Integrating Autonomy into Traffic Systems: Scalable Control and Optimization

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Electrical and Computer Engineering

SOC Lab

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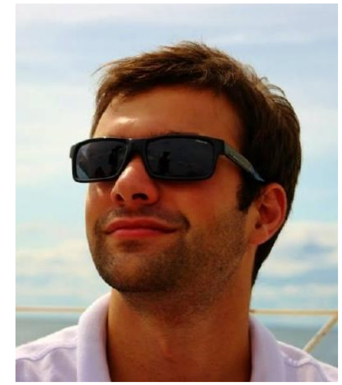

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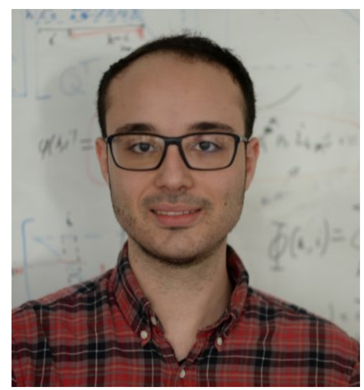


Luca Furieri
EPFL

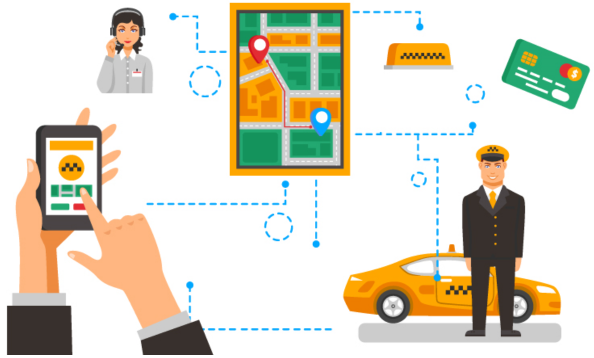
Maryam Kamgarpour
EPFL

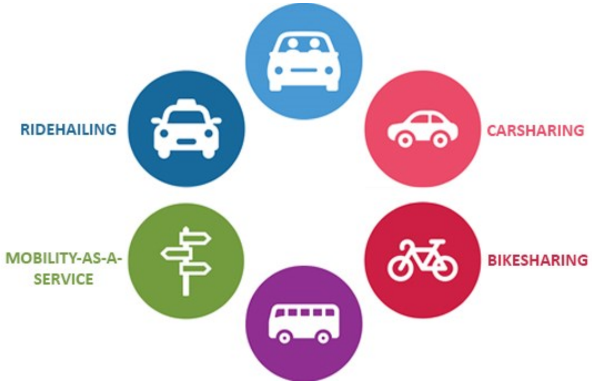
Autonomous Vehicles

- **Reduce traffic accidents**
  - 37,000 fatalities
  - 41% deaths of young adults (ages 15-24)
  - **94%** of serious crashes caused by human error

U.S. Census Bureau, 2017.

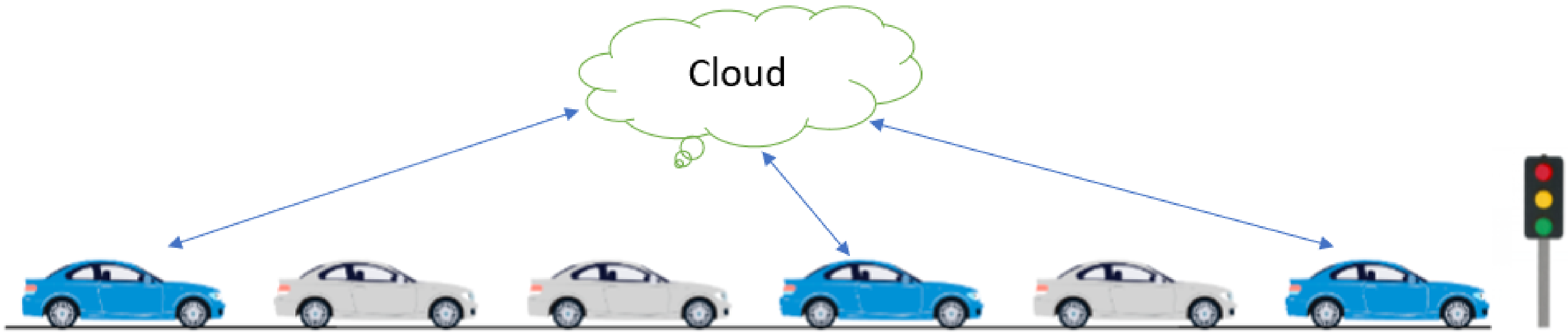
- **Ease traffic congestion**
  - **6.9 billion hours** wasted annually
  - Cost of traffic congestion is **$1740** per person annually in US/Europe.
- **Improve energy efficiency**
  - 28% of greenhouse gas emission is from transportation
- **New mobility patterns**: on-demand mobility, mobility as service etc.





Mix-Autonomy Mobility

A long stage of mixed-autonomy mobility

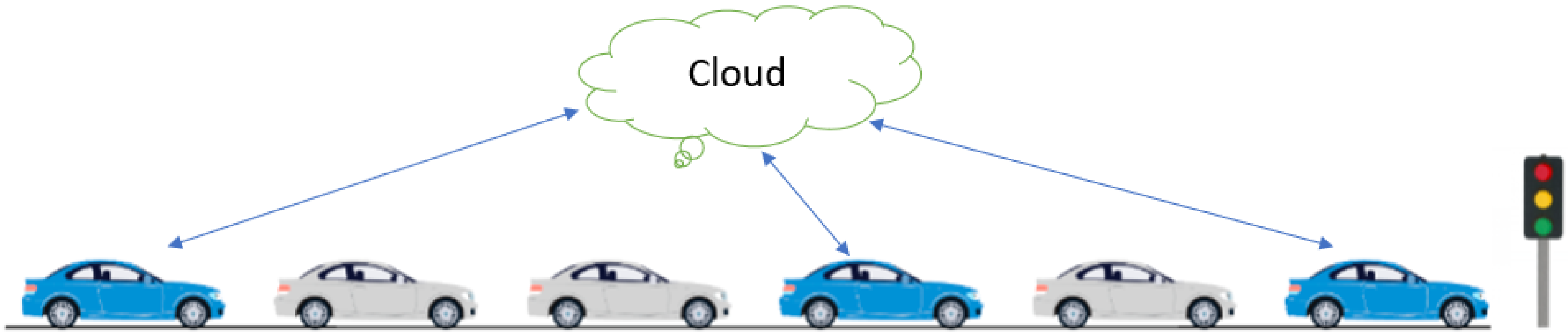


Mixed-autonomy mobility: a traffic condition where both autonomous vehicles and human-driven vehicles co-exist.

- **Q1:** How will **a small scale of autonomous vehicles** change traffic dynamics?
- **Q2:** How to integrate **a small scale of autonomous vehicles** to improve traffic performance?

Research questions

Mixed-autonomy mobility



- **Q1:** How will **a small scale of autonomous vehicles** change traffic dynamics?
- **Q2:** How to integrate **a small scale of autonomous vehicles** to improve traffic performance?

Theoretical evidence of the high potential of autonomous vehicles

Practical design via distributed control and scalable optimization

Benchmark Ring Road Experiment

Traffic jams

Sugiyama, et al.

1950s >10,000 papers for traffic control **2008** 2021

Setting:

22 human drivers

Instructions:

drive at 30 km/h /following its preceding vehicle

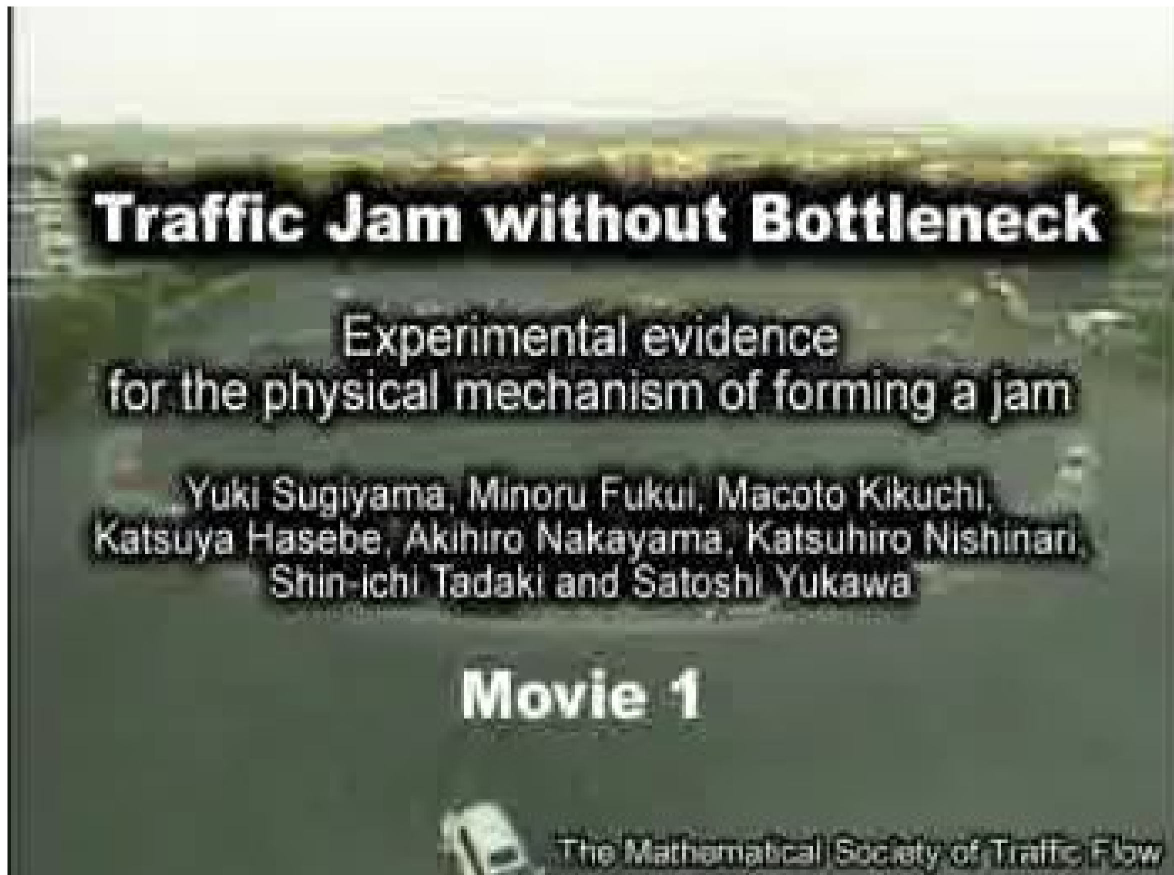
Environment

Single lane

No traffic lights,

No stop signs,

No lane changes.



Video credits: NewScientist.com

Benchmark Ring Road Experiment

Traffic jams

Sugiyama, et al. **Stern, et al.**

1950s >10,000 papers for traffic control 2008 **2018** 2021

Setting:

21 human drivers

+ 1 AV

Instructions:

drive at 30km/h /following its preceding vehicle

Environment

Single lane

No traffic lights,

No stop signs,

No lane changes.

Dissipation of stop-and-go traffic waves via control of a single autonomous vehicle

Recent advances

Traffic jams

Reinforcement learning:

Wu, Cathy, et al., 2018 (MIT & Berkeley); Vinitsky, E., Kreidieh, A., Le Flem, L., Kheterpal, N., Jang, K., Wu, C., ... & Bayen, 2018, In Conference on robot learning.

Adaptive and PDE control:

Yu, Huan, and Miroslav Krstic. Automatica, 2019. Yu, Huan, Saurabh Amin, and Miroslav Krstic. 2020, IEEE CDC.

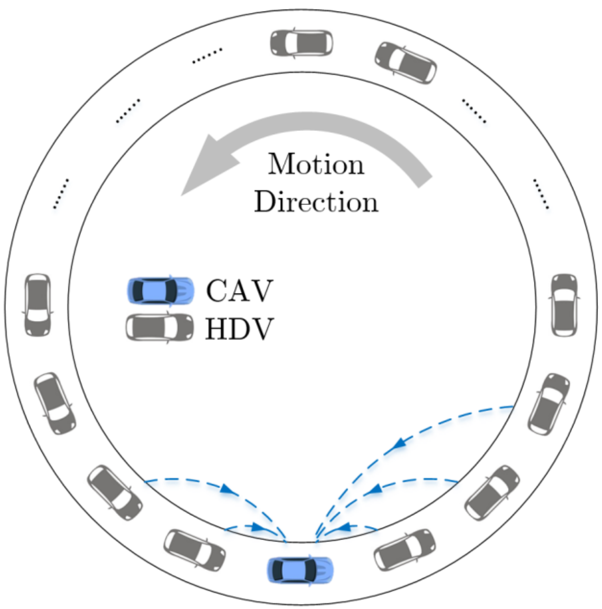
Hinf control:

Mousavi, Shima Sadat, Somayeh Bahrami, and Anastasios Kouvelas. 2021 (ETH Zurich)

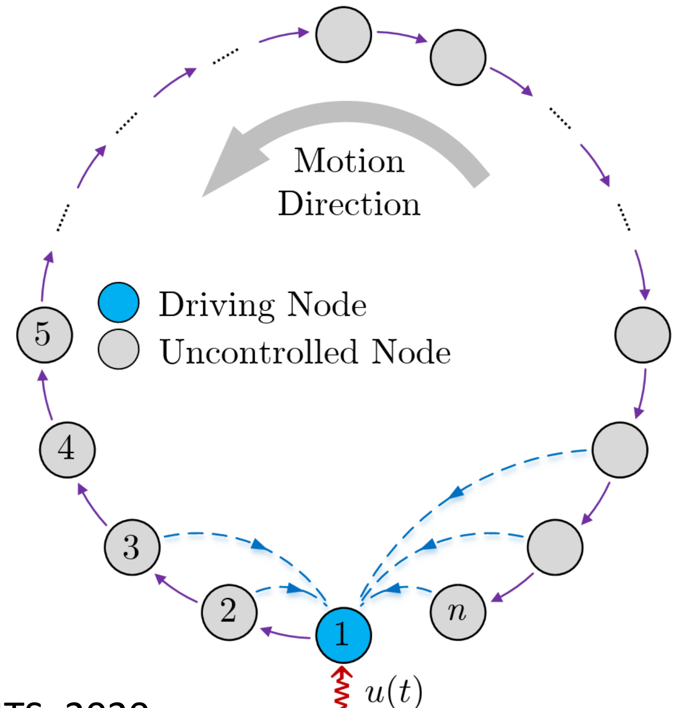
Theoretical Evidence in mixed traffic

❑ Theoretical Evidence & Controller design

- Why does it work?
- Does it work in other setups (e.g., different number of HDVs, different human-driver behavior, open straight road scenario)?



Sparse network control

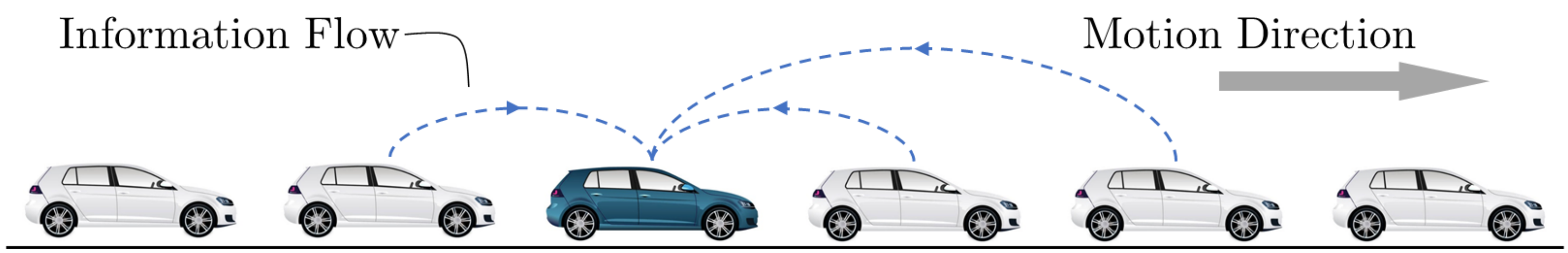


Zheng, Wang, & Li, IEEE IoT, 2019; Wang, & **Zheng**, et al., IEEE TITS, 2020

Scalable Control & Optimization

❑ Theoretical Evidence & Controller design

- ➢ How to design distributed controllers with limited communication?
- ➢ How to scale up the computation efficiency?



- Furieri, L., **Zheng**, Y., Papachristodoulou, A., & Kamgarpour, M. (2020). Sparsity invariance for convex design of distributed controllers. IEEE Transactions on Control of Network Systems. (***Best Student Paper Finalist***, ECC 2019)
- **Zheng**, Y., Fantuzzi, G., Papachristodoulou, A., Goulart, P., & Wynn, A. (2020). Chordal decomposition in operator-splitting methods for sparse semidefinite programs. ***Mathematical Programming***, *180*(1), 489-532.

Today’s talk

Integrating Autonomy into Traffic Systems

Part 1: Theoretic potential of autonomy in traffic

- Stabilizability of mixed traffic flow;
- Autonomous vehicles as mobile actuators in traffic networks;
- Leading Cruise Control (LCC)

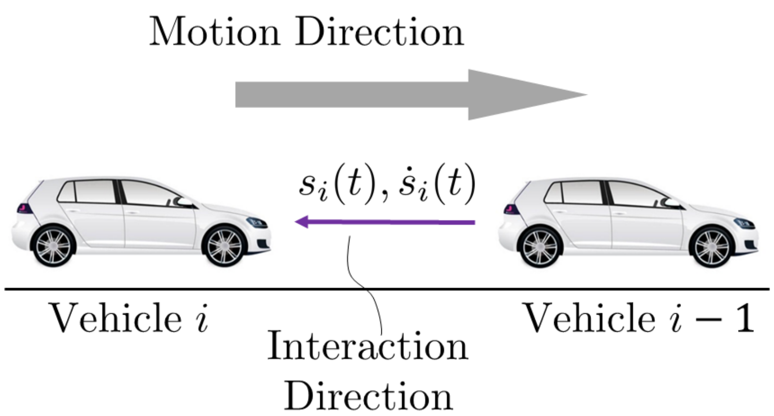
Part 2: Practical design via control & optimization

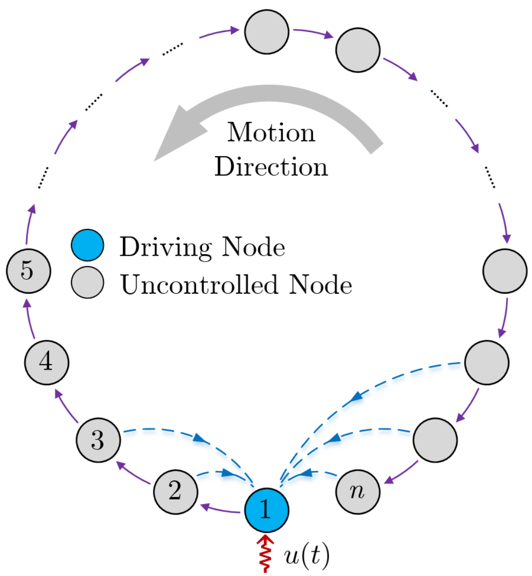
- Convex design of distributed control over traffic network;
- Scalable optimization for large-scale convex problems;

Mixed-autonomy in a ring road

❑ System modeling

1. Human drivers → car-following dynamics

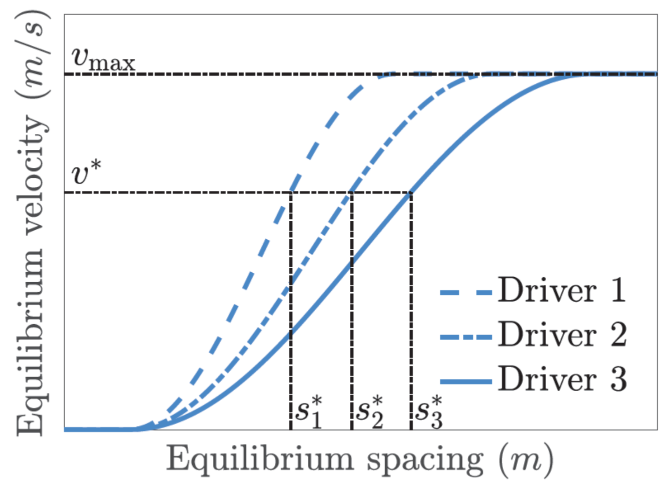




$$\dot{v}_i(t) = F_i(s_i(t), \dot{s}_i(t), v_i(t))$$

- $v_i(t)$: Velocity of vehicle i
- $s_i(t)$: Spacing between vehicle i and vehicle $i-1$

$$0 = F_i(s_i(t), 0, v_i(t))$$

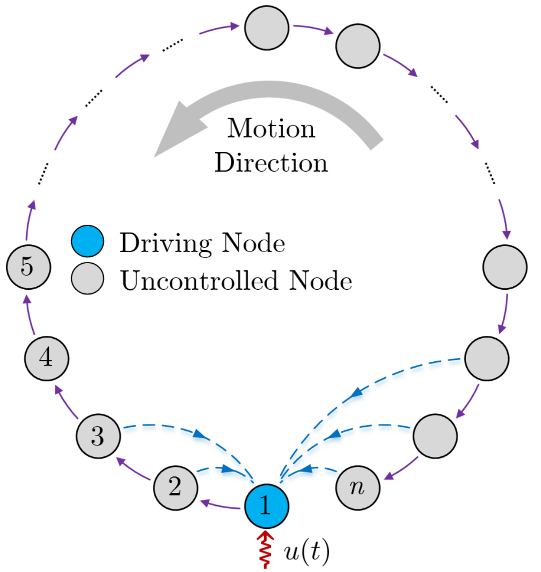


Large spacing ↔ Large velocity

Dirk Helbing, 2001; Orosz, Wilson, and Stepan, 2010.

Mixed-autonomy in a ring road

❑ System modeling



2. Autonomous vehicle → direct control

$$\begin{cases} \dot{s}_1(t) &= v_n(t) - v_1(t) \\ \dot{v}_1(t) &= u_1(t) \end{cases}$$

3. Assuming an equilibrium traffic state $v^*(t)$

$$\dot{x}(t) = Ax(t) + Bu(t),$$

where the system matrices have the following structure

$$A = \begin{bmatrix} C_1 & 0 & \dots & \dots & 0 & C_2 \\ A_2 & A_1 & 0 & \dots & \dots & 0 \\ 0 & A_2 & A_1 & 0 & \dots & 0 \\ \vdots & \ddots & \ddots & \ddots & \ddots & \vdots \\ 0 & \dots & 0 & A_2 & A_1 & 0 \\ 0 & \dots & \dots & 0 & A_2 & A_1 \end{bmatrix}, B = \begin{bmatrix} 0 \\ 1 \\ 0 \\ \vdots \\ 0 \end{bmatrix},$$

A network system with only one controllable node

Mixed-autonomy in a ring road

❑ Theoretical evidence 1: Unstable behavior

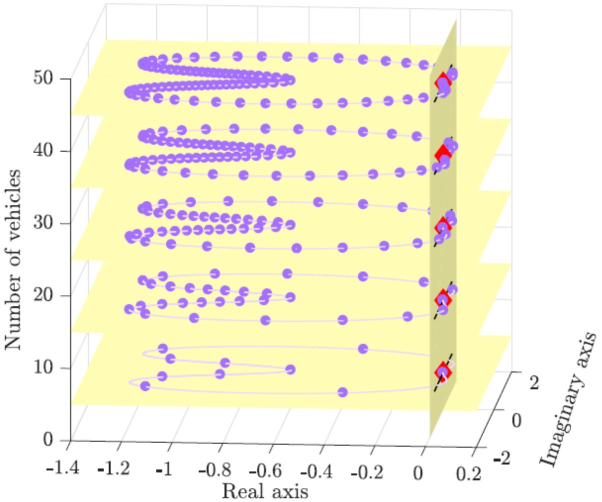
$$\dot{x}(t) = \hat{A}x(t)$$

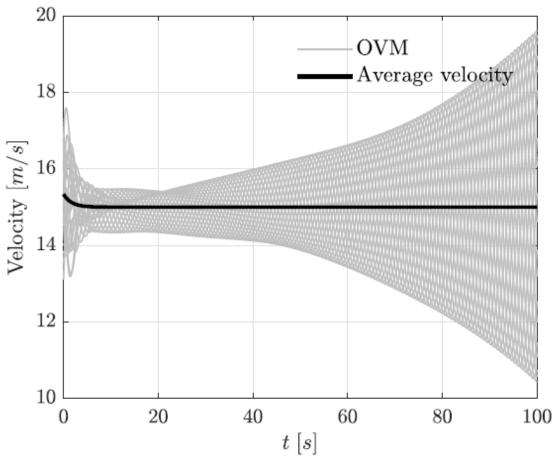
(Informal) The traffic system in a ring-road can be unstable if drivers' sensitivity to speed and spacing errors is small (e.g. Cui et al., 2017)

$$\alpha + 2\beta < \text{Constant}$$

Sensitivity to speed and spacing errors

Slow response to spacing; To catch up, it drives to a large velocity → **Oscillation**





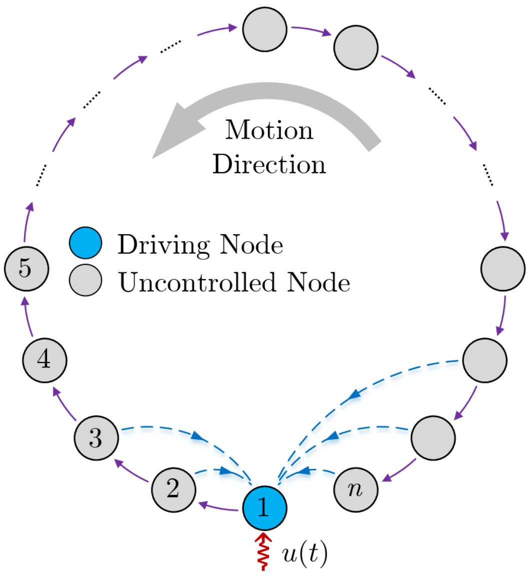
Mixed-autonomy in a ring road

❑ Theoretical evidence 2: Fundamental change of dynamics

$$\dot{x}(t) = \hat{A}x(t)$$

Theorem (zheng *et al.*, 2019)**: The mixed traffic system in the ring-road setup is not controllable, but stabilizable.**

1. **Independent of the number of human-driven vehicles**
2. **Independent of car-following dynamics**
3. **Offer a strong control-theoretic support for the potential of autonomy in mixed traffic**



Integrating autonomy is a fundamental change of traffic dynamics (more control freedom)!

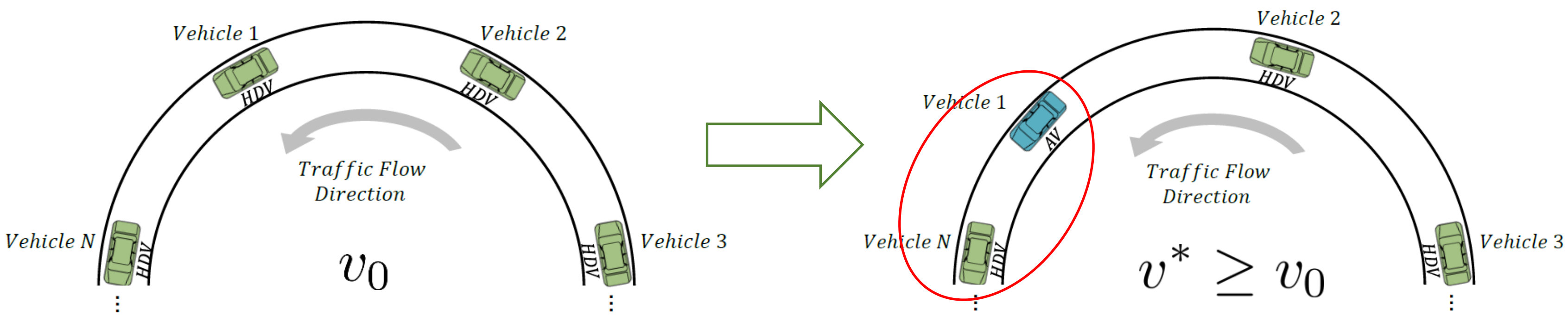
Zheng, Wang, & Li, IEEE IoT, 2019

Mixed-autonomy in a ring road

❑ Theoretical evidence 3: Beyond stabilization/increase traffic speed

Theorem (zheng *et al.*, 2019)**: The global traffic velocity can be increased to a larger value:**

$$0 \leq v^* < v_{\max}$$



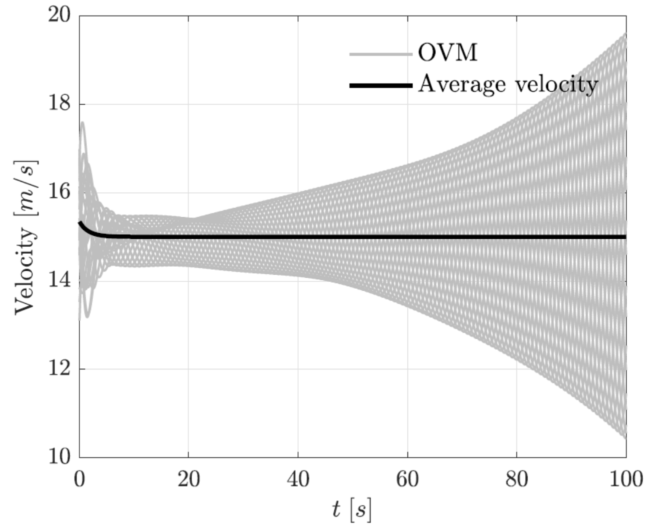
❑ Physical interpretation

✓ The AV can change its own spacing to influence other HDVs' spacing, and thus change traffic velocity v^*.

Zheng, Wang, & Li, IEEE IoT, 2019

Numerical Experiments with Nonlinear Dynamics

Unstable traffic system

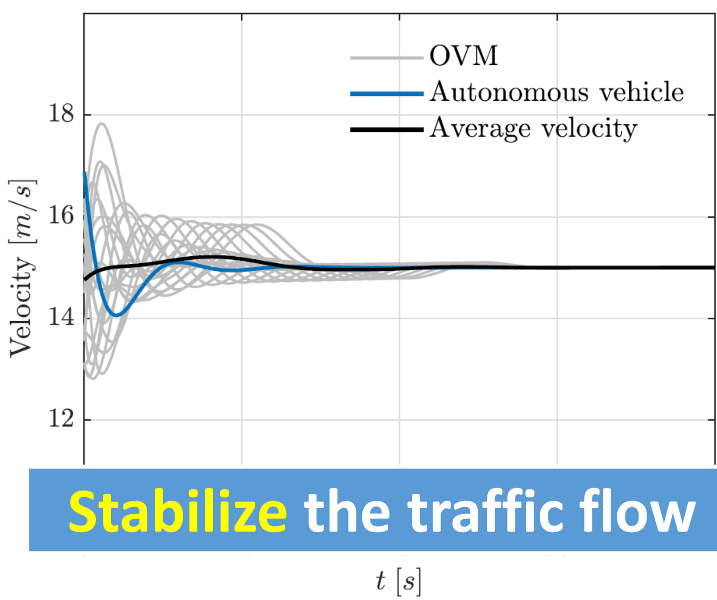


OVM: Optimal Velocity Model

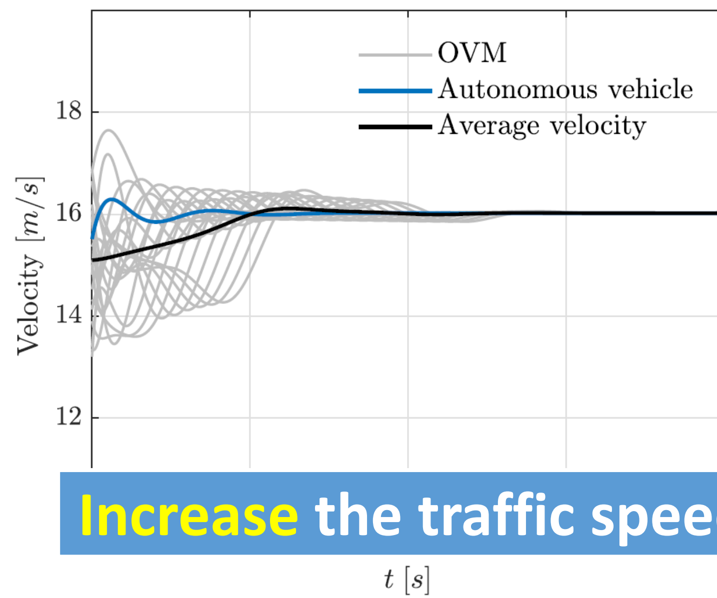
$$F_i = \alpha(V(s_i(t)) - v_i(t)) + \beta \dot{s}_i(t)$$

$$V(s) = \begin{cases} 0, & s \le s_{\text{st}}, \\ f_v(s), & s_{\text{st}} < s < s_{\text{go}}, \\ v_{\max}, & s \ge s_{\text{go}}, \end{cases}$$

$$f_v(s) = \frac{v_{\max}}{2}\left(1 - \cos(\pi \frac{s - s_{\text{st}}}{s_{\text{go}} - s_{\text{st}}})\right).$$



Stabilize the traffic flow

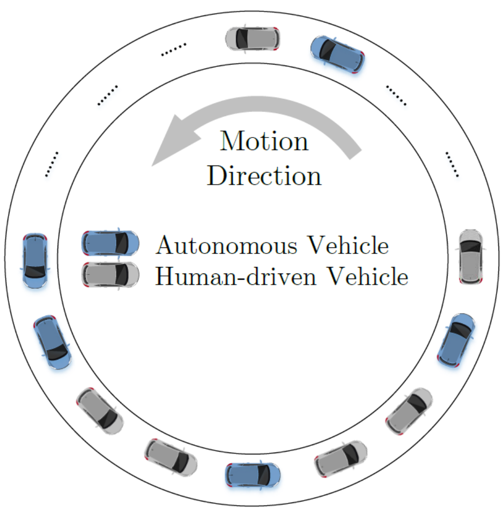


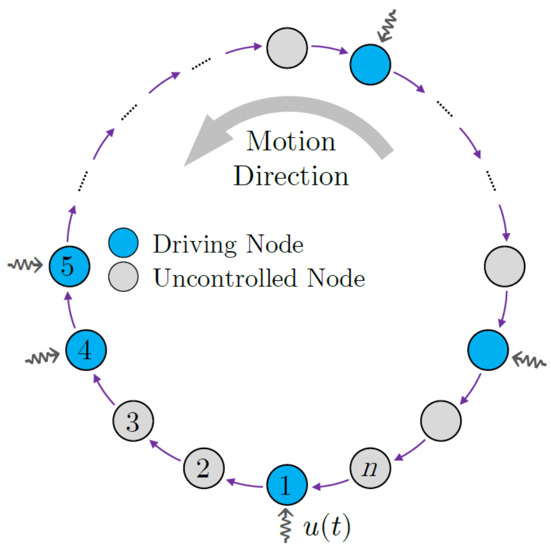
Increase the traffic speed

The existence of **5% AVs** (1 out of 20) can bring **6% improvement** on traffic velocity

Integrating Autonomy: Multiple AVs

Main question: How to coordinate multiple autonomous vehicles in traffic flow? Is platooning the optimal choice?





Set function optimization

$$\max_{S} \quad J(S)$$

$$S \subseteq \Omega, |S| = k$$

$\Omega = \{1, 2, \ldots, n\}$: all the vehicles

$S = \{i_1, \ldots, i_k\} \subseteq \Omega$: k autonomous vehicles

Li, Wang, & **Zheng,** (2020), IEEE TITS, under review

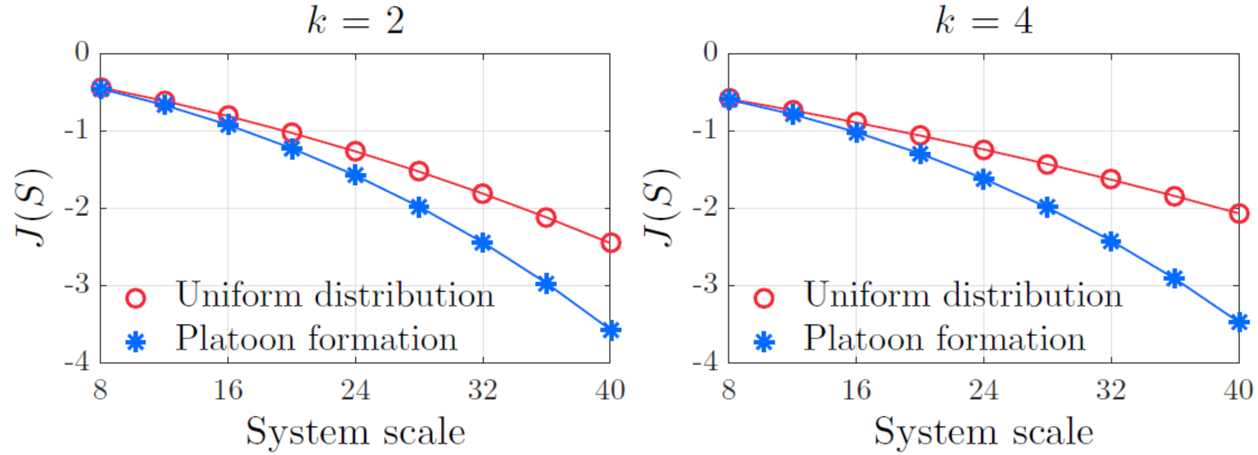
Integrating Autonomy: Multiple AVs

Set function optimization

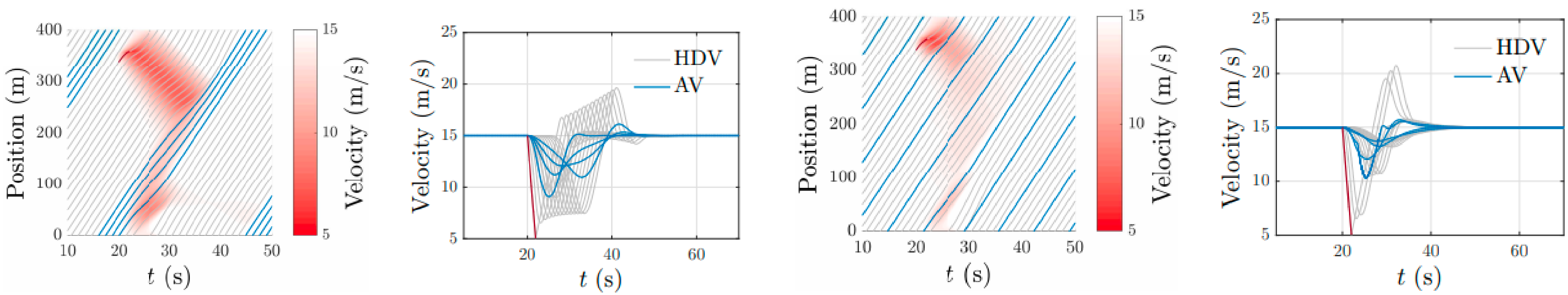
$$\max_{S} \quad J(S)$$

$$S \subseteq \Omega, |S| = k$$

Platooning is not always optimal



Simulation with Nonlinear Car-following Dynamics



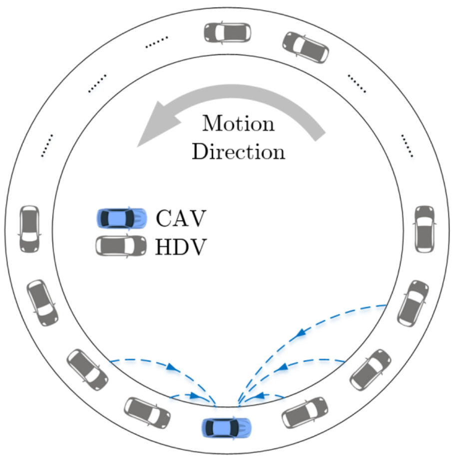
Platoon formation: $S = \{9, 10, 11, 12\}$

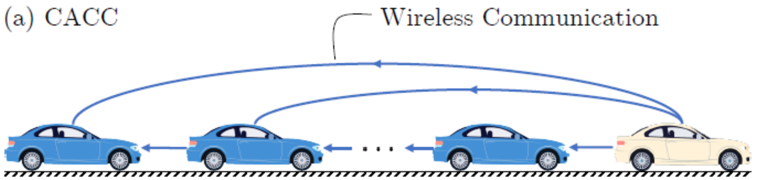
Li, Wang, & **Zheng,** (2020), IEEE TITS, under review

Uniform distribution: $S = \{3, 8, 13, 18\}$

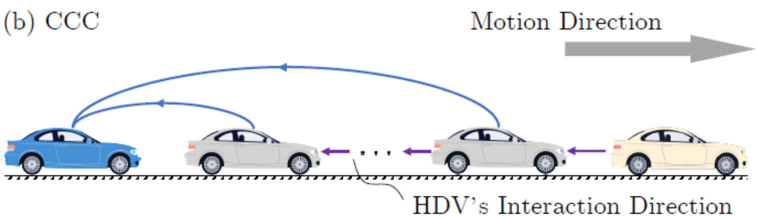
Integrating Autonomy in Open-straight roads

Closed-ring road setup



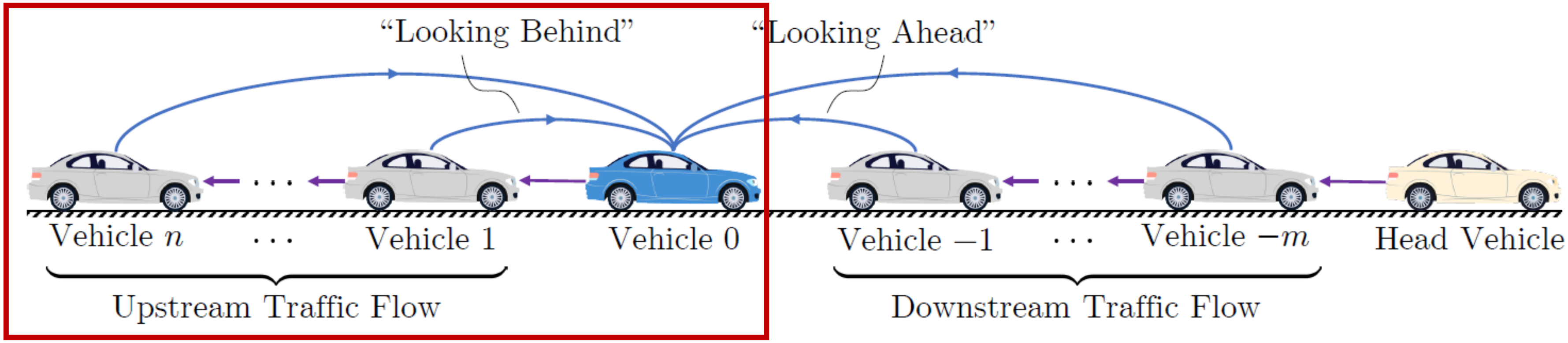


CACC: Fully-autonomous scenario



Connected Cruise Control: downstream traffic flow

➢ Leading Cruise Control

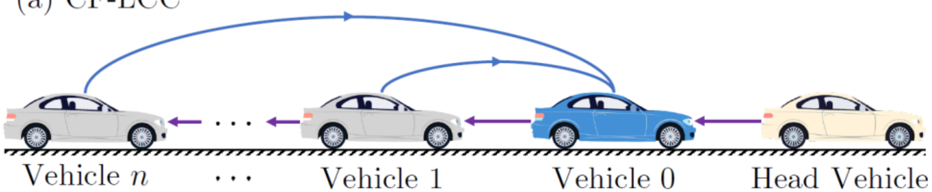


Lead the motion of the vehicles behind + **Adapt to the motion of the vehicles ahead**

Leading Cruise Control (LCC)

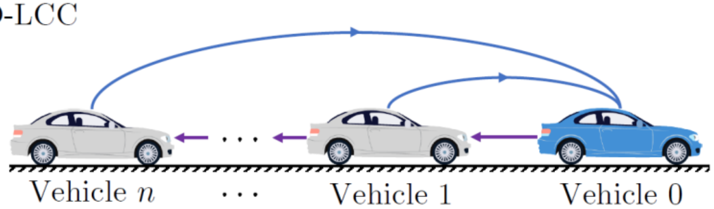
Special case 1: car-following LCC

(a) CF-LCC

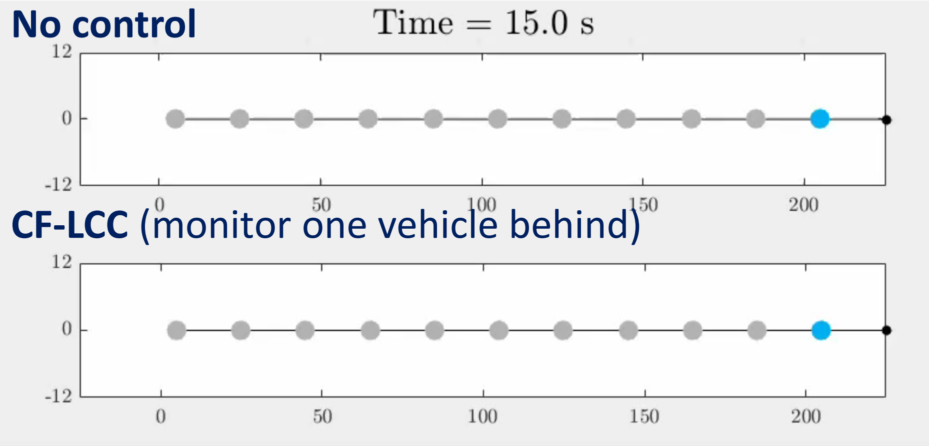


Special case 2: free driving LCC

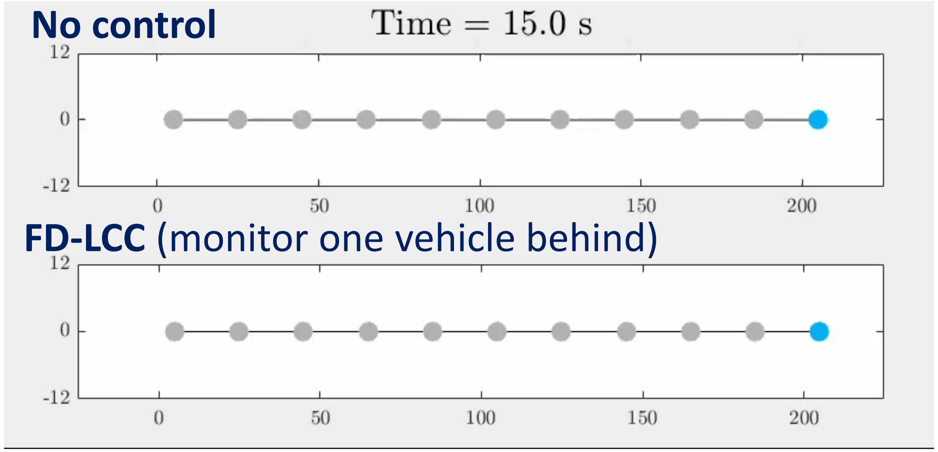
(b) FD-LCC



1. **The motion after AV is controllable (leading motion behind)**
2. **String stability can be improved (attenuating perturbation ahead)**



Reduce velocity perturbations by 28%



Reduce velocity perturbations by 35%

Wang, J., **Zheng, Y.**, Chen, C., Xu, Q., & Li, K. (2021). Leading cruise control in mixed traffic flow: System modeling, controllability, and string stability. IEEE Transactions on Intelligent Transportation Systems.

Today's talk

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Part 1: Theoretic potential of autonomy in traffic

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Part 2: Practical design via control & optimization

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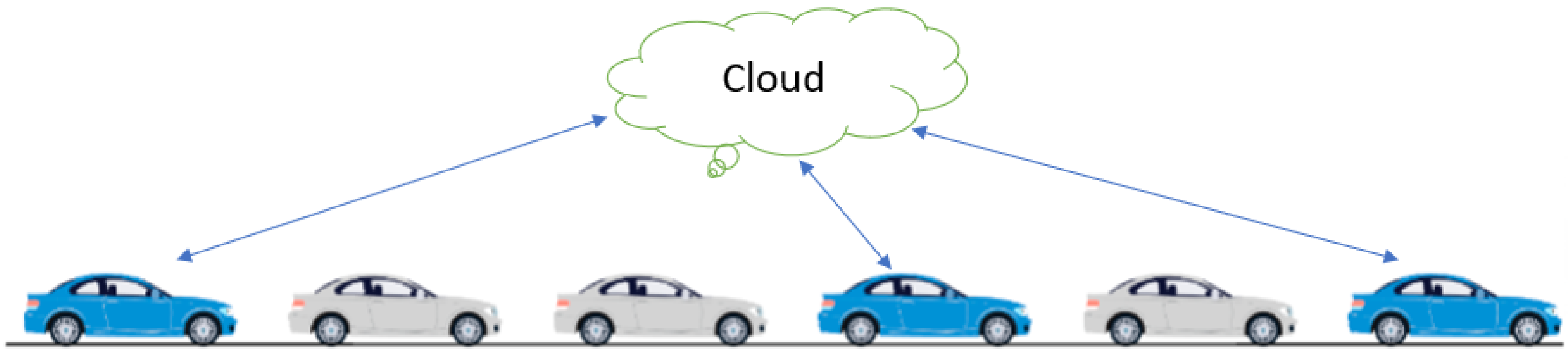
General Procedure



Control Problem Formulation

↓

Convex reformulation as LMI or SDP

↓

Call a numerical solver

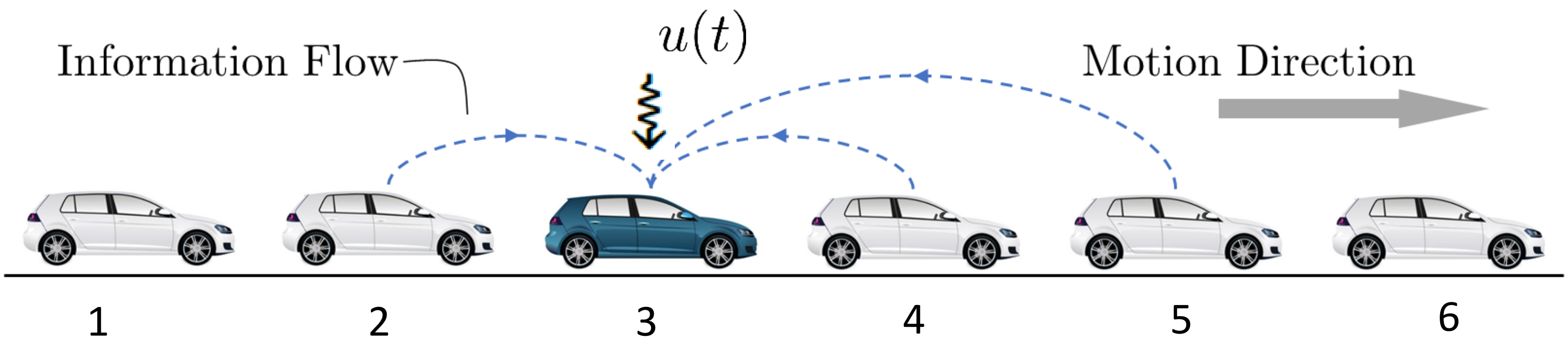
Challenge 1: How to recover convexity

Challenge 2: How to deal large-scale problems (Scalability)

Problem formulation: distributed controller

❑ Why distributed?

- No need of a centralized coordinator
- Allow for local communication



$$u(t) = -(k_1 x_1 + k_2 x_2 + k_3 x_3 + k_4 x_4 + k_5 x_5 + k_6 x_6)$$

$$k_1 = k_6 = 0$$

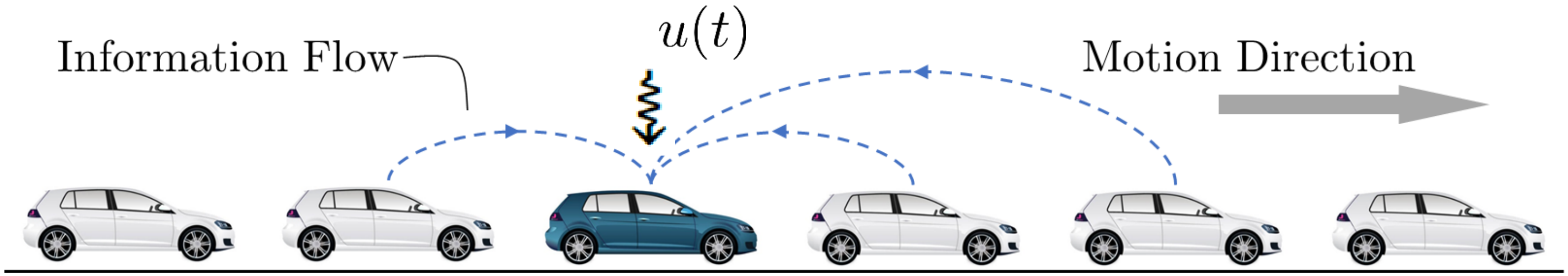
Compact form

$$u(t) = -Kx(t), \quad K \in \mathrm{Sparse}(S)$$

$$S = \begin{bmatrix} 0 & 1 & 1 & 1 & 1 & 0 \end{bmatrix}$$

encodes local communication

Problem formulation: distributed controller



$$\min_{K} \quad J(K)$$ → System performance (e.g., speed oscillation)

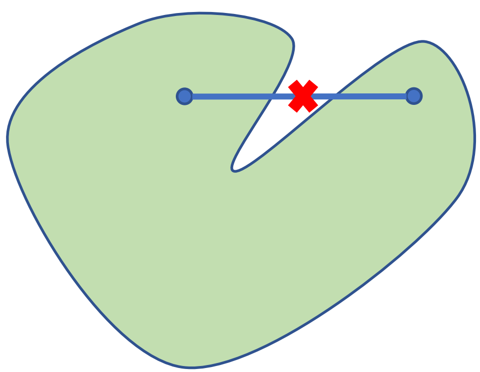
$$\text{subject to} \quad K \in \mathcal{C}_{\text{stab}},$$ → Stable controller

$$K \in \text{Sparse}(S)$$ → Distributed controller

- This is **a non-convex optimization problem**

$$\exists \quad K_1 \in \mathcal{C}_{\text{stab}}, K_2 \in \mathcal{C}_{\text{stab}}$$

$$\Rightarrow \quad \frac{1}{2}(K_1 + K_2) \notin \mathcal{C}_{\text{stab}}$$



- The presence of the sparsity constraint makes the problem **even more challenging** (NP-hard in general).

Previous work on distributed control

90's: Feasibility & Stabilization

1) **Structural controllability:** Glover & Silverman, TAC 1976; Wang & Davison, TAC 1973; Davison, Automatica 1977; Mayeda and Yamada, SICON 1979, etc.
2) **Decentralized/distributed fixed mode:** Anderson & Clements, TAC 1981; Sezer & Šiljak, SCL 1981; Davison & Özgüner, Automatica 1983; etc.
3) **Decentralized stabilization & pole placement:** Davison & Chang, TAC 1995; Ravi et al, TAC 1995
4) **Early survey paper:** Sandell, Varaiya, Athans & Safonov, TAC 1978.

Late 90's- Now: Performance enhancement via optimization

1) **Exact solutions for special classes of systems:** Quadratic Invariance (Rotkowitz & Lall, TAC 2005); Partially ordered sets (Shah & Parrilo, TAC 2013);
2) **Tractable convex approximation:** Dvijotham et al, TCNS 2015; Fazelnia et al, TAC 2016;
3) **Suboptimal solutions using iterative algorithms:** Fu, Fardad, & Jovanovic, TAC 2011;
4) **Structure regularization and system-level synthesis:** Jovanović & Dhingra, 2016; Wang et al., TAC 2019;

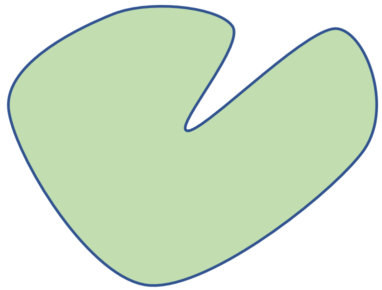
Recover Convexity

A new framework based on Sparsity Invariance for convex design of distributed control

Change of Variables

- **Do not optimize the controller K directly:** Convex reformation via a change of variables (convex SDP; Boyd *et al.*, 1994);

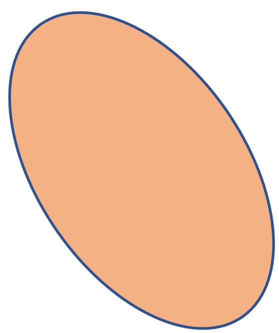
$$\begin{aligned} &\text{minimize} && J(K) \\ &\text{subject to} && K \in \mathcal{C}_{\text{Stab}}. \end{aligned}$$



$$\begin{aligned} &\text{minimize} && J(K) \\ &\text{subject to} && K \in \mathcal{C}_{\text{stab}}, \\ &&& {\color{red} K \in \text{Sparse}(S)} \end{aligned}$$

$$K = YX^{-1}$$

$$\begin{aligned} &\text{minimize} && g(X,Y) \\ &\text{subject to} && (X,Y) \in \hat{\mathcal{C}}_{\text{Stab}}. \end{aligned}$$



$$\begin{aligned} &\text{minimize} && g(X,Y) \\ &\text{subject to} && (X,Y) \in \hat{\mathcal{C}}_{\text{Stab}} \\ &&& {\color{blue} YX^{-1} \in \text{Sparse}(S)}. \end{aligned}$$

Non-convex constraint

Sparsity Invariance

$$\begin{aligned} \text{minimize} \quad & g(X,Y) \\ \text{subject to} \quad & (X,Y) \in \hat{\mathcal{C}}_{\text{Stab}} \\ & YX^{-1} \in \text{Sparse}(S). \end{aligned}$$

→ **Non-convex constraint**

Sparsity invariance (SI)

$$X \in \text{Sparse}(R), \; Y \in \text{Sparse}(T)$$
$$\Rightarrow$$
$$K = YX^{-1} \in \text{Sparse}(S)$$

- **Translate the constraint on the controller to separate constraints on new decision variables**

Convex approximation

$$\begin{aligned} \text{minimize} \quad & g(X,Y) \\ \text{subject to} \quad & (X,Y) \in \hat{\mathcal{C}}_{\text{Stab}} \\ & X \in \text{Sparse}(R) \\ & Y \in \text{Sparse}(T). \end{aligned}$$

Recover Convexity

Best Student Paper Finalist, European Control Conference 2019

Sparsity Invariance

Sparsity invariance (SI)

$$X \in \text{Sparse}(R),\ Y \in \text{Sparse}(T)$$
$$\Rightarrow$$
$$K = YX^{-1} \in \text{Sparse}(S)$$

Special case: the widely used diagonal assumption

$R = I, T = S$ is a trivial choice; (Geromel et al., 1994; Conte et al.,2012; Rubio et al., 2013;)

Further contributions

1. A full characterization

$$TR^{n-1} \leq S$$

2. A practical optimal design of the patterns R, T

Best Student Paper Finalist, European Control Conference 2019

Unified framework for distributed control

Sparsity invariance (SI)

$$X \in \text{Sparse}(R),\ Y \in \text{Sparse}(T)$$
$$\Rightarrow$$
$$K = YX^{-1} \in \text{Sparse}(S)$$

Recover Convexity

A new framework based on Sparsity Invariance for convex design of distributed control

Static feedback

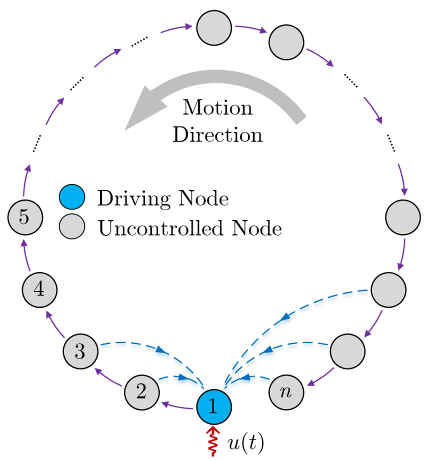
- Strictly better than the widely used **diagonal approximation strategy** (Geromel et al., 1994; Conte et al.,2012; Rubio et al., 2013; Han et al., 2017)

Dynamical feedback (past information + memory)

- Guaranteed to be optimal when a notion of **Quadratic Invariance (QI)** holds (Rotkowitz & Martins, 2012)
- Best known performance for non-QI cases

Furieri, **Zheng**, et al. IEEE TCNS, 2020.

Numerical Experiments with Nonlinear Dynamics

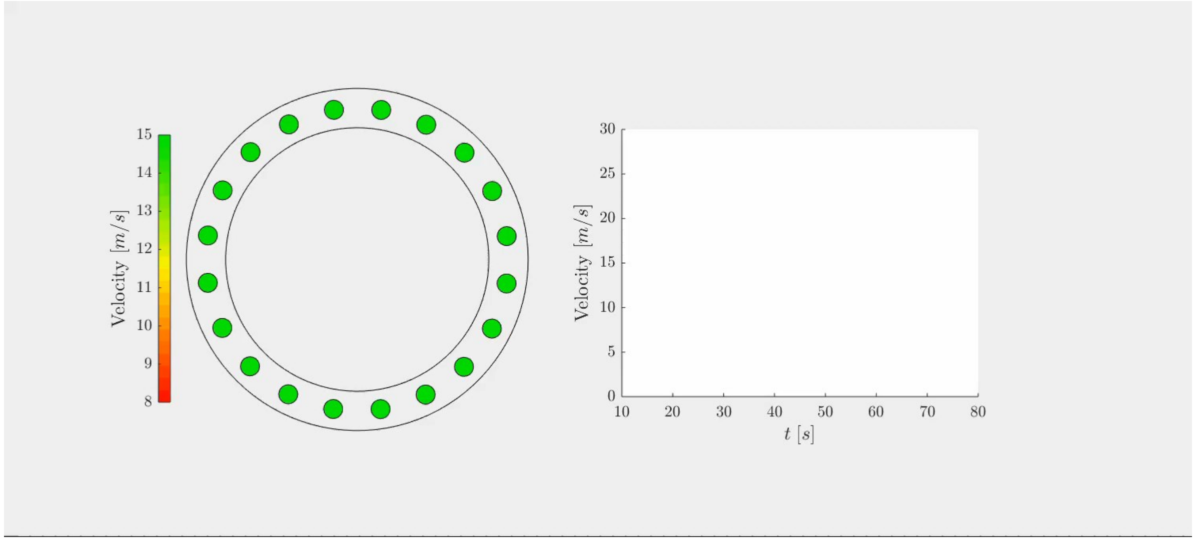


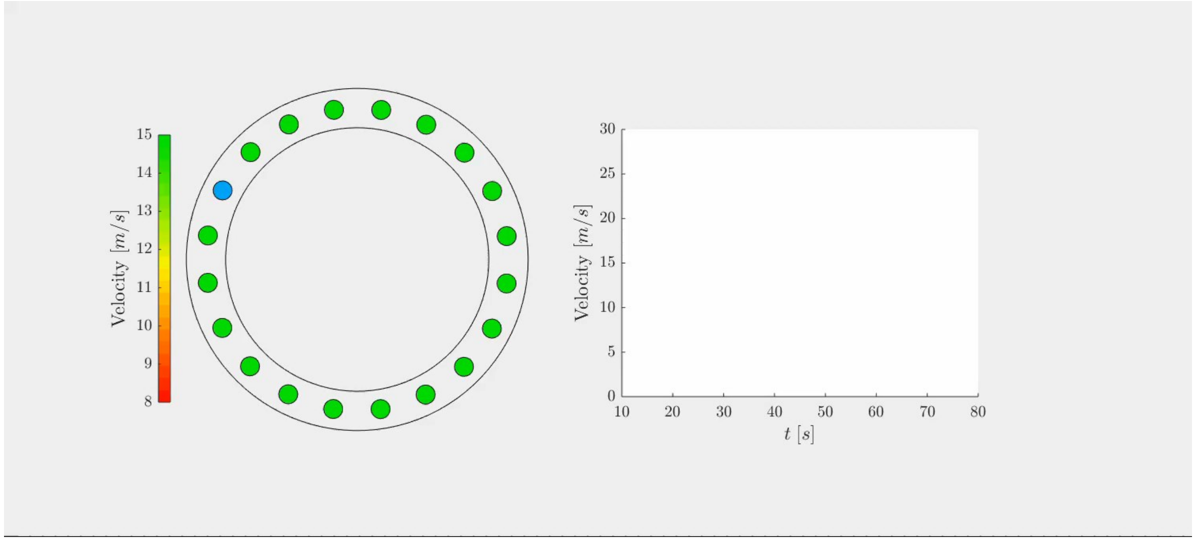
OVM: Optimal Velocity Model

$$F_i = \alpha(V(s_i(t)) - v_i(t)) + \beta \dot{s}_i(t)$$

$$V(s) = \begin{cases} 0, & s \leq s_{\mathrm{st}}, \\ f_v(s), & s_{\mathrm{st}} < s < s_{\mathrm{go}}, \\ v_{\max}, & s \geq s_{\mathrm{go}}, \end{cases}$$

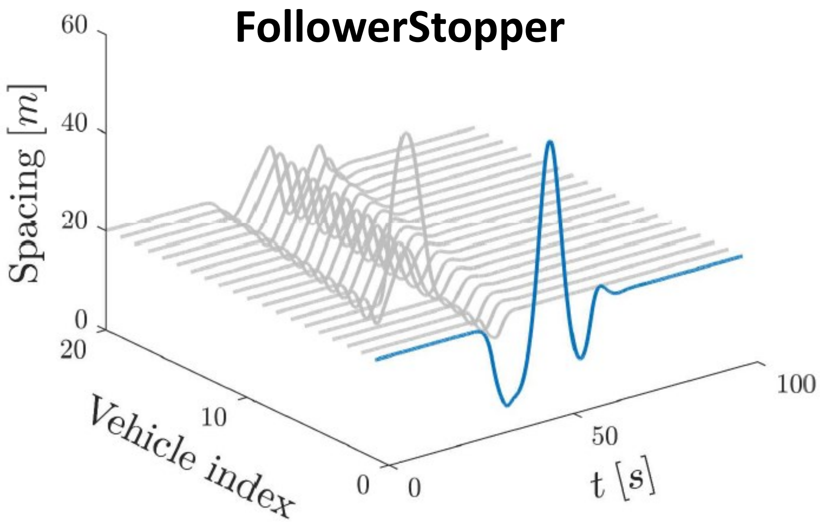
$$f_v(s) = \frac{v_{\max}}{2}\left(1 - \cos(\pi \frac{s - s_{\mathrm{st}}}{s_{\mathrm{go}} - s_{\mathrm{st}}})\right).$$

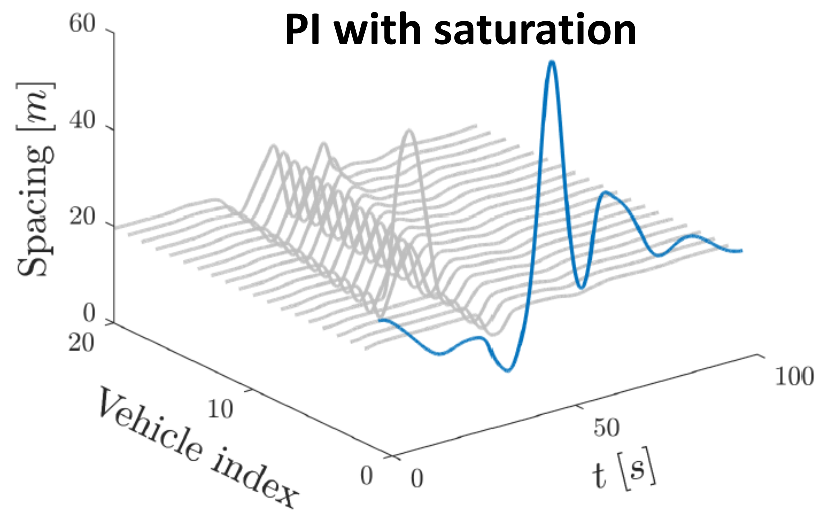




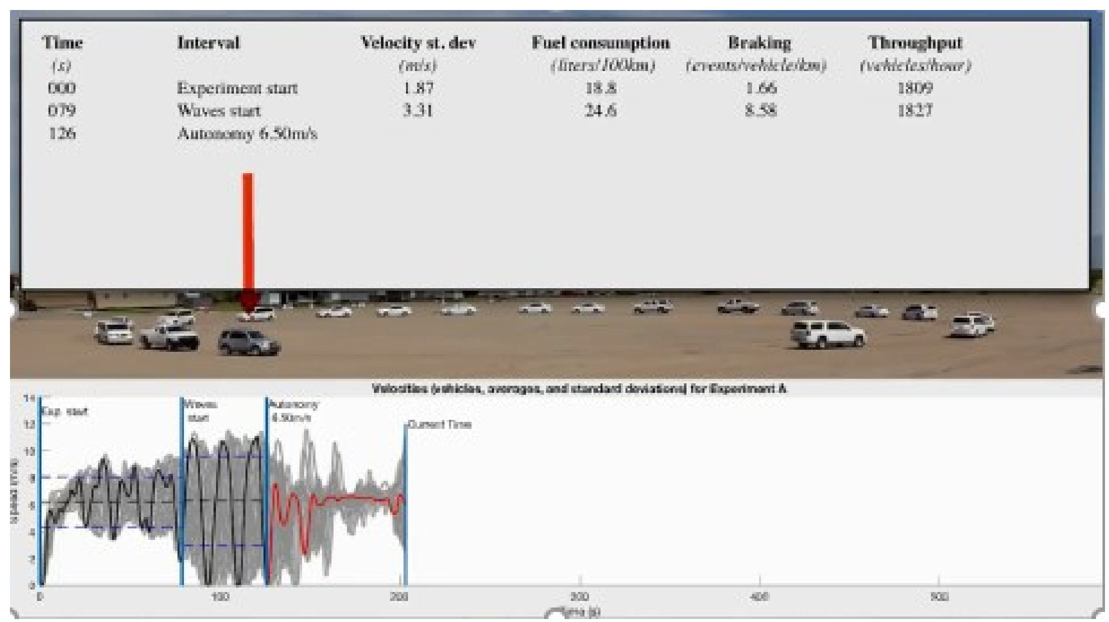
Comparison with existing methods

❑ Comparison with the heuristic methods in Stern et al. 2018



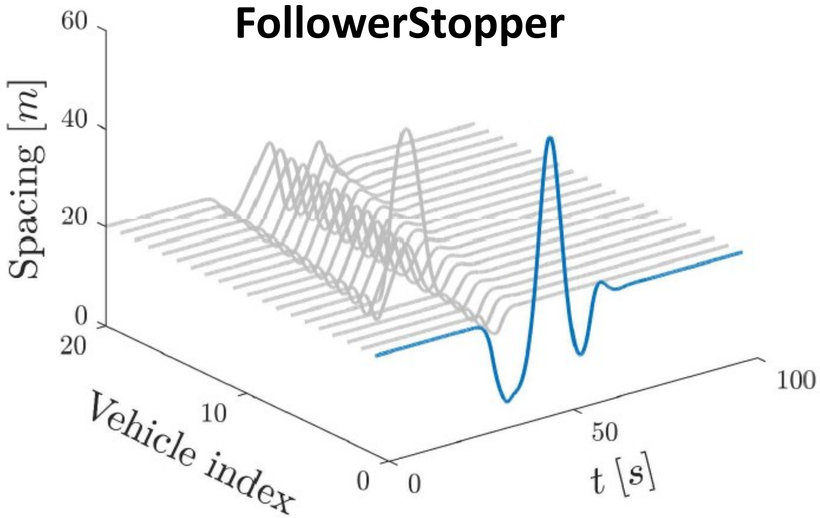


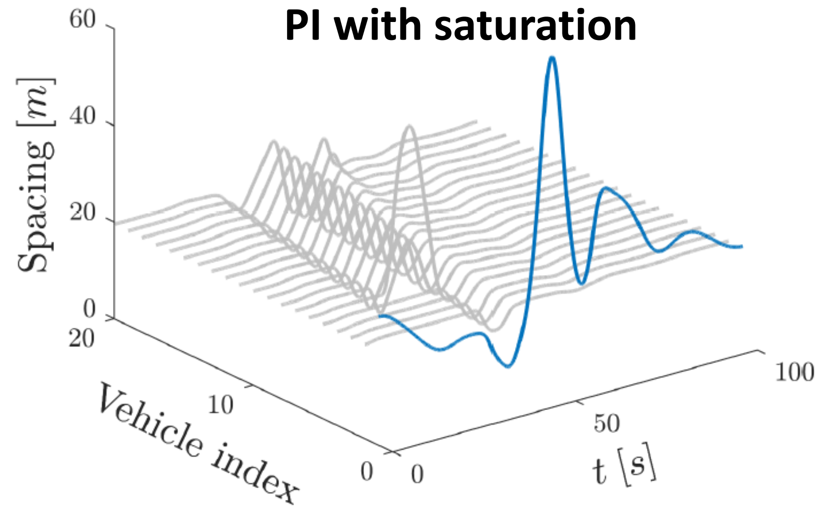
- These methods are conservative
- They lead to large spacing, which may cause other vehicle to cut-in

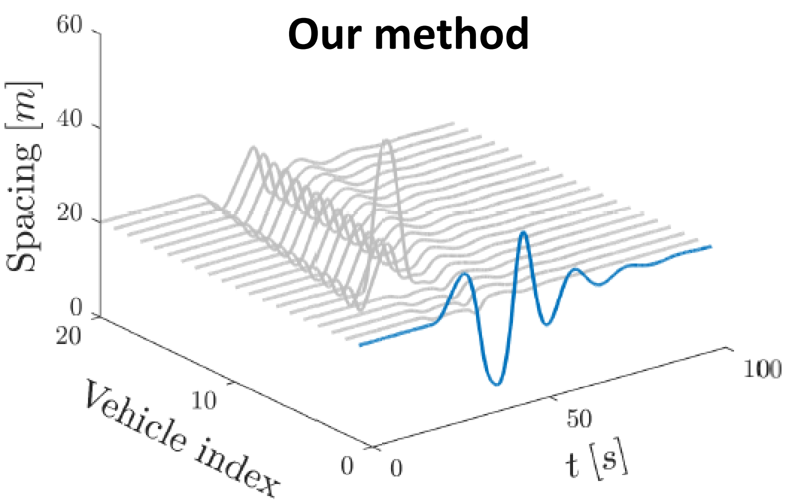


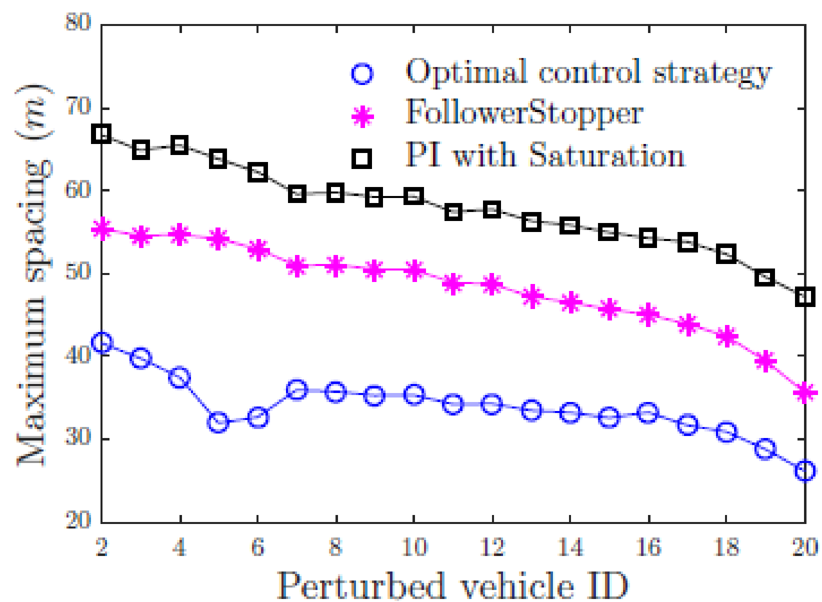
Comparison with existing methods

❑ Comparison with the heuristic methods in Stern et al. 2018









General Procedure

Control Problem Formulation

↓

Convex reformulation as LMI or SDP

↓

Call a numerical solver

Challenge 1: How to recover convexity

Sparsity Invariance

Challenge 2: How to deal large-scale problems (Scalability)

Sparsity Structure Matters

General convex optimization

Semidefinite program

$$\max_{y,Z} \quad \langle b, y\rangle$$
$$\text{subject to} \quad Z + \sum_{i=1}^{m} A_i y_i = C,$$
$$Z \in \mathbb{S}^n_+$$

- **Applications:** control theory, fluid mechanics, polynomial optimization, combinatorics, operations research, finance.
- **Standard interior-point solvers:** SeDuMi, SDPT3, Mosek (suitable for small and medium-sized problems; say $n < 1000$);
- **Practical large-scale instances**: Standard interior point solvers will fail on large-scale problems (say n being a few thousands).

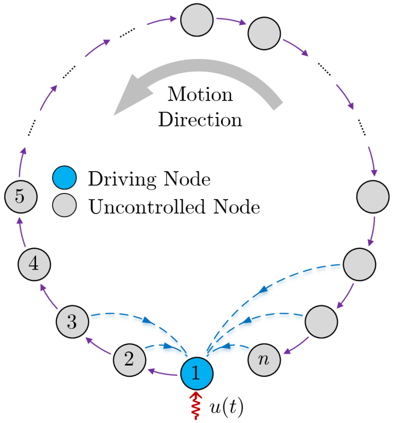
Sparsity Structure Matters

Decompose a big positive semidefinite constraint into multiple smaller ones

Sparsity Structure

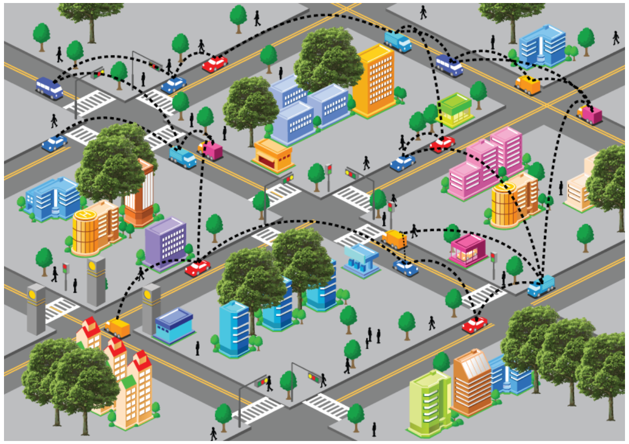
Sparsity structure appears in many places of real cyber-physical systems

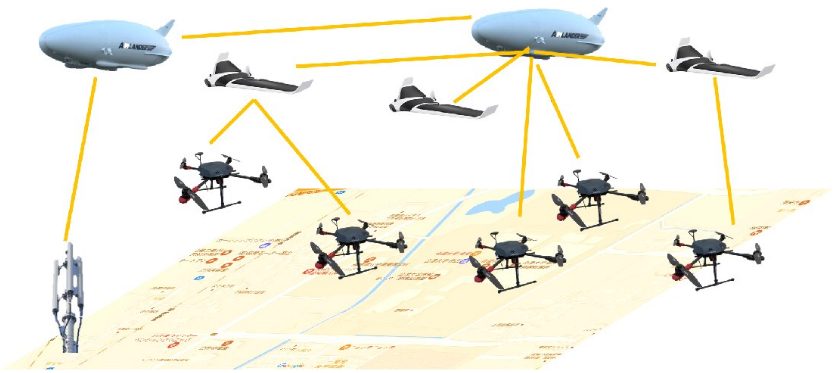
- System dynamics data



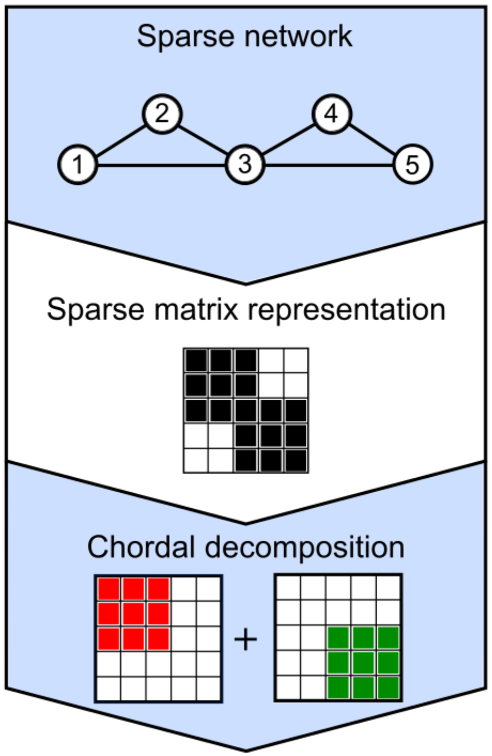
$$A = \begin{bmatrix} C_1 & 0 & \dots & \dots & 0 & C_2 \\ A_2 & A_1 & 0 & \dots & \dots & 0 \\ 0 & A_2 & A_1 & 0 & \dots & 0 \\ \vdots & \ddots & \ddots & \ddots & \ddots & \vdots \\ 0 & \dots & 0 & A_2 & A_1 & 0 \\ 0 & \dots & \dots & 0 & A_2 & A_1 \end{bmatrix}, B = \begin{bmatrix} 1 \\ 0 \\ 0 \\ \vdots \\ 0 \end{bmatrix},$$

- Sparse communication





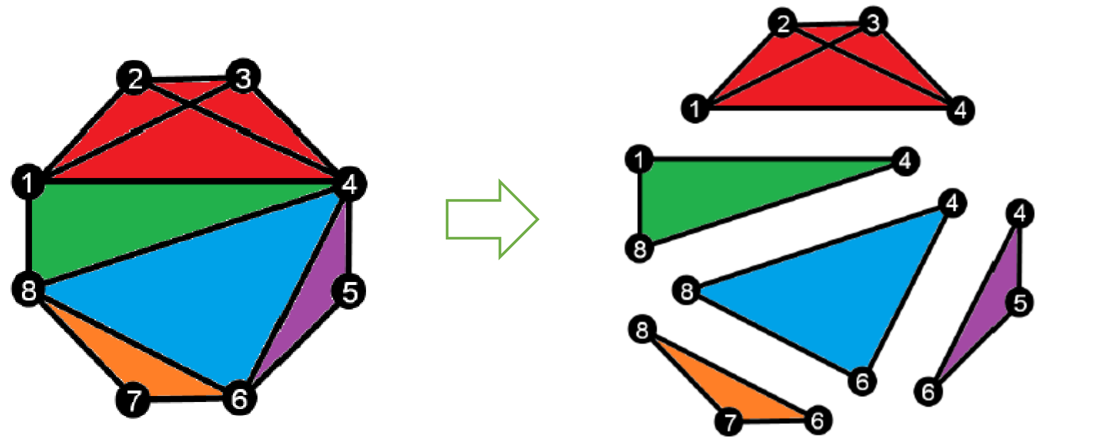
Graph Decomposition



Vandenberghe & Andersen (2015).

$$A = \underbrace{\begin{bmatrix} 3 & 1 & 0 \\ 1 & 1 & 1 \\ 0 & 1 & 3 \end{bmatrix}}_{\succeq 0} = \underbrace{\begin{bmatrix} 3 & 1 & 0 \\ 1 & 0.5 & 0 \\ 0 & 0 & 0 \end{bmatrix}}_{\succeq 0} + \underbrace{\begin{bmatrix} 0 & 0 & 0 \\ 0 & 0.5 & 1 \\ 0 & 1 & 3 \end{bmatrix}}_{\succeq 0}$$

Chordal graph decomposition



- This allows for the decomposition of a big positive semidefinite constraint
- Exploiting this decomposition → a new scalable algorithm for sparse SDP (**Zheng, Y.**, et al. ***Math. Prog.,*** *2019*)

Open-source Solver: CDCS

CDCS: Cone Decomposition Conic Solver

- Open-source MATLAB solver for sparse conic optimization problems (SDPs, QPs, LPs, SOCPs, etc)
- Can be called from modeling packages, like YALMIP and SOSTOOLS.
- Available from: https://github.com/oxfordcontrol/CDCS

Numerical comparison

1. Standard interior-point solver: **SeDuMi**
2. State-of-the-art first-order solver: **SCS**

Zheng, Y., Fantuzzi, G., Papachristodoulou, A., Goulart, P., & Wynn, A. (2019). Chordal decomposition in operator-splitting methods for sparse semidefinite programs. ***Mathematical Programming, Series A***,1-44.

Open-source Solver: CDCS

Case 1: Test on sparse benchmark problems (from Andersen, et al, 2010)

	rs1555			rs1907		
	Time (s)	# Iter.	Objective	Time (s)	# Iter.	Objective
SeDuMi (high)	***	***	***	***	***	***
SeDuMi (low)	***	***	***	***	***	***
SCS (direct)	139,314	2000	34.20	50,047	2000	45.89
CDCS-primal	1721	2000	61.22	330	349	62.87
CDCS-dual	317	317	69.54	271	252	63.30
CDCS-hsde	1413	2000	61.36	393	414	63.14

Entries marked *** indicate that the problem could not be solved due to memory limitations

Problem instance: rs1907

- PSD size 5357× 5357
- > **10 million** decision variables

✓ SeDuMi ran out of memory

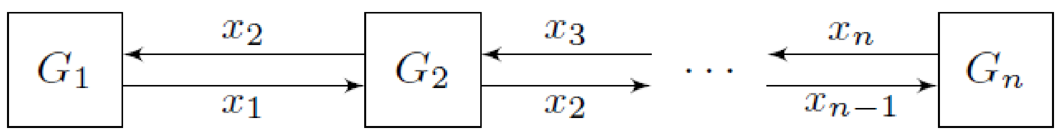
✓ The first-order solver SCS took over **13 hours** to return a solution

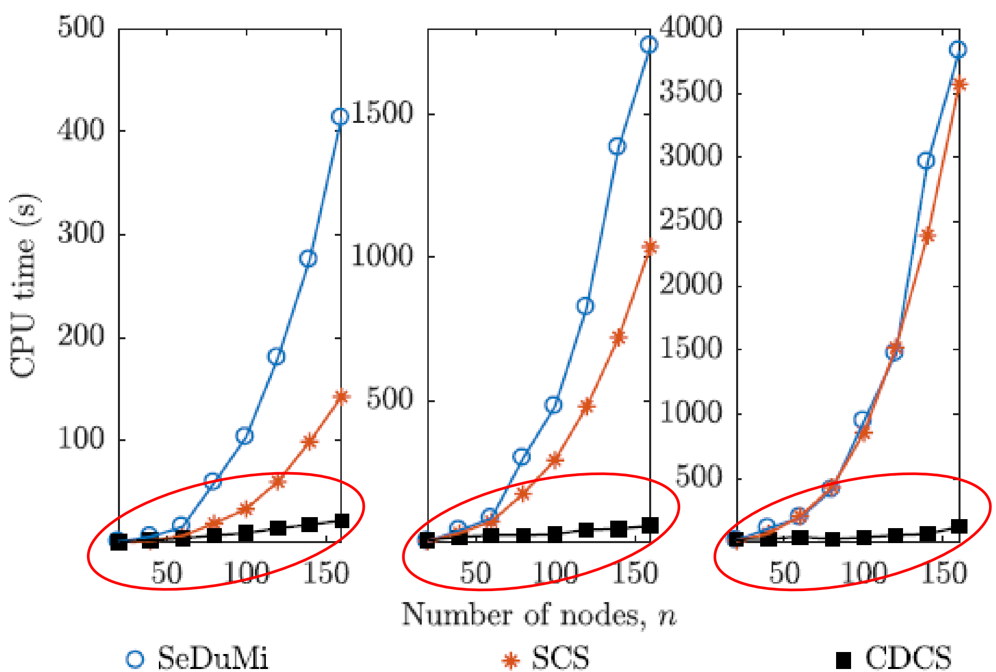
✓ **CDCS** took **6 minutes** to get a solution; **100 × speedup!**

Exploiting sparsity achieves massive scalability!

Open-source Solver: CDCS

Case 2: Test on stability/H2/Hinf analysis of linear cascaded systems

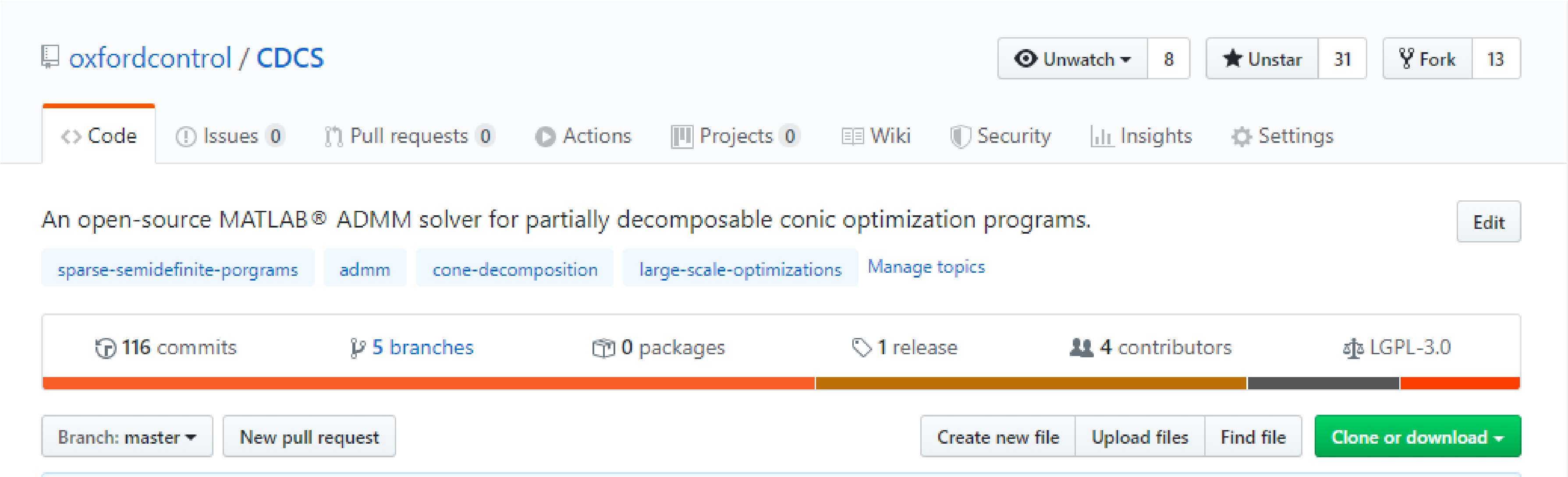




Order of magnitude faster
→ Massive Scalability

Open-source Solver: CDCS

Large-scale practical problems



- ❑ **Signal recovery problem**
  - Fosson, S. M., & Abuabiah, M. (2019). Recovery of binary sparse signals from compressed linear measurements via polynomial optimization. *IEEE Signal Processing Letters*.
- ❑ **Optimal power flow problem**
  - Eltved, A., Dahl, J., & Andersen, M. S. (2018). On the robustness and scalability of semidefinite relaxation for optimal power flow problems. *Optimization and Engineering*, 1-18.
- ❑ **Nonlinear systems analysis**
  - Driggs & Fawzi (2019). “AnySOS: An anytime algorithm for semidefinite programming" IEEE CDC, 1-6.

Conclusion

Two main takeaways

Theoretic potential of autonomy in traffic

- Mixed traffic systems is always **stabilizable**;
- Autonomous vehicles can not only **smooth traffic wave**, but also guide traffic velocity to **a higher value**;
- Autonomous vehicles can change traffic dynamics fundamentally (**Leading Cruise Control**)

Integrating Autonomy via Control and Optimization

- **Convexity** of distributed control: a new framework based on sparsity invariance
- **Scalability** of convex optimization: Sparsity-exploiting methods based on graph decomposition

References

Mixed autonomy analysis

1. **Zheng, Y.,** Wang, J., & Li, K. (2020). Smoothing traffic flow via control of autonomous vehicles. IEEE Internet of Things Journal, 7(5), 3882-3896**.**
2. Li, K., Wang, J., & **Zheng, Y.** (2020). Cooperative Formation of Autonomous Vehicles in Mixed Traffic Flow: Beyond Platooning. arXiv preprint arXiv:2009.04254.
3. Wang, J., **Zheng, Y.**, Xu, Q., Wang, J., & Li, K. (2020). Controllability Analysis and Optimal Control of Mixed Traffic Flow with Human-driven and Autonomous Vehicles. *IEEE Transactions on Intelligent Transportation Systems*, accepted.
4. Wang, J., Zheng, Y., Chen, C., Xu, Q., & Li, K. (2021). Leading cruise control in mixed traffic flow: System modeling, controllability, and string stability. *IEEE Transactions on Intelligent Transportation Systems*.

Controller Design & Scalability

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2. **Zheng, Y.**, Furieri, L., Papachristodoulou, A., Li, N., & Kamgarpour, M. (2020). On the Equivalence of Youla, System-Level, and Input–Output Parameterizations. *IEEE Transactions on Automatic Control*, 66(1), 413-420.
3. **Zheng, Y.**, Fantuzzi, G., Papachristodoulou, A., Goulart, P., & Wynn, A. (2020). Chordal decomposition in operator-splitting methods for sparse semidefinite programs. *Mathematical Programming*, 1-44.

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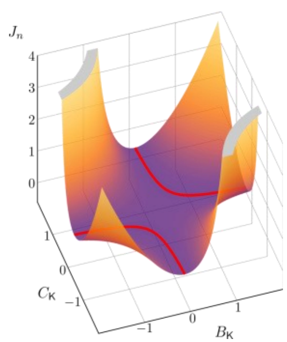
SOC Lab

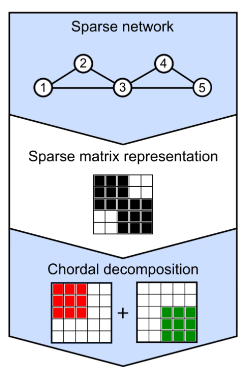
Data-driven and learning-based control

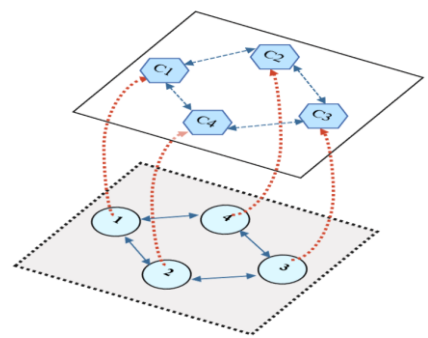
Sparse conic optimization

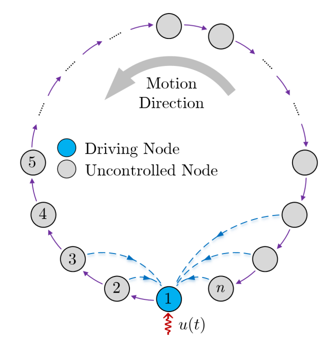
Scalable distributed control

Connected and autonomous vehicles (CAVs)





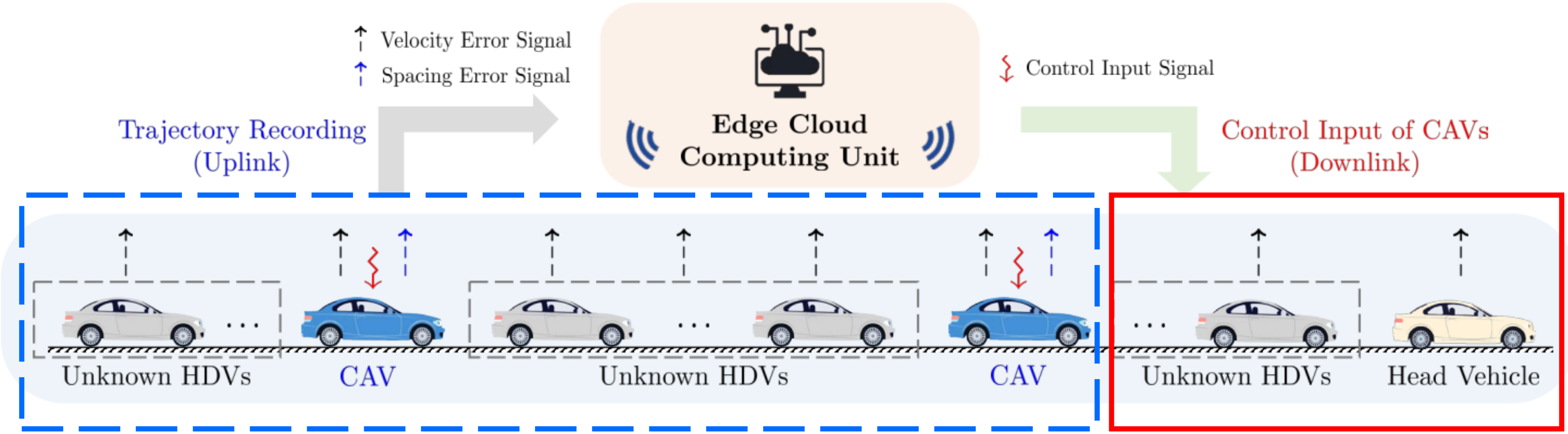




Check out our webpage: https://zhengy09.github.io/soclab.html

Extra slides

Data-driven MPC



Controllable subspace

Uncontrollable subspace

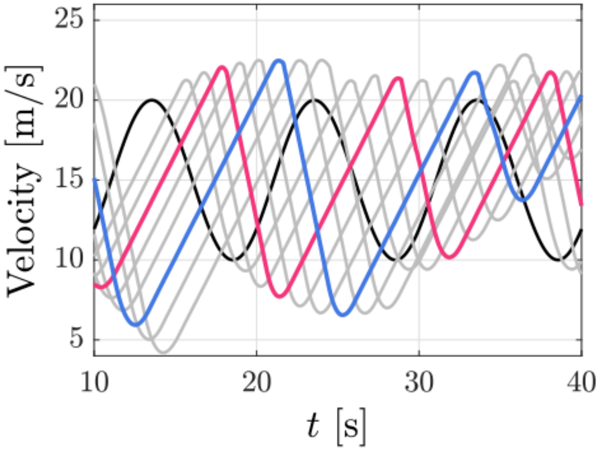
$$\min_{g,u,y,\sigma_y} \quad \|y\|_Q^2 + \|u\|_R^2 + \lambda_g \|g\|_2^2 + \lambda_y \|\sigma_y\|_2^2$$

$$\text{s.t.} \quad \begin{bmatrix} U_\mathrm{p} \\ E_\mathrm{p} \\ Y_\mathrm{p} \\ U_\mathrm{f} \\ E_\mathrm{f} \\ Y_\mathrm{f} \end{bmatrix} g = \begin{bmatrix} u_\mathrm{ini} \\ \epsilon_\mathrm{ini} \\ y_\mathrm{ini} \\ u \\ \epsilon \\ y \end{bmatrix} + \begin{bmatrix} 0 \\ 0 \\ \sigma_y \\ 0 \\ 0 \\ 0 \end{bmatrix},$$

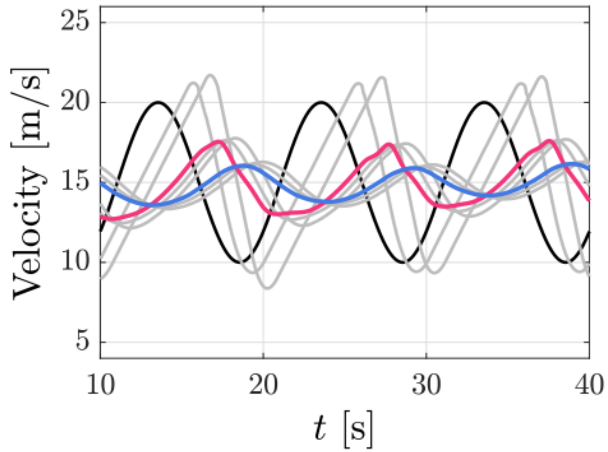
$$\epsilon = 0, \ u \in \mathcal{U}, \ y \in \mathcal{Y}.$$

Experiments

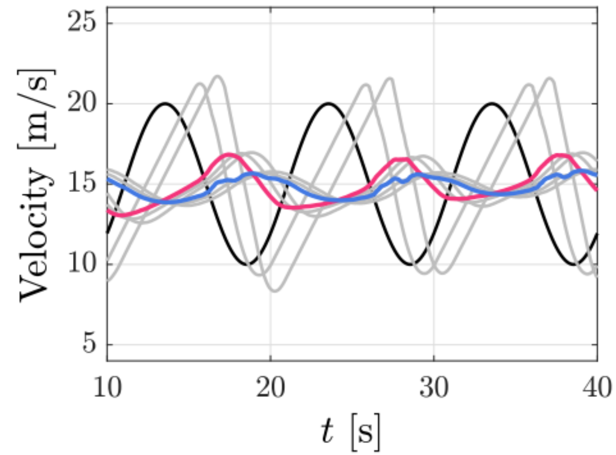
Comparison with MPC (Head Vehicle→2 HDVs→1 CAV→2 HDVs→1 CAV→2 HDVs)



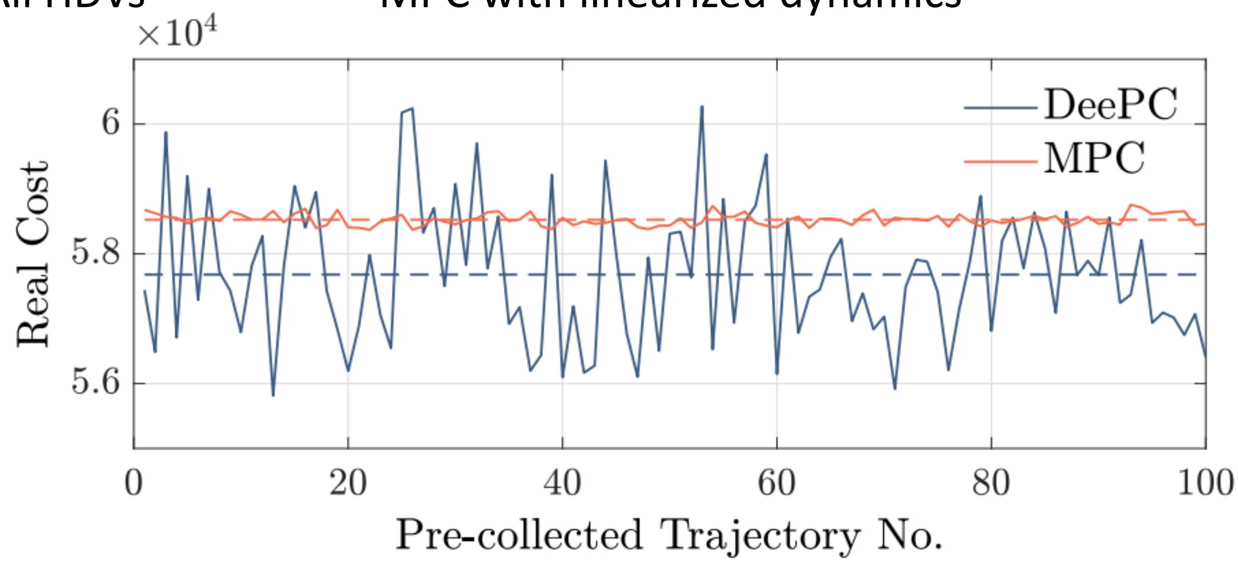
All HDVs



MPC with linearized dynamics

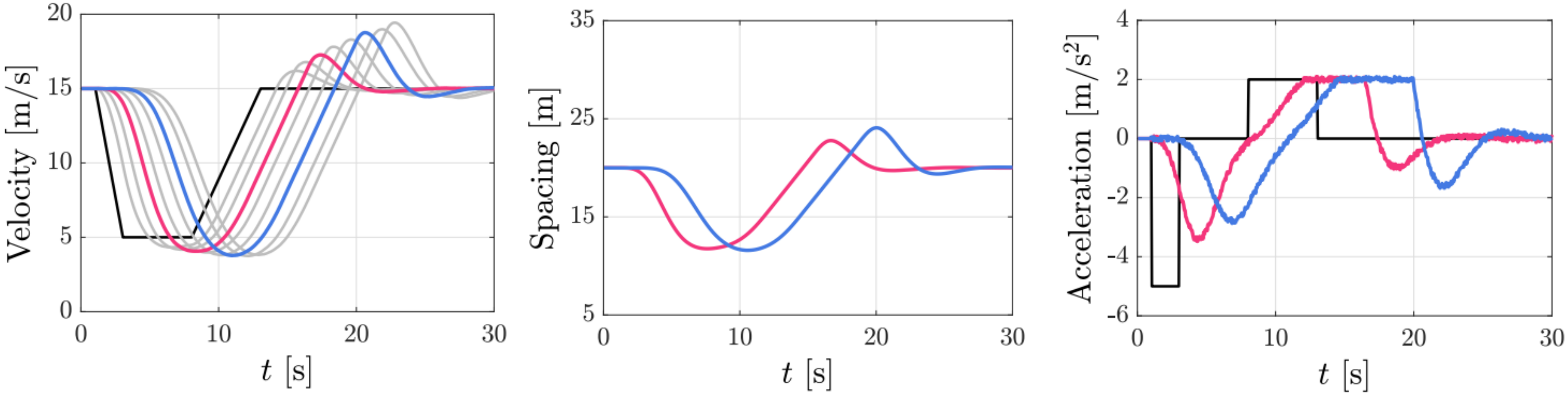


DeePC

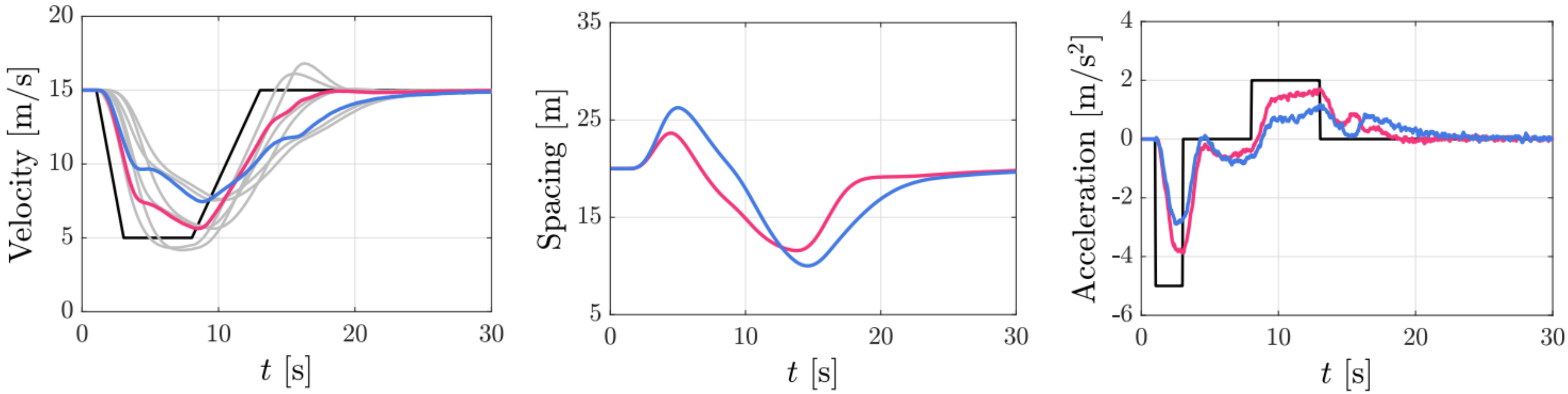


Experiments

Simulation at safety-critical scenario



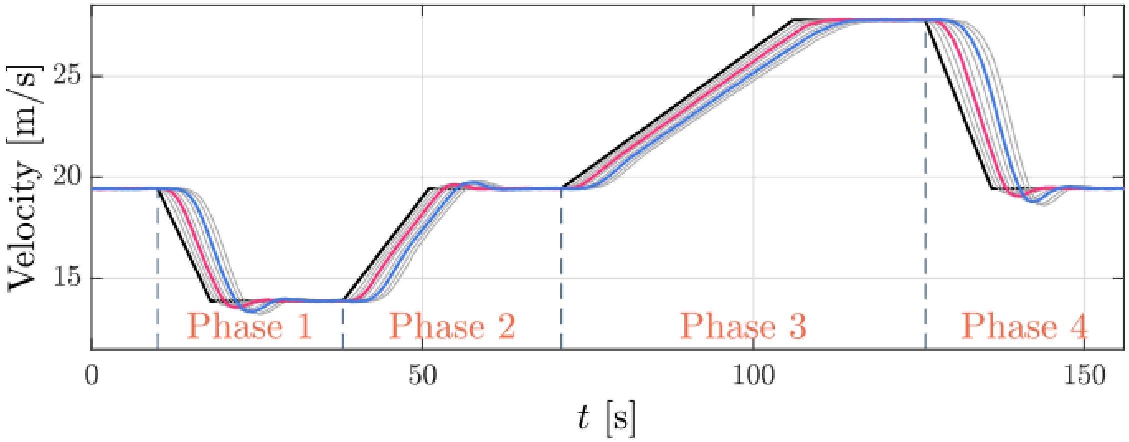
All HDVs

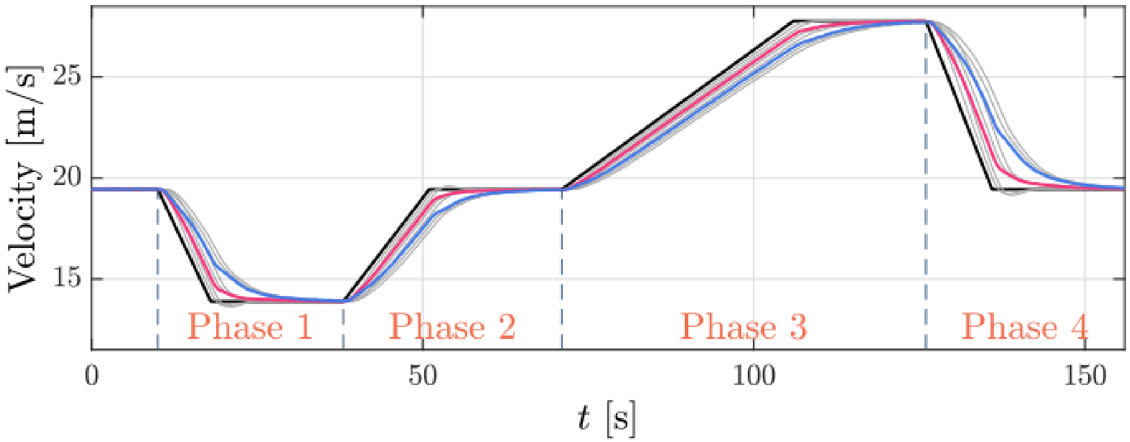


DeePC

Experiments

Comprehensive simulation





Fuel consumption reduction	
Phase 1	7.59%
Phase 2	1.20%
Phase 3	0.53%
Phase 4	5.39%
Tracking error reduction	
Phase 1	15.16%
Phase 2	12.08%
Phase 3	4.52%
Phase 4	11.32%

Wang, J., Zheng, Y., Xu, Q., & Li, K. (2021). Data-Driven Predictive Control for Connected and Autonomous Vehicles in Mixed Traffic. *arXiv preprint arXiv:2110.10097*.

Modeling and Control of Traffic Flow

- **Modeling techniques**
  - Ordinary differential equations
  - Partial differential equations
  - Queuing theory
  - Cell transmission model
  - Cascaded nonlinear systems
  - etc.

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- **Control methods**
  - Adaptive control
  - Model predictive control
  - Optimal cooperative control
  - Reinforcement Learning
  - Formal methods
  - etc.

Hegyi, A., De Schutter, B., & Hellendoorn, H. Model predictive control for optimal coordination of ramp metering and variable speed limits. *TRC, 2005*

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