Adaptive perimeter control of traffic networks with closed-loop data

W.F. MA[a], G.D. YANG[a], Y.P. HUANG[b], C. CHEN[b] and R.X. ZHONG[a,*]

[a] Sun Yat-Sen University, Shenzhen, China
[b] The Hong Kong Polytechnic University, Hong Kong, China
[*] Corresponding author

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1 INTRODUCTION

Macroscopic fundamental diagram (MFD) describes the relationship between vehicle accumulation and network production at the stationary condition (Daganzo, 2007, Geroliminis & Daganzo, 2008). Leveraging recent advances in MFDs, perimeter control presents an efficient and effective way to improve network performance by managing traffic flow at a macroscopic level and reducing spatial dimensions in large-scale network traffic optimization.

Previous studies on perimeter control generally assume that the network dynamics are known and will not change during the simulation horizon (Haddad & Geroliminis, 2012, Zhong *et al.*, 2018b). However, due to the complex and stochastic network scenarios, it is less likely to know even the structure of all possible network traffic configurations and interactions. Consequently, the conventional perimeter control schemes would be fragile to uncertainties. To address this challenge, data-driven control (Chen *et al.*, 2022, Su *et al.*, 2023) that seeks to learn accurate traffic dynamics from past measurements is pursued. Conventional machine learning approaches to traffic dynamics are regression-oriented and prioritize fitting input-output data via supervised learning with powerful function approximators. The dynamics are learned using the "open-loop data", i.e., the data collected before the control is devised and deployed. However, the deployment of controllers will change the characteristics of the traffic system conversely, e.g., a new traffic signal control scheme can not only change the network capacity but also induce a demand pattern variation. The regression-oriented control that learns traffic dynamics solely from open-loop data may be inadequate for dealing with the traffic dynamics influenced by controller deployment. Therefore, the learning process of traffic dynamics should be tailored to the control objective, as the learning task is tied to the control purpose.

In this work, we propose a closed-loop learning ideology (using the "closed-loop data" and it is known as Control Oriented Learning), which is tailored to the underlying control objective (Sznaier, 2020). The iterative operation of controller design and traffic dynamics learning based on closed-loop data facilitated obtaining the optimal control strategy. Moreover, closed-loop data are generated from a microscopic simulation platform of real traffic networks (or real traffic data collected after the control is deployed). Preliminary experiments verify the effectiveness of the proposed method and the necessity of injecting the underlying control objective into the perimeter control process.

2 METHODOLOGY

A heterogeneous traffic network divided into $L(L > 1)$ homogeneous regions is considered in accordance with (Zhong *et al.*, 2018a), with its dynamics formulated in the following affine form:

$$\dot{n}(t) = \mathbf{F}(n(t), q) + \mathbf{S}(n(t)) \cdot u(t) \tag{1}$$

where $n(t) \in \mathbb{R}^{\alpha_n}$ and $q(t) \in \mathbb{R}^{\alpha_q}$ denotes the state vector and demand vector, and $u(t) \in \mathbb{R}^{\alpha_u}$ is the perimeter control vector. $\mathbf{F}$ and $\mathbf{S}$ are the drift dynamics and input dynamics, respectively.

For MFD systems with constant travel demand, the steady-state n^* and the corresponding control inputs u^* can be solved from the steady-state equation (Zhong *et al.*, 2018a). Let $\tilde{n} \triangleq n - n^*$ and $\tilde{u} \triangleq u - u^*$. The control inputs $\tilde{u}$ are designed to minimize the objective function as:

$$\min_{\tilde{u}} J_c(\tilde{n}) = \int_0^T \|(n(t) - n^*)\|_2 \mathrm{d}t = \int_0^T \|\tilde{n}(t)\|_2 \mathrm{d}t \tag{2}$$

where simulation time horizon $T > 0$, and $\|\tilde{n}(t)\|_2$ denotes the l^2 norm of continuous function $\tilde{n}(t)$. In the context of constant demand scenarios, we propose to train a neural network model to approximate the control inputs $\tilde{u}(\tilde{n})$:

$$\tilde{u}(\tilde{n};\ A,\ \theta_y) = A \cdot y(\tilde{n}; \theta_y) \tag{3}$$

where $y(\tilde{n}; \theta_y)$ consists of all the hidden layers of the network parameterized by θ_y, and A is the output layer. As previously mentioned, the traffic dynamics are influenced by the controller deployment. To get rid of the limitation, we propose a closed-loop adaptive control algorithm, in which there are two iterative operations for each simulation:

- Controller design: Given the traffic state $\tilde{n}^k(t)$, gain $\tilde{u}^k(\tilde{n}^k(t))$ via the neural network.

$$\tilde{u}^k(\tilde{n}^k(t)) = A^{(k-1)*} \cdot y(\tilde{n}^k(t); \theta_y^{(k-1)*}), \quad k = 0, 1, \ldots \tag{4}$$

- Dynamics learning: Update the traffic state $\tilde{n}^k(t + dt)$, which is derived from equations Equation 1 using $\tilde{n}^k(t), \tilde{u}^k(t)$ by ODE solver.

where $\theta^{(k-1)*} = (A^{(k-1)*}, \theta_y^{(k-1)*})$ denotes the optimal neural network parameters in the last training simulation, and k is the simulation index.

For MFD systems with time-varying demand, the steady-state and the corresponding control inputs are intractable to solve. Another perimeter control objective that minimizes the total time spent (TTS) is adopted as follows. Additionally, it's noted that the controller design is similar to the constant demand scenario, except for the different objective functions.

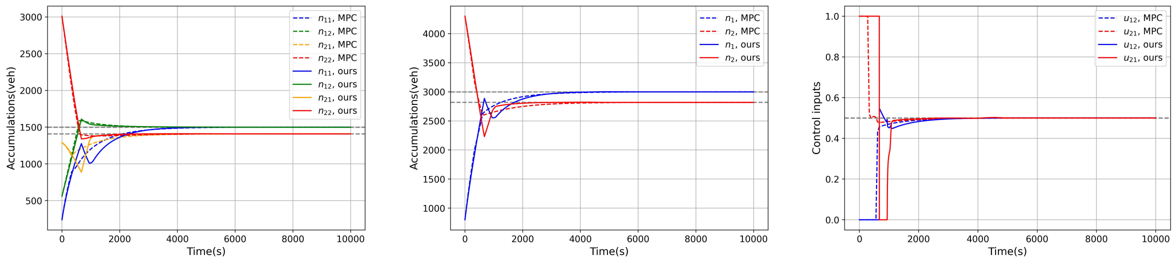
$$\min_{\tilde{u}} J_t(\tilde{n}) = \int_0^T (\sum_{i=1}^{L} n_i(t) + \rho \|u(t)\|_2) \mathrm{d}t \tag{5}$$

3 RESULTS

3.1 Numerical Experiments

A two-region network as depicted by Zhong *et al.* (2018a) is considered in this scenario. The simulation settings are $n(0) = [240, 560, 1290, 3010]$(veh), $q(t) = [1.58, 1.56, 1.54, 1.52]$(veh/s), and the MFD function is $G_i(n_i) = (1.4877 \cdot 10^{-7} n_i^3 - 2.9815 \cdot 10^{-3} n_i^2 + 15.0912 \cdot n_i)/3600$ (veh/s). In line with (Zhong *et al.*, 2018a), the equilibrium is chosen as $n_1^* = 3000$ (veh) and $n_2^* = 2819$ (veh), resulting in accumulations for each direction are $n^* = [1500.5, 1499.5, 1410, 1409]$ (veh), and the corresponding control inputs are $u^* = [0.5003, 0.4997]$ by solving steady-state equation.

The state and control inputs evolutions are shown in Figure 1(a)-1(c), respectively. The accumulation states can asymptotically converge in less than 4000 sec, and the control inputs converge even faster (less than 3000 sec). Compared with the state and control evolutions under Model Predictive Control (MPC), the proposed closed-loop control algorithm can achieve comparative performance with the MPC, which validates the effectiveness and efficiency of the proposed method.



(a) The four-state evolution (b) The two-state evolution (c) Control inputs evolution

Figure 1 – *The simulation results*

3.2 Microscopic simulation

A microscopic simulation as depicted in Figure 2 is adopted to further validate the performance of the proposed control algorithm. The simulated network represents a two-region MFD system (colored orange and green, respectively). The network comprises a total of 70 roads and 18 intersections (10 normal intersections applying the max-pressure algorithm, 6 sink intersections, and 2 perimeter intersections applying the proposed algorithm). The roads within each region are 500 meters long and comprise 4 lanes, while the boundary roads are 1000 meters long. The total simulation time is 3 hours.

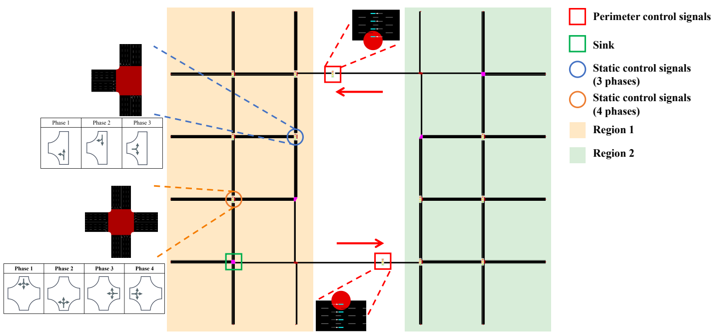
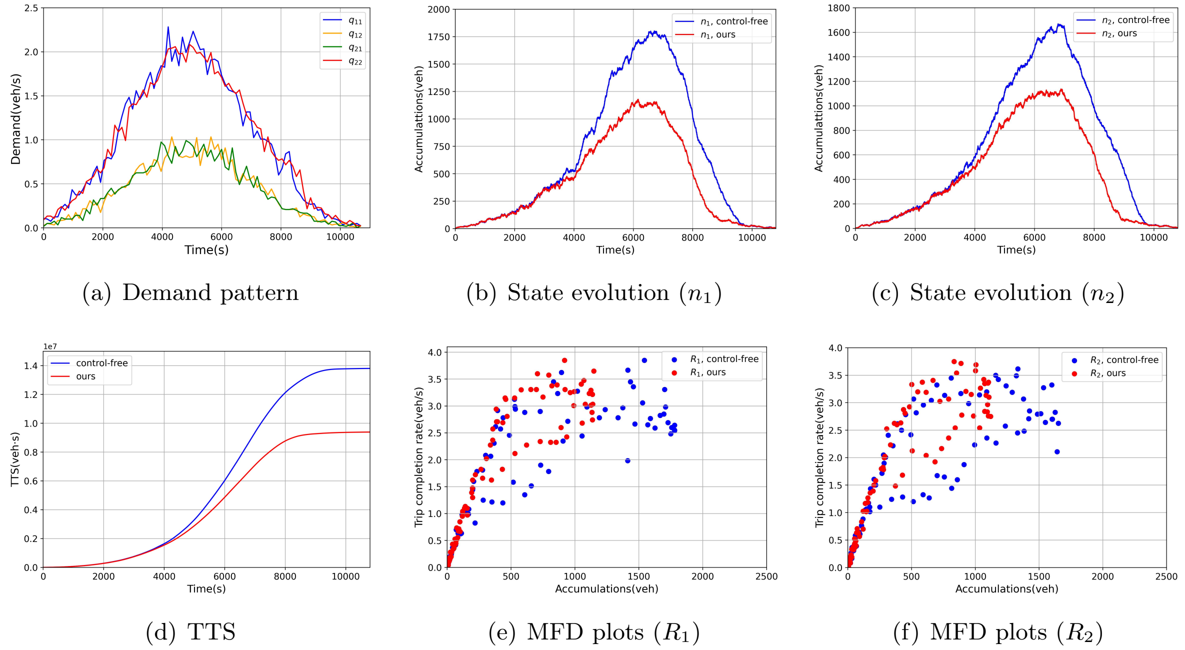


Figure 2 – *The simulated grid network*

The time-varying demand input is shown in Figure 3(a), with both regions initially empty. The compared scene is control-free, i.e., $u_{12} = u_{21} = 1$. Figure 3(b)-3(c) illustrate the evolution of network accumulation, demonstrating a significant improvement in network states, and verifying the efficiency of the proposed control algorithm in regulating traffic. The TTS comparison is shown in Figure 3(d), which decreases about 35% after the controller deployment. The macroscopic data plots for the two regions are presented in Figure 3(e) and 3(f), revealing a higher critical maximal throughput post-controller deployment. Furthermore, the network traffic turns into a dissolving process earlier rather than falling into extreme congestion. These macroscopic results further validate the effectiveness of the proposed adaptive perimeter control algorithm with closed-loop data.



(a) Demand pattern (b) State evolution (n_1) (c) State evolution (n_2)

(d) TTS (e) MFD plots (R_1) (f) MFD plots (R_2)

Figure 3 – *The microscopic simulation results*

4 CONCLUSION

This paper proposed a closed-loop learning framework for robust adaptive perimeter traffic control. Different from previous algorithms that learn traffic dynamics solely from open-loop data, ignoring the effect of controller deployment, the proposed algorithm learned the dynamics from closed-loop data. The iterative operation of controller design and traffic dynamics learning based on closed-loop data facilitated obtaining the optimal control strategy. Preliminary experiments and microscopic simulations validated the feasibility of the proposed method.

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