



The exclusive bus lane (XBL) is one of the most popular bus transit systems in US. The Lincoln Tunnel utilizes an XBL through the tunnel in the AM peak period. This paper proposes a novel data-driven cooperative adaptive cruise control (CACC) algorithm for connected and autonomous buses. Different from existing model-based CACC algorithms, the proposed approach employs the idea of adaptive dynamic programming (ADP), which does not rely on the accurate knowledge of bus dynamics. A distributed cruise controller is learned by online headway, velocity, acceleration data collected from system trajectories. The convergence of the proposed algorithm and the stability of the closed-loop system are rigorously analyzed. The effectiveness of the proposed approach is also demonstrated by Paramics microscopic traffic simulations. Simulation results show that the travel times in the autonomous exclusive bus lanes are close to the present day travel times even when the traffic demand is increased by 30%.

### Paramics Model of the Lincoln Tunnel Corridor

Taking the advantage of buses equipped with GPS devices, travel time and headway information of buses is extracted via New Jersey Transit (NJT) "MyBus Now" platform (20), a real-time service information system that provides estimated vehicle arrival times and map locations for NJT buses.



Paramics simulation network



# Data-driven Cooperative Adaptive Cruise Control of Buses on the Exclusive Bus Lane of the Lincoln Tunnel Corridor

Weinan Gao\*, Ph.D., Zhong-Ping Jiang\*\*, Ph.D., Kaan Ozbay\*\*, Ph.D., Jingqin Gao\*\*, Ms.c. \*Georgia Southern University, \*\*New York University



### Paramics simulation architecture

# Adaptive Dynamic Programming

The proposed control strategy employs the idea of **adaptive dynamic programming** (ADP). The main feature of ADP is that it is able to approximate the optimal control strategy and the corresponding cost function in an iterative fashion, without the accurate knowledge of the vehicle dynamics.



### **Actor-critic structure in Adaptive Dynamic Programming**

### Design of the CACC Algorithm

Consider a platoon of *n* autonomous buses. The dynamics of the *i*th bus can be described by

Given the unknown system dynamics, a suboptimal distributed controller can be learned by the proposed data-driven Algorithm.

### Algorithm 1 Data-driven CACC Algorithm

- 1:  $i \leftarrow 1$
- 2: repeat
- Apply an initial control policy  $u_i = -K_{i0}x + e_i$  with exploration noise  $e_i$  and  $A_i B_i K_{i0}$  a Hurwitz matrix
- $i \leftarrow 0$
- repea
- Solve  $P_{ij}$  and  $K_{i,j+1}$  from (10) via online input-state data.
- $j \leftarrow j + 1$
- **until**  $|P_{ij} P_{i,j-1}| < \epsilon_i$  with  $\epsilon_i$  a small positive constant.
- $^{*} \leftarrow$
- Obtain the following suboptimal controller 10:

```
11: i \leftarrow i + 1
12: until i = n + 1
```

$$\dot{x}_i = A_i x_i + B_i u_i + D_i x_{i-1}$$

$$u_i = -K_{i,j^*}\zeta_i$$

# **Micro-simulation Results**

### Velocity errors and spacing errors



### Data-driven CACC Algorithm Without Data-driven CACC Algorithm Velocity errors of buses $\Delta v_i [m/s]$ Velocity errors of buses $\Delta v_i[m/s]$ 0.008 0.006 0.004 0.002 150 200 250 300 100 Spacing errors of buses $\Delta h_i[m]$ Spacing errors of buses $\Delta h_i [m]$ **Travel Time with different bus demand** Field Data-driven CACC Algorithr O 30% increase in Vol, Data-driven CACC Algorithm 35% increase in Vol, Data–driven CACC Algorithm 6:15-6:30 6:30-6:45 6:45-7:00 7:00-7:15 7:15-7:30 7:30 :45–8:00 8:00–8:15 8:15–8:30 8:30–8:45 8:45–9:00 9:15–9:30 9:15–9:30 9:30–9:45



- malfunctions.

(11)

### Paper 18-02161

### Contact: wgao@georgiasouthern.edu

### Contributions

1) We propose a novel data-driven CACC method for connected and autonomous buses. This is different from existing model-based CACC methods in that the former essentially relies on the collected online headway, velocity, and acceleration data, instead of the knowledge of vehicle dynamics.

2) This paper distinguishes itself from our previous work through combining the ideas of ADP and distributed control. It should be noticed that, compared with centralized control, distributed control strategies no longer relies on the assumption that each vehicle can communicate with a central location and share information by a fully connected network, which is able to effectively reduce communication cost. Moreover, the latter is robust to communicative