

# Online Optimization of Switched LTI Systems

**Emiliano Dall'Anese**



University of Colorado  
Boulder

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# Acknowledgments

Gianluca Bianchin



Jorge I. Poveda



**Reference:** G. Bianchin, J. I. Poveda, and E. Dall'Anese, "Online Optimization of Switched LTI Systems Using Continuous-Time and Hybrid Accelerated Gradient Flows," 2020. [Online] <https://arxiv.org/abs/2008.03903>.

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## Switched LTI plant

$$\dot{x} = A_\sigma x + B_\sigma u + E_\sigma w$$

$$y = Cx + Dw$$

$w \rightarrow$  Unknown disturbance

$u \rightarrow$  Control input

$y \rightarrow$  Output

$\sigma(t) \rightarrow$  Switching signal

**Objective:** output regulation

$$\min_{u,x} g(u) + h(y)$$

$$\text{s.t.} \quad 0 = A_\sigma x + B_\sigma u + E_\sigma w$$

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Regulate the plant to the equilibrium points that minimize a given cost

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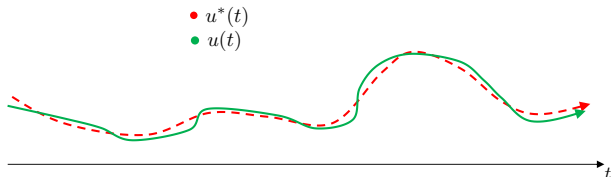
$\sigma(t) \rightarrow$  Switching signal

**Objective:** tracking of solutions

$$\min_{u,x} g(u, t) + h(y, t)$$

$$\text{s.t.} \quad 0 = A_{\sigma}x + B_{\sigma}u + E_{\sigma}w(t) \\ y = Cx + Dw$$

Output **tracks** optimal solution trajectory implicitly defined by a time-varying problem



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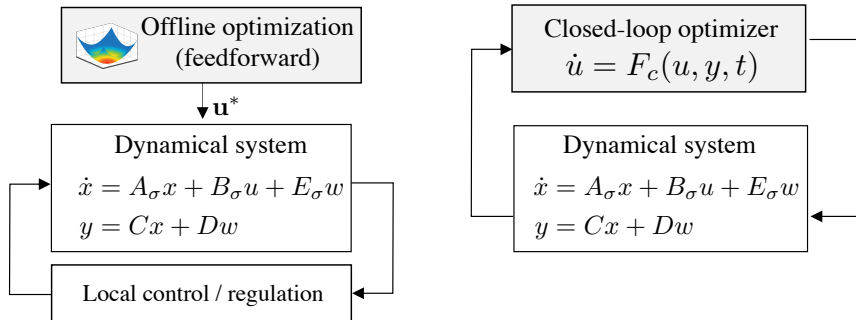
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**Key quantity in this talk:**  $\dot{w} \rightarrow$  time-variability of an optimal solution  
i.e.,  $\dot{w} \leftrightarrow \dot{u}^*$

Model-based and with  
time-scale separation



Online optimization

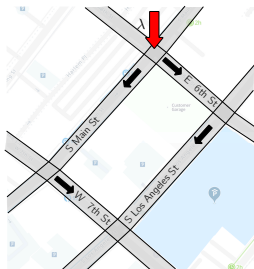






# Motivating Examples From Traffic Control

Suboptimal controllers (i.e., route selection)  $\rightarrow$  instabilities



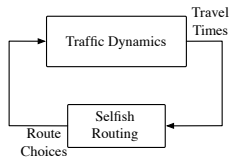
Two parallel roads:

$$\dot{x}_1 = -f(x_1) + r\lambda$$

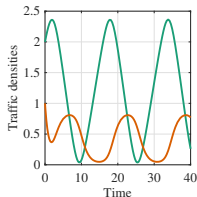
$$\dot{x}_2 = -f(x_2) + (1-r)\lambda$$

Drivers select the fastest route:

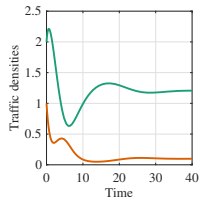
$$\dot{r} = r(1-r)(x_2 - x_1)$$



“free” selfish routing

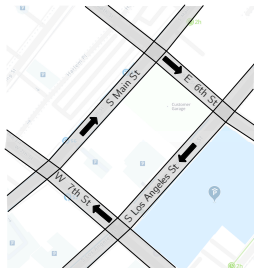


With controller



# Motivating Examples From Traffic Control (2)

Uncontrolled traffic → instabilities



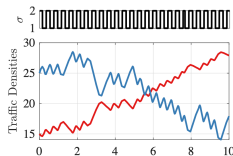
A more accurate model: CTM

$$\dot{x}_1 = -\min\{d_1 x_1, s_2 x_2\} + r_{21} \min\{d_2 x_2, s_1 x_1\} + w_1$$

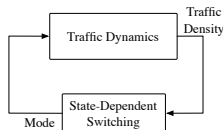
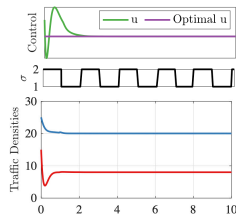
$$\dot{x}_2 = -\min\{d_2 x_2, s_1 x_1\} + r_{12} \min\{d_1 x_1, s_2 x_2\} + w_2$$

Roads have two modes: **free-flow** and **congested**

Uncontrolled system



With controller



## Related Work (a short list)

- Related to feedback-based optimization (with plant  $\infty$  fast)  
[Jokic et al'09], [Bolognani et al'13], [Bernstein et al'13], [Dall'Anese-Simonetto'16], [Bernstein et al'19], [Colombino et al'19], ...
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- [Lawrence et al'18] Joint stabilization and regulation, static, LTI
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**Today:** switched LTI, time-varying, exponential ISS, gradient flow

**In the paper:** Hybrid Nesterov, practical stability, other results ...

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Recall: gradient flow (if plant is  $\infty$  fast and  $w$  is known)

$$\begin{aligned}y &= -CA^{-1}Bu + (D - CA^{-1}E)w \\ \dot{u} &= -\nabla g(u) - G^\top \nabla h(Gu + Hw)\end{aligned}$$

“solves” the optimization

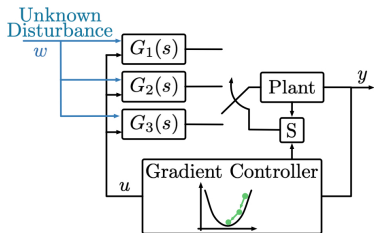
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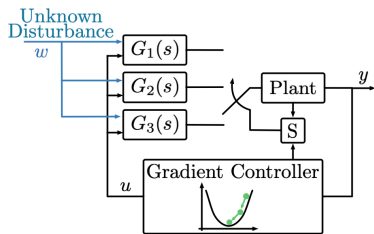
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## Proposed online gradient-based controller:



$$\begin{aligned}\varepsilon_\sigma \dot{x} &= A_\sigma x + B_\sigma u + E_\sigma w \\ y &= Cx + Dw \\ \dot{u} &= -\nabla g(u) - G^\top \nabla h(y)\end{aligned}$$

# Framework: Hybrid Dynamical Systems



$$\begin{aligned}\varepsilon_\sigma \dot{x} &= A_\sigma x + B_\sigma u + E_\sigma w \\ y &= Cx + Dw \\ \dot{u} &= -\nabla g(u) - G^\top \nabla h(y)\end{aligned}$$

Hybrid dynamical system (HDS):

$$\text{Flow: } \dot{z} \in F(z, \dot{w})$$

$$\text{Jumps: } z^+ \in G(z, \dot{w})$$

HDS for interconnection between gradient flow and plant:

$$\text{Flow: } \varepsilon_\sigma \dot{x} = A_\sigma x + B_\sigma u + E_\sigma w$$

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$$u^+ = u$$

$$\dot{\sigma} = 0$$

$$\sigma^+ \in \mathcal{S}$$

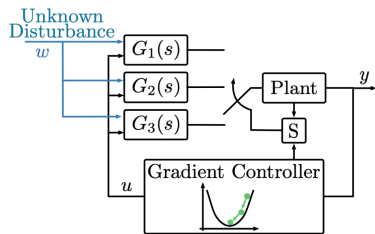
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$\tau_d \rightarrow$  average "dwell time"

$$\tau^+ = \tau - 1$$



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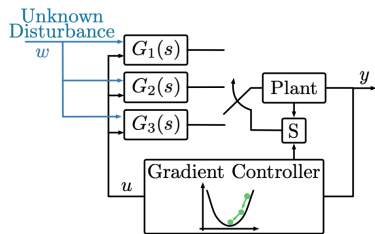
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HSD with flows  $\dot{z} \in F(x, \dot{w})$  and jumps:  $\dot{z}^+ \in G(x, \dot{w})$

**Definition** [Nešić et al '13]. The compact set  $\mathcal{A}$  is ISS if:

$$\|z(t, j)\|_{\mathcal{A}} \leq \beta(\|z(0, 0)\|_{\mathcal{A}}, t, j) + \gamma(\sup_{\tau \geq 0} \|\dot{w}(\tau)\|)$$

where  $\beta \in \mathcal{KL}$  and  $\gamma \in \mathcal{K}_{\infty}$ .

**Definition.** The set  $\mathcal{A}$  is exponentially ISS (E-ISS) if:

$$\|z(t, j)\|_{\mathcal{A}} \leq a_0(e^{-\frac{1}{2}(b_0 t + c_0 j)}) \|z(0, 0)\|_{\mathcal{A}} + d_0 \sup_{\tau \geq 0} \|\dot{w}(\tau)\|$$

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**As.** Individual modes are exponentially stable:

$$A_\sigma^\top P_\sigma + P_\sigma A_\sigma \preceq -Q_\sigma, \quad P_\sigma \succ 0, Q_\sigma \succ 0$$

**As.** Modes have common equilibrium points:

$$\exists u, w \mid 0 = A_\sigma x + B_\sigma u + E_\sigma w \text{ for all } \sigma$$

**Note:** We focus switching signals for which the number of discontinuities in every open interval  $(s, t) \subset \mathbb{R}_+$  satisfies [Hespanha-Morse '99] :

$$N(t, s) \leq N_0 + \frac{t-s}{\tau_d}$$

**As.** The cost functions have a Lipschitz-continuous gradient:

$$\|\nabla h(u) - \nabla h(u')\| \leq \ell_u \|u - u'\| \quad \|\nabla g(y) - \nabla g(y')\| \leq \ell_y \|y - y'\|$$

**As.** Cost satisfies Polyak-Łojasiewicz (PL) inequality:

$$\frac{1}{2} \|\nabla f(u)\|^2 \geq \mu (f(u) - f(u^*))$$

A strongly convex function satisfies the PL inequality, but the inverse implication does not hold. PL inequality implies invexity [Karimi et al'16]

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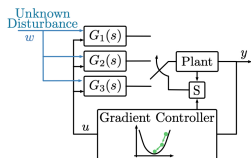
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# Tracking: Single Mode



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Define:  $z = [u, x]$ ,  $z^* = [u^*, x^*]$

**Proposition.** Suppose that the plant has a single mode. If

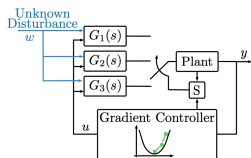
$$\varepsilon_\sigma < \frac{\underline{\lambda}(Q_\sigma)}{4\ell_y \|C\| \|G\| \|P_\sigma A_\sigma^{-1} B_\sigma\|}$$

then the set  $\{z - z^*\}$  is E-ISS with rate  $b_0 = \mu^2/\ell$ ,  $c_0 = 0$ .

Details:  $a_0 = \sqrt{\bar{a}_\sigma/\underline{a}_\sigma}$ ,  $\bar{a}_\sigma = \max\left\{(1 - \theta_\sigma)\frac{\ell}{2}, \theta_\sigma \bar{\lambda}(P_\sigma)\right\}$ ,  $\underline{a}_\sigma = \min\left\{(1 - \theta_\sigma)\frac{\mu}{2}, \theta_\sigma \underline{\lambda}(P_\sigma)\right\}$

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**Theorem.** Consider the interconnection above with state  $(\tilde{z}, \tau, \sigma)$ , where  $\tilde{z} = z - z^*$  is the tracking error. If

$$\varepsilon_\sigma < \frac{\underline{\lambda}(Q_\sigma)}{4\ell_y \|C\| \|G\| \|P_\sigma A_\sigma^{-1} B_\sigma\|} \quad \text{and} \quad \tau_d > \frac{\ell}{2\mu^2} \ln\left(\frac{\bar{a}}{\underline{a}}\right), \quad N_0 \in \mathbb{Z}_{>0}$$

then the set  $\mathcal{A} = \{0\} \times \mathcal{S} \times \mathcal{T}_C$ , with  $\mathcal{T}_C := [0, N_0] \times \mathcal{S}$ , is E-ISS with parameters  $b_0 = \mu^2/\ell - \frac{\varrho}{\tau_d}$ ,  $c_0 = \varrho - \ln\left(\frac{\bar{a}}{\underline{a}}\right)$ .

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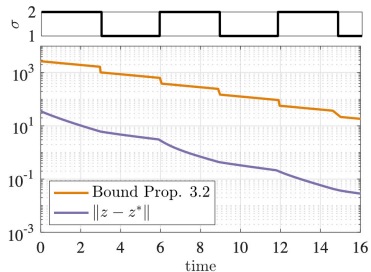
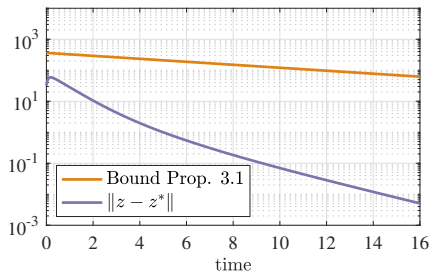
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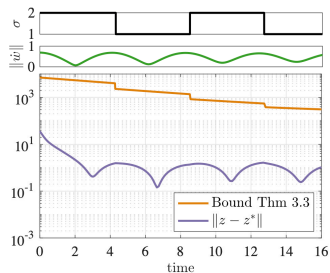
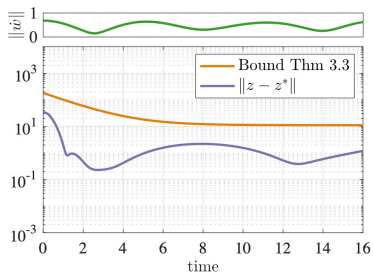
# Constant Disturbance: Illustrations

$$\|z(t, j)\|_{\mathcal{A}} \leq a_0 e^{-\frac{1}{2}(b_0 t + c_0 j)} \|z(0, 0)\|_{\mathcal{A}}$$



# Tracking: Illustrations

$$\|z(t, j)\|_{\mathcal{A}} \leq a_0 e^{-\frac{1}{2}(b_0 t + c_0 j)} \|z(0, 0)\|_{\mathcal{A}} + d_0 \sup_{\tau \geq 0} \|\dot{w}(\tau)\|$$



# Teaser: Hybrid Restarted Nesterov

Hybrid feedback controller inspired by Nesterov's accelerated gradient

$$\varepsilon_\sigma \dot{x} = A_\sigma x + B_\sigma u_1 + E_\sigma w$$

$$\dot{u}_1 = \frac{\rho}{u_3} (u_2 - u_1)$$

$$\dot{u}_2 = -\frac{\kappa u_3}{\rho} (\nabla h(u_1) + G^\top \nabla g(y)) \quad u_2^+ = r_0 u_1 + (1 - r_0) u_2$$

$$\dot{u}_3 = 1 \quad u_3^+ = T$$

1) Resolves the lack of robustness of accelerated methods when online and in closed loop with dynamical system [Hauswirth et al '20]

2) Outperforms the gradient-flow controller for strongly convex costs

See our paper!

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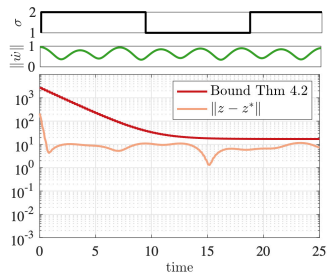
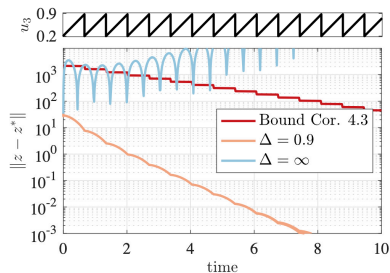
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Hybrid feedback controller inspired by Nesterov's accelerated gradient



- Work at the intersection of online optimization, control, and HDS
- E-ISS for switched LTI and costs that satisfy the PL inequality
- Under strong convexity, hybrid restarted Nesterov method
- Next steps:
  - Constrained problems
  - Robustness to inexact gradient information
  - Connections with MPC (with J. Cortes)

# Thanks!

