



Decentralized Traffic Signal Control with Deep Reinforcement Learning in a Multi-modal Network: Seeking for a Trade-off between Bus Service and Traffic

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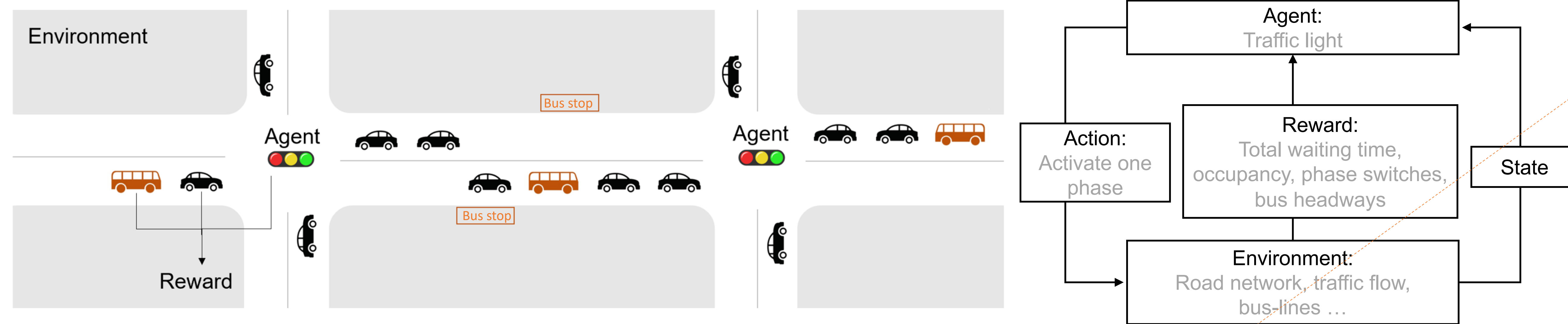
Decentralized Traffic Signal Control with Deep Reinforcement Learning in a Multi-modal Network: Seeking for a Trade-off between Bus Service and Traffic

Motivation:

- Unbalanced bus headway leads to long waiting time for passengers.
- Classical bus holding strategies may not be well-perceived by users.
- Holding can be achieved silently at traffic signals with proper control.

A decentralized Deep Reinforcement Learning (DRL) traffic signal control framework is proposed to increase traffic efficiency and equalize bus headways simultaneously.

Model formulation:



State

- Total waiting time $D_{i,t}$
- Occupancy $O_{i,t}$
- Forward and backward bus headways $h_{i,t}^f, h_{i,t}^b$
- Number of yellow phases in last 10 decision steps $n_{i,t}^y$

Action

- Predefined phase
- Yellow phase for switch

Reward

$$r_{i,t} = r_{i,t}^{traffic_1} + r_{i,t}^{traffic_2} + r_{i,t}^{agent} + c \times r_{i,t}^{bus}$$

Reduction degree of total waiting time

$$r_{i,t}^{traffic_1} = \begin{cases} 1 & , D_{i,t} < D_{i,t-1} \\ 0 & , D_{i,t} = D_{i,t-1} \\ -1 & , D_{i,t} > D_{i,t-1} \end{cases}$$

Occupancy of incoming lanes

$$r_{i,t}^{traffic_2} = \begin{cases} 0 & , O_{i,t} < 0.5 \\ -1 & , O_{i,t} > 0.5 \end{cases}$$

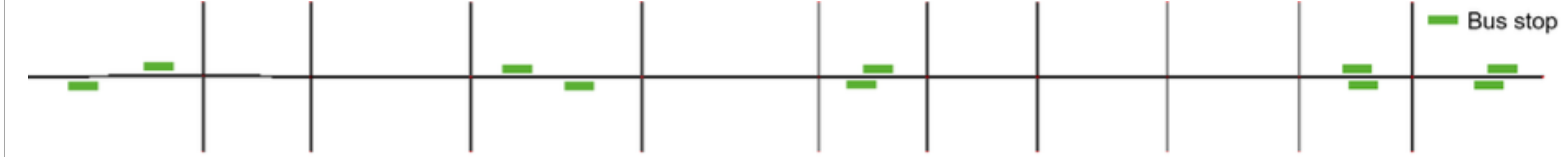
Stability of decisions taken

$$r_{i,t}^{agent} = \begin{cases} 0 & , n_{i,t}^y \leq 2 \\ -1 & , n_{i,t}^y > 2 \end{cases}$$

Bus headway control performance

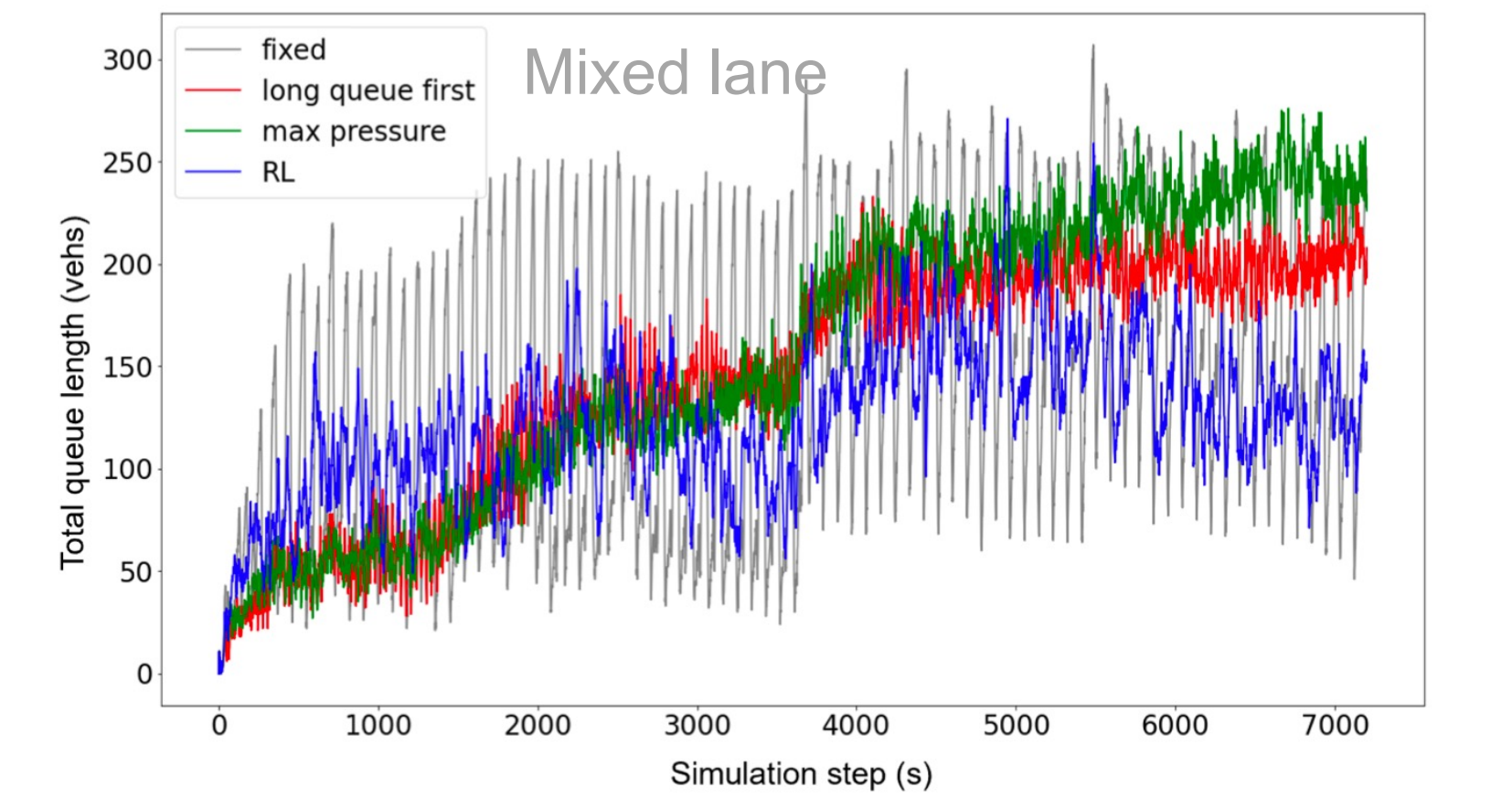
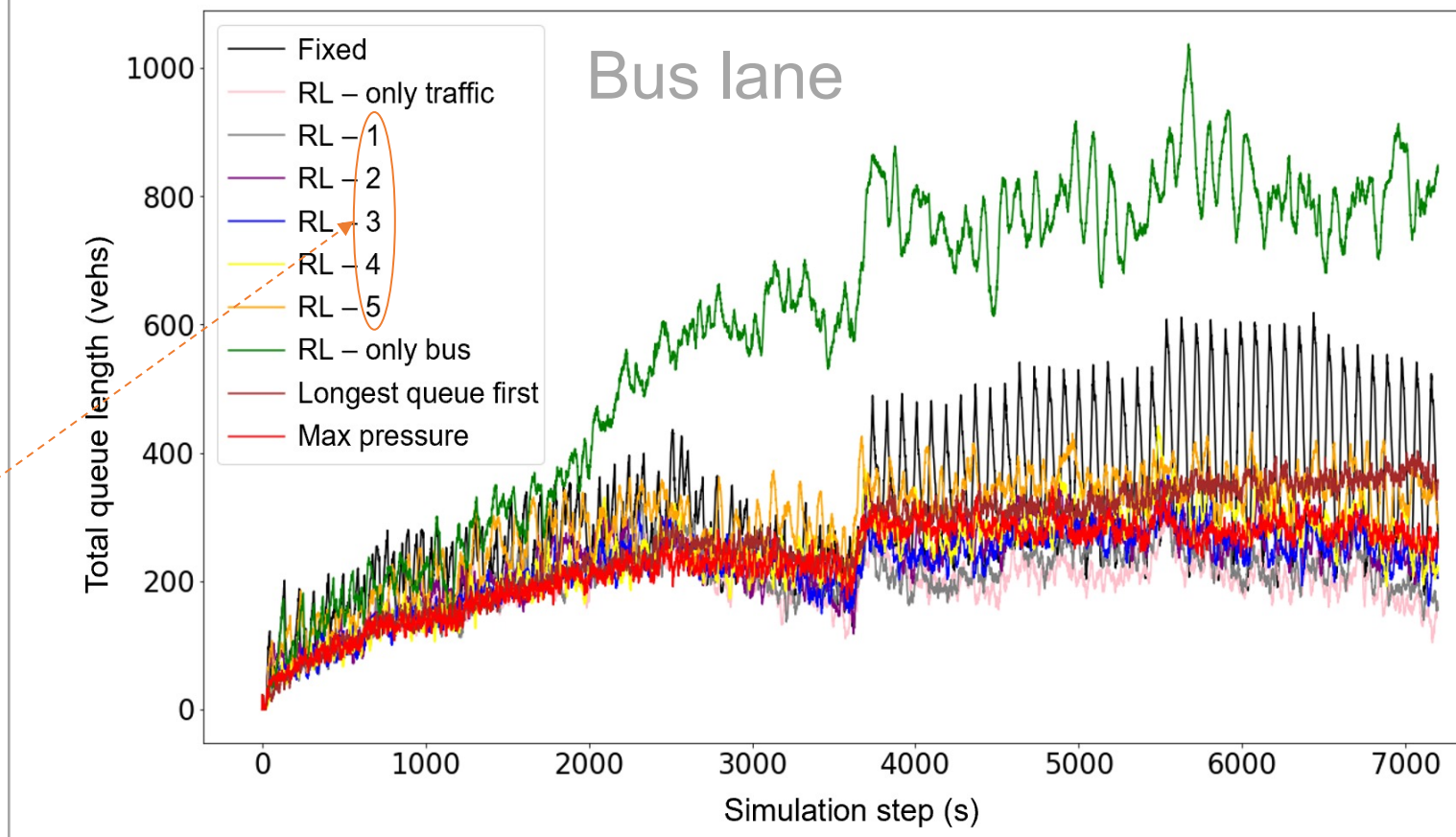
$$r_{i,t}^{bus} = \begin{cases} 1 & , h_{i,t}^f > h_{i,t}^b \text{ and bus gets green} \\ 1 & , h_{i,t}^f < h_{i,t}^b \text{ and bus gets red} \\ 0 & , h_{i,t}^f = h_{i,t}^b \\ -1 & , \text{otherwise} \end{cases}$$

Numerical tests:

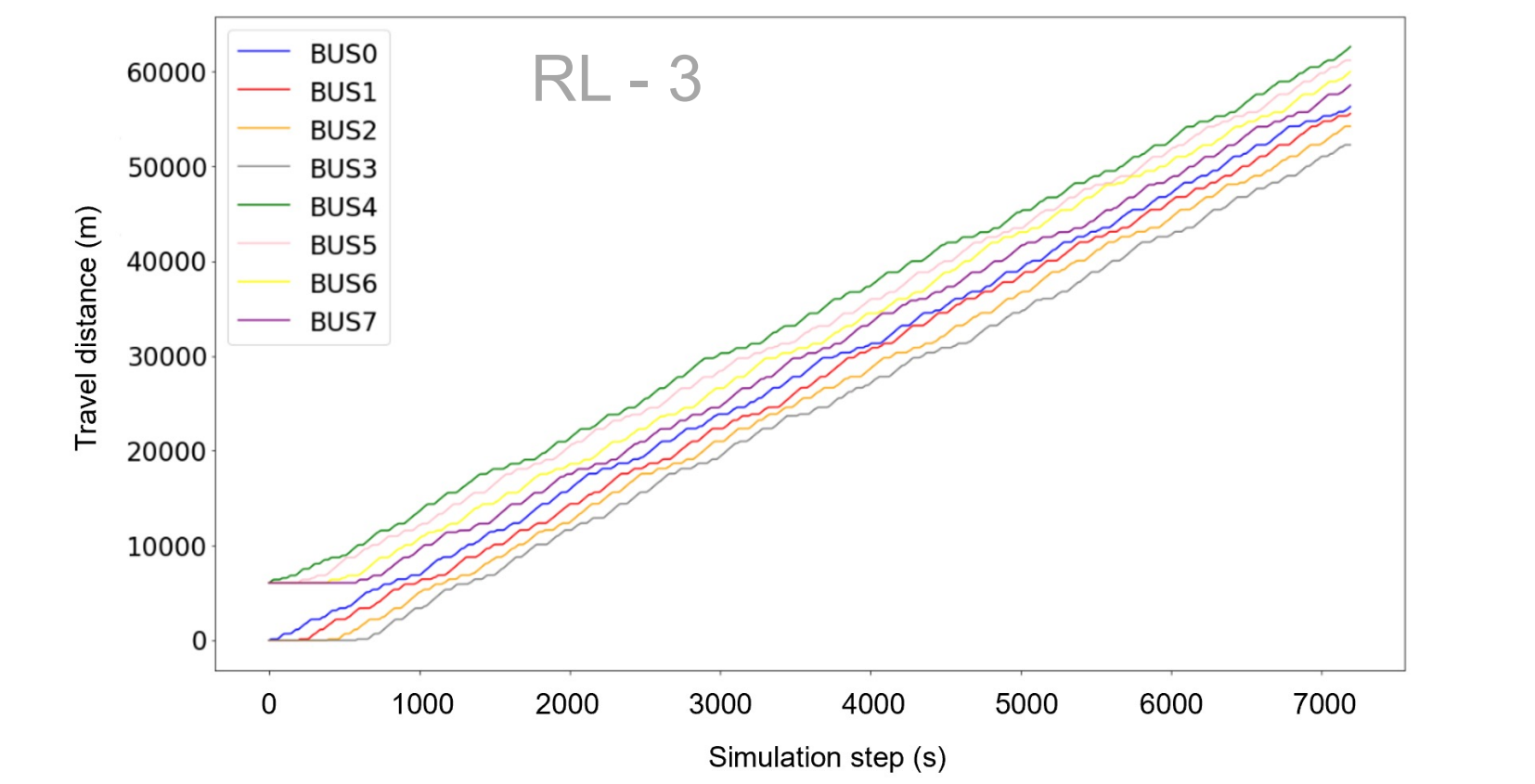
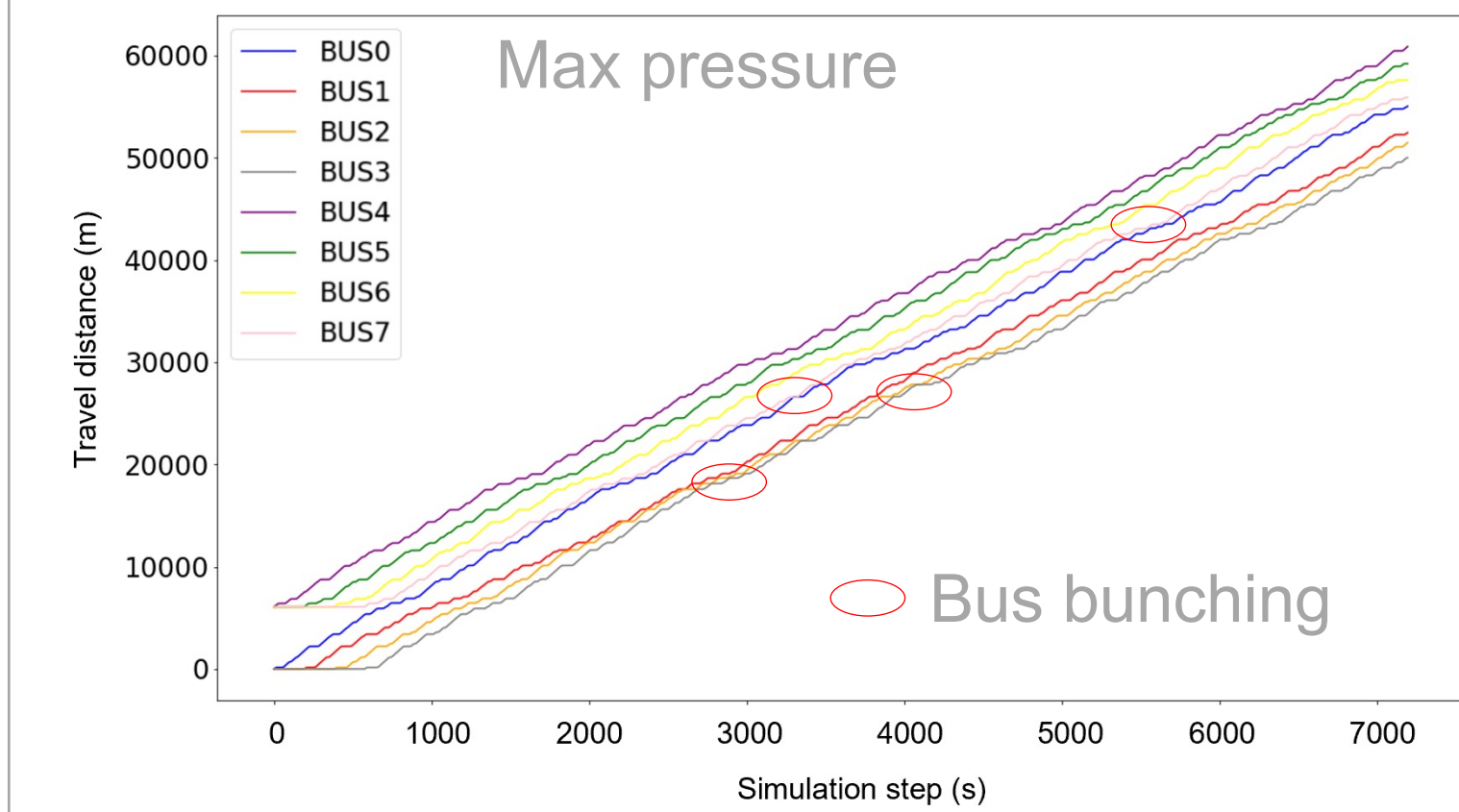


Training network: 5-signal arterial, 4 buses.

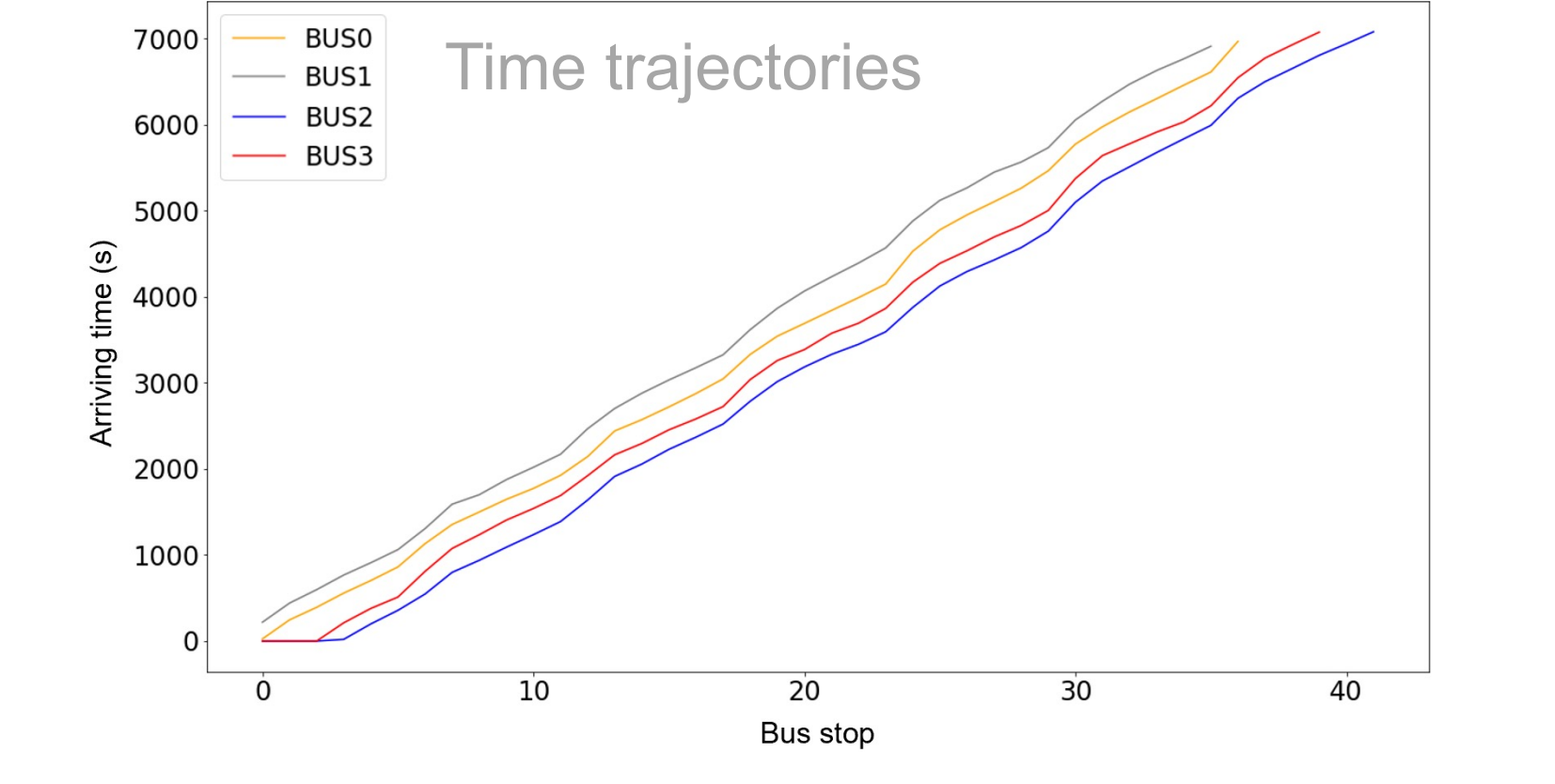
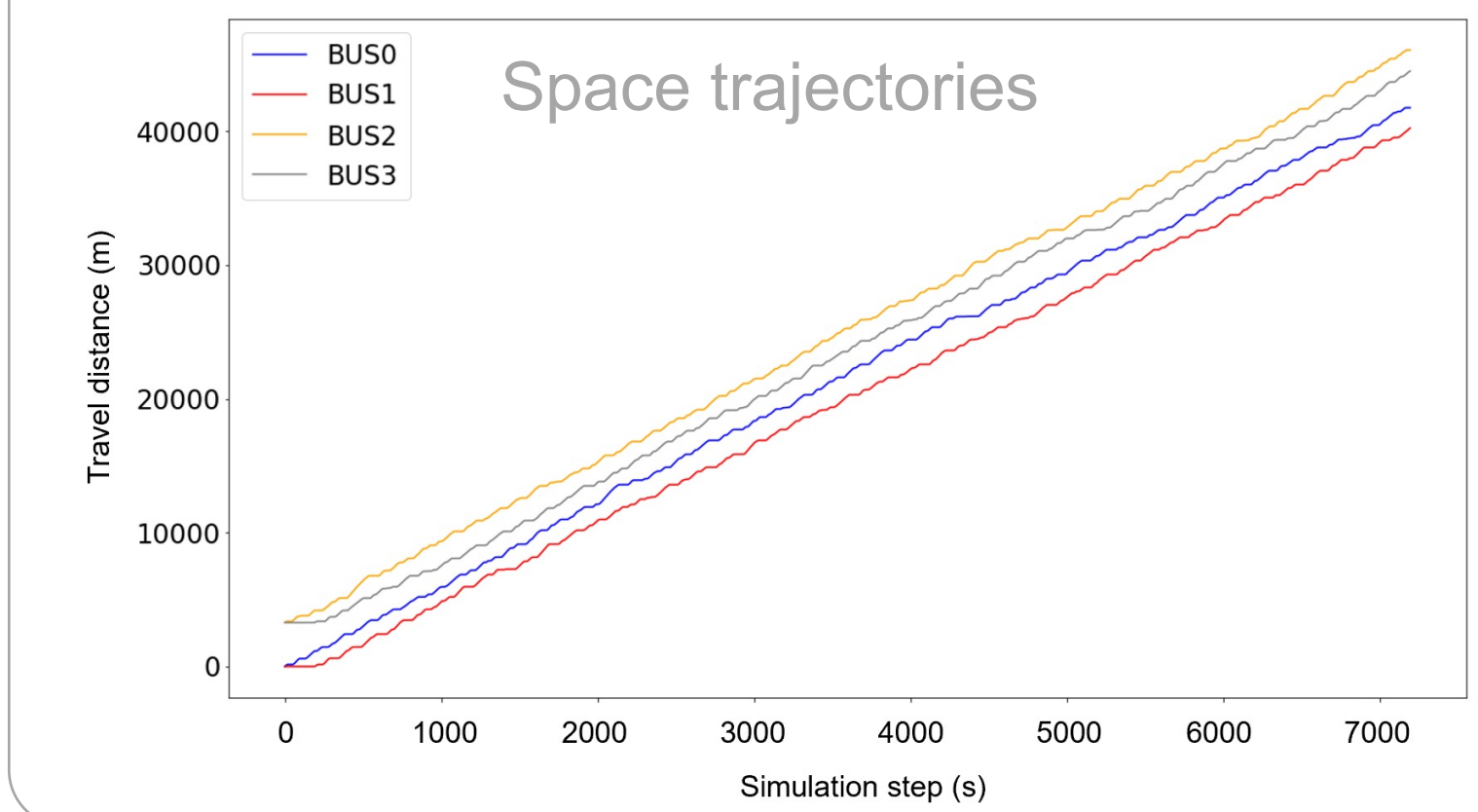
Testing network: 10-signal arterial, 8 buses.



Space trajectories of buses (bus lane):



Space and time trajectories of buses (mixed lane, RL - 3):



Value-function approximation:

Since the state-space is continuous, we adopt a process based on Deep Q-Learning to achieve value function approximation. Optimal action value:

$$Q_i^*(s, a) = \max_{\pi} E \left[r_{i,t} + \gamma r_{i,t+1} + \gamma^2 r_{i,t+2} + \dots \mid S_{i,t} = s, a_{i,t} = a, \pi \right]$$

Update value function:

$$Q_i(s, a) = Q_i(s, a) + \alpha (r_{i,t} + \gamma \max_{a'} Q(s', a') - Q(s, a))$$

Loss function:

$$L_k(\theta_k) = E_{(s,a,r,s') \sim U(M)} \left[\left(r + \gamma \max_{a'} Q(s', a'; \theta_k^-) - Q(s, a; \theta_k) \right)^2 \right]$$

Strategies	Bus lane		Mixed lane	
	SD of space headway	Average queue length (vehs)	SD of space headway	Average queue length (vehs)
RL - 3	508.05	219.02	392.98	124.51
Actuated	748.32	258.18	539.51	144.02
MP	779.26	227.16	569.34	153.94
Fixed	778.64	305.35	738.18	137.26

Conclusions:

- Compared with benchmarks, the proposed method decreases the traffic delay by 28.27% and the standard deviation of bus headways by 34.75% simultaneously.
- Both scalability and portability are demonstrated by transferring locally learned strategies to similar intersection configurations.