \quad (1)$$

$$= \sum_{t \in \mathbb{T}} \sum_{i \in \mathbb{I}} \sum_{j \in \mathbb{L}_i^{in}} q_{ij}(t) (\Delta t - \hat{b}_{ij}(t) / v_{ij}^*) - \lambda_1 \sum_{t \in \mathbb{T}} \sum_{i \in \mathbb{I}} \sum_{j \in \mathbb{L}_i^{in}} f_{ij}(t) \Delta t \quad (2)$$

Given the fixed total number of vehicles and pre-defined planning routes for each vehicle, the total number of times

all intersections are crossed by all vehicles over the entire planning horizon is a constant  $N$  defined by:

$$N = \sum_{t \in \mathbb{T}} \sum_{i \in \mathbb{I}} \sum_{j \in \mathbb{L}_i^{in}} f_{ij}(t) \Delta t \quad (3)$$

Combining (3) into (2), we obtain:

$$\sum_{t \in \mathbb{T}} \sum_{i \in \mathbb{I}} -r'_i(t) = \sum_{n \in \mathbb{N}} [T_n - T_n^*] - \lambda_1 N$$

We now complete the proof that the regularizer  $f_{ij}(t) \Delta t$  does not affect the optimality of the original objective function.

**Remark 1.** For a corridor with two intersections, if the total traffic demand over the planning horizon is 1, with planning routes that involve crossing both intersections, then  $N = 2$ .

## APPENDIX C

In this section, we examine the Markovian property of traffic dynamics under oversaturated traffic.

**Lemma C** (Chapman-Kolmogorov equation [1, pp. 346]). *The necessary condition for the system dynamics to be Markovian is that its transition function  $P$  satisfies the Chapman-Kolmogorov (CK) equation as follows:*

$$\begin{aligned} & P(X_{g+t} = \Gamma \mid X_0 = x) \\ &= \sum_y P(X_{g+t} = \Gamma \mid X_g = y) \cdot P(X_g = y \mid X_0 = x) \end{aligned}$$

for every  $t \geq 0$  and  $g \geq 0$ , where  $X$  represents the stochastic variable.

The C-K equation, as presented in (4), describes the probability of transitioning from the initial state  $x$  to state  $\Gamma$  after  $g + t$  steps. This probability is obtained by summing up the probabilities of transitioning from state  $x$  to an intermediate state  $y$  at step  $g$  and then to state  $\Gamma$ , considering all possible intermediate states  $y$  at step  $g$ .

The necessary condition presented in Lemma C can be assessed by examining the absolute errors between the left-hand side and the right-hand side of the C-K equation (4), denoted as  $\Xi(t)$ . The definition of  $\Xi(t)$  is as follows:

$$\begin{aligned} & \Xi(t) \\ &= |P(X_{g+t} = \Gamma \mid X_0 = x) - \sum_y P(X_{g+t} = \Gamma \mid X_g = y) \cdot P(X_g = y \mid X_0 = x)| \end{aligned} \quad (4)$$

The Markovian property holds when  $\Xi(t) = 0$ , otherwise it is violated. We examine Lemma C on an intersection in

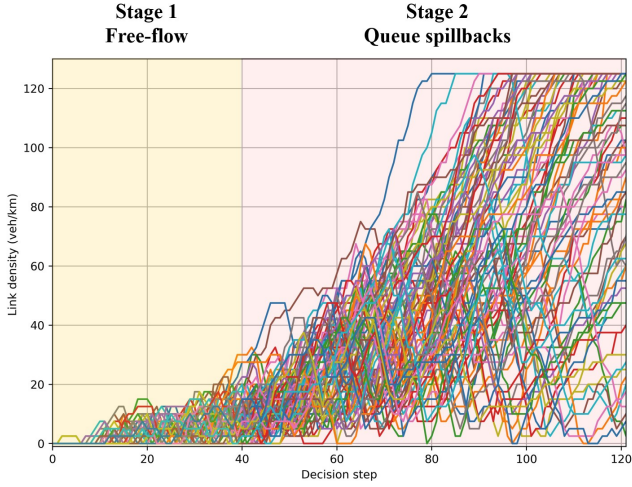


Fig. 1: Profiles of upstream link density with queue spillbacks.

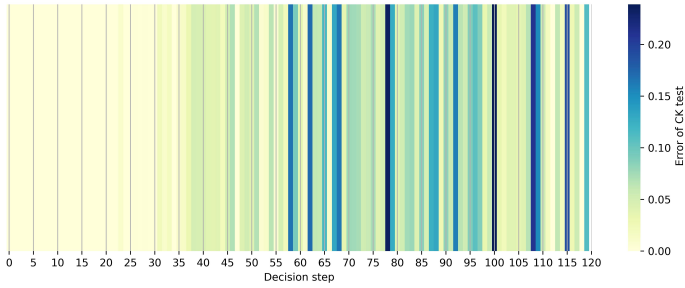


Fig. 2: Absolute errors of the C-K equation along the simulation horizon.

the Hangzhou network under oversaturated traffic conditions with 100 simulation runs. We set the number of transition steps  $g$  as 5 decision intervals and discretize the link density with an interval of 10 veh/km. Figure 1 depicts the profiles of upstream link density and Figure 2 presents the absolute errors  $\Xi(t)$  along the simulation horizon. Note that during the first 40 steps, the majority of trajectories experience free-flow conditions and therefore  $\Xi(t)$  equals 0. This observation suggests that the traffic dynamics under the free-flow condition conform to a Markov chain. After that, as queues from the downstream section begin to spill over, the upstream link densities start to accumulate. Consequently,  $\Xi(t)$  exceeds 0 and reaches a maximum value of 0.25, which indicates a violation of the Markovian property. With the above validation of the C-K equation, we demonstrate that the fundamental MDP assumption in RL approaches to traffic signal control is no longer valid when there is queue spillover.

## REFERENCES

- [1] W. Feller, *An introduction to probability theory and its applications, second edition*. John Wiley & Sons, 1971, vol. 2.