Combining Learning and Control in Cyber-Physical Systems

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CDC 2023 Lunch Session
Mathworks

December 14, 2023

…the world is changing…

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outline

- Learning for Cyber-physical systems (CPS)
  - Advanced powertrain systems
- Optimal model-based control for CPS
  - Connected and automated vehicles
- Combining learning and control
  - Separated control strategies

information and decision science (IDS) lab

The overarching goal of the IDS Lab is to enhance understanding of complex cyber-physical systems (CPS) and establish rigorous theories and algorithms for making CPS able to realize how to improve their performance over time while interacting with their environment.

Information and Decision Science Lab

IEEE control systems

DECEMBER 2022 VOLUME 42 NUMBER 6

From Inertial Measurements to Smart Cities

IEEE Control Systems Society

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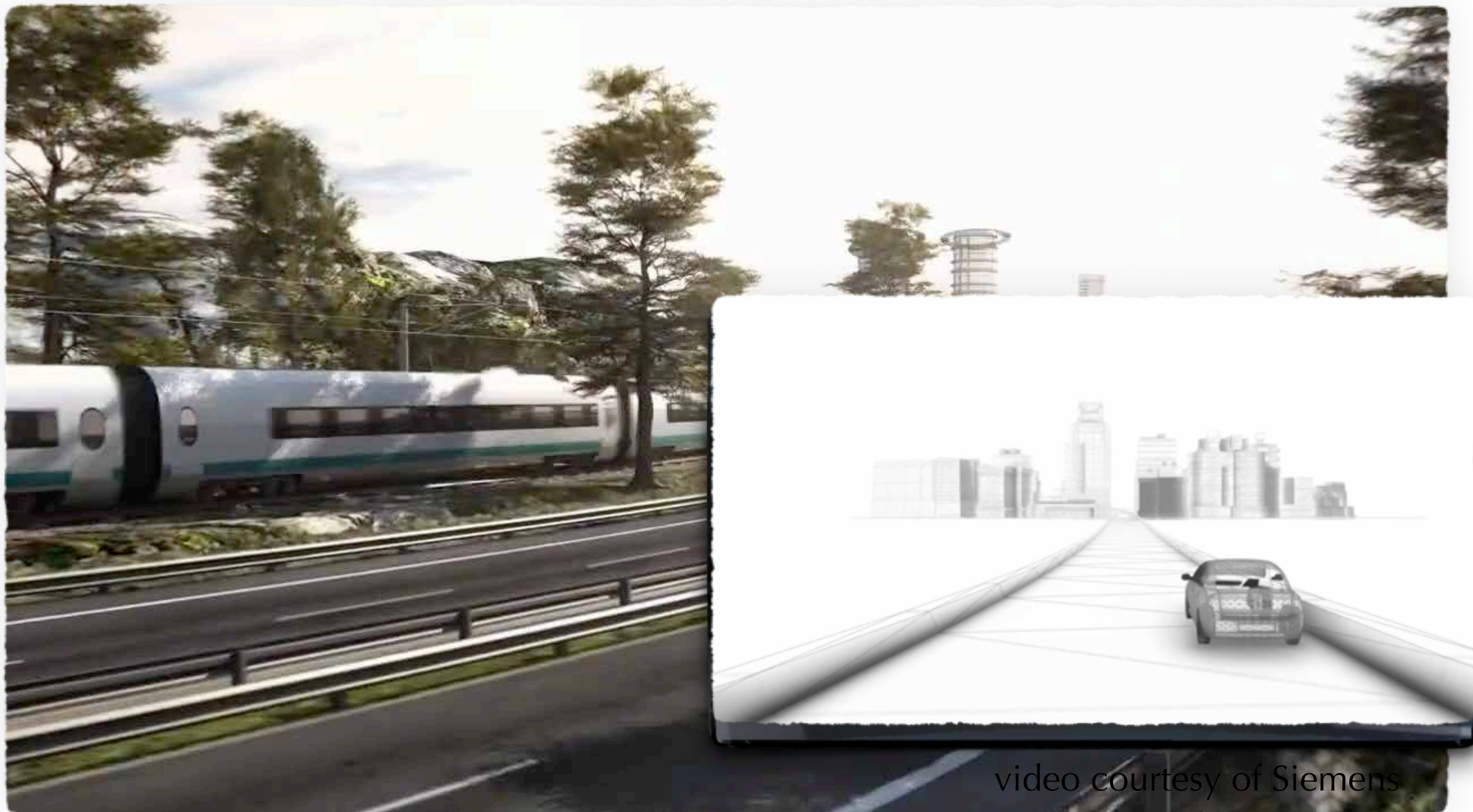
information and decision science (IDS) lab



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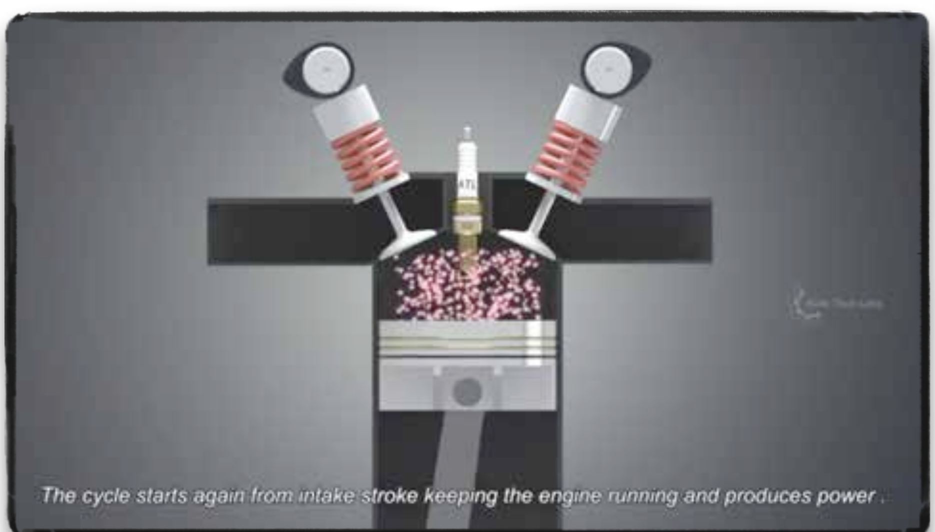

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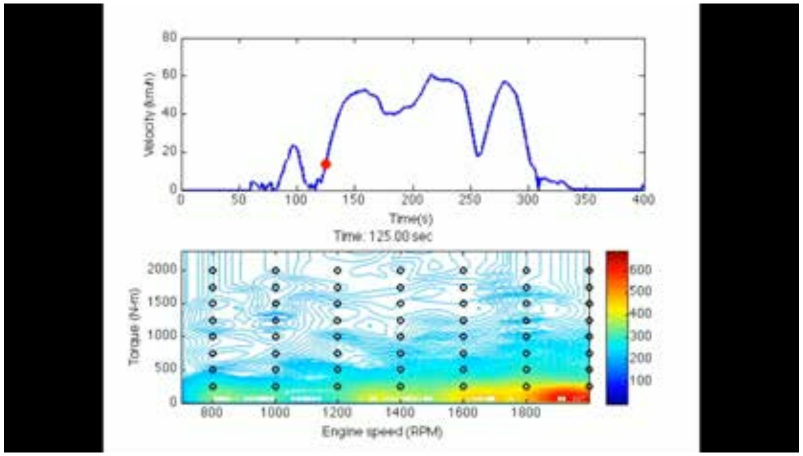
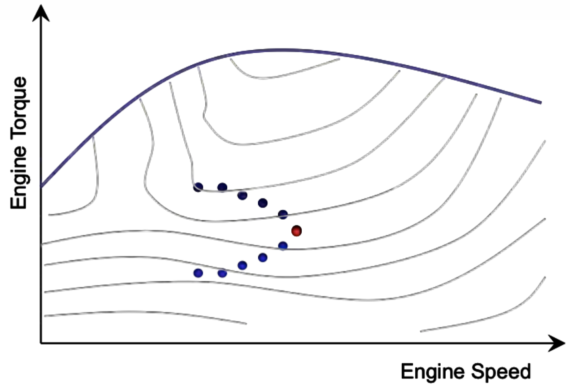
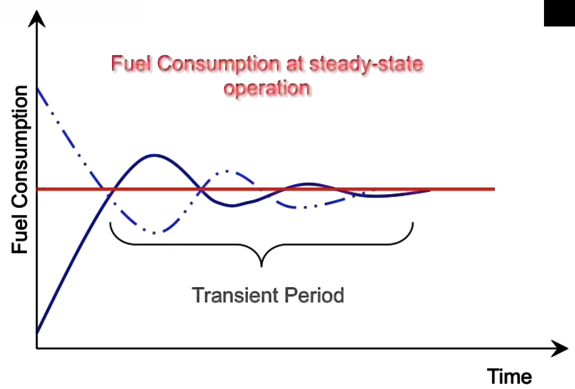
my dissertation

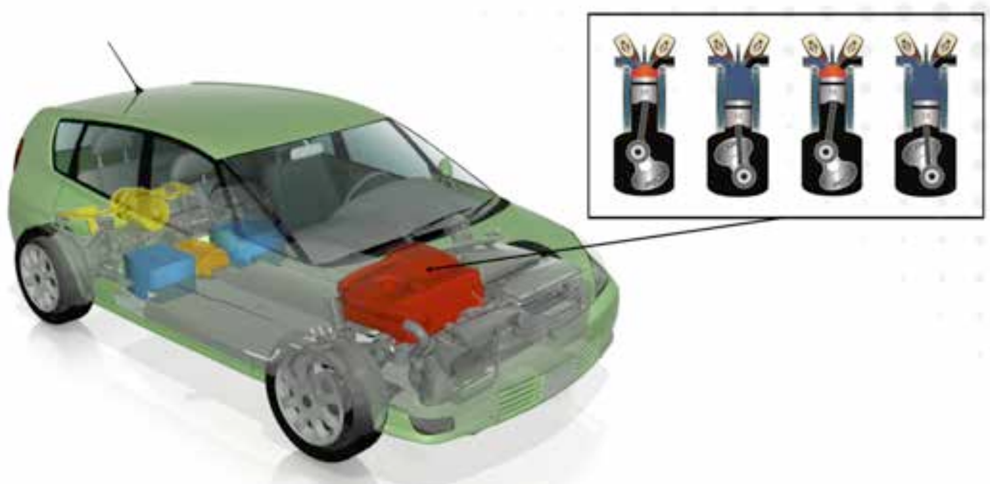
…Why we cannot achieve the mpg posted on the window sticker…?

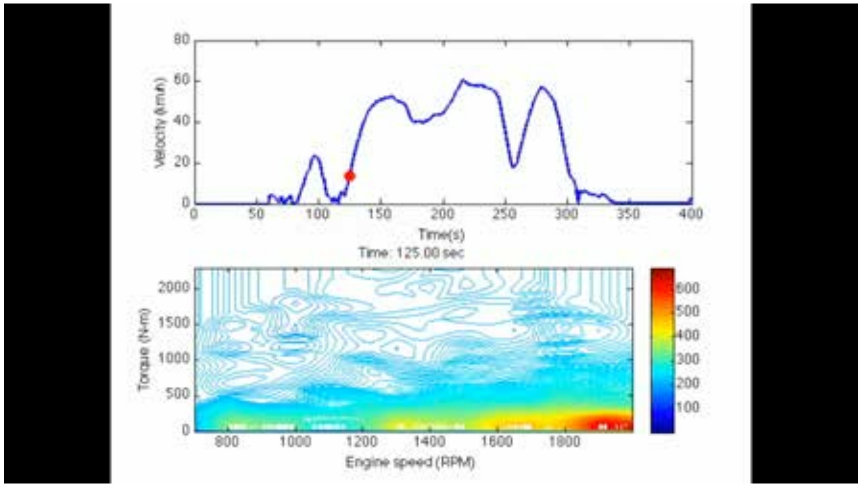
how engines are optimized today



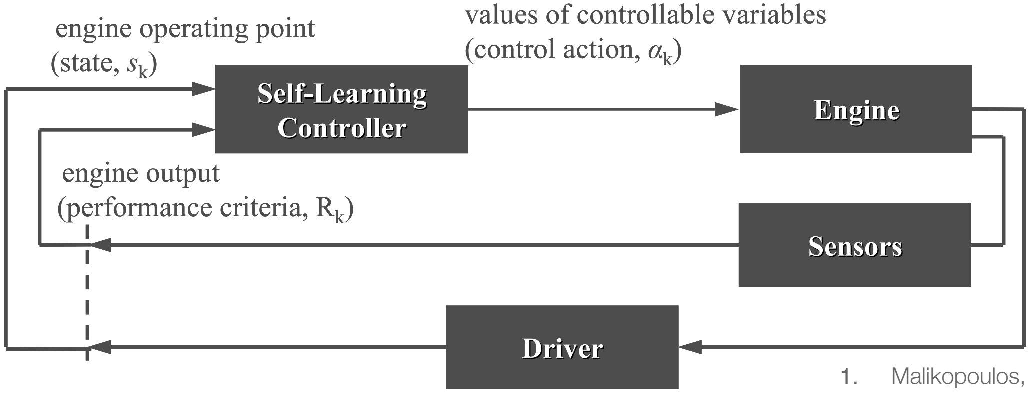




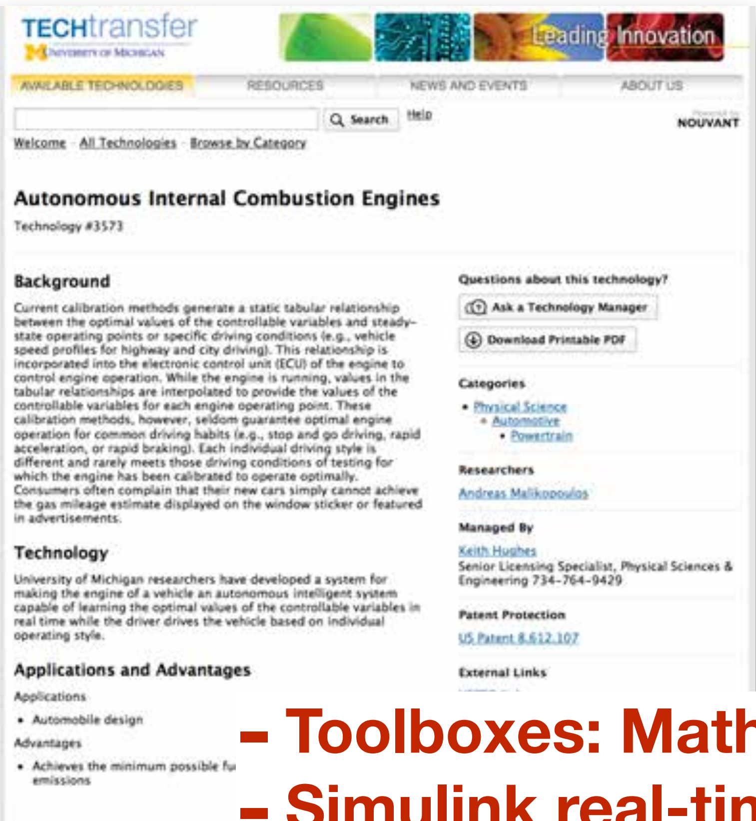




learning individual driver's driving style[1]



Fuel economy improvement > 8.7%



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Autonomous Internal Combustion Engines

Technology #3573

Background

Current calibration methods generate a static tabular relationship between the optimal values of the controllable variables and steady-state operating points or specific driving conditions (e.g., vehicle speed profiles for highway and city driving). This relationship is incorporated into the electronic control unit (ECU) of the engine to control engine operation. While the engine is running, values in the tabular relationships are interpolated to provide the values of the controllable variables for each engine operating point. These calibration methods, however, seldom guarantee optimal engine operation for common driving habits (e.g., stop and go driving, rapid acceleration, or rapid braking). Each individual driving style is different and rarely meets those driving conditions of testing for which the engine has been calibrated to operate optimally. Consumers often complain that their new cars simply cannot achieve the gas mileage estimate displayed on the window sticker or featured in advertisements.

Technology

University of Michigan researchers have developed a system for making the engine of a vehicle an autonomous intelligent system capable of learning the optimal values of the controllable variables in real time while the driver drives the vehicle based on individual operating style.

Applications and Advantages

Applications

- Automobile design

Advantages

- Achieves the minimum possible fu
emissions

Questions about this technology?

Ask a Technology Manager

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Categories

- Physical Science
  - Automotive
    - Powertrain

Researchers

Andreas Malikopoulos

Managed By

Keith Hughes
Senior Licensing Specialist, Physical Sciences & Engineering 734-764-9429

Patent Protection

US Patent 8,612,107

External Links

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– Toolboxes: Math and Optimization, and Code Generation

– Simulink real-time simulation and testing, code generation

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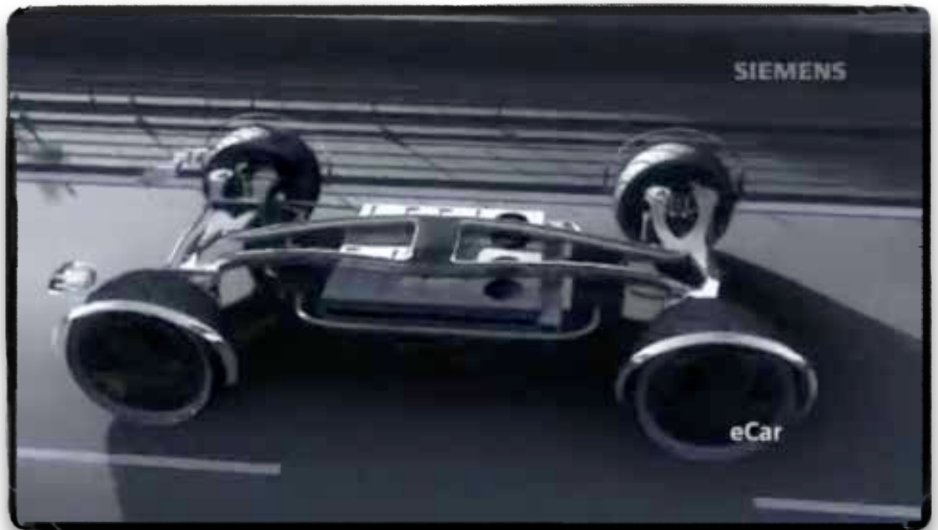

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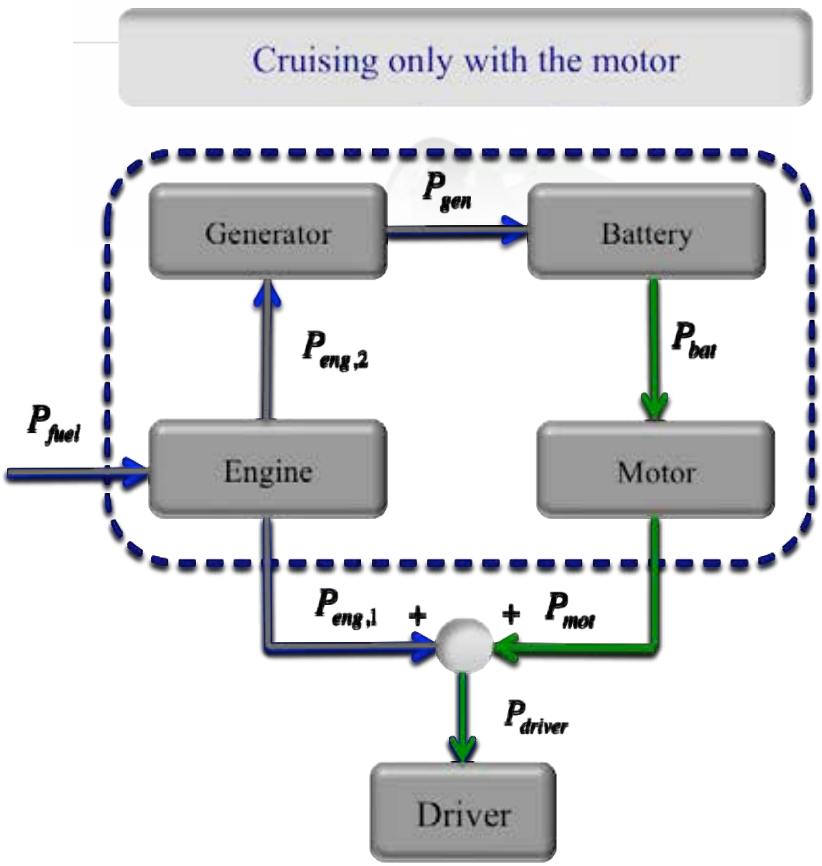
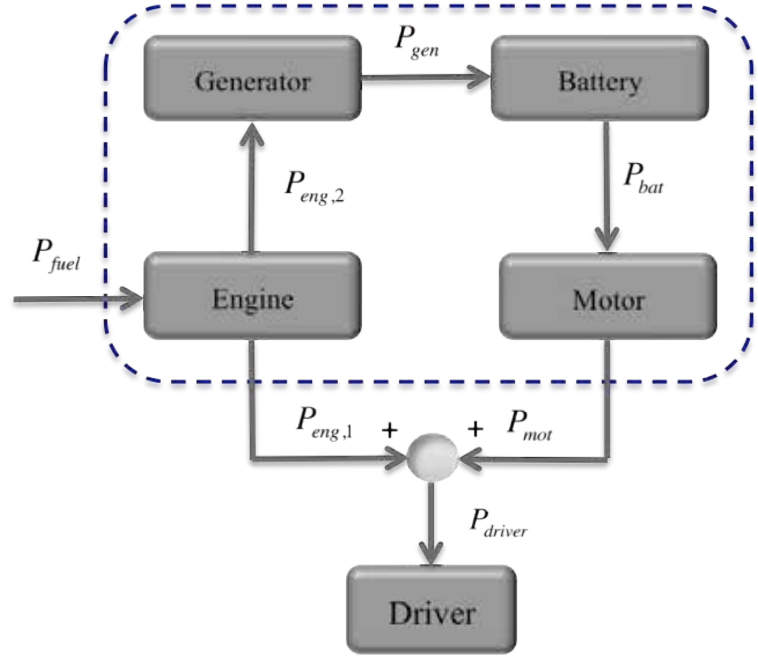
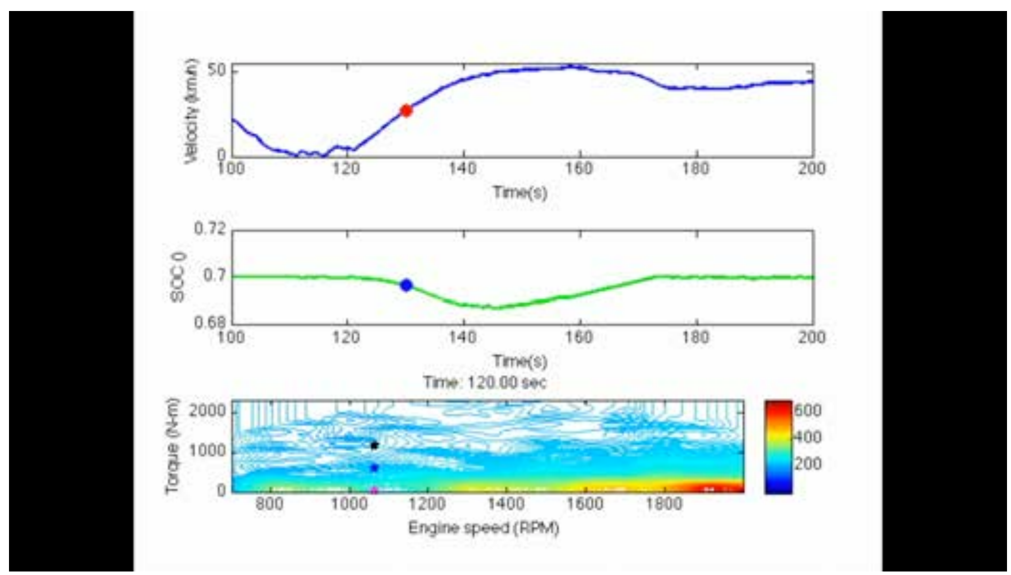
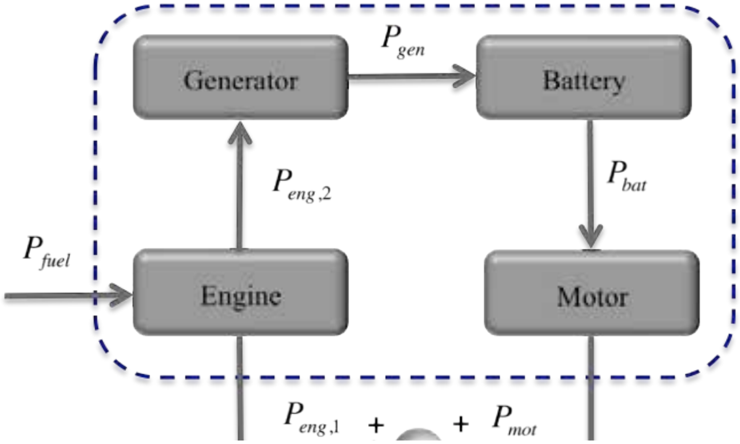
moving to Oak Ridge National Lab







Pareto optimal control strategy



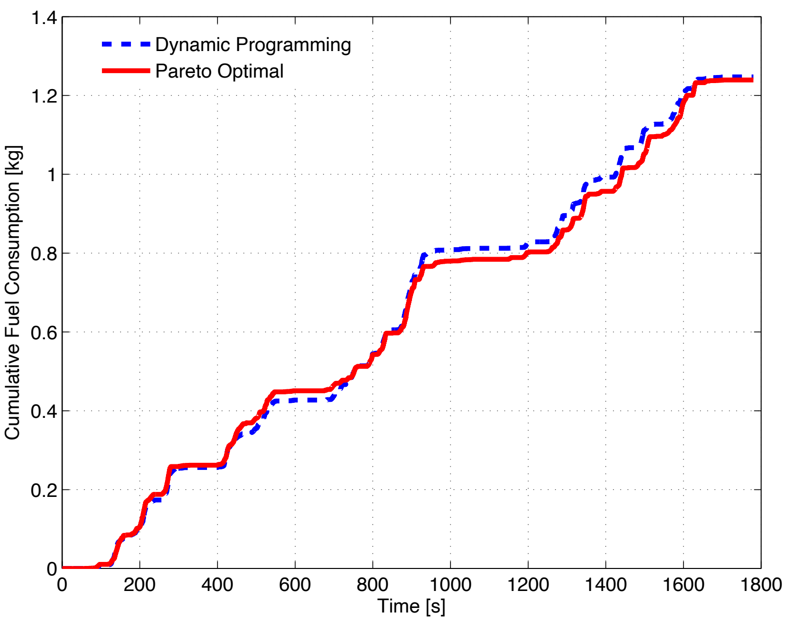
$$X_{t+1(1:N)} = f(X_{t(1:N)}, U_{t(1:N)}, W_{t(1:N)})$$

$$\Gamma_{(i)} := \{(x_{(i)}, u_{(i)}) | x_{(i)} \in \mathcal{S}_{(i)} \text{ and } u_{(i)} \in \mathcal{C}(x_{(i)})\}$$

Theorem [1]

The Pareto control strategy is the optimal control strategy that

- **Toolboxes: Math and Optimization, and Code Generation**
- **Simulink real-time simulation and testing, and Verification, Validation, and Test**



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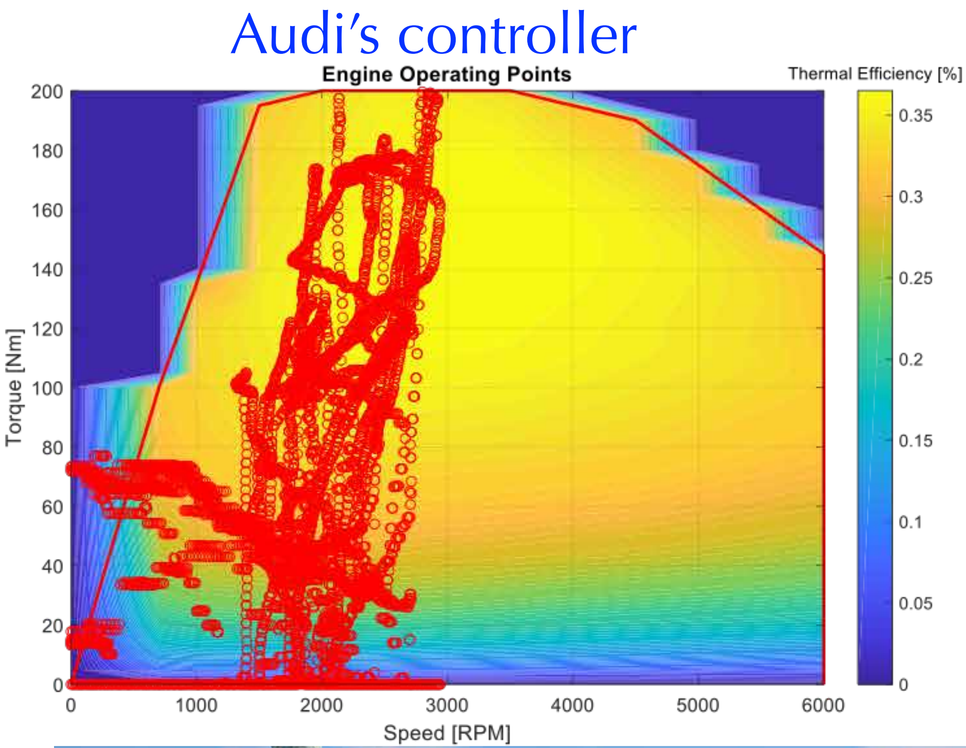
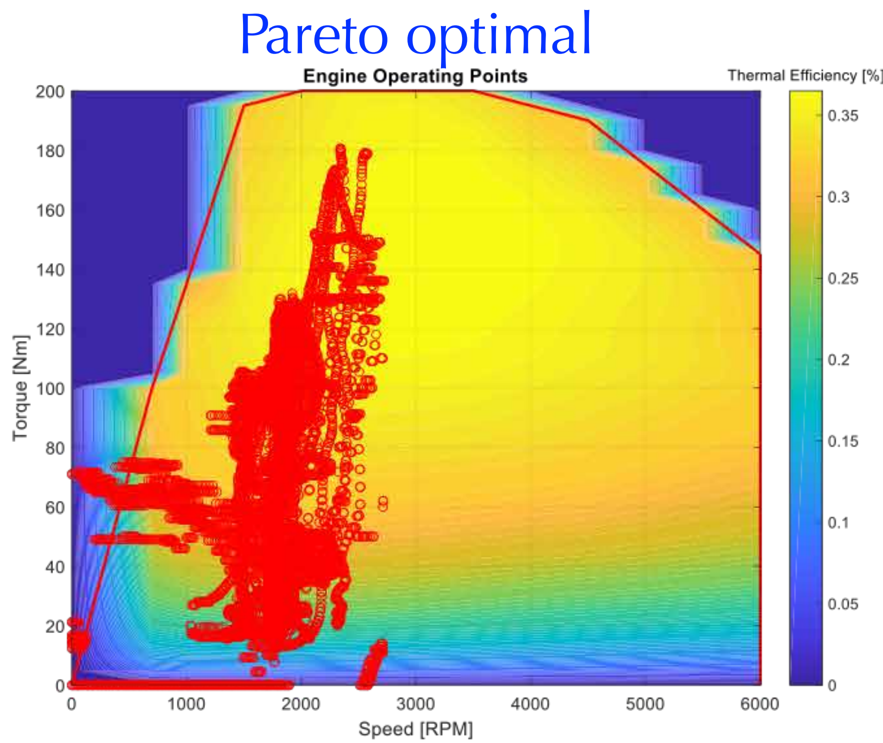
Pareto optimal control strategy





	Pareto Optimal
Fuel Economy [MPGe]	35.3
Improvement	>12%

Pareto strategy— sustainable buildings

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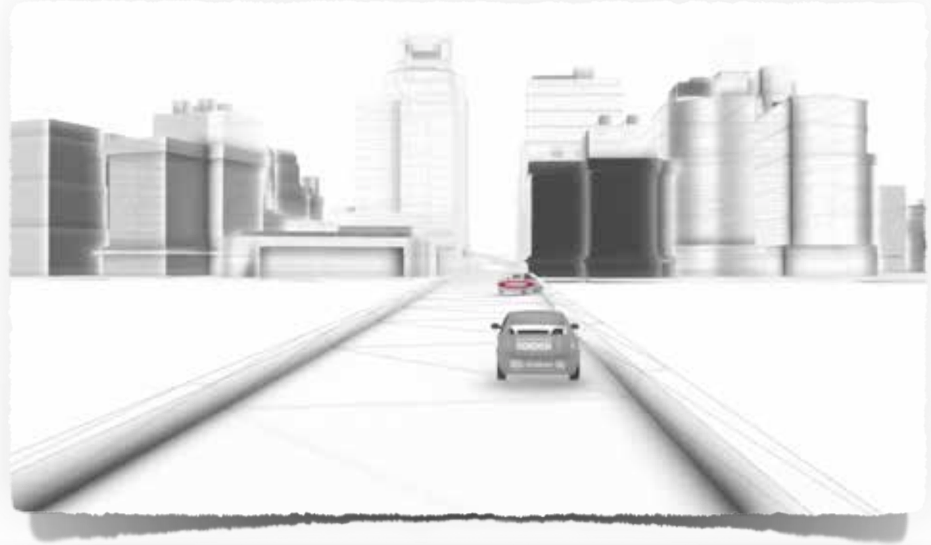

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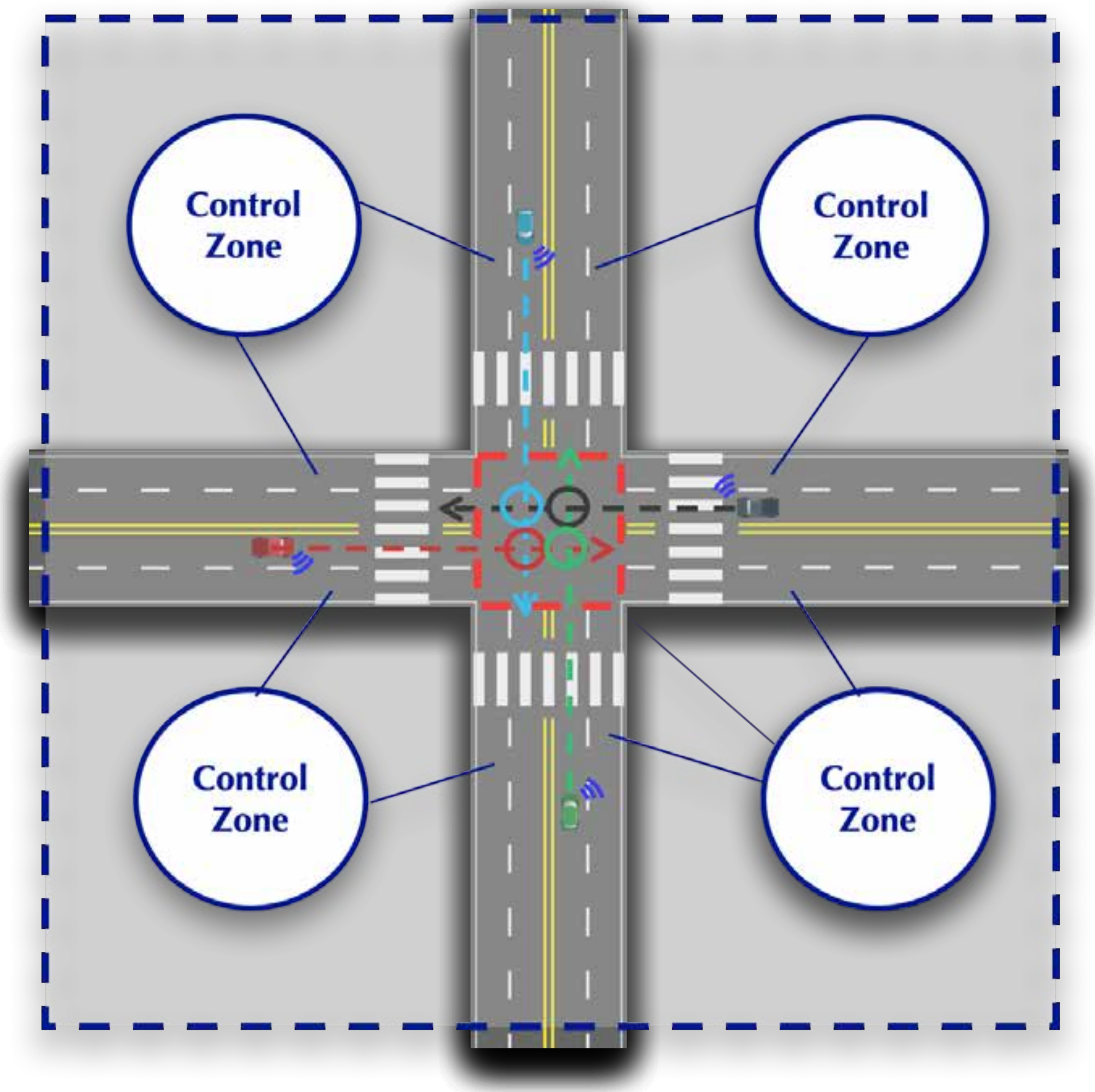
connected and automated vehicles (CAVs)

1939: New York World's Fair - Futurama

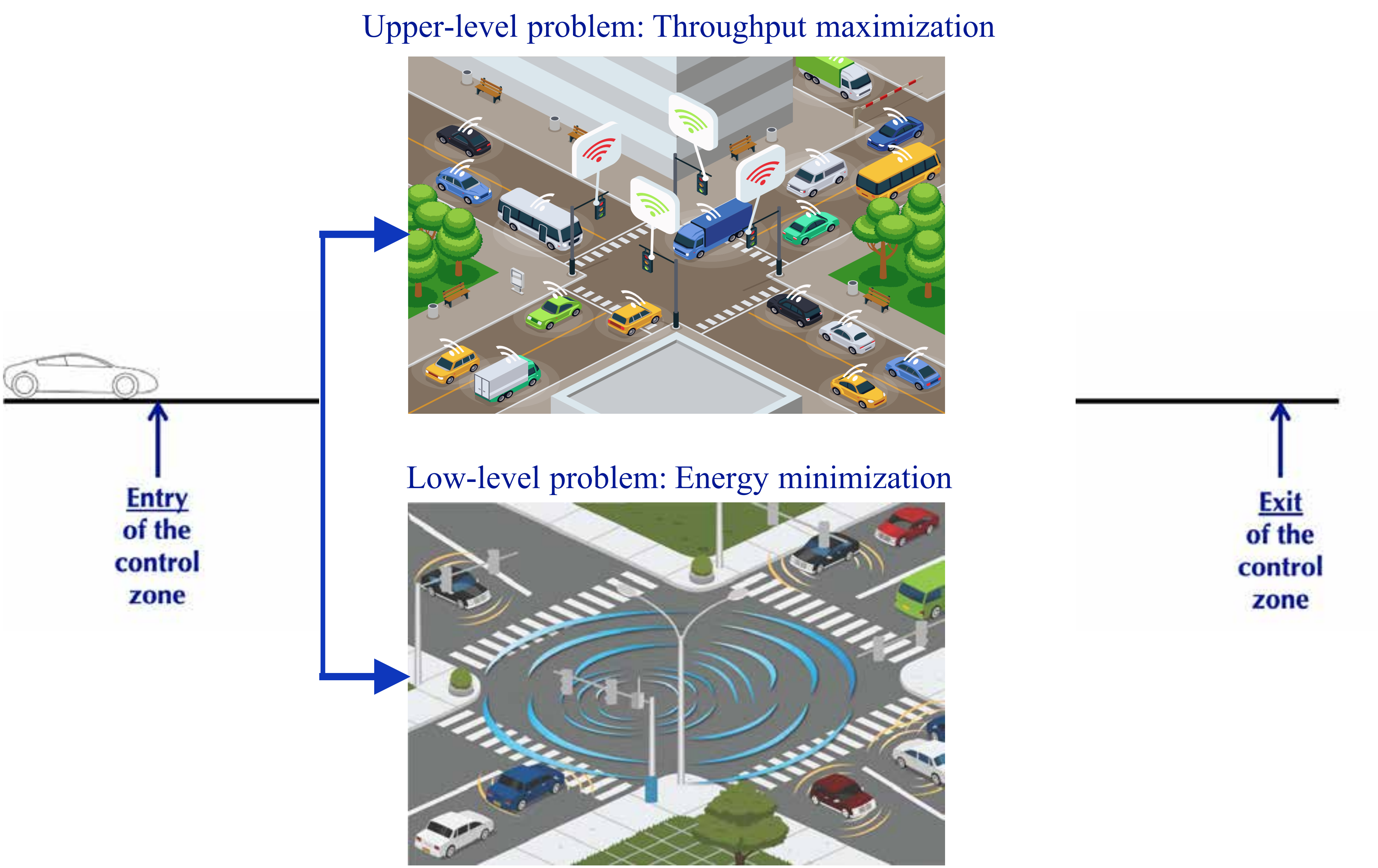
1956: GM's future car in 1976

coordination of CAVs

problem formulation



problem formulation



problem formulation

- $\mathcal{N}(t) = \{1, \ldots, N(t)\}$

$$\begin{aligned} \dot{p}_i &= v_i(t), \\ \dot{v}_i &= u_i(t), \\ \dot{s}_i &= \xi_i \cdot (v_k(t) - v_i(t)), \ i \in \mathcal{N}(t), \end{aligned} \tag{1}$$

where $p_i(t) \in \mathcal{P}_i$, $v_i(t) \in \mathcal{V}_i$, $u_i(t) \in \mathcal{U}_i$, $\xi_i \in [0,1]$, and $t \in \mathbb{R}^+$.

- $\mathcal{P}_i$, $\mathcal{V}_i$ and $\mathcal{U}_i$, $i \in \mathcal{N}(t)$, are complete and totally bounded subsets of $\mathbb{R}$.

- Control and state constraints

$$\begin{aligned} &u_{min} \leq u_i(t) \leq u_{max}, \quad \text{and} \\ &0 < v_{min} \leq v_i(t) \leq v_{max}, \ t \in [t_i^0, t_i^f], \ i \in \mathcal{N}(t). \end{aligned} \tag{2}$$

- To ensure the absence of rear-end collision between two CAVs, we impose

$$s_i(t) = \xi_i \cdot (p_k(t) - p_i(t)) \geq \delta_i(t), \ t \in [t_i^0, t_i^f], \tag{3}$$

where $\delta_i(t) = \gamma + \rho_i \cdot v_i(t)$, is a predefined minimum safe distance.

- To ensure the absence of lateral collision inside the merging zone, we impose

$$s_i(t) = \xi_i \cdot (p_{k,i} - p_i(t)) \geq \delta_i(t), \ t \in [t_i^0, t_i^m], \tag{4}$$

where $p_{k,i}$ is the (constant) distance of CAV k from the entry point that CAV i entered the control zone.

Problem 1

$$\min_{u(t) \in U_i} J_i(u(t)) = \frac{1}{2} \int_{t_i^0}^{t_i^f} u_i^2(t) \, dt, \tag{5}$$

$$\textit{given } t_i^0, v_i^0, p_i(t_i^0), t_i^f, p_i(t_i^f),$$

subject to:

1. *Dynamics* (1)
2. *State, control, and safety constraints* (2), (3), (4)

- The augmented Hamiltonian becomes:

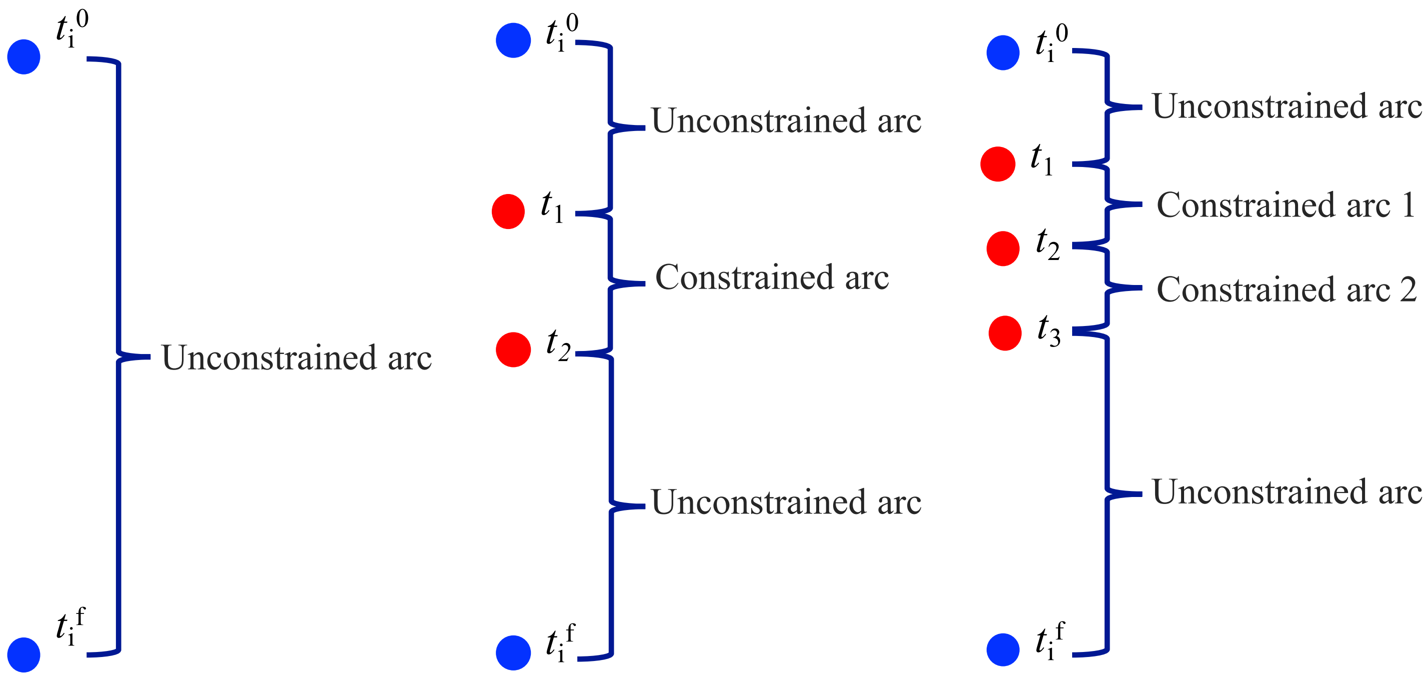
$$\begin{aligned} &H_i\big(t, p_i(t), v_i(t), s_i(t), u_i(t)\big) \\ &= \frac{1}{2} u_i(t)^2 + \lambda_i^p \cdot v_i(t) + \lambda_i^v \cdot u_i(t) + \lambda_i^s \cdot \xi_i \cdot (v_k(t) - v_i(t)) \\ &+ \mu_i^a \cdot (u_i(t) - u_{\max}) + \mu_i^b \cdot (u_{\min} - u_i(t)) + \mu_i^c \cdot u_i(t) \\ &- \mu_i^d \cdot u_i(t) + \mu_i^s \cdot \big(\rho_i \cdot u_i(t) - \xi_i\big(v_k(t) - v_i(t)\big)\big). \end{aligned}$$

Optimal solution – none of the constraints is active

$$\begin{aligned} u_i^*(t) &= a_i \cdot t + c_i, \ t \in [t_i^0, t_i^f], \\ v_i^*(t) &= \frac{1}{2} a_i \cdot t^2 + c_i \cdot t + d_i, \ t \in [t_i^0, t_i^f], \\ p_i^*(t) &= \frac{1}{6} a_i \cdot t^3 + \frac{1}{2} c_i \cdot t^2 + d_i \cdot t + e_i, \ t \in [t_i^0, t_i^f], \end{aligned}$$

where a_i, c_i, d_i and e_i are constants of integration.

constrained optimal analytical solution[1],[2]



[1] Malikopoulos, A.A., Beaver, L.E., and Chremos, I.V., "Optimal Time Trajectory and Coordination for Connected and Automated Vehicles," Automatica, 125, 109469, 2021.
[2] Mahbub, A M. I., and Malikopoulos, A.A., "Conditions to Provable System-Wide Optimal Coordination of Connected and Automated Vehicles," Automatica, 131, 109751, 2021.

discontinuities in the influence functions and Hamiltonian

Optimal solution

- Let $N_i(t, x(t)) = \gamma_i + \rho_i v_i^*(t) - \xi_i p_k^*(t) + \xi_i p_i^*(t), \; i \in \mathcal{N}(t)$.
- Since $N_i(t_1, x(t_1)) = 0$, then $\dot{N}_i(t_1, x(t_1)) = 0$, hence, the value of the optimal control at $t = t_1^+ \in [t_i^0, t_i^f]$ is given by

$$u_i^*(t_1^+) = \frac{\xi_i(v_k^*(t_1^+) - v_i^*(t_1^+))}{\rho_i}.$$

- The interior boundary conditions at the junction point t_1 for the influence functions are

$$\lambda_i^p(t_1^-) = \lambda_i^p(t_1^+) + \pi_i \frac{\partial N_i(t_1, x_i(t_1))}{\partial p_i} = \lambda_i^p(t_1^+) + \pi_i \xi_i,$$

$$\lambda_i^v(t_1^-) = \lambda_i^v(t_1^+) + \pi_i \frac{\partial N_i(t_1, x_i(t_1))}{\partial v_i} = \lambda_i^v(t_1^+) + \pi_i \rho_i,$$

$$\lambda_i^s(t_1^-) = \lambda_i^s(t_1^+) + \pi_i \frac{\partial N_i(t_1, x_i(t_1))}{\partial s_i} = \lambda_i^s(t_1^+) - \pi_i.$$

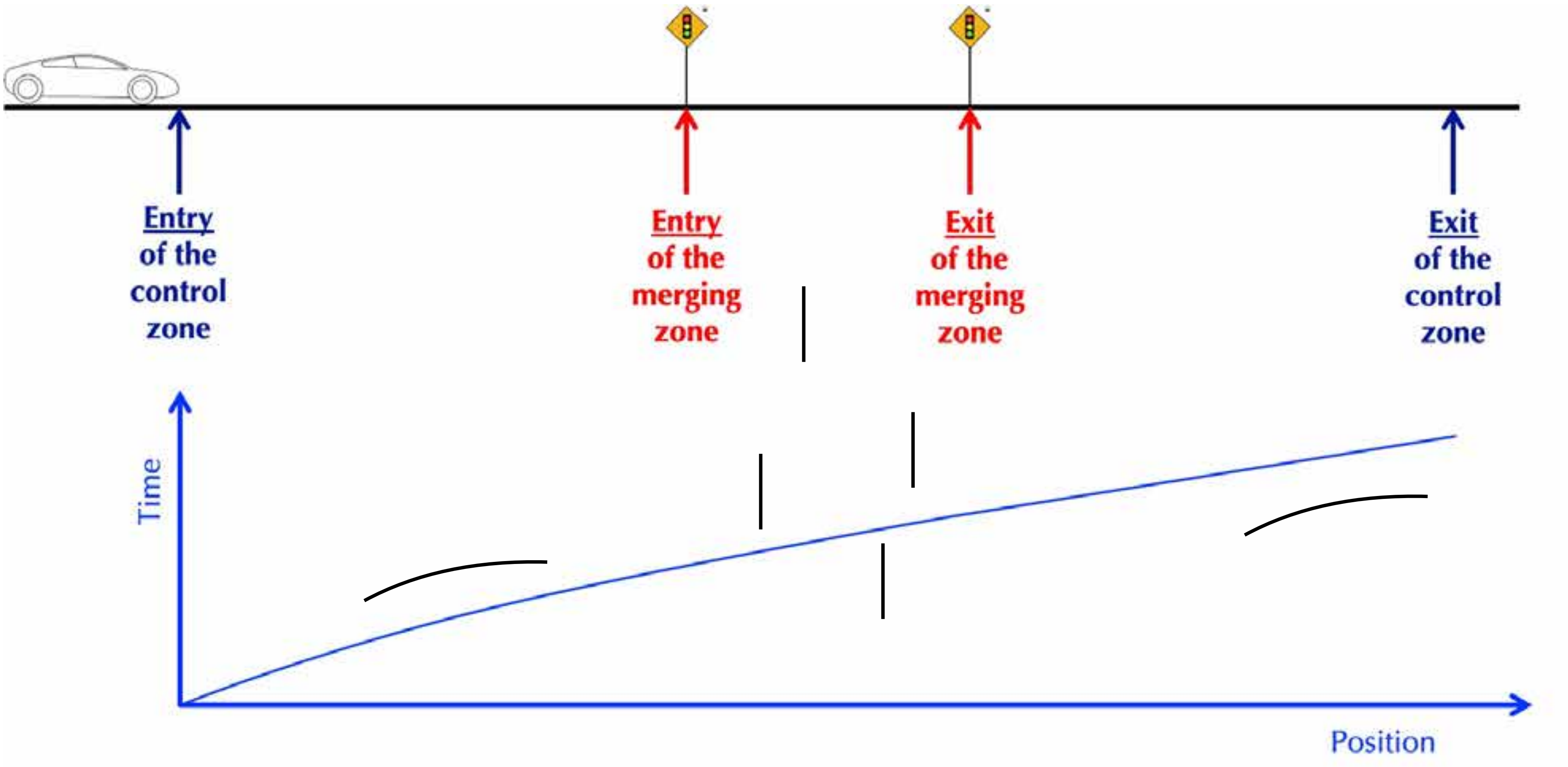
- The Hamiltonian at the junction point t_1 is

$$H_i(t_1^-) = H_i(t_1^+) - \pi_i \frac{\partial N_i(t_1, x_i(t_1))}{\partial t_1}.$$

upper-level optimal control problem

$$p_i^*(t) = \phi_{i,3} \cdot t^3 + \phi_{i,2} \cdot t^2 + \phi_{i,1} \cdot t + \phi_{i,0}, \ t \in [t_i^0, t_i^f],$$

where $\phi_{i,3}, \phi_{i,2}, \phi_{i,1}, \phi_{i,0} \in \mathbb{R}$ are the constants of integration.



existence of time trajectory[1]

$$p_i^*(t) = \phi_{i,3} \cdot t^3 + \phi_{i,2} \cdot t^2 + \phi_{i,1} \cdot t + \phi_{i,0}, \ \ t \in [t_i^0, t_i^f],$$

where $\phi_{i,3}, \phi_{i,2}, \phi_{i,1}, \phi_{i,0} \in \mathbb{R}$ are the constants of integration.

For any fixed $p_i \in [p_i^0, p_i^f]$, the time trajectory $t_{p_i}(p_i^*)$, can be written as a function of the constants $\phi_i = (\phi_{i,3}, \phi_{i,2}, \phi_{i,1}, \phi_{i,0})$.

- Hence, in our analysis, we consider the function $f_i : \Phi_i \to [t_i^0, t_i^f]$ such that

$$f_i(\phi_i) = t_{p_i}(p_i^f).$$

[1] Malikopoulos, A.A., Beaver, L.E., and Chremos, I.V., “Optimal Time Trajectory and Coordination for Connected and Automated Vehicles,” Automatica, 125, 109469, 2021.

constraints[1]

For each CAV $i \in \mathcal{N}(t)$, we have the following inequality constraints:

- $g_i^{(1)}(\phi_i) \leq 0$: maximum speed
- $g_i^{(2)}(\phi_i) \leq 0$: minimum speed
- $g_i^{(3)}(\phi_i) \leq 0$: maximum control input
- $g_i^{(4)}(\phi_i) \leq 0$: minimum control input
- $g_i^{(5)}(\phi_i) \leq 0$: rear-end safety constraint
- $g_i^{(6)}(\phi_i) \leq 0$: lateral colision constraint
- $g_i^{(7)}(\phi_i) \leq 0$: maximum speed at the entry of the merging zone

[1] Malikopoulos, A.A., Beaver, L.E., and Chremos, I.V., "Optimal Time Trajectory and Coordination for Connected and Automated Vehicles," Automatica, 125, 109469, 2021.

upper-level optimal control problem[1]

$$\min_{\phi_i} f_i(\phi_i)$$

$$\text{subject to} \quad \phi_i \in \Phi_i, \quad h_i^{(r)}(\phi_i) = 0, \; r = 1, \ldots, 5,$$
$$g_i^{(m)}(\phi_i) \le 0, \; m = 1, \ldots, 7.$$

Note that the set Φ_i is determined by the occupancy sets of the lanes, i.e.,

$$\Phi_i = \Big\{ \phi_i \mid f_i(\phi_i) \notin \bigcup_{\theta \in C_{o_i}} O_\theta \Big\},$$

and can be formed by each $i \in \mathcal{N}(t)$ at t_i^0 by accessing the intersection's crossing protocol $\mathcal{I}(t)$.

Proposition 2

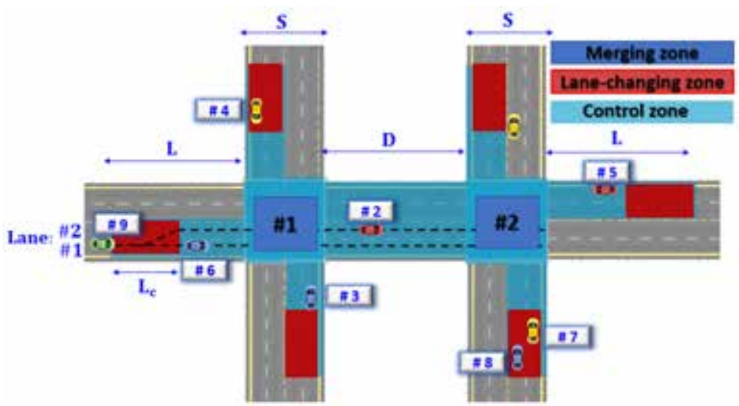
The functions $f_i(\phi_i)$, $h_i^{(r)}(\phi_i), r = 1, \ldots, 5$, $g_i^{(m)}(\phi_i), m = 1, \ldots, 7$, are convex.

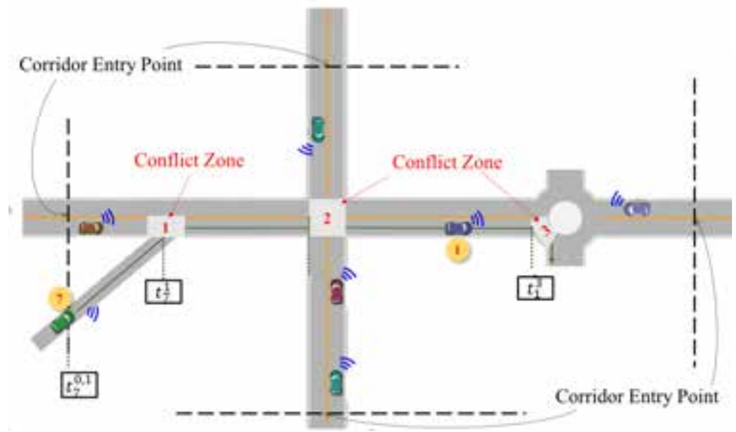
Theorem 7

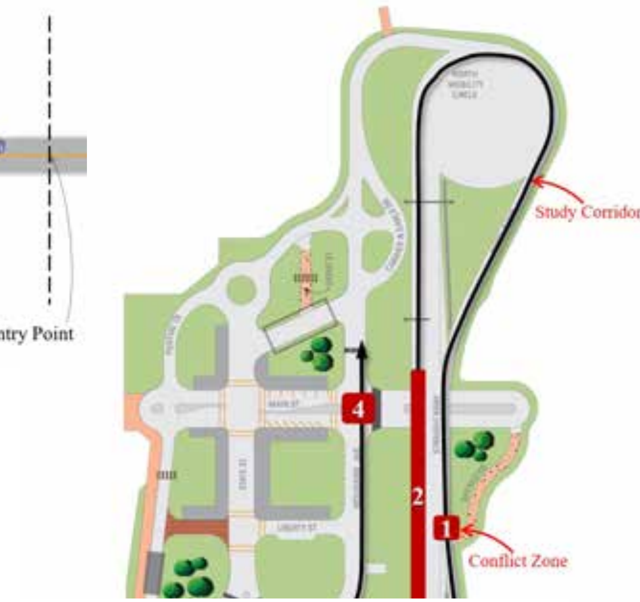
There is no duality gap in the upper-level problem.

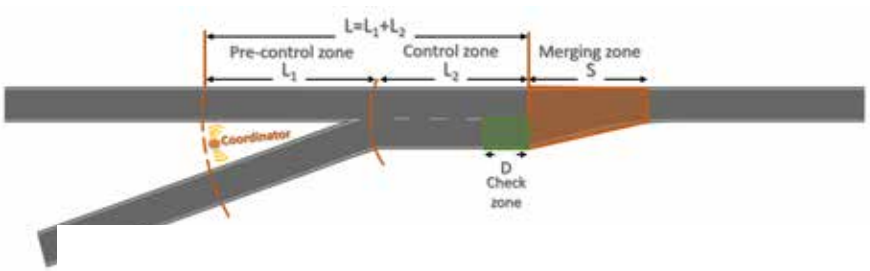
[1] Malikopoulos, A.A., Beaver, L.E., and Chremos, I.V., "Optimal Time Trajectory and Coordination for Connected and Automated Vehicles," Automatica, 125, 109469, 2021.

multiple scenarios[1]-[6]





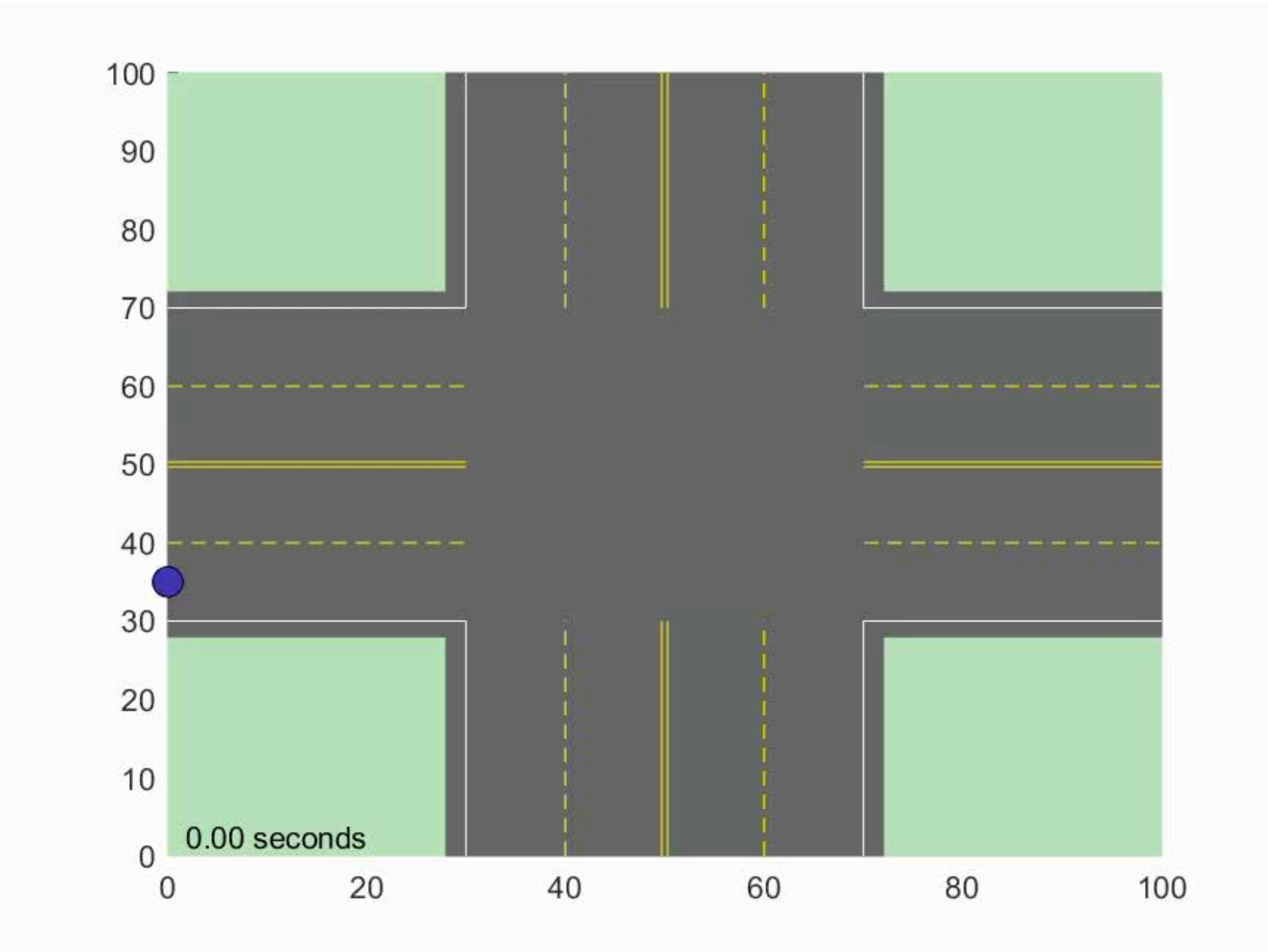




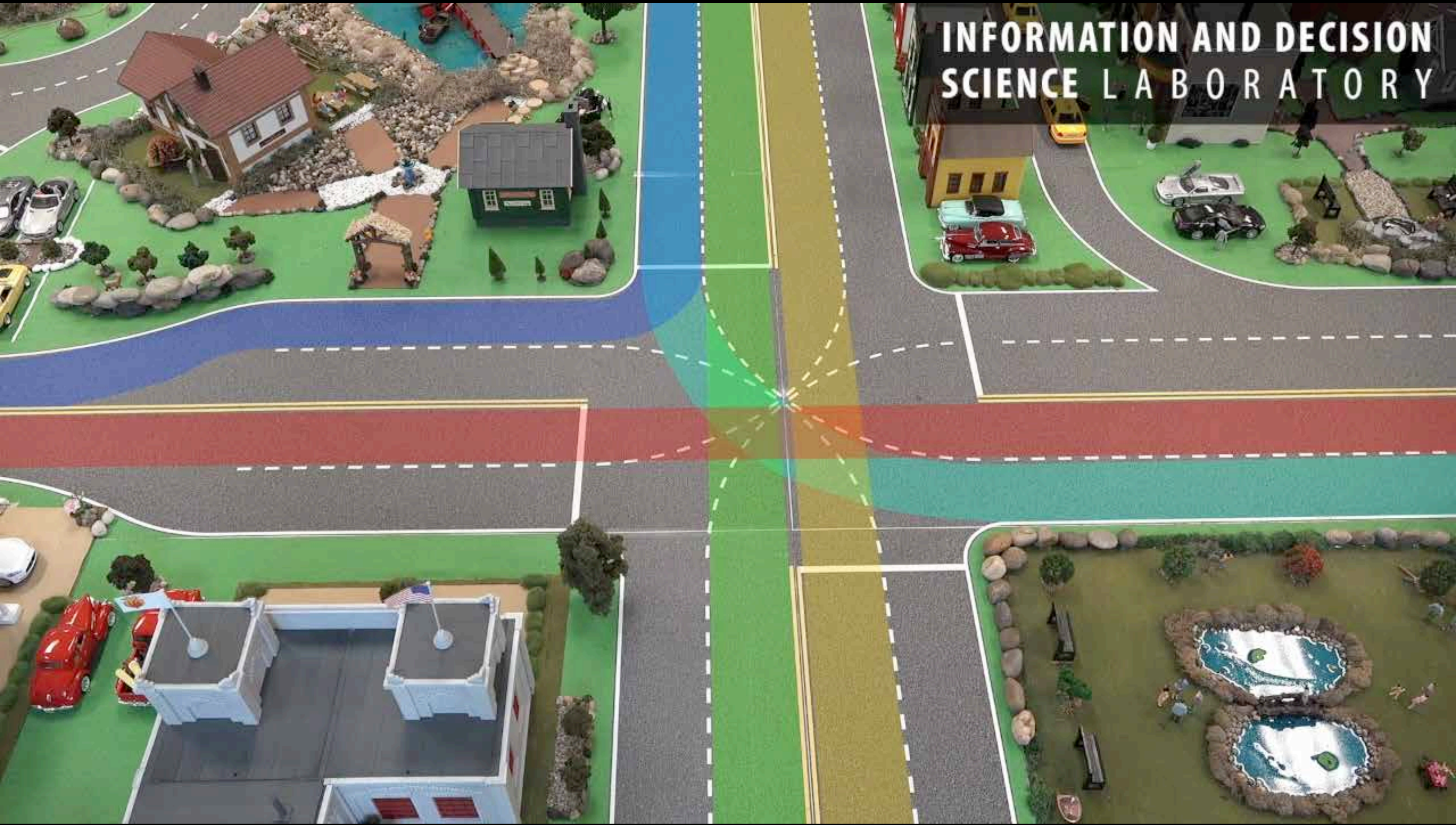
– Toolboxes: Math and Optimization, Code Generation, and Application Deployment

[1] Mahbub, A M. I., and Malikopoulos, A.A., "A Platoon Formation Framework in a Mixed Traffic Environment," IEEE Control Systems Letters, 6, 1370–1375, 2022.
[2] Chalaki, B., and Malikopoulos, A.A., "Optimal Control of Connected and Automated Vehicles at Multiple Adjacent Intersections," IEEE Trans. on Control Systems Tech., 2021.
[3] Chalaki, B., and Malikopoulos, A.A., "Time-Optimal Coordination for Connected and Automated Vehicles at Adjacent Intersections," IEEE Trans. Intell. Transp. Syst., 2021.
[4] Kumaravel, S.D., Malikopoulos, A. A., and Ayyagari, R., "Optimal Coordination of Platoons of Connected and Automated Vehicles at Signal-Free Intersections," IEEE Trans. Intell. Veh., 2021.
[5] Mahbub, A M. I., Malikopoulos, A.A., and Zhao, L., "Decentralized Optimal Coordination of Connected and Automated Vehicles for Multiple Traffic Scenarios," Automatica, 117, 108958, 2020.
[6] Malikopoulos, A. A., Hong, S., Park, B., Lee, J., and Ryu, S. "Optimal Control for Speed Harmonization of Automated Vehicles," IEEE Trans. Intell. Transp. Syst., 20, 7, 2405–2417, 2019.

simulation results



experimental results in IDS^{3}C

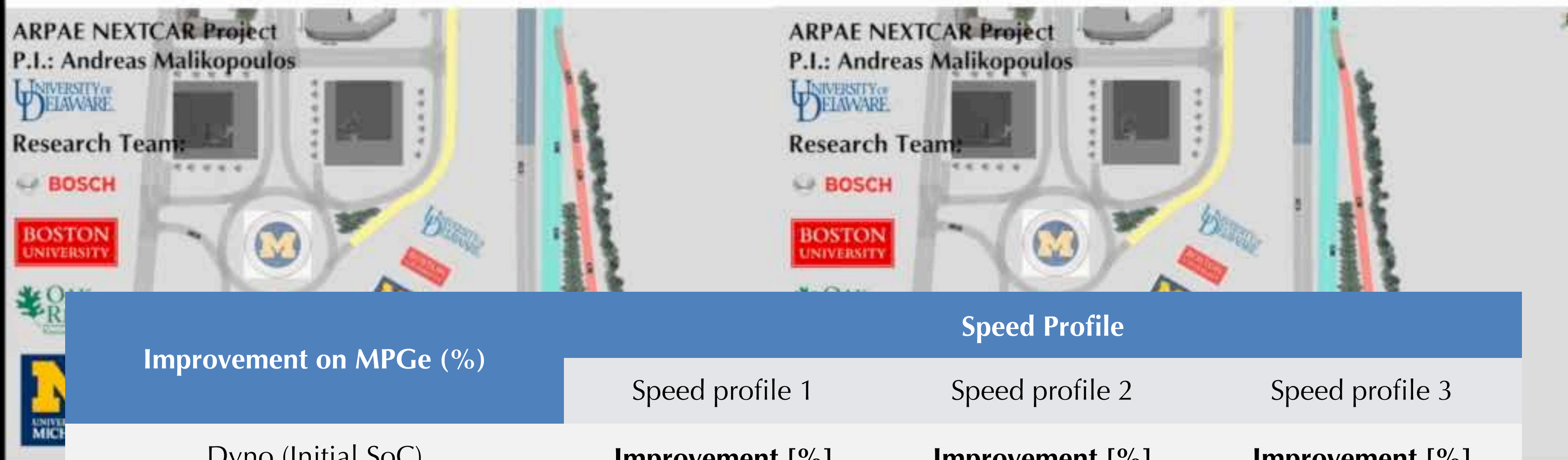


coordination of CAVs

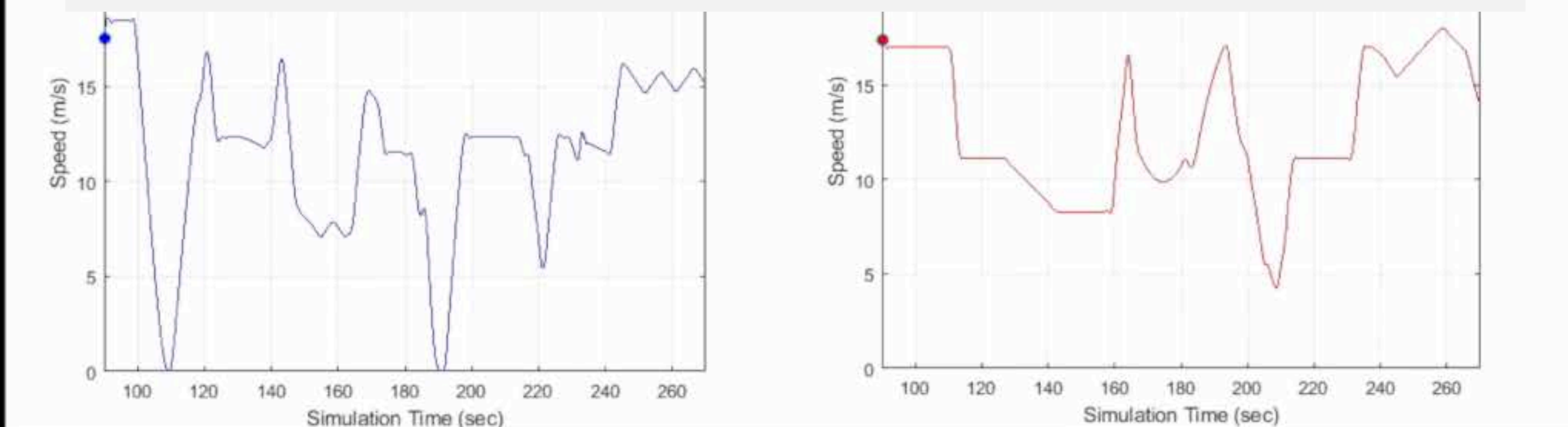
ARPAE NEXTCAR —field test in Mcity

vehicle-in-the-loop test in Bosch facilities

Scenario with human-driven vehicles | Scenario with CAVs

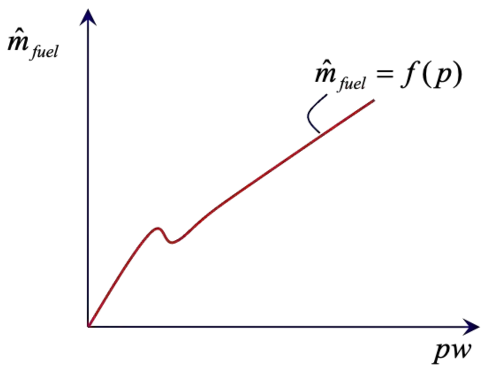


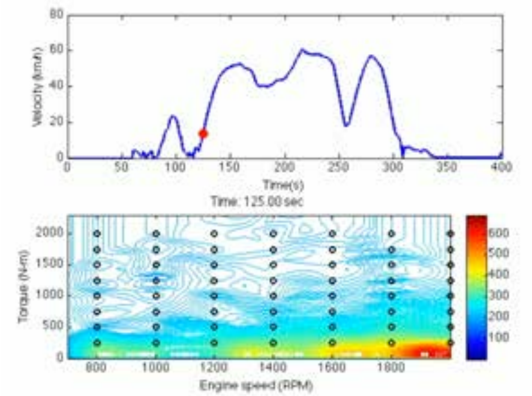
Improvement on MPGe (%)	Speed Profile		
	Speed profile 1	Speed profile 2	Speed profile 3
Dyno (Initial SoC)	**Improvement [%]**	**Improvement [%]**	**Improvement [%]**
60%	13.8	33.7	18.7
75%	29.0	17.4	34.2

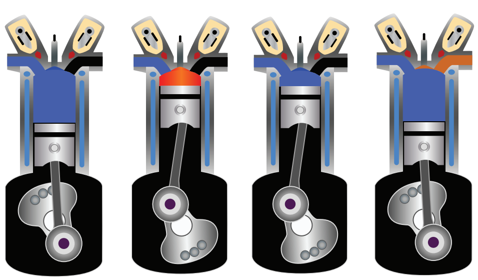


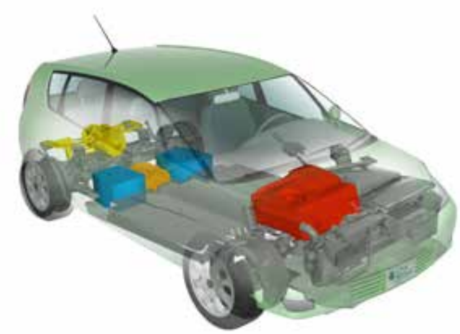
can we combine both learning and control?

- Supervised learning
- Model-based control
- Reinforcement learning

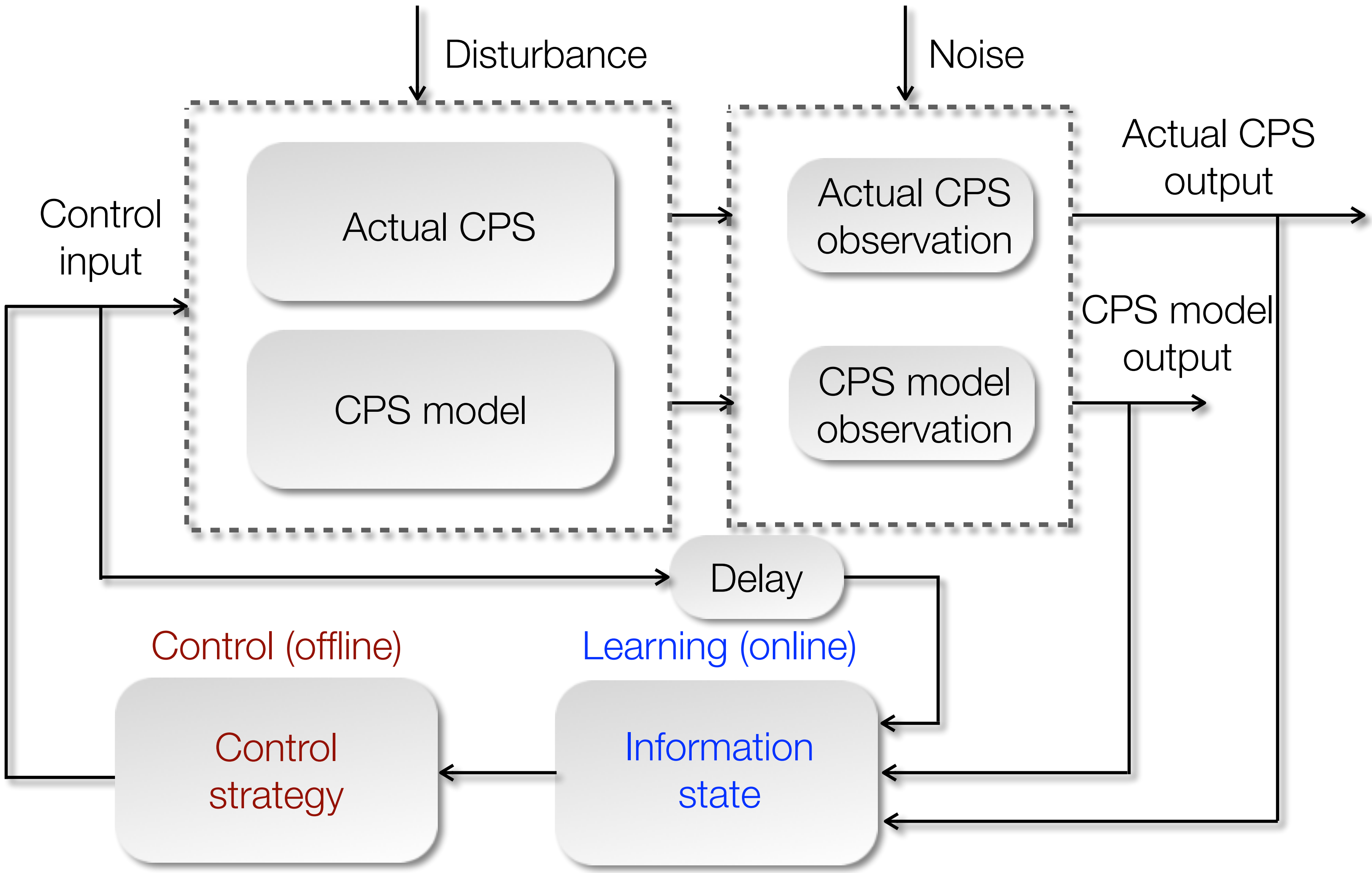








separation of learning and control for CPS[1],[2]



[1] Malikopoulos, A.A., "Separation of Learning and Control for Cyber-Physical Systems," *Automatica*, 2023.
[2] Malikopoulos, A.A., "On Team Decision Problems with Nonclassical Information Structures," *IEEE Transactions on Automatic Control,* 2023.



SELF-DRIVING
SEARCH
75 Km



E = MC²
y = ax + b
f(x) = a (x-x₁)(x-x₂)



Your Text
01
02
03
04
05

IDEA

acknowledgements

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Thank you for your attention!
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