

From application to theory and back again: a collection of experiences in nonlinear control

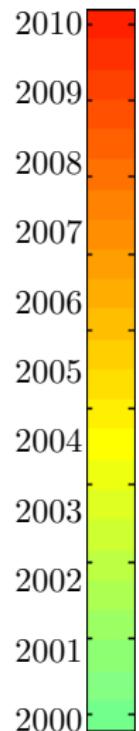
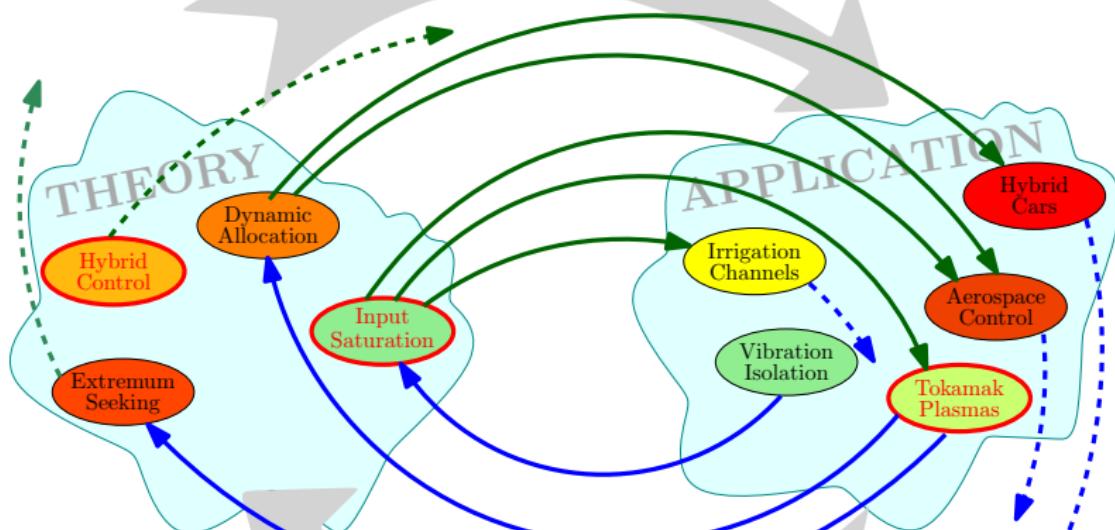
Luca Zaccarian

University of Rome, Tor Vergata

September 9, 2010
Technische Universität München

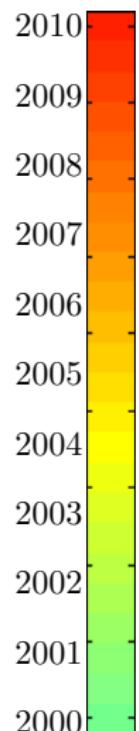
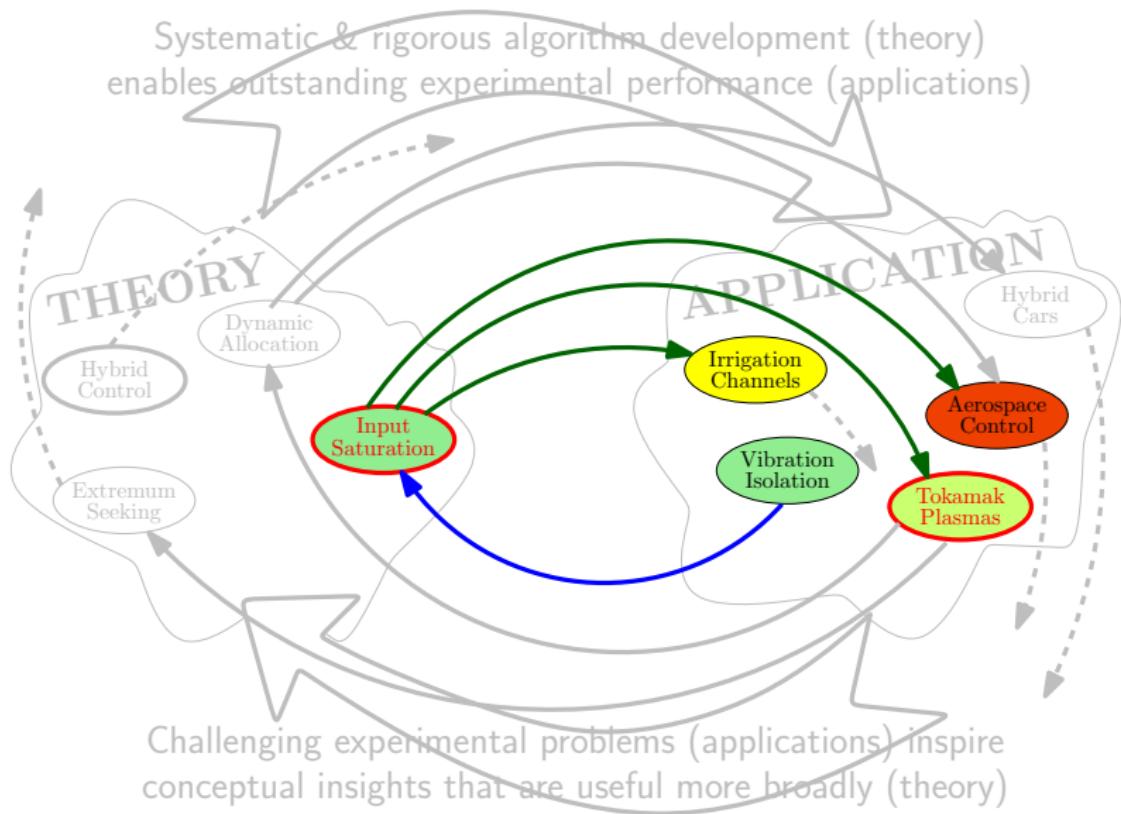
Interplay between applications/theory sustains my research

Systematic & rigorous algorithm development (theory)
enables outstanding experimental performance (applications)



Challenging experimental problems (applications) inspire conceptual insights that are useful more broadly (theory)

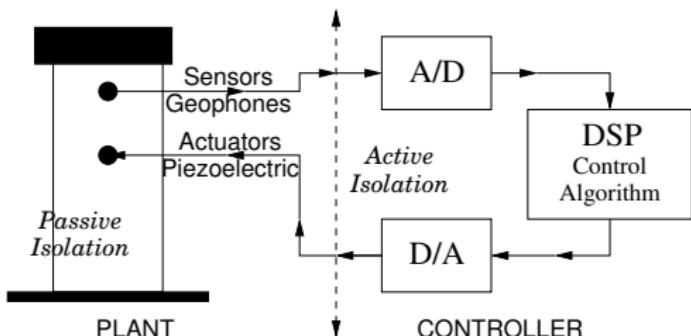
Input saturation interplay provided fertile research ground



Active control provides extreme vibration isolation

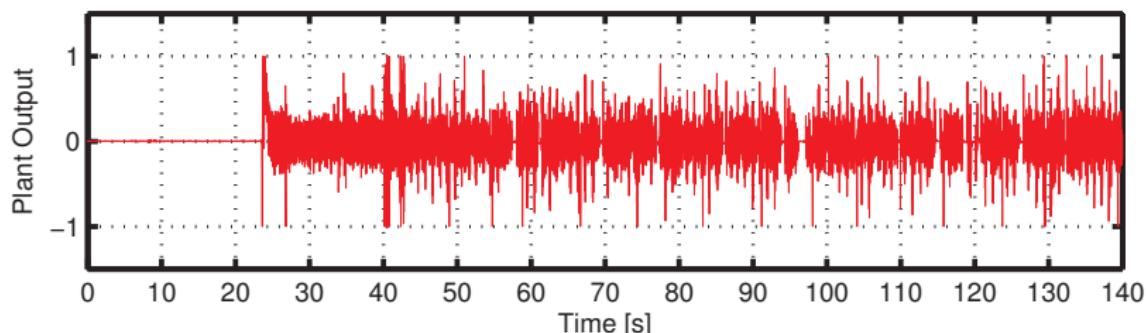
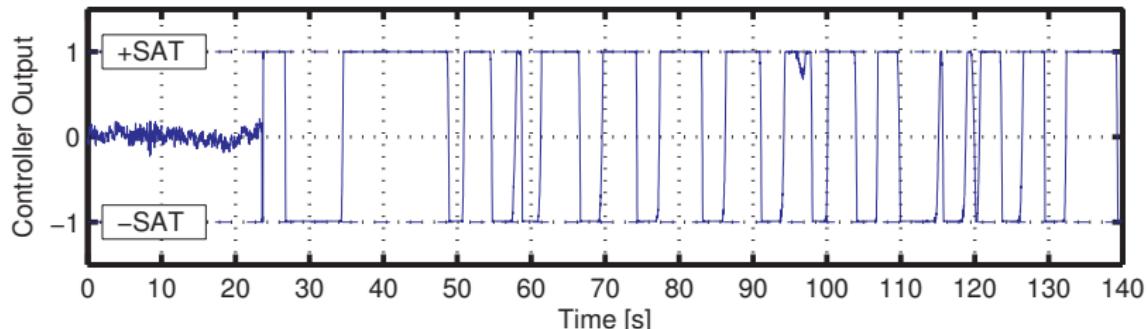
Newport Corporation's Elite 3™ vibration isolation table

- Useful, for example, in
 - high-precision microscopy
 - semiconductor manufacturing
 - Actuators: piezoelectric stack
 - Sensors: geophones



Input saturation confuses the base control algorithm

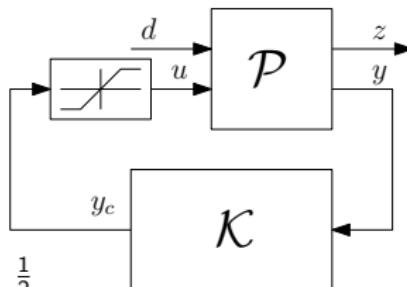
- Extreme vibration suppression (40 dB) up to $t = 23$ s



- At $t = 23$ s someone walks close to the table

Performance with saturation depends on size of disturbance

- Ssaturation: an abrupt nonlinearity:
 - Small signals: $\text{sat}(y_c) = y_c \Rightarrow$ no effect
 - Large signals: $\text{sat}(y_c)$ bounded \Rightarrow severe effect
 - Signal size (\mathcal{L}_2 norm): $\|z\|_2 := \left(\int_0^\infty |z(t)|^2 \right)^{1/2}$
 - $z \in \mathcal{L}_2$ (square integrable) if $\|z\|_2 < \infty$
 - Closed-loop performance measures:



$$\|z\|_2 < \bar{\gamma}_{dz} \|d\|_2 \quad \text{for all } d \in \mathcal{L}_2$$

- **Nonlinear \mathcal{L}_2 gain:** a function $s \mapsto \gamma_{dz}(s)$: [Megretski '95]

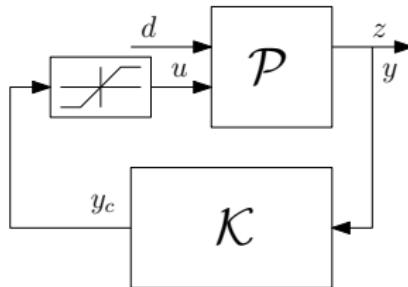
$\|z\|_2 \leq \gamma_{dz}(s) \|d\|_2$ for all d satisfying $\|d\|_2 \leq s$

Example demonstrates relevance of nonlinear gains

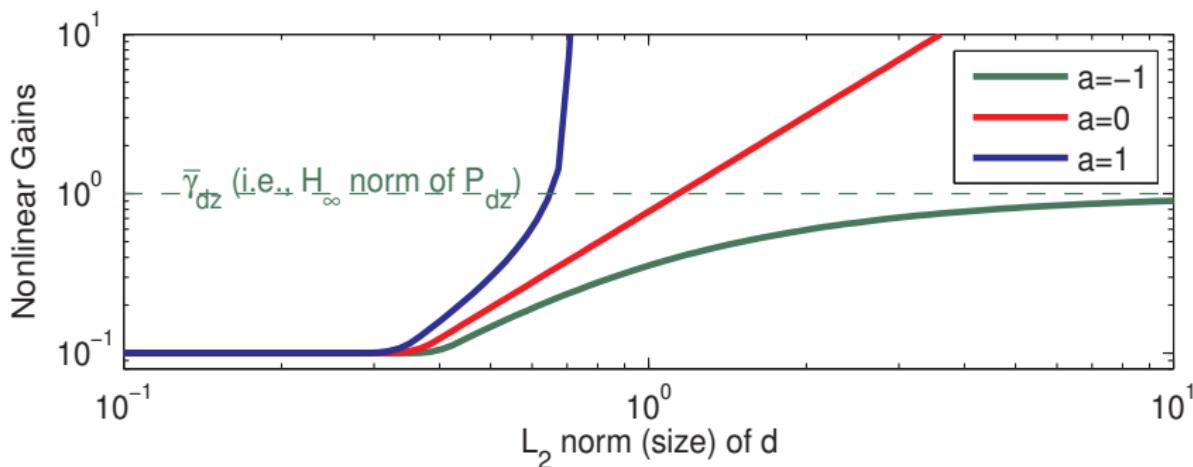
Controller \mathcal{K} cancels the plant dynamics
and **stabilizes** (before saturation)

$$\mathcal{P} : \dot{z} = az + \text{sat}(y_c) + d$$

$$\mathcal{K} : y_c = -az - 10z$$



Three representative cases [Sontag '84, Lasserre '92]



Nonlinear \mathcal{L}_2 gains are estimated using Lyapunov functions

- **Quadratic** functions (LMIs [Boyd '95])

$$V_1(x) = x^T P x$$

$$\dot{V} + \frac{1}{\gamma_{dz}(s)} |z|^2 - \gamma_{dz}(s) |w|^2 < 0$$

- Max of quadratics (BMIs)

$$V_2(x) = \max_{j \in \{1, \dots, J\}} x^T P_j x$$

- Convex Hull of quadratics (BMIs)

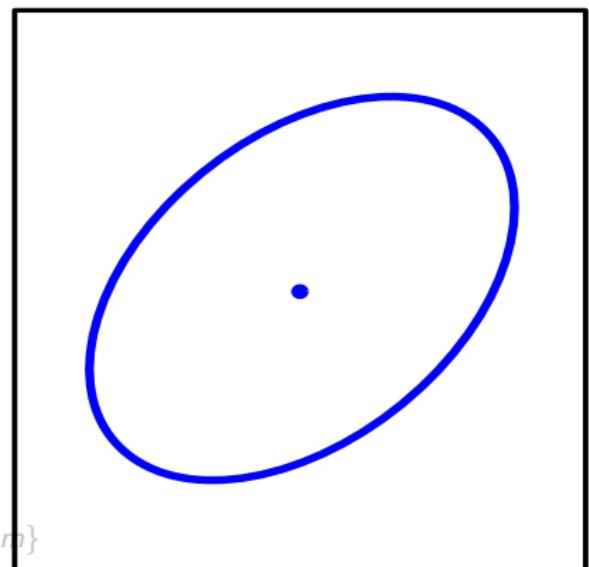
$$V_3(x) = \min_{\gamma_j \geq 0: \sum_j \gamma_j = 1} x^T \left(\sum_j \gamma_j Q_j \right)^{-1} x$$

- Piecewise quadratic (LMI-BMI)

$$V_4(x) = \begin{bmatrix} x \\ \text{sat}(y_c(x)) \end{bmatrix}^T \bar{P} \begin{bmatrix} x \\ \text{sat}(y_c(x)) \end{bmatrix}$$

- Piecewise Polynomial (LMI-BMI)

$$V_5(x) = \begin{bmatrix} x \\ \text{sat}(y_c(x)) \end{bmatrix}^{\{m\}T} \hat{P} \begin{bmatrix} x \\ \text{sat}(y_c(x)) \end{bmatrix}^{\{n\}}$$



A possible level set

Nonlinear \mathcal{L}_2 gains are estimated using Lyapunov functions

- **Quadratic** functions (LMIs [Boyd '95])

$$V_1(x) = x^T P x$$

$$\dot{V} + \frac{1}{\gamma_{dz}(s)} |z|^2 - \gamma_{dz}(s) |w|^2 < 0$$

- **Max of quadratics** (BMIs)

$$V_2(x) = \max_{j \in \{1, \dots, J\}} x^T P_j x$$

- **Convex Hull** of quadratics (BMIs)

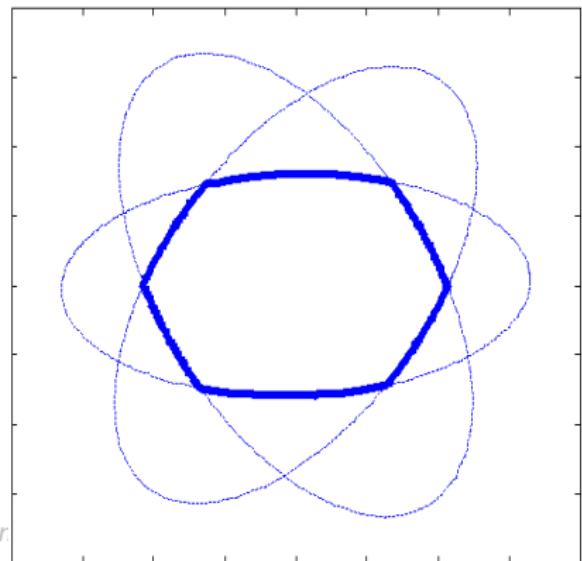
$$V_3(x) = \min_{\gamma_j \geq 0: \sum_j \gamma_j = 1} x^T \left(\sum_j \gamma_j Q_j \right)^{-1} x$$

- **Piecewise quadratic** (LMI-BMI)

$$V_4(x) = \begin{bmatrix} x \\ \text{sat}(y_c(x)) \end{bmatrix}^T \bar{P} \begin{bmatrix} x \\ \text{sat}(y_c(x)) \end{bmatrix}$$

- **Piecewise Polynomial** (LMI-BMI)

$$V_5(x) = \begin{bmatrix} x \\ \text{sat}(y_c(x)) \end{bmatrix}^{\{m\}T} \hat{P} \begin{bmatrix} x \\ \text{sat}(y_c(x)) \end{bmatrix}^{\{r\}}$$



A possible level set

Nonlinear \mathcal{L}_2 gains are estimated using Lyapunov functions

- **Quadratic** functions (LMIs [Boyd '95])

$$V_1(x) = x^T P x$$

$$\dot{V} + \frac{1}{\gamma_{dz}(s)} |z|^2 - \gamma_{dz}(s) |w|^2 < 0$$

- **Max** of quadratics (BMIs)

$$V_2(x) = \max_{j \in \{1, \dots, J\}} x^T P_j x$$

- **Convex Hull** of quadratics (BMIs)

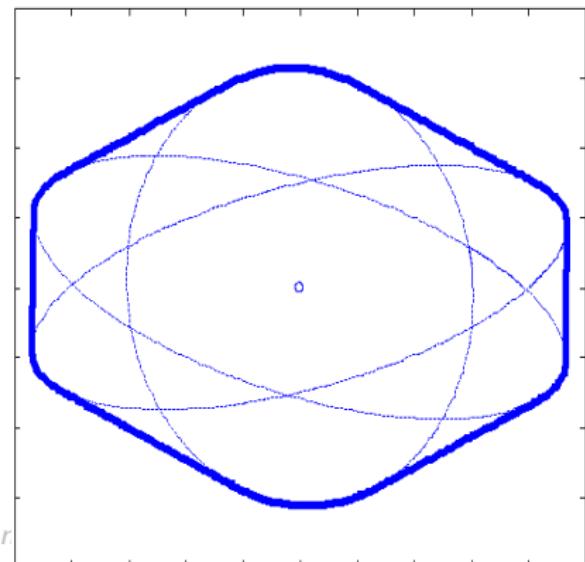
$$V_3(x) = \min_{\gamma_j \geq 0: \sum_j \gamma_j = 1} x^T \left(\sum_j \gamma_j Q_j \right)^{-1} x$$

- Piecewise quadratic (LMI-BMI)

$$V_4(x) = \begin{bmatrix} x \\ \text{sat}(y_c(x)) \end{bmatrix}^T \bar{P} \begin{bmatrix} x \\ \text{sat}(y_c(x)) \end{bmatrix}$$

- Piecewise **Polynomial** (LMI-BMI)

$$V_5(x) = \begin{bmatrix} x \\ \text{sat}(y_c(x)) \end{bmatrix}^{\{m\}T} \hat{P} \begin{bmatrix} x \\ \text{sat}(y_c(x)) \end{bmatrix}^{\{r\}}$$



A possible level set

Nonlinear \mathcal{L}_2 gains are estimated using Lyapunov functions

- **Quadratic** functions (LMIs [Boyd '95])

$$V_1(x) = x^T P x$$

$$\dot{V} + \frac{1}{\gamma_{dz}(s)} |z|^2 - \gamma_{dz}(s) |w|^2 < 0$$

- **Max** of quadratics (BMIs)

$$V_2(x) = \max_{j \in \{1, \dots, J\}} x^T P_j x$$

- **Convex Hull** of quadratics (BMIs)

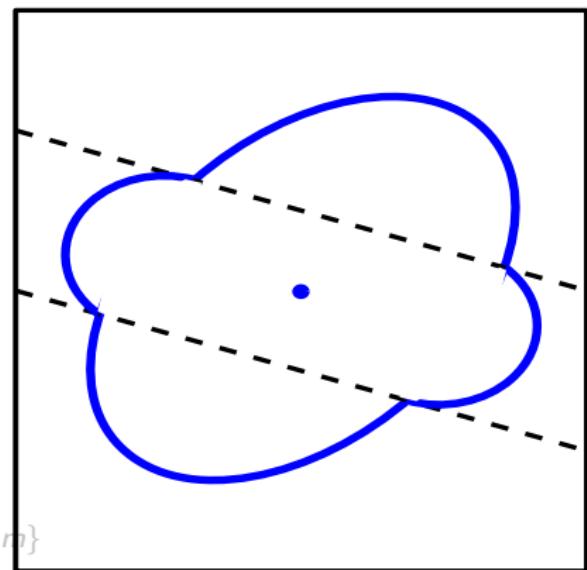
$$V_3(x) = \min_{\gamma_j \geq 0: \sum_j \gamma_j = 1} x^T \left(\sum_j \gamma_j Q_j \right)^{-1} x$$

- **Piecewise quadratic** (LMI-BMI)

$$V_4(x) = \begin{bmatrix} x \\ \text{sat}(y_c(x)) \end{bmatrix}^T \bar{P} \begin{bmatrix} x \\ \text{sat}(y_c(x)) \end{bmatrix}$$

- **Piecewise Polynomial** (LMI-BMI)

$$V_5(x) = \begin{bmatrix} x \\ \text{sat}(y_c(x)) \end{bmatrix}^{\{m\}T} \hat{P} \begin{bmatrix} x \\ \text{sat}(y_c(x)) \end{bmatrix}^{\{n\}}$$



A possible level set

Nonlinear \mathcal{L}_2 gains are estimated using Lyapunov functions

- **Quadratic** functions (LMIs [Boyd '95])

$$V_1(x) = x^T P x$$

$$\dot{V} + \frac{1}{\gamma_{dz}(s)} |z|^2 - \gamma_{dz}(s) |w|^2 < 0$$

- **Max** of quadratics (BMIs)

$$V_2(x) = \max_{j \in \{1, \dots, J\}} x^T P_j x$$

- **Convex Hull** of quadratics (BMIs)

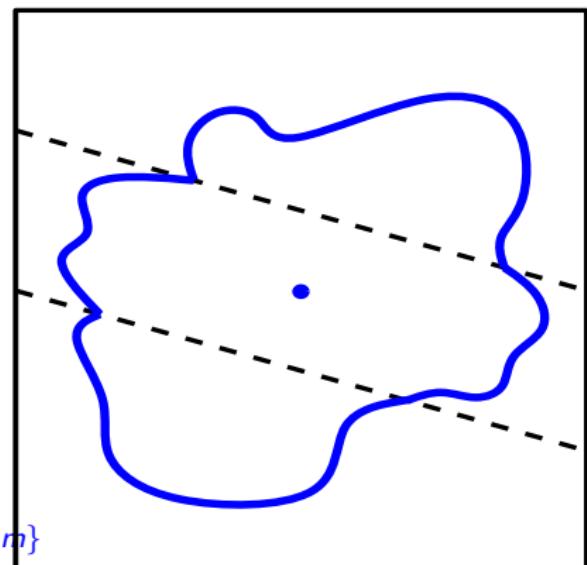
$$V_3(x) = \min_{\gamma_j \geq 0: \sum_j \gamma_j = 1} x^T \left(\sum_j \gamma_j Q_j \right)^{-1} x$$

- **Piecewise quadratic** (LMI-BMI)

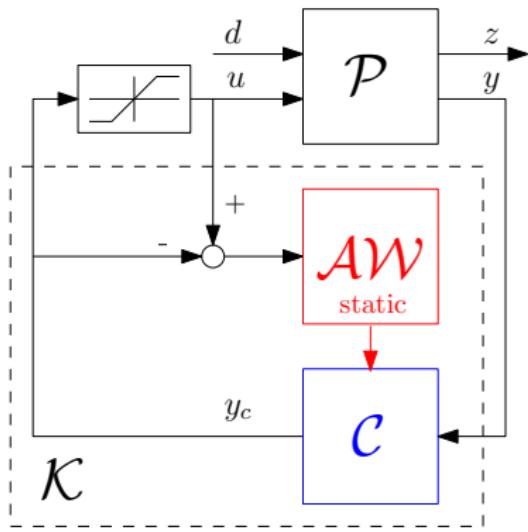
$$V_4(x) = \begin{bmatrix} x \\ \text{sat}(y_c(x)) \end{bmatrix}^T \bar{P} \begin{bmatrix} x \\ \text{sat}(y_c(x)) \end{bmatrix}$$

- **Piecewise Polynomial** (LMI-BMI)

$$V_5(x) = \begin{bmatrix} x \\ \text{sat}(y_c(x)) \end{bmatrix}^{\{m\}T} \hat{P} \begin{bmatrix} x \\ \text{sat}(y_c(x)) \end{bmatrix}^{\{m\}}$$



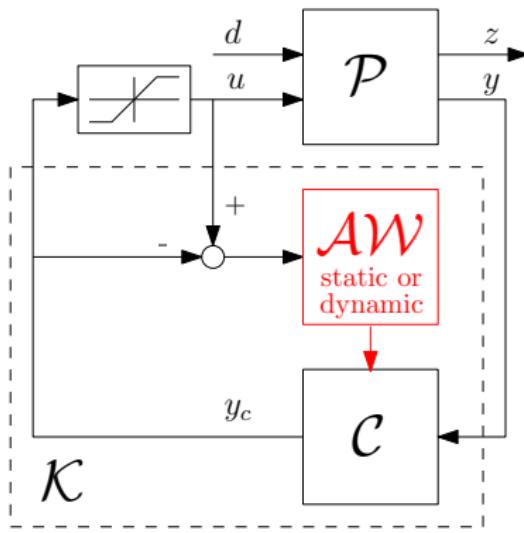
\mathcal{H}_∞ design generalizes to linear input-saturated plants



- Given \mathcal{P} linear, **design** \mathcal{K} , namely
 - \mathcal{C} linear plant-order
 - \mathcal{AW} static: linear gain
- Performance objective:**
given s^* , minimize $\gamma_{dz}(s^*)$
- Linear **controller** \mathcal{K} **equations**
$$\dot{x}_c = Ax_c + By + E_1(\text{sat}(y_c) - y_c)$$
$$y_c = Cx_c + Dy + E_2(\text{sat}(y_c) - y_c)$$

- Synthesis is a convex problem (generalizes LMI- \mathcal{H}_∞ [Gahinet 1994])
- Synthesis without \mathcal{AW} is nonconvex
- Recently used in satellite control project (μ synthesis [Doyle, 1985])

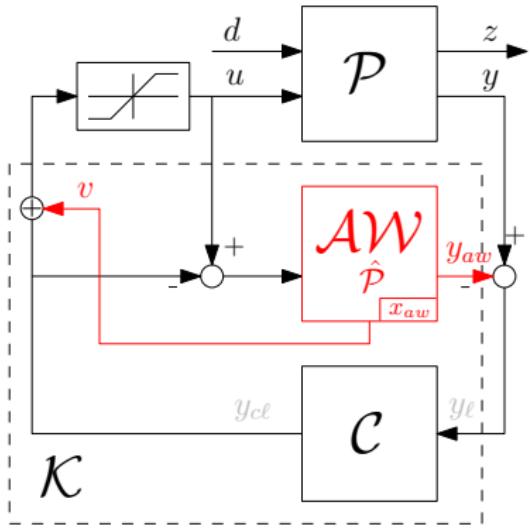
Pure anti-windup design is also convex



- Given \mathcal{P} linear, \mathcal{C} linear, **design** only
 - $\textcolor{red}{AW}$ linear static or plant-order
- Performance objective:**
given s^* , minimize $\gamma_{dz}(s^*)$
- Necessary conditions:**
 - linear feedback $(\mathcal{P}, \mathcal{C})$ exp stable
 $(\exists \textcolor{blue}{V}([x_p]) = [x_p]^T \begin{bmatrix} Q_p & Q_{pc} \\ Q_{pc}^T & Q_c \end{bmatrix}^{-1} [x_p])$
 - $\exists \textcolor{green}{K}$ s.t. $A_p + B_{p,u}\textcolor{green}{K}$ exp stable
 $(V_K(x_p) = x_p^T \overline{Q}_p^{-1} x_p, |\textcolor{green}{K}| \xrightarrow{s^* \rightarrow \infty} 0)$

- Static anti-windup construction (convex, LMIs)
 - feasible if $Q_p = \overline{Q}_p$: quasi-common quadratic Lyapunov function
- Plant-order anti-windup construction (convex, LMIs)
 - always feasible as long as V_K and $\textcolor{blue}{V}$ above exist

Anti-windup extends to fully nonlinear compensation

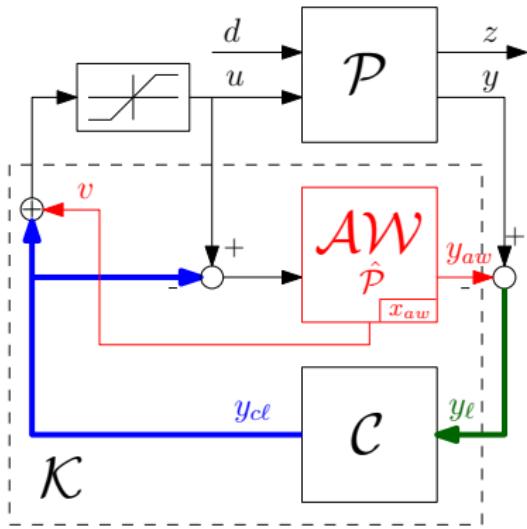


Model Recovery Anti-Windup (MRAW)

- Framework for **nonlinear** \mathcal{AW} :
 - \mathcal{AW} is a model $\hat{\mathcal{P}}$ of \mathcal{P}
 - $v = k(x_{aw})$ is a (nonlinear) stabilizer whose construction depends on \mathcal{P}
- \mathcal{AW} is **controller-independent**:
 - any (nonlinear) \mathcal{C} allowed
- Useful feature of MRAW:
 - \mathcal{C} “receives” linear plant output y_{cl}
 - $\Rightarrow \mathcal{C}$ “delivers” linear plant input y_{cl}

- Reduced order $\hat{\mathcal{P}}$ possible (tested on adaptive noise suppression)
- MRAW allows for **bumpless transfer** among controllers
- MRAW generalizes to **rate** and **curvature** saturation
- MRAW generalizes to **dead time** plants (Smith predictor)

Anti-windup extends to fully nonlinear compensation

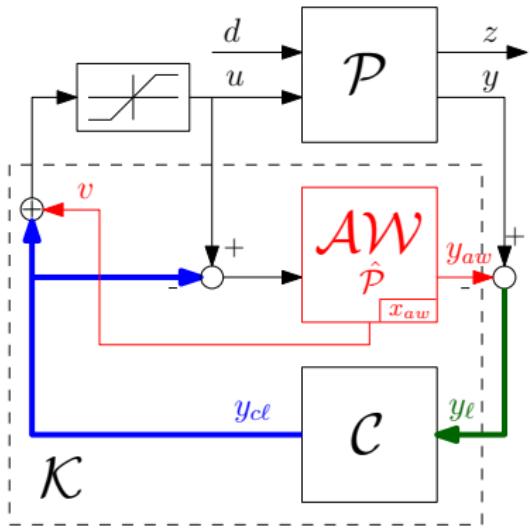


Model Recovery Anti-Windup (MRAW)

- Framework for **nonlinear** \mathcal{AW} :
 - \mathcal{AW} is a model $\hat{\mathcal{P}}$ of \mathcal{P}
 - $v = k(x_{aw})$ is a (nonlinear) stabilizer whose construction depends on \mathcal{P}
- \mathcal{AW} is **controller-independent**:
 - any (nonlinear) \mathcal{C} allowed
- Useful feature of MRAW:
 - \mathcal{C} “receives” linear plant output y_ℓ
 - $\Rightarrow \mathcal{C}$ “delivers” linear plant input y_{cl}

- Reduced order $\hat{\mathcal{P}}$ possible (tested on adaptive noise suppression)
- MRAW allows for **bumpless transfer** among controllers
- MRAW generalizes to **rate** and **curvature** saturation
- MRAW generalizes to **dead time** plants (Smith predictor)

Anti-windup extends to fully nonlinear compensation

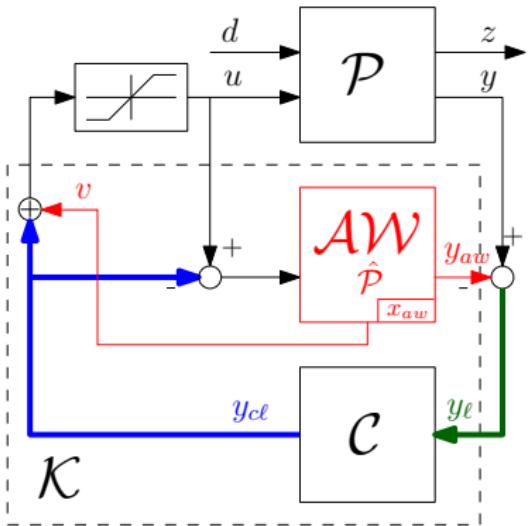


Model Recovery Anti-Windup (MRAW)

- Framework for **nonlinear** \mathcal{AW} :
 - \mathcal{AW} is a model $\hat{\mathcal{P}}$ of \mathcal{P}
 - $v = k(x_{aw})$ is a (nonlinear) stabilizer whose construction depends on \mathcal{P}
- \mathcal{AW} is **controller-independent**:
 - any (nonlinear) \mathcal{C} allowed
- Useful feature of MRAW:
 - \mathcal{C} “receives” linear plant output y_{cl}
 - $\Rightarrow \mathcal{C}$ “delivers” linear plant input y_{cl}

- **Reduced order** $\hat{\mathcal{P}}$ possible (tested on adaptive noise suppression)
- MRAW allows for **bumpless transfer** among controllers
- MRAW generalizes to **rate** and **curvature** saturation
- MRAW generalizes to **dead time** plants (Smith predictor)

Anti-windup extends to fully nonlinear compensation

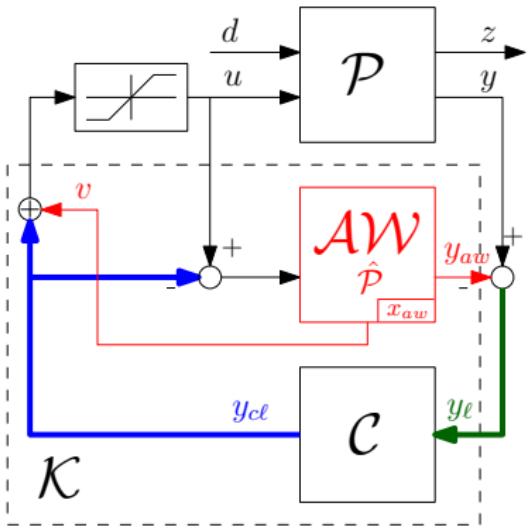


Model Recovery Anti-Windup (MRAW)

- Framework for **nonlinear** \mathcal{AW} :
 - \mathcal{AW} is a model $\hat{\mathcal{P}}$ of \mathcal{P}
 - $v = k(x_{aw})$ is a (nonlinear) stabilizer whose construction depends on \mathcal{P}
- \mathcal{AW} is **controller-independent**:
 - any (nonlinear) \mathcal{C} allowed
- Useful feature of MRAW:
 - \mathcal{C} “receives” linear plant output y_{cl}
 - $\Rightarrow \mathcal{C}$ “delivers” linear plant input y_{cl}

- **Reduced order** $\hat{\mathcal{P}}$ possible (tested on adaptive noise suppression)
- MRAW allows for **bumpless transfer** among controllers
- MRAW generalizes to **rate** and **curvature** saturation
- MRAW generalizes to **dead time** plants (Smith predictor)

Anti-windup extends to fully nonlinear compensation

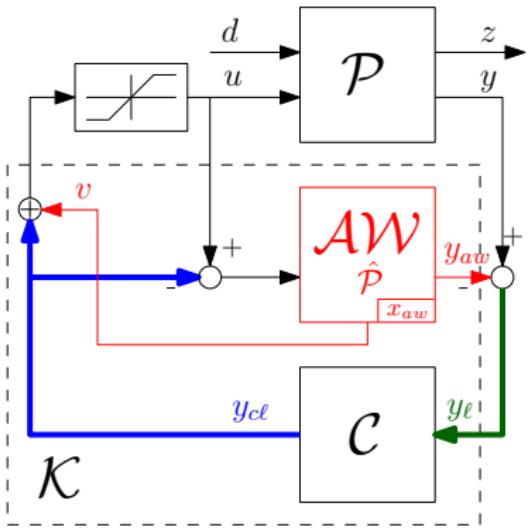


Model Recovery Anti-Windup (MRAW)

- Framework for **nonlinear** \mathcal{AW} :
 - \mathcal{AW} is a model $\hat{\mathcal{P}}$ of \mathcal{P}
 - $v = k(x_{aw})$ is a (nonlinear) stabilizer whose construction depends on \mathcal{P}
- \mathcal{AW} is **controller-independent**:
 - any (nonlinear) \mathcal{C} allowed
- Useful feature of MRAW:
 - \mathcal{C} “receives” linear plant output y_{cl}
 - $\Rightarrow \mathcal{C}$ “delivers” linear plant input y_{cl}

- **Reduced order** $\hat{\mathcal{P}}$ possible (tested on adaptive noise suppression)
- MRAW allows for **bumpless transfer** among controllers
- MRAW generalizes to **rate** and **curvature** saturation
- MRAW generalizes to **dead time** plants (Smith predictor)

Anti-windup extends to fully nonlinear compensation



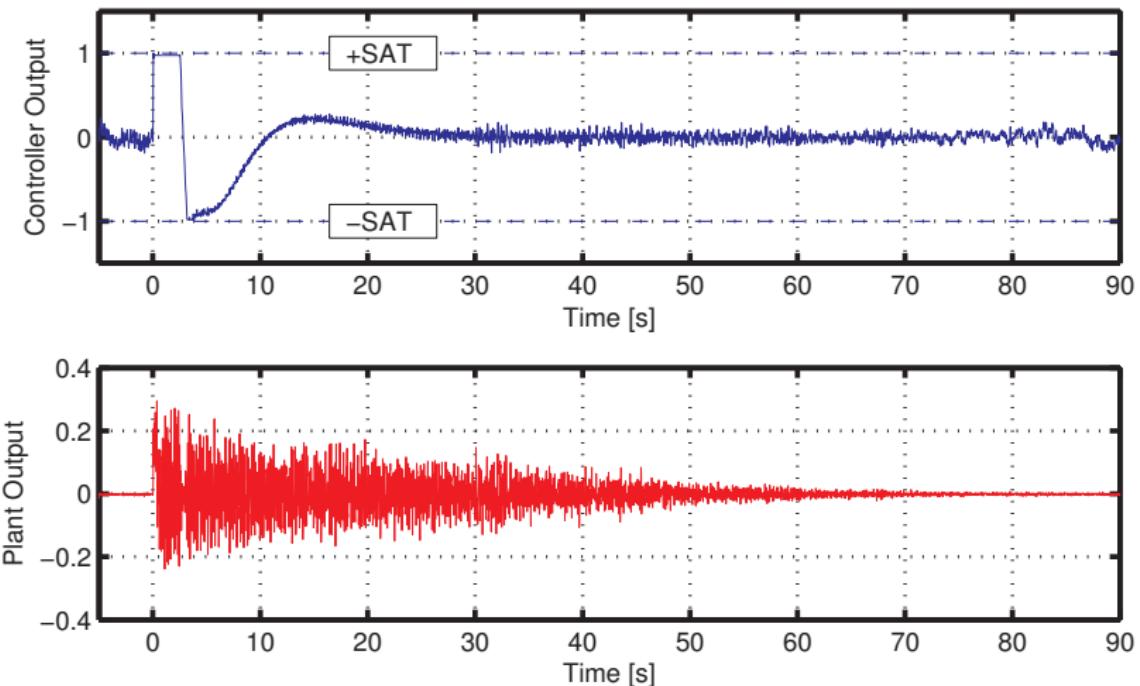
Model Recovery Anti-Windup (MRAW)

- Framework for **nonlinear** \mathcal{AW} :
 - \mathcal{AW} is a model $\hat{\mathcal{P}}$ of \mathcal{P}
 - $v = k(x_{aw})$ is a (nonlinear) stabilizer whose construction depends on \mathcal{P}
- \mathcal{AW} is **controller-independent**:
 - any (nonlinear) \mathcal{C} allowed
- Useful feature of MRAW:
 - \mathcal{C} “receives” linear plant output y_ℓ
 - $\Rightarrow \mathcal{C}$ “delivers” linear plant input y_{cl}

- **Reduced order** $\hat{\mathcal{P}}$ possible (tested on adaptive noise suppression)
- MRAW allows for **bumpless transfer** among controllers
- MRAW generalizes to **rate** and **curvature** saturation
- MRAW generalizes to **dead time** plants (Smith predictor)

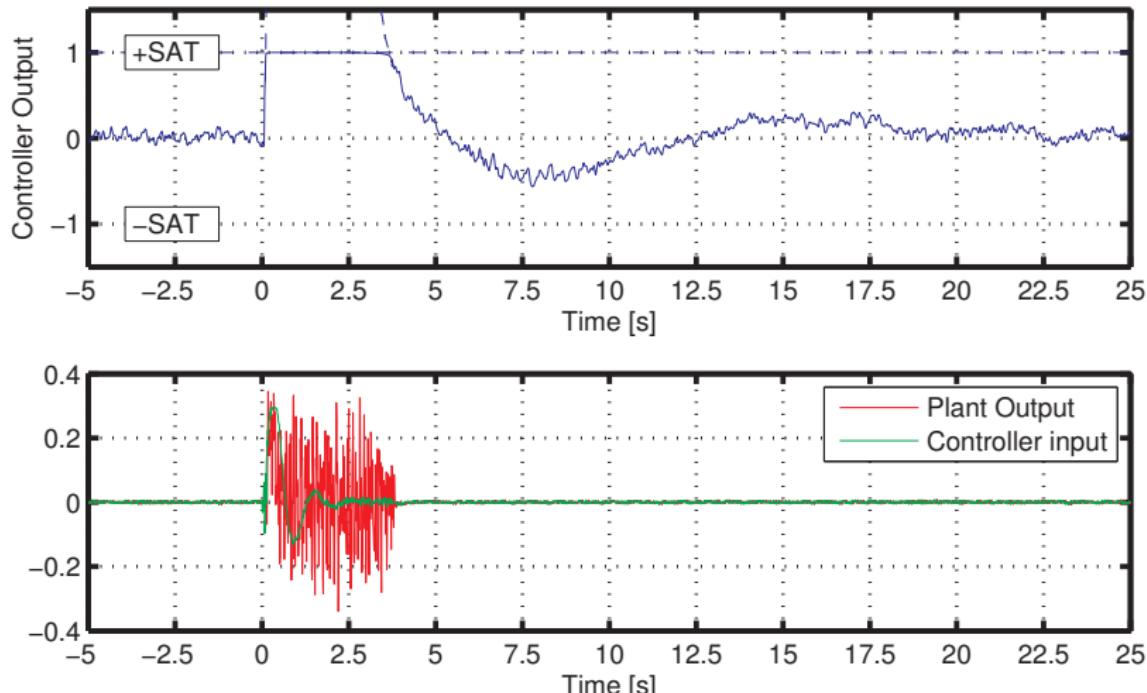
Ad hoc gain adaptation induces very slow isolation recovery

- Effect of a footstep at the side of the table (recovery > 1 minute)



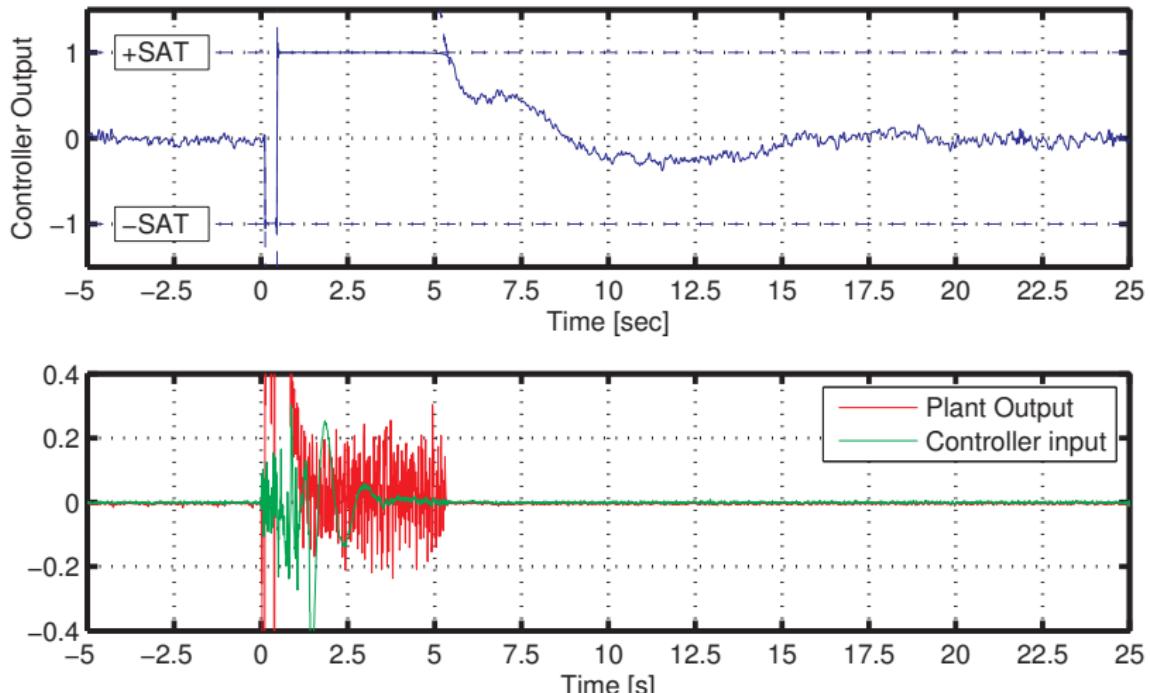
MRAW dramatically reduces isolation recovery time

- Effect of a footstep at the side of the table (recovery ≈ 4 s)



Even a bat strike does not confuse the MRAW controller

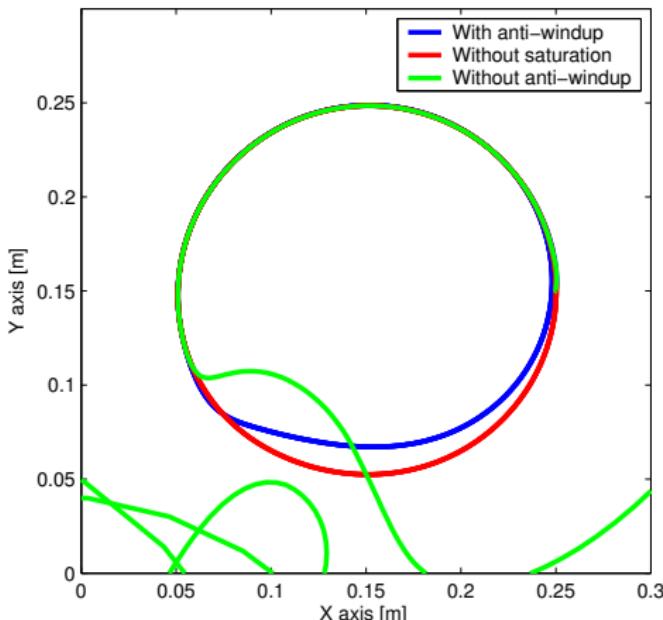
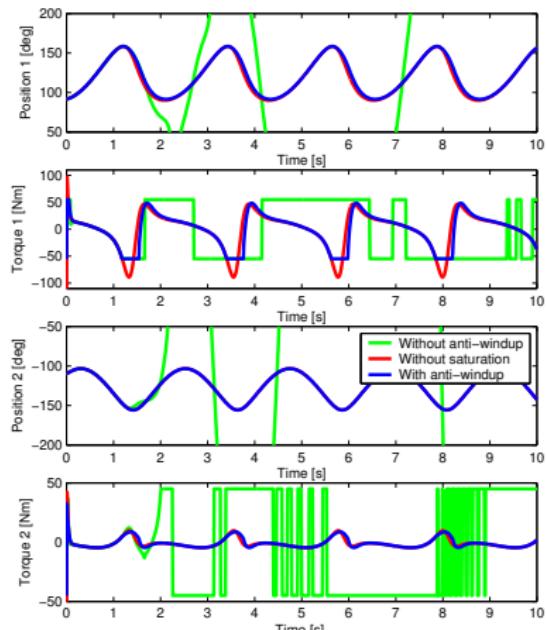
💡 Hitting with a baseball bat the table leg (recovery ≈ 5 s)



MRAW applies to nonlinear fully actuated robots

Example: a **SCARA robot** (planar robot) following a circular motion

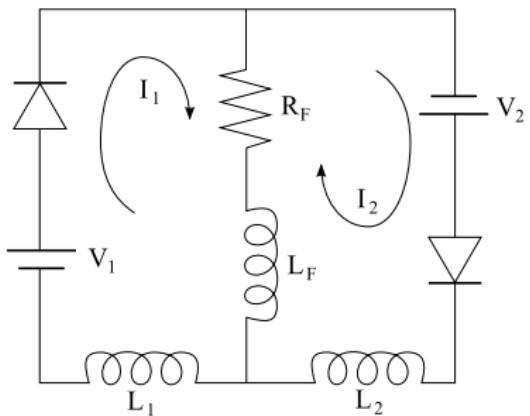
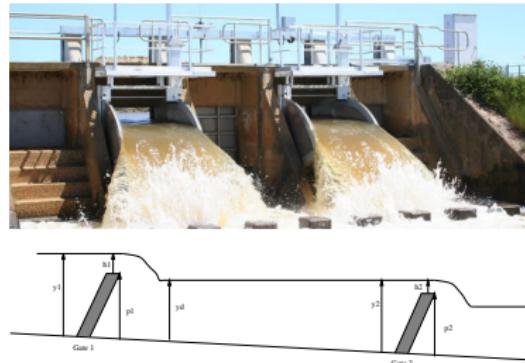
- Saturated “computed torque” controller goes postal (unstable)
- Nonlinear MRAW provides slight performance degradation



Anti-windup designs apply to a wide range of applications

Control of irrigation channels

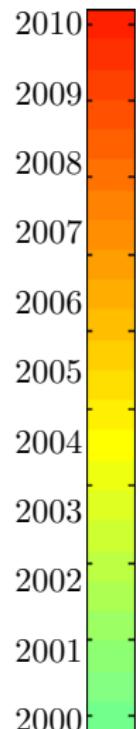
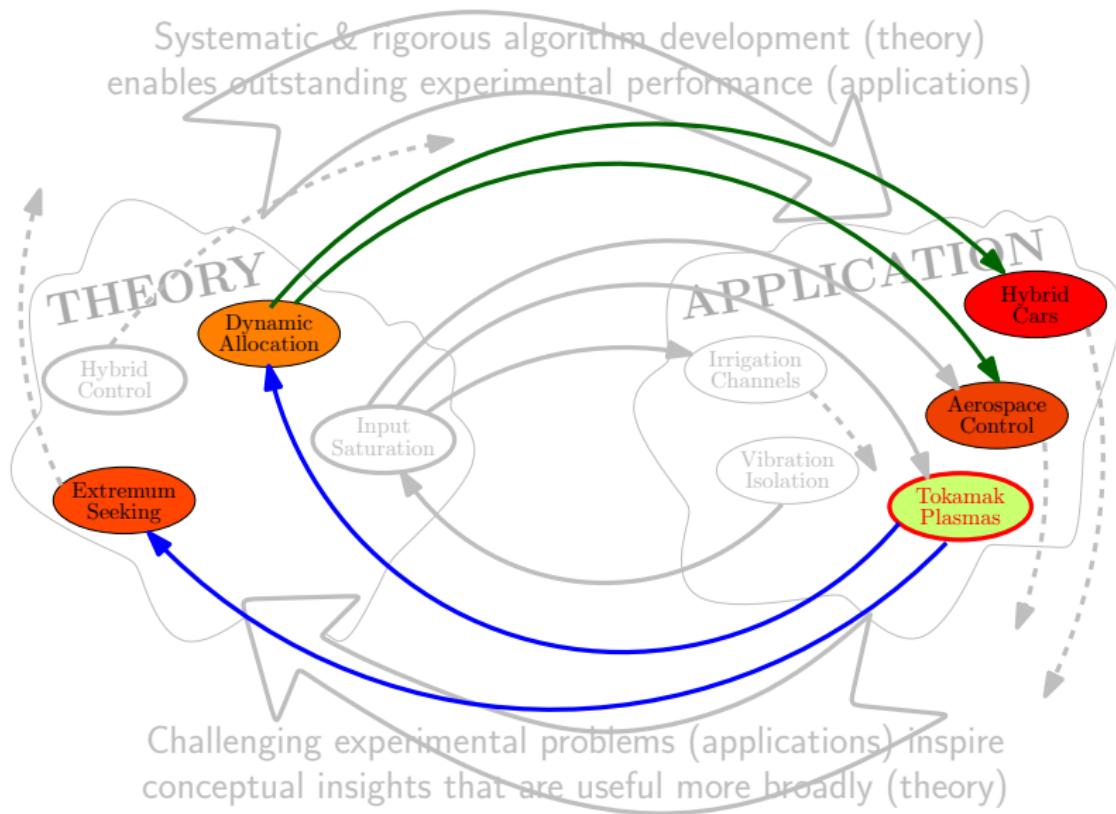
- Gate saturation problems:
 - bumpless transfer from manual control
 - with small flows in the pools
 - with large disturbances (rain, etc)
- **Challenge:** plant is ANCBC (poles in 0)



Small signal nonlinearity compensation in high-power circulating current amps

- Thyristors have a min current threshold:
 - below the threshold: circulating current
 - this generates a undesired nonlinearity
 - possibly destabilizing outer feedback
- **Challenge:** reverse anti-windup problem

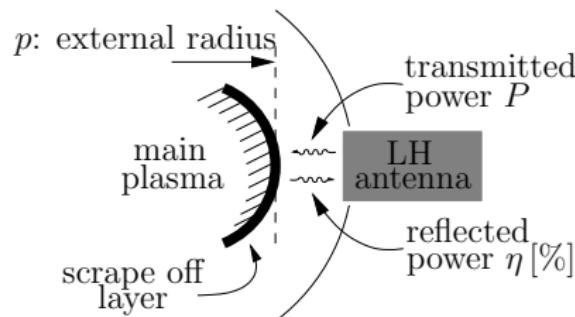
Tokamaks inspire useful conceptual insights



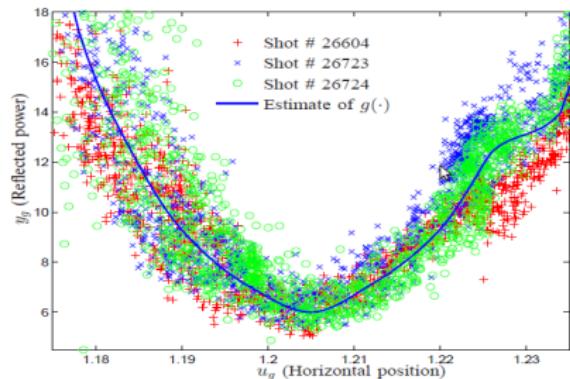
Goal: position plasma to minimize reflected power

Plasma is sometimes **heated via radiofrequency** power (microwave oven heating) transmitted by a powerful antenna (8 MW)

- Reflected power depends on plasma *horizontal position*



- Dependence is *quasi-convex*



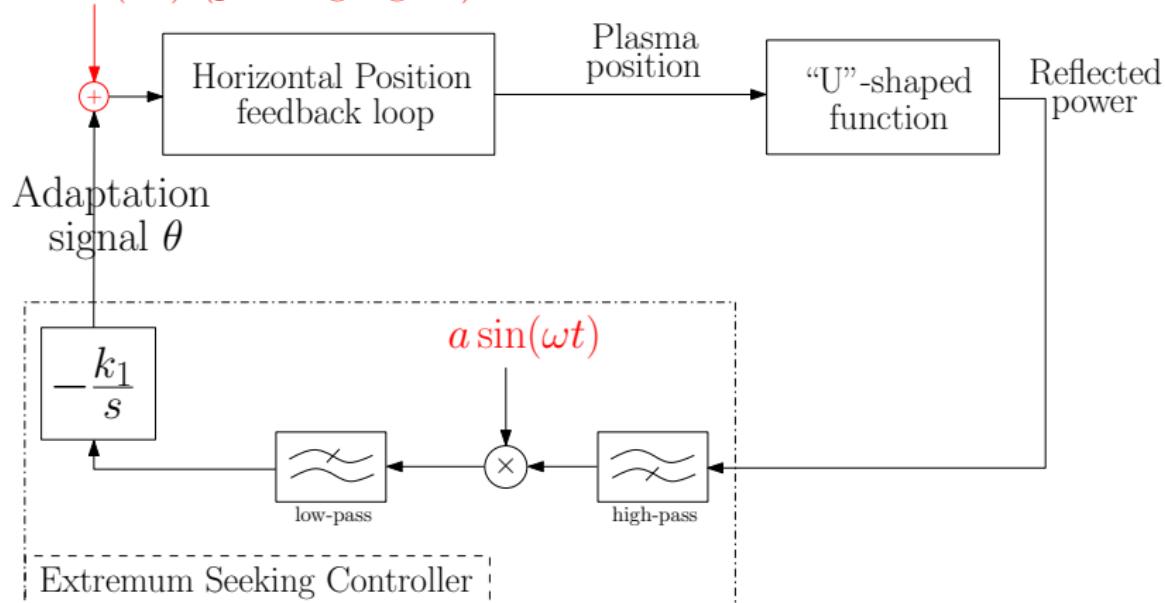
Goal: move plasma horizontally to minimize the reflected power

1) maximize plasma heating and 2) avoid forced shutdown (safety)

Problem: the "U" shaped function is unknown (varies among "shots")

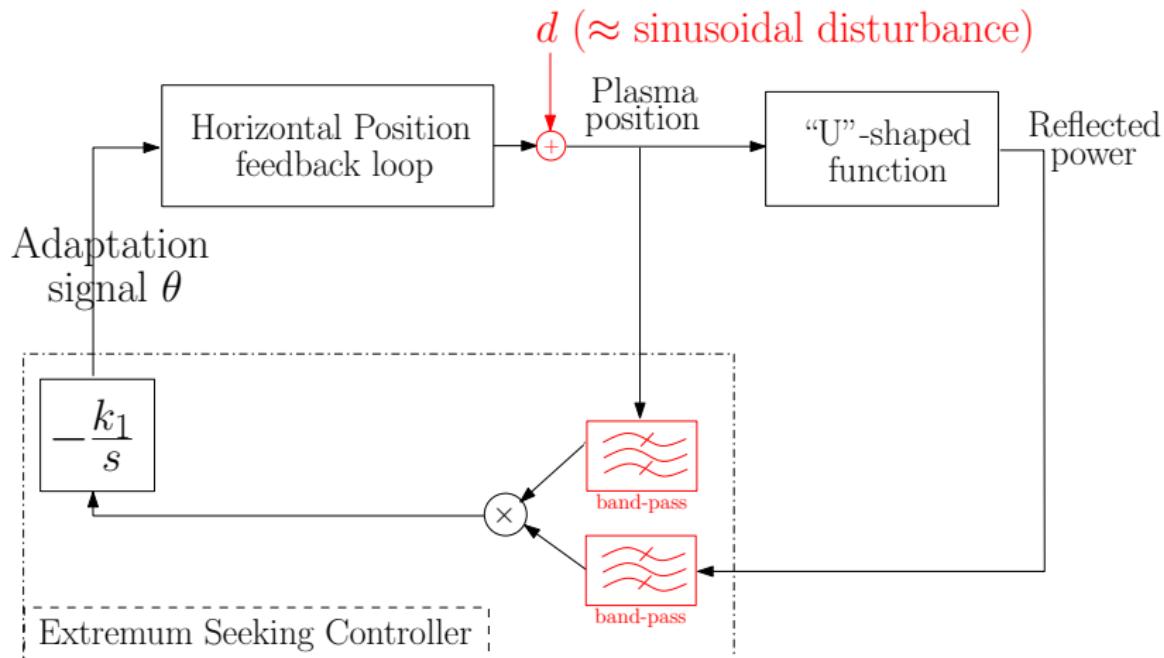
Extremum seeking algorithms provide a good starting point

[Ostrovskii, 1957; Meerkov, 1967; Krstic, 2000; Nesic 2006]
 $a \sin(\omega t)$ (probing signal)



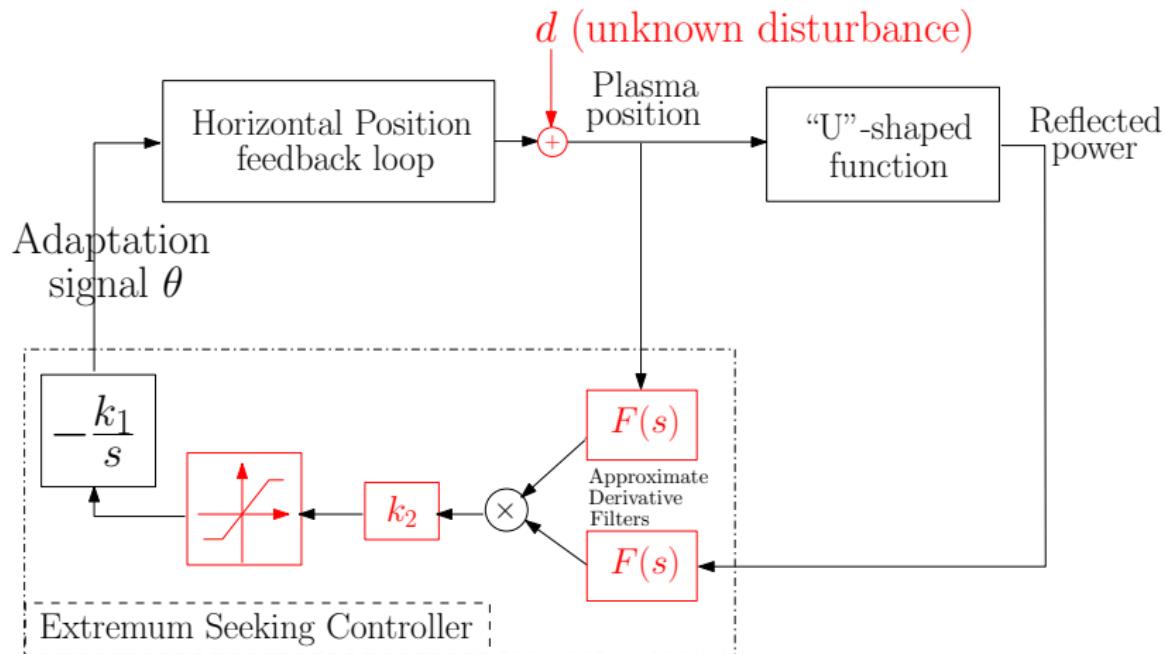
Problem: It is **forbidden** to inject the probing signal $a \sin(\omega t)$ in the plasma control scheme (physicists refuse to do it)

Scheme must be modified for practical implementation



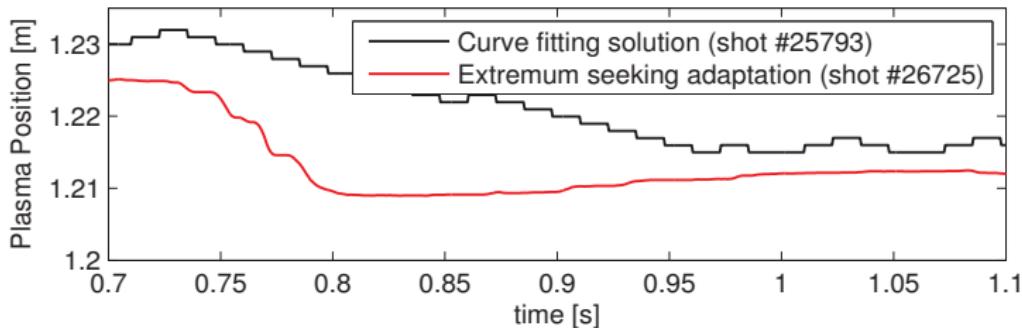
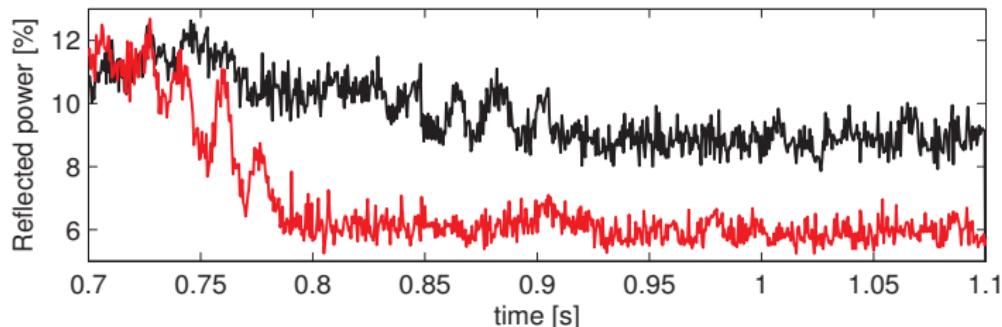
Stretched scheme with no supporting theory: Works well in some experiments but **sometimes** also exhibits **unpredictable behavior**

More rigorous *extended scheme* provides guaranteed results



Theorem: Under mild assumptions on d (regularity + persistence of excitation), **convergence** to the minimum of “U” is **guaranteed**

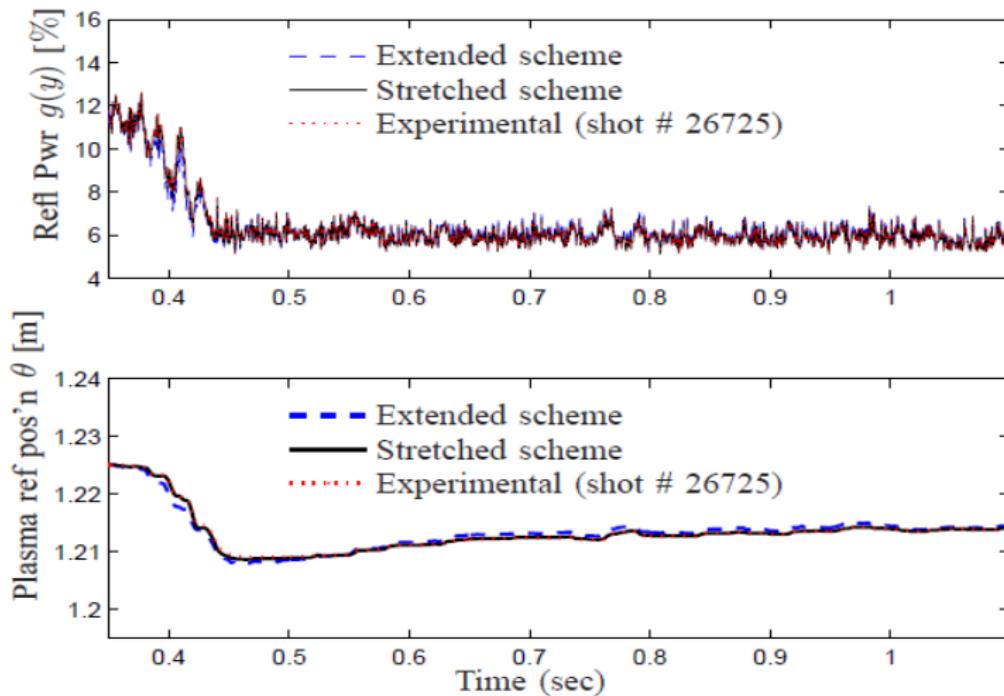
Extremum seeking solution outperforms existing solution



Existing solution is based on a curve fitting algorithm

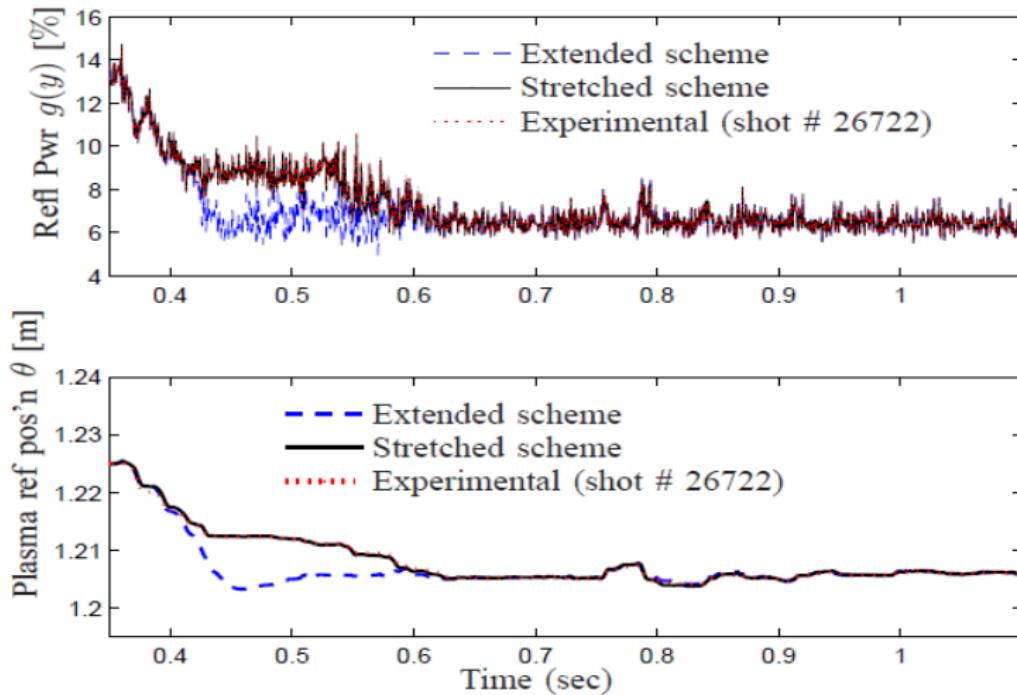
Stretched extremum seeking, experimented, improves response

Stretched scheme **good**, extended scheme **comparable**



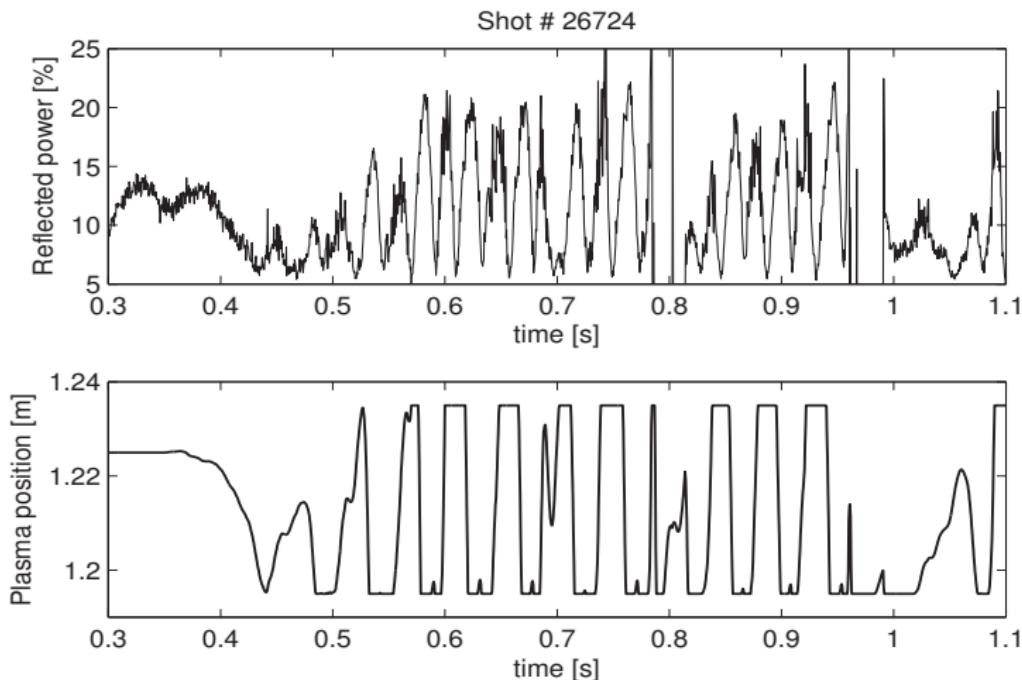
Simulation of stretched scheme reproduces experimental data
Simulation of extended scheme performs comparably

Stretched scheme **bad**, extended scheme **improves**



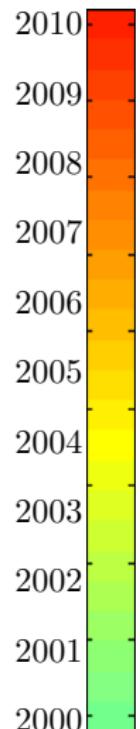
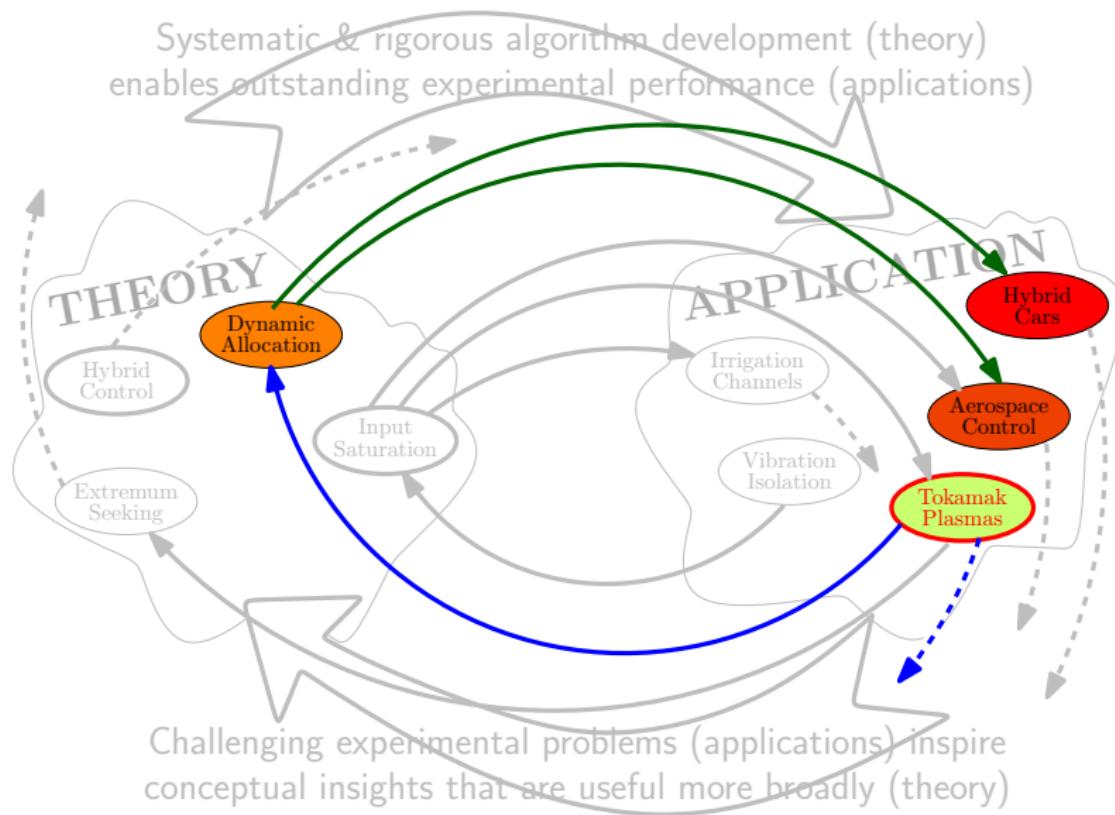
Simulation of stretched scheme reproduces **experimental data**
Simulation of extended scheme induces faster convergence

Stretched scheme **destabilizes**, extended scheme **reliable**



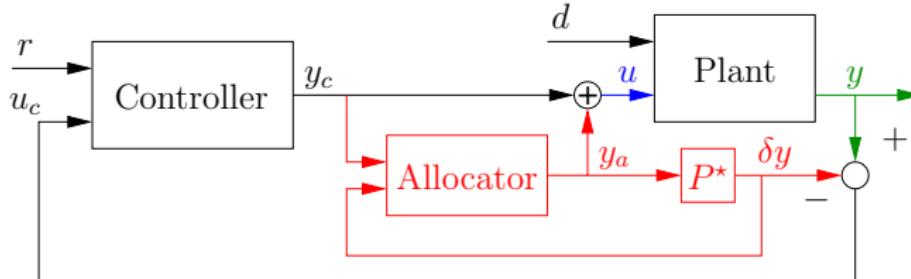
Experiment using stretched scheme **becomes unstable**
Extended scheme **can't generate this behavior** by saturation block

Tokamaks inspire useful conceptual insights



JET current limits avoidance \Rightarrow dynamic input allocation

- JET: 9 PF coil currents (inputs) affect 32 shape descriptors (outputs)
- Idea: trade in some output performance to increase input authority



- A dynamical system is inserted between controller and plant to:
 - enforce “slow” drift of the **plant input u** to desirable values
 - leave the **plant output y** (almost) unaffected (δy “small”)

[Boskovic, Sparks, '02; Fossen, Johansen '06; Serrani, '06; Bolender '06; ...]

- Theorem:** Under mild conditions on a cost function $J(\mathbf{u}, \delta\mathbf{y})$,
- the closed-loop is asymptotically stable
 - $(\mathbf{u}(t), \delta\mathbf{y}(t))$ converge to the minimum of J

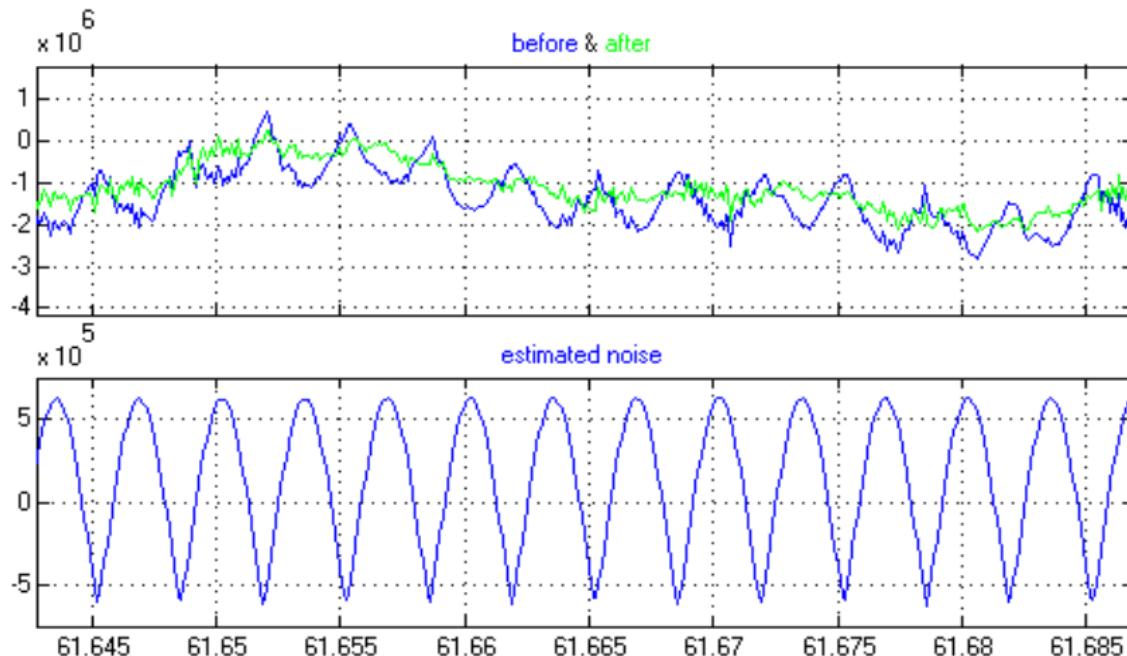
From application to theory and back again to applications

Recent applications of dynamic input allocation theory:

- **Control of hybrid cars** (parallel HEV): EM and ICE allocated focusing on SOC and emissions specs
- **Plasma elongation control at FTU**: two almost redundant coils: V (large and slow) and F (small and fast) allocated to achieve desirable plasma elongation
- **Dual-stage actuation in robot joints**: Allocate pneumatic muscles and electrical motor for effective torque control within actuators' rate and magnitude saturation limits
- **Overactuated hypersonic vehicles**: Use redundant actuation (scramjet engine + control surfaces) for trajectory tracking within actuators limits
- **Satellite attitude control**: allocate redundant reaction wheels (or CMG) to avoid singular configurations

Nonlinear adaptive noise filtering (JET magnetic probes)

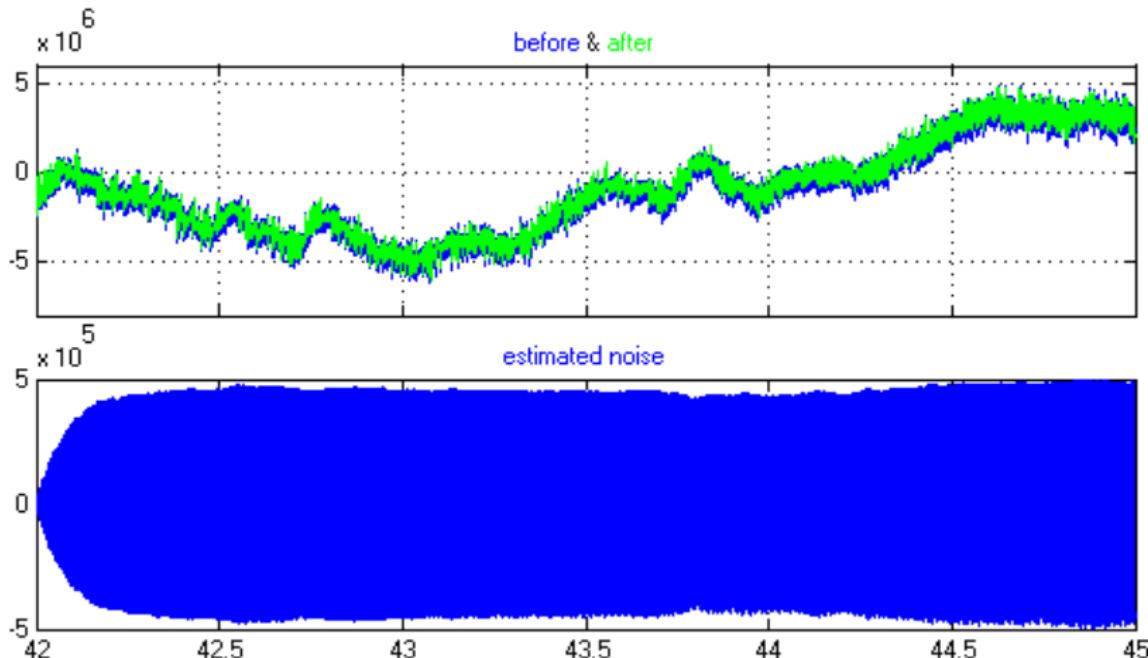
Goal: Remove periodic disturbance induced by power amplifiers ripple



Intuition: parametrize distortion level and construct an adaptive filter

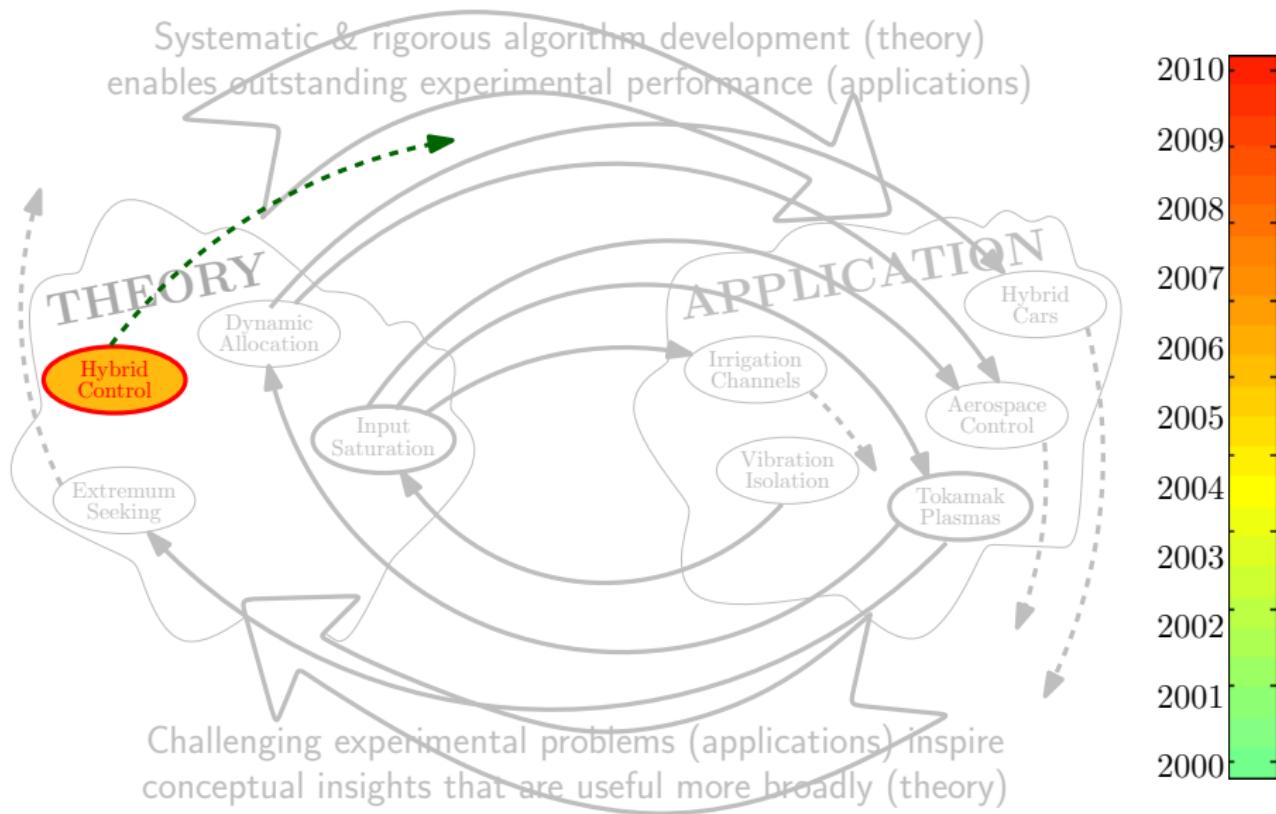
Nonlinear adaptive noise filtering (JET magnetic probes)

Result: Filter converges to correct phase, amplitude, distortion level



Next step: develop supporting theory

A fascinating theory with many challenging open questions



From discrete + continuous to hybrid dynamical systems

[Branicky, Collins, Henzinger, Liberzon, Lygeros, Sastry, Tavernini, Teel, Van der Schaft ...]

Continuous dynamical system

$$\frac{dx(t)}{dt} = f(x(t)), \quad \forall t \in \mathbb{R}_{\geq 0}$$

Discrete dynamical system

$$x(k+1) = g(x(k)), \quad \forall k \in \mathbb{Z}_{\geq 0}$$

(possible discrete variables)

Hybrid dynamical system

$$\begin{cases} \frac{dx(t, k)}{dt} = f(x(t, k)), & \text{if } x(t, k) \in F \subset \mathbb{R}^n \text{ (a.e.)} \\ x(t, k+1) = g(x(t, k)), & \text{if } x(t, k) \in G \subset \mathbb{R}^n \end{cases}$$

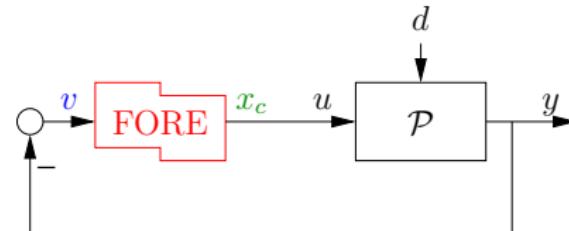
- Continuous time domain $t \in \mathbb{R}_{\geq 0}$ and Discrete time domain $k \in \mathbb{Z}_{\geq 0}$ merged into Hybrid time domain $(t, k) \in \mathbb{R}_{\geq 0} \times \mathbb{Z}_{\geq 0}$
- Solution x can “flow” if $\in F$, can “jump” if $\in G$
- Fundamental stability results now available (Converse Lyapunov theorems, ISS, invariance principle, \mathcal{L}_p stability) [Teel '04 → '09]

Stabilization using hybrid jumps to zero

First Order Reset Element:

$$\begin{aligned}\dot{x}_c &= a_c x_c + b_c v, && \text{if } v x_c \geq 0, \\ x_c^+ &= 0, && \text{if } v x_c \leq 0,\end{aligned}$$

[Clegg '56, Horowitz '73, Hollott '06]



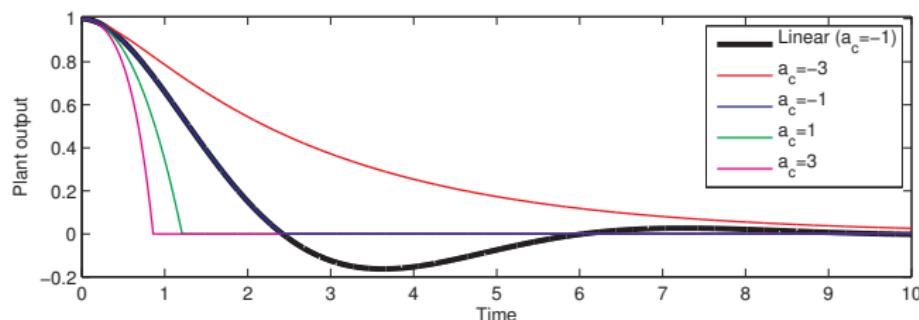
Theorem If \mathcal{P} is linear, minimum phase and relative degree one, **then**
 a_c, b_c or (a_c, b_c) large enough \Rightarrow global exponential stability

Simulation

uses:

$$\mathcal{P} = \frac{1}{s}$$

$$b_c = 1$$



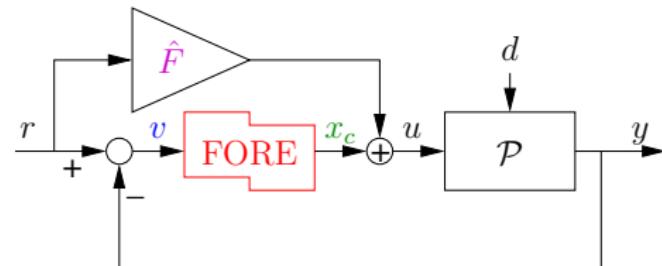
Interpretation: Resets remove overshoots, instability improves transient

Set point adaptive regulation using hybrid jumps to zero

- Relies on the DC gain \hat{F} of \mathcal{P}

$$\begin{aligned}\dot{x}_c &= a_c x_c + b_c v, & \text{if } vx_c \geq 0, \\ \dot{\hat{F}} &= 0, & \end{aligned}$$

$$\begin{aligned}x_c^+ &= 0, \\ \hat{F}^+ &= \varphi(\hat{F}, x_c, r), & \text{if } vx_c \leq 0,\end{aligned}$$



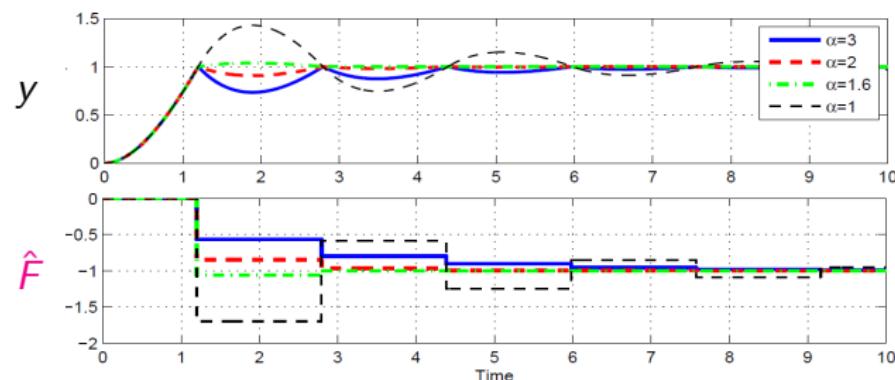
- Estimate \hat{F} of F^{-1} only updated at jumps

Simulation uses:

$$\mathcal{P} = -\frac{2}{s+2}$$

$$b_c = 2$$

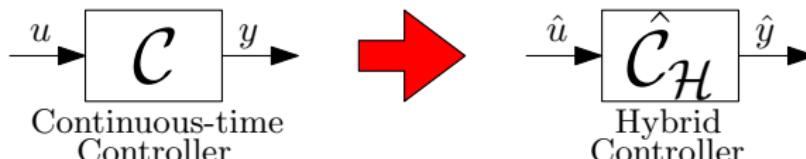
$$a_c = 1$$



Promising idea: hybrid adaptive controllers only adapting at jumps

Hybrid resets induce passivity in nonlinear controllers

- Inspired by [Carrasco, Banos, Van der Schaft, 2009]
- Given any (nonlinear) controller \mathcal{C} [under mild growth conditions]



a hybrid modification $\hat{\mathcal{C}}_{\mathcal{H}}$ is given such that

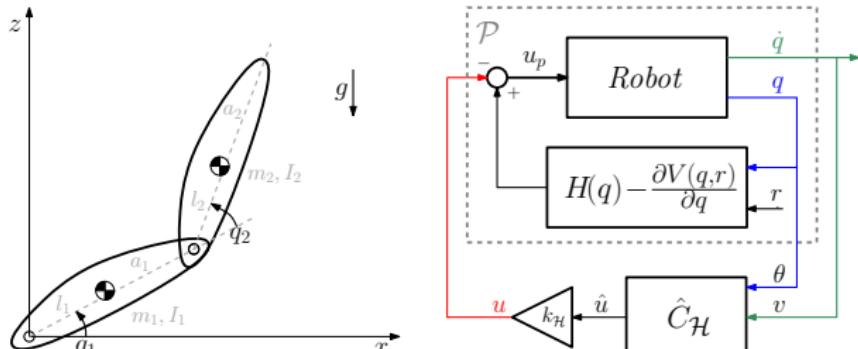
- the state \hat{x}_c of $\hat{\mathcal{C}}_{\mathcal{H}}$ is sometimes reset to zero
- whenever $\hat{\mathcal{C}}_{\mathcal{H}}$ flows, it mimicks \mathcal{C}
- (continuous-time) output strict passivity of $\hat{\mathcal{C}}_{\mathcal{H}}$ holds:

$$\int_0^{\infty} \hat{y}(t)^T \hat{u}(t) dt \geq \varepsilon_2 \|\hat{y}(\cdot)\|_2^2$$

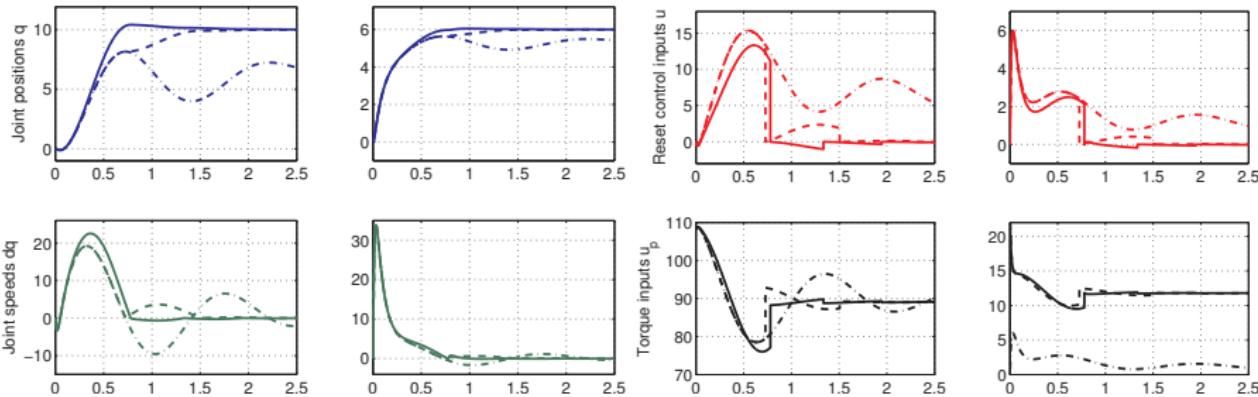
- Promising for HMI, to avoid man-induced instabilities (PIO, etc)

Example: Reset passivation of a robot controller

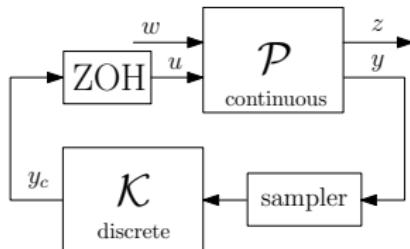
Two-link robot
passivated by an
inner loop



stable, no resets (dash-dot); stable with resets (dash); unstable (solid)



Hybrid systems tools utilized in diverse scenarios

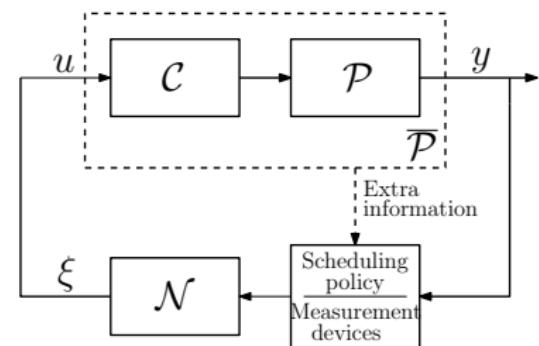


Sampled-data control design with saturation

- uniform sampling time assumed
- jumps correspond to sampling actions

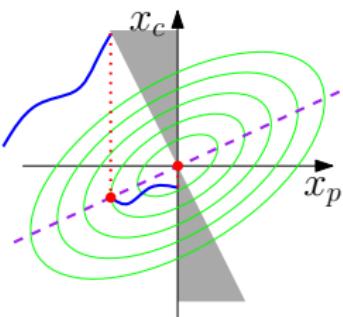
Lazy sensors for reduced transmission rate

- reduce sample transmission over networks
- a special case of event driven sampling
- jumps occur at samples transmissions

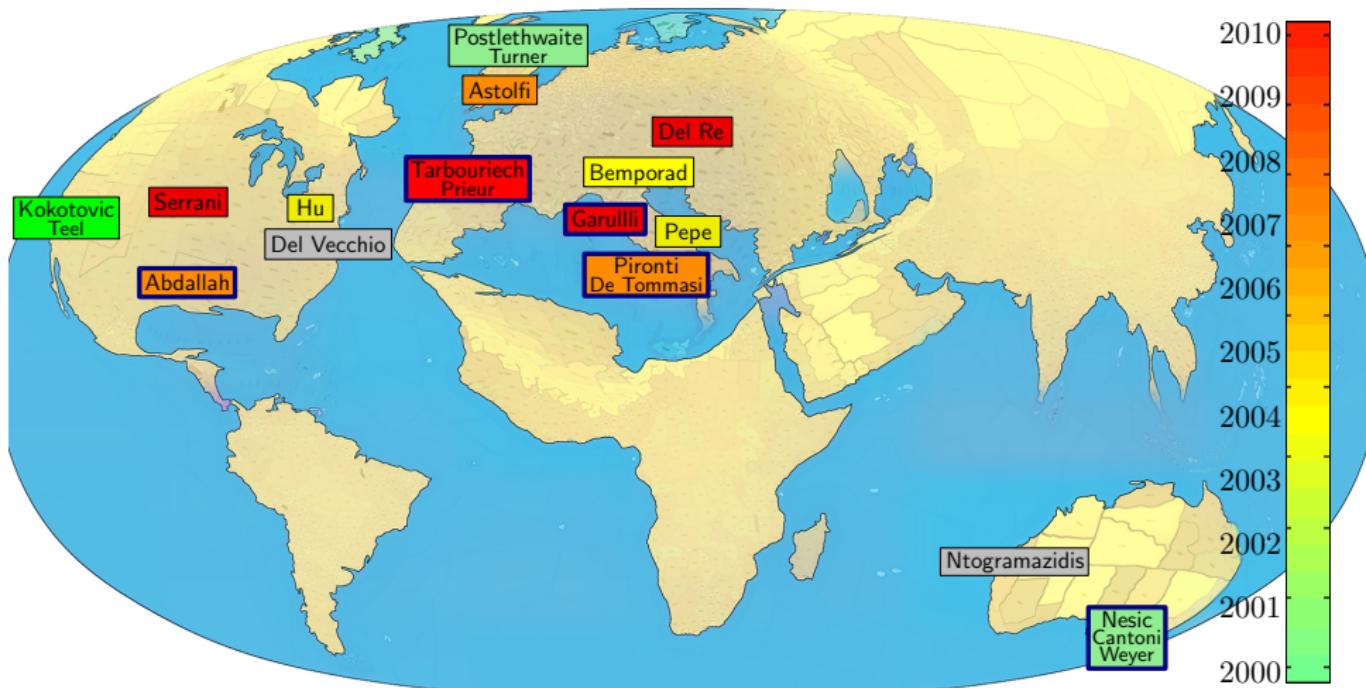


Nonlinear stabilization via hybrid loops

- enforces jumps of the controller state in some sets
- so as to guarantee decrease of suitable functions
- state jumps to the minimum of a Lyapunov function
- useful, e.g., for overshoot reduction with SISO plants



Thanks to my mentors, coauthors, collaborators



Colleagues: Carnevale, Galeani, Grasselli, Martinelli, Menini, Nicosia, Tornambè
PhD's: Dai, Forni, Grimm, Li, Loquen, Onori, Pangione, Sadeghi, Varano, Vitelli