From vehicle dynamics control to autonomous driving in urban environments

Vertical Dynamics Control: semi active damping and stiffness control

4/7/2023, Bertinoro

Matteo Corno

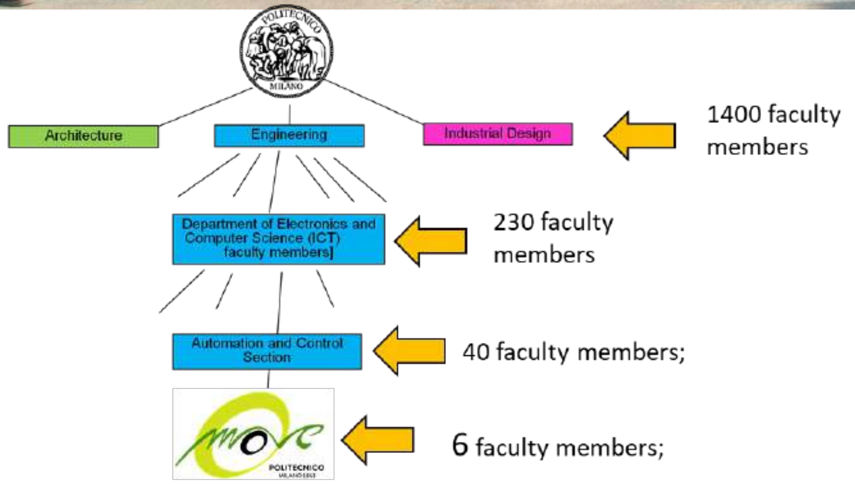
Politecnico di Milano

Dipartimento di Elettronica, Informazione e Biongegneria

- Founded in 1863
- Polytechnic: Engineering, Architecture and Design
- 40.000 students; 1400 Faculty members

Politecnico di Milano

Move Research Team



Faculty: 6
PhD: 15-20
MSc: 40-50

Prof. **Matteo Corno**

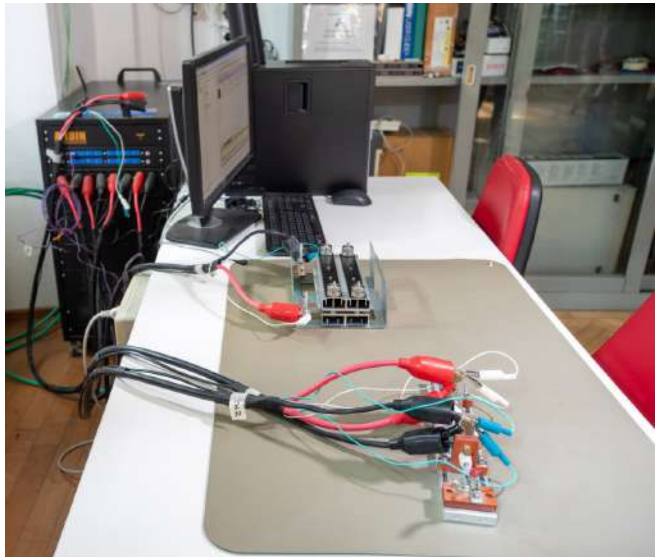
- Master of Science in Computer Science and Engineering, Politecnico di Milano
- Master of Science in Electronic Engineering, University of Illinois at Chicago, USA
- PhD in Systems and Control, Politecnico di Milano, Italia
- Post-Doc, Linz, University Austria
- Assistant professor at TU Delft, The Netherlands
- Associate professor, Politecnico di Milano.

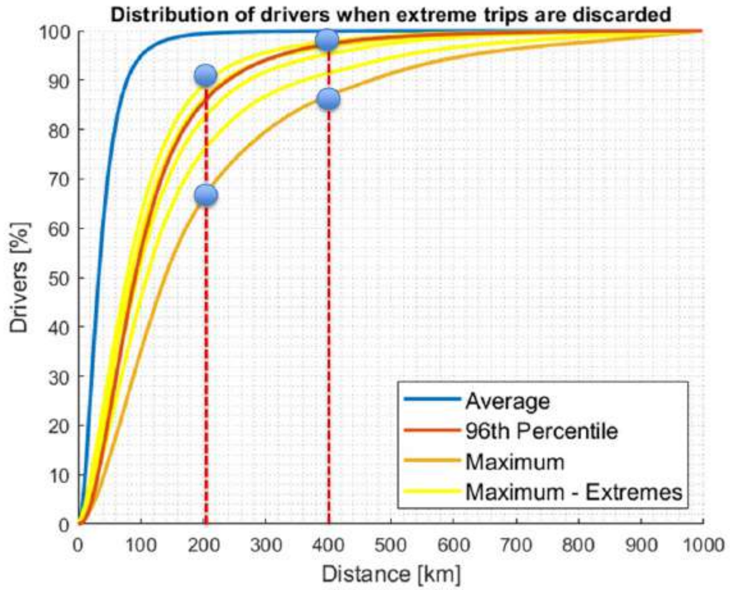
Research Interests: ***Automation and Control in Land Vehicles***

https://www.move.deib.polimi.it/

mOve carries out research, innovation and technology transfer activities in the areas of automotive controls, intelligent vehicles and smart mobility.

From component level → To fleet management





Politecnico di Milano

Move Research Team

- Winners of the Indy Autonomous Challenge (Las Vegas, 2022-2023, Texas, 2023, Monza 2023)
- Rercord holders for the fastest autonomous car (@ Kennedy Space Center) 310 km/h (May 2022)

Outline

- Introduction
- Semi-Active Damping Control
  - Actuators
  - Models
  - Benchmark
  - Causal Control
- Semi-Active Stiffness Control
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- Sensing Preliminaries
- A look at the future
- Conclusions

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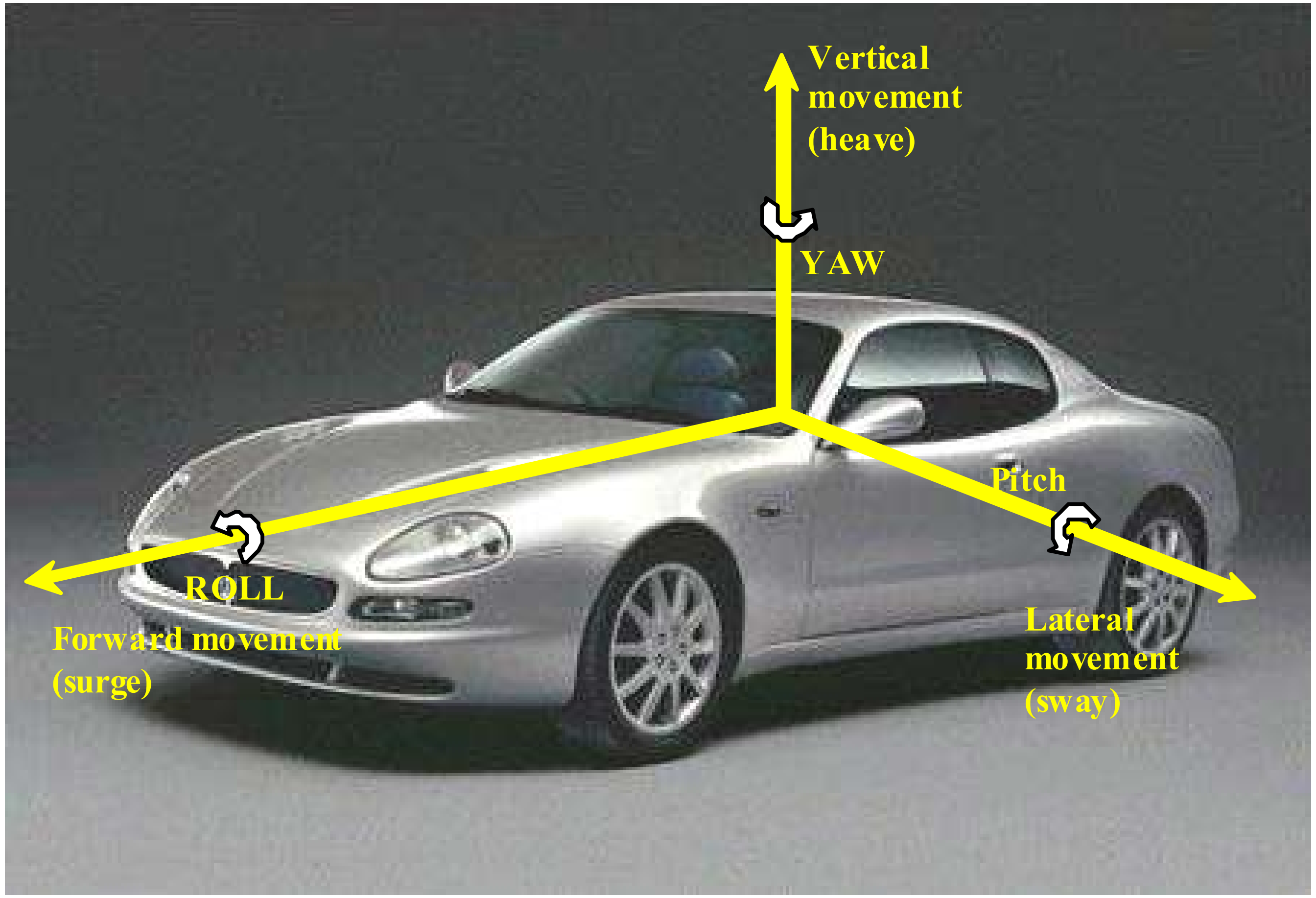


General goal: filter the road-to-vehicle interaction

Related movements (main):

- **Heave**
- Roll
- Pitch

Can influence (indirectly) also yaw/sway/surge.

Introduction to Vertical Dynamics

Why suspensions in 2023?

Goals of Suspension System:

1) <u>Comfort</u> → chassis vertical acceleration, pitch and roll movements

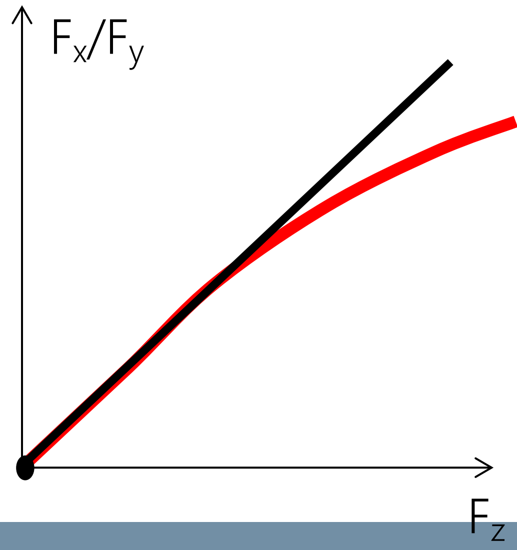
Goals of Suspension System:

1) Comfort → chassis vertical acceleration, pitch and roll movements

2) Road Holding → keep vertical load as constant as possible

$$F_x = \mu_x(F_z)$$
$$F_y = \mu_y(F_z)$$

$$F_z = (M+m)g + DynamicLoad + [AerodynamicLoad]$$

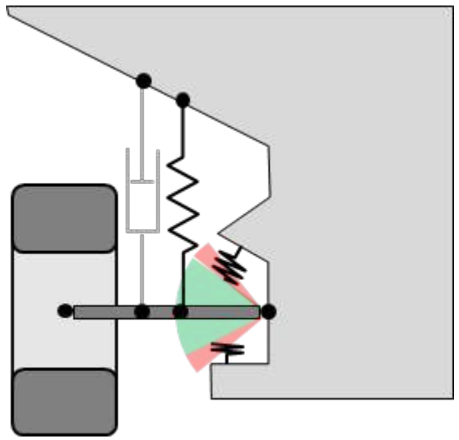


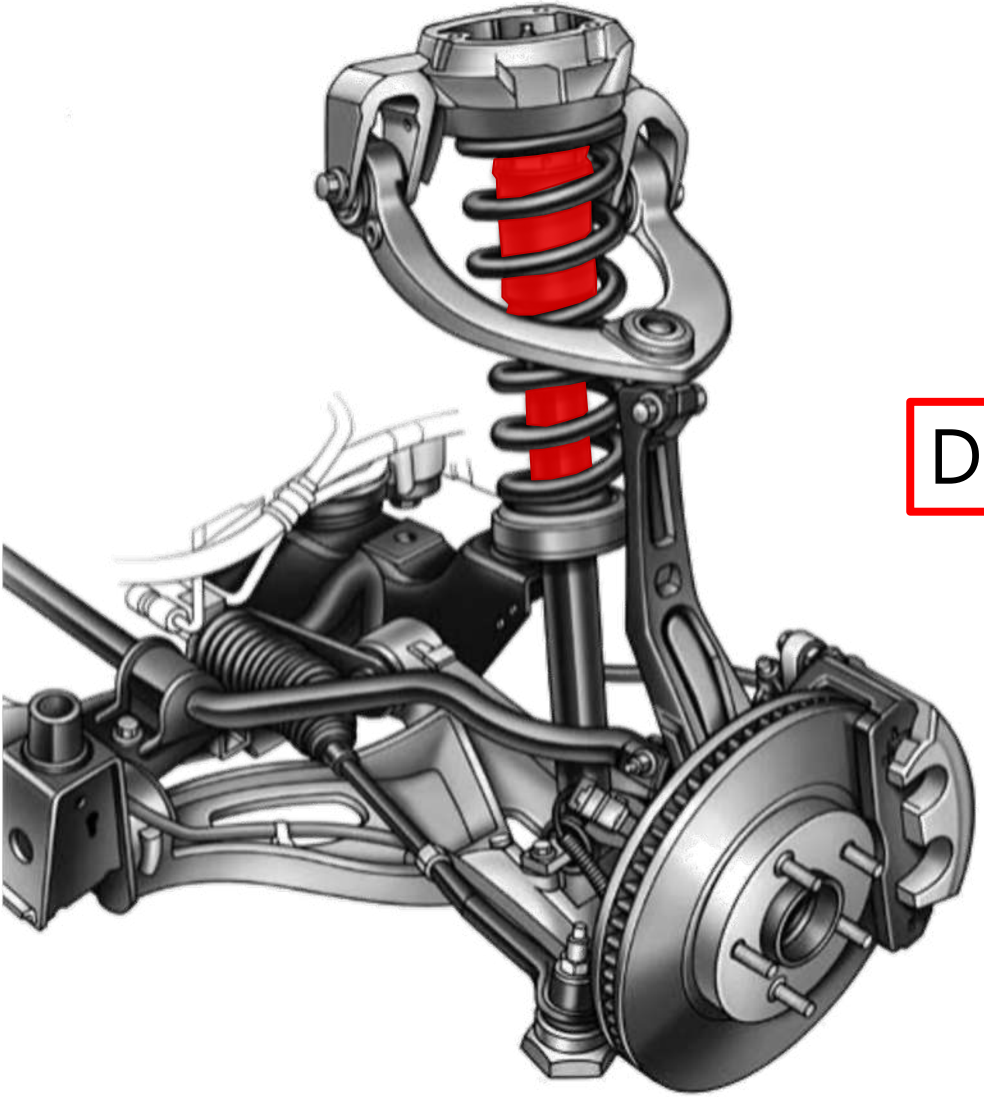
Goals of Suspension System:

1) Comfort → chassis vertical acceleration, pitch and roll movements

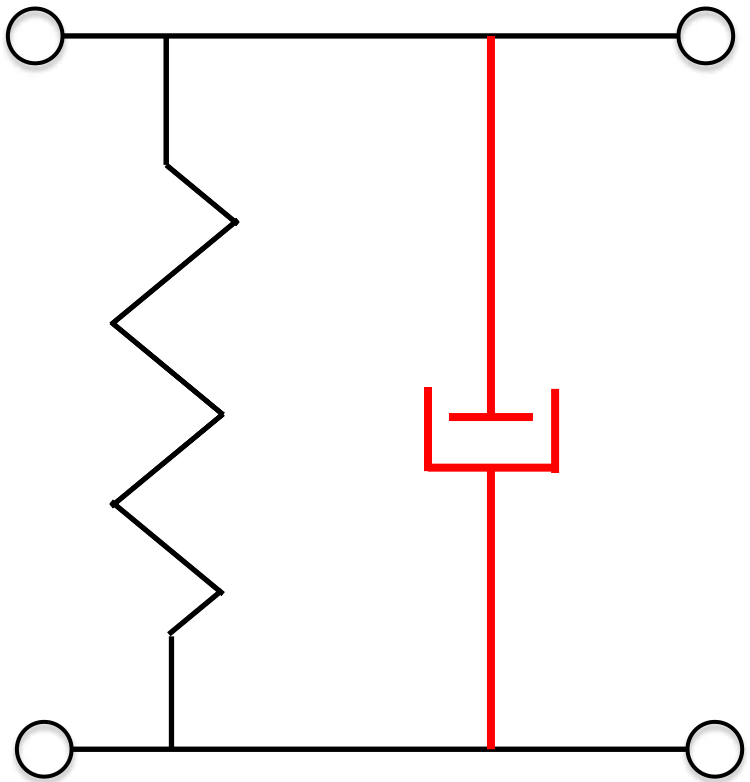
2) Road Holding → keep vertical load as constant as possible

3) Avoid hitting bump stops → keep the stroke of the suspension limited

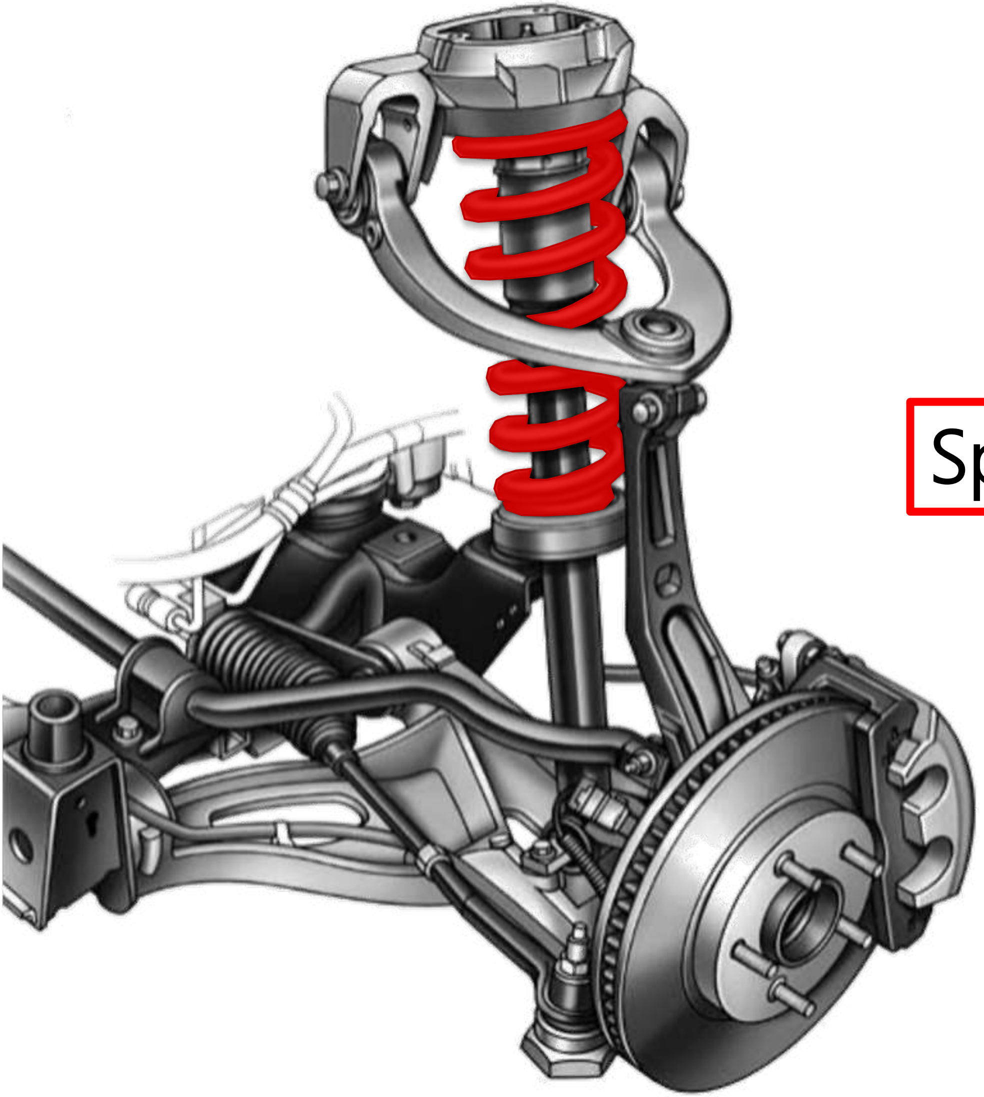




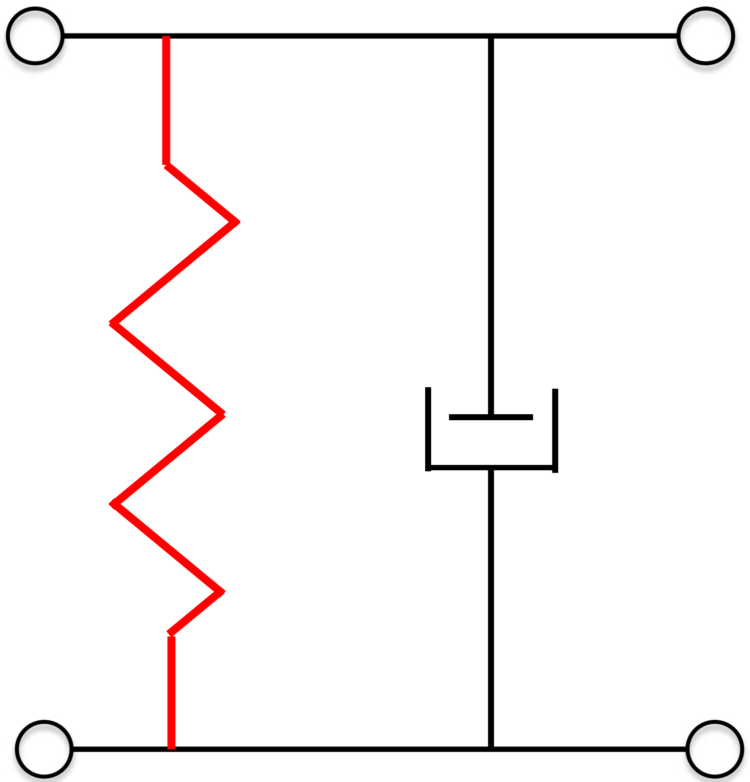
Damper (c)



Damper: force function of stroke speed

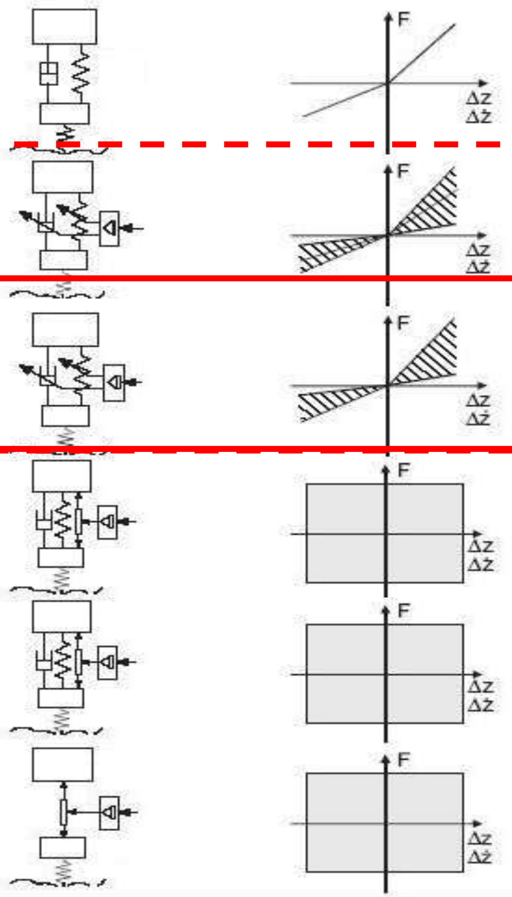


Spring (k)



Spring: force function of stroke

Classification of suspension systems. Natural frequencies: f_B body and f_W wheel



System	System representation	Force range	Operation range	Max. energy demand
Passive			—	—
Slowly variable/adaptive			*Quasi static*	ca. 50 W
Semi-active			*High frequency*	ca. 50 W
Load-leveling (height adjuster)			*Quasi static*	ca. 50 W
Active partially loaded («slow-active»)			*Mid frequency*	1–2 kW
Active fully loaded («full-active»)			*High frequency*	1.5–7 kW

Industrially viable, but control is challenging

They change the characteristics without injecting mechanical energy

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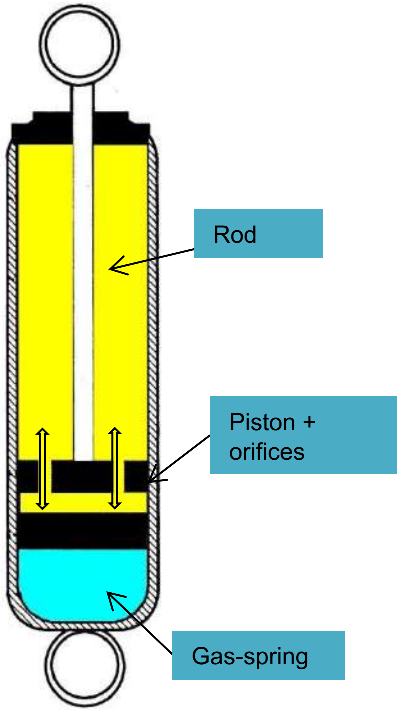
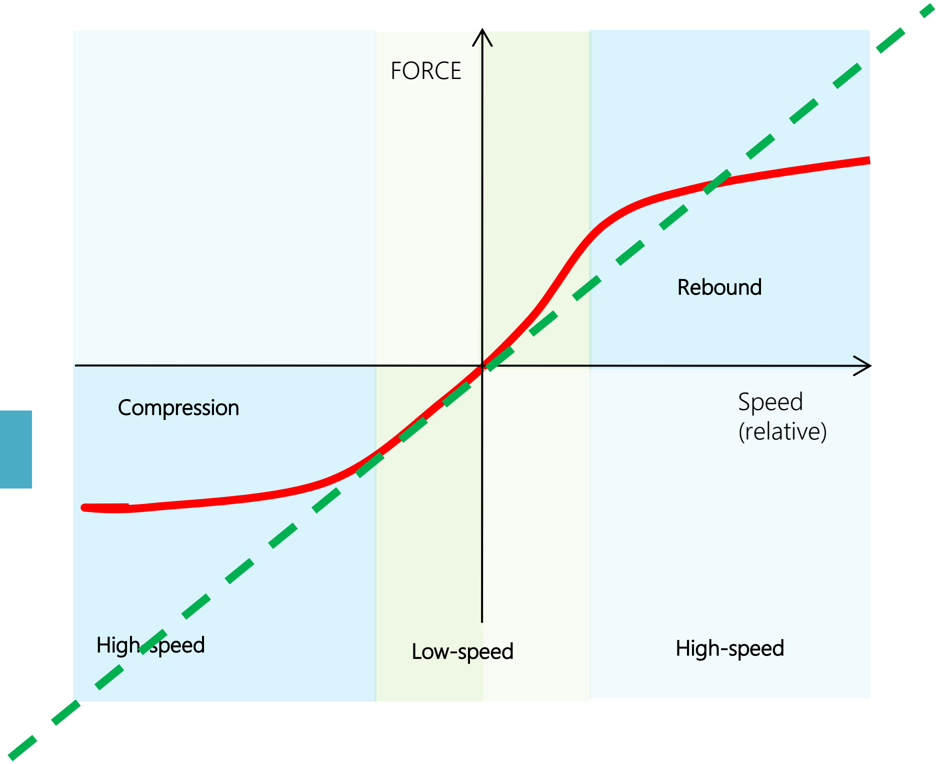
Semi-Active Damping Control

Actuator Technology





Semi-Active Damping Control

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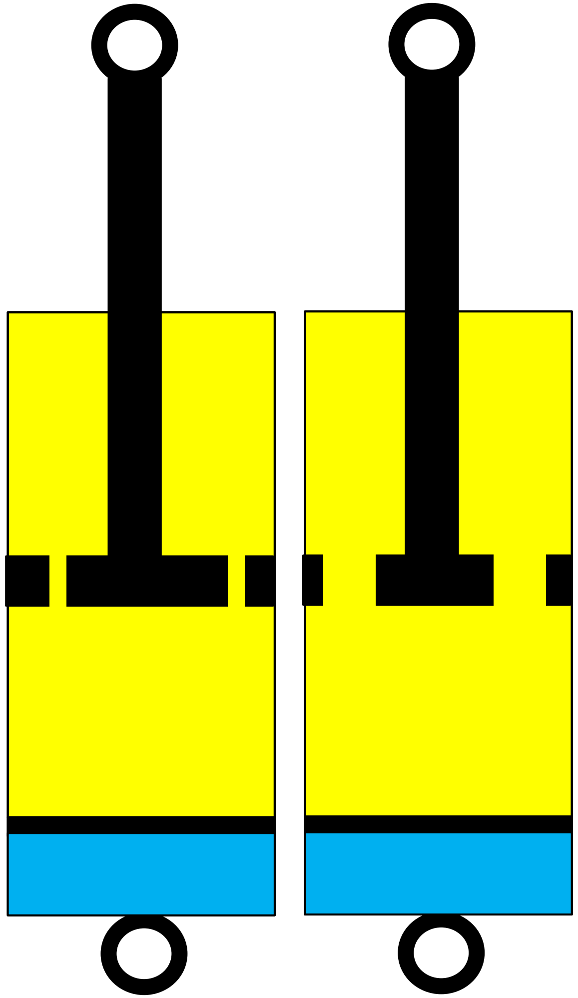


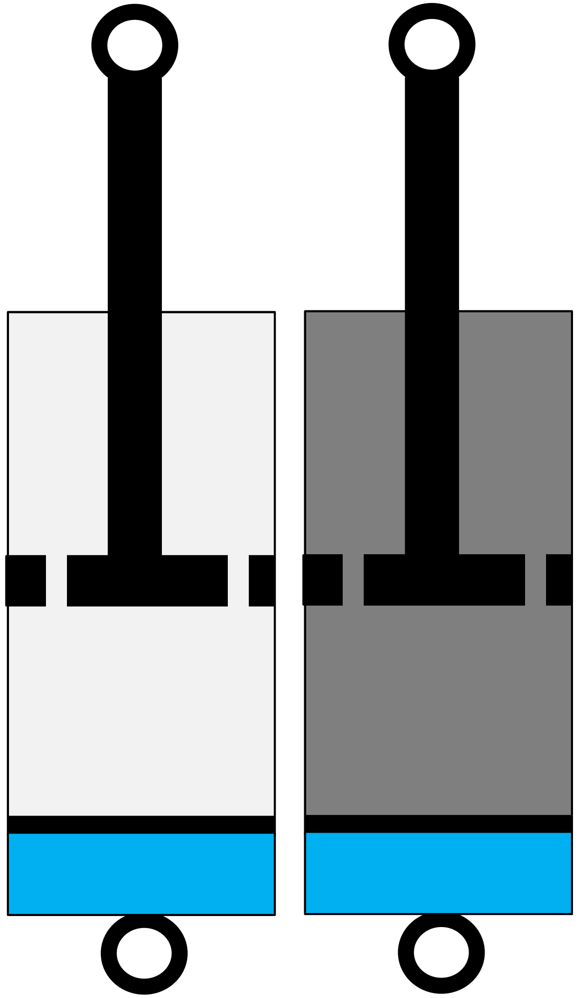
High damping   Low damping

EH damper
damper

Electro-Hydraulic valve opens and closes (mechanical variation of orifices size)

MR damper   ER

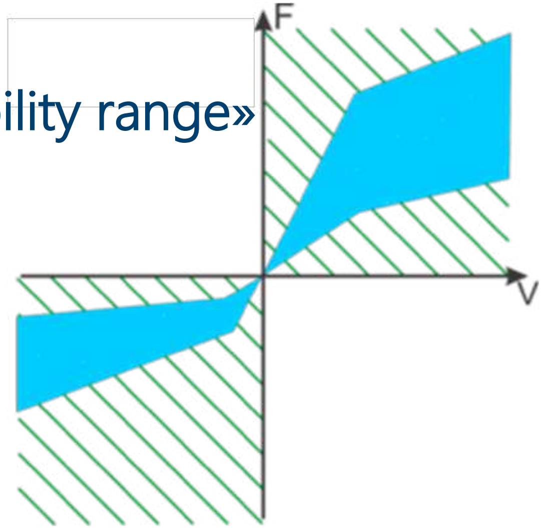
Magnetic or Electric field changes viscosity of the (Magneto-Rheologic or Electro-



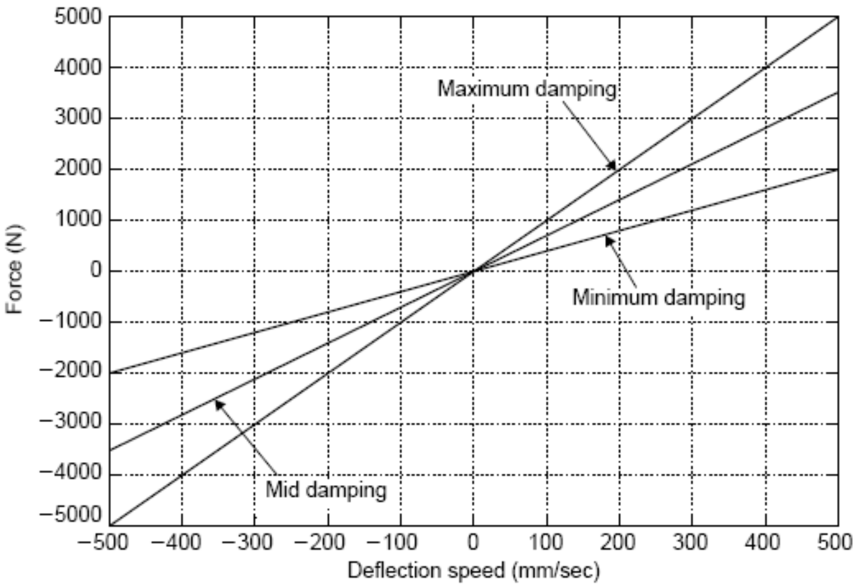
Low damping   High damping

Actuator Technology – Static Characteristics

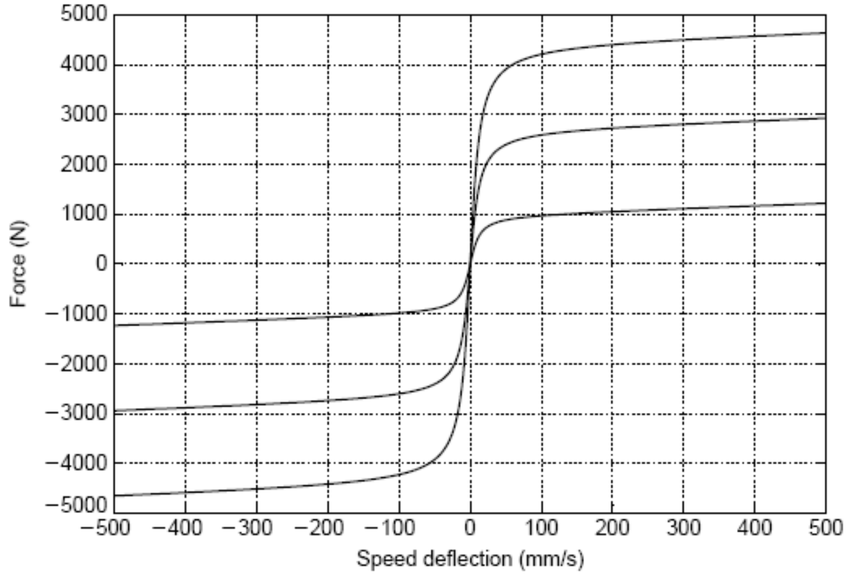
«Controllability range»



EH damper

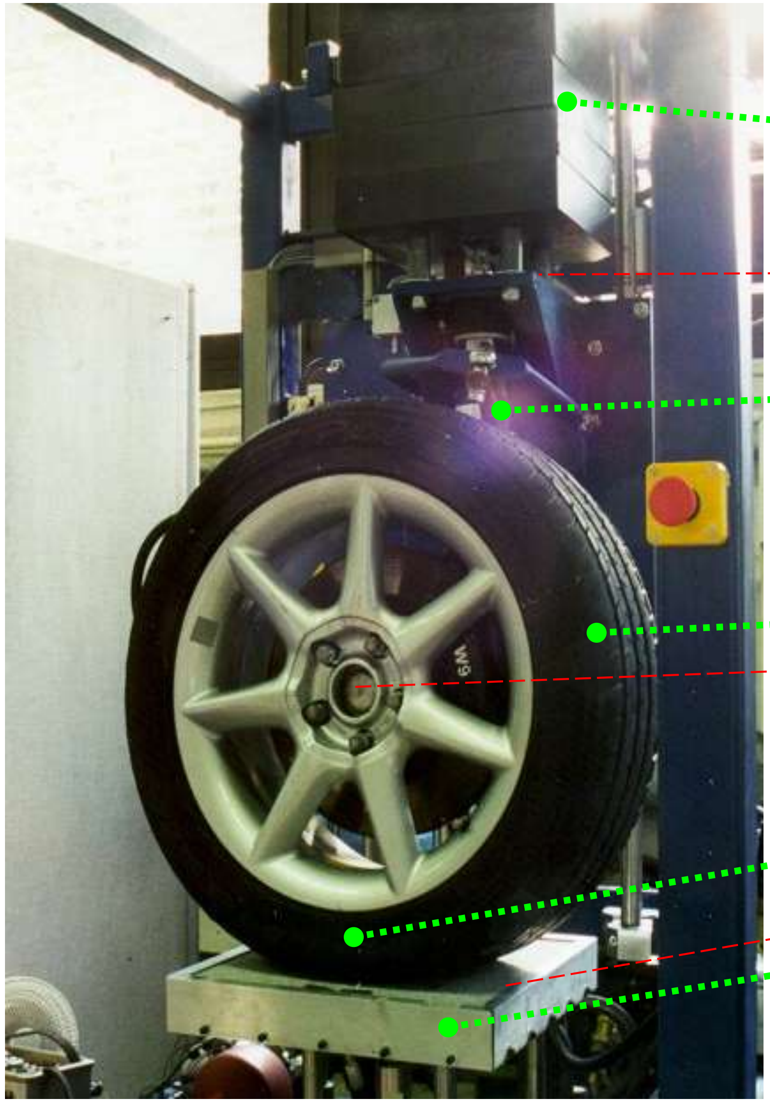


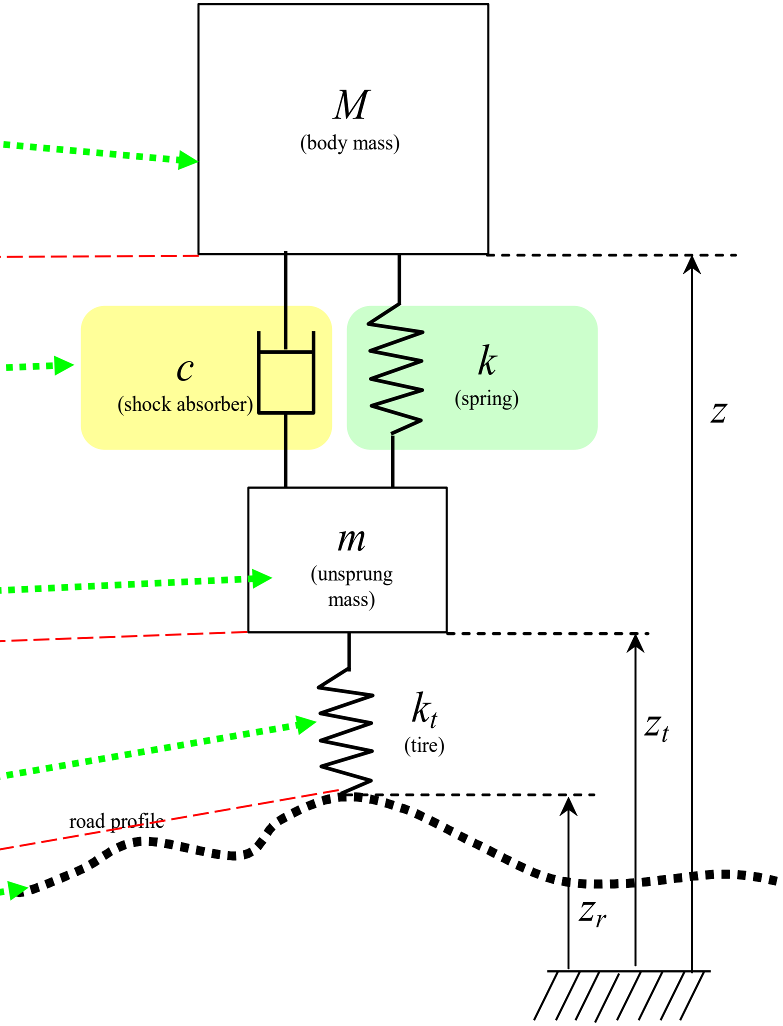
MR damper

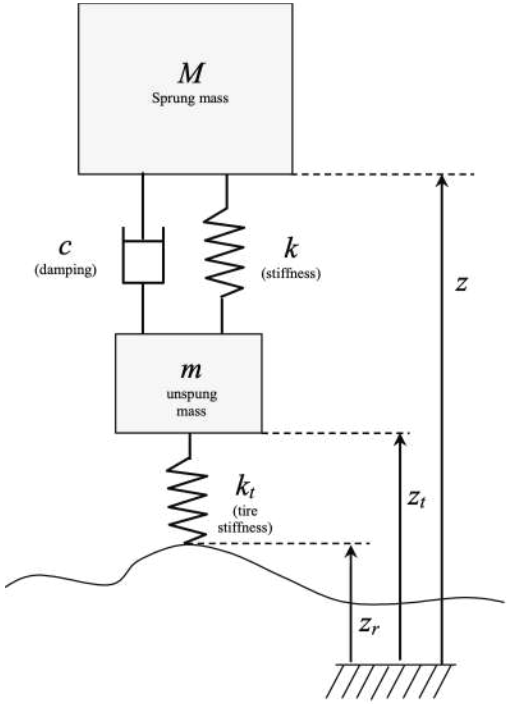


Semi-Active Damping Control

The quarter-car model and its features







$$x = \begin{bmatrix} z \\ \dot{z} \\ z_t \\ \dot{z}_t \end{bmatrix} \qquad u = z_r \qquad y = \begin{bmatrix} z \\ z_t \end{bmatrix}$$

Example of parameters

$M = 400Kg$

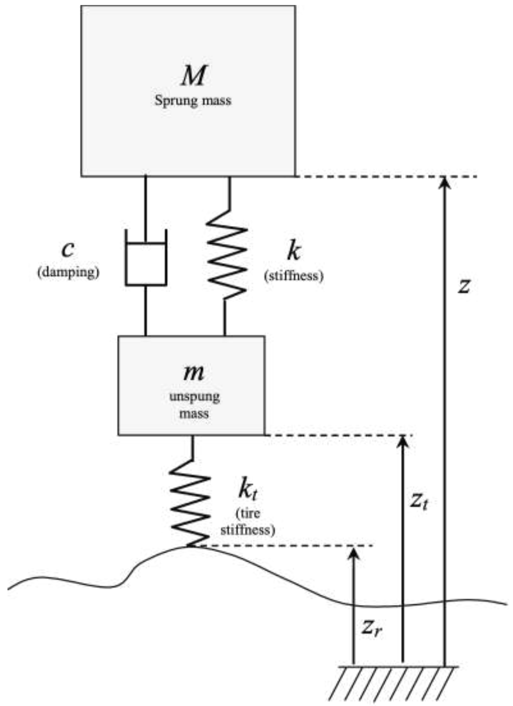
$m = 50Kg$

$\mathrm{k} = 20KN/m$

$\mathrm{k}_t = 250KN/m$

$\mathrm{c} = 1{,}3KN \cdot s/m$

$$\begin{cases} M\ddot{z}(t) = -c\left(\dot{z}(t) - \dot{z}_t(t)\right) - k\left(z(t) - z_t(t) - \Delta_s\right) - Mg \\ m\ddot{z}_t(t) = +c\left(\dot{z}(t) - \dot{z}_t(t)\right) + k\left(z(t) - z_t(t) - \Delta_s\right) - k_t\left(z_t(t) - z_r(t) - \Delta_t\right) - mg \end{cases}$$



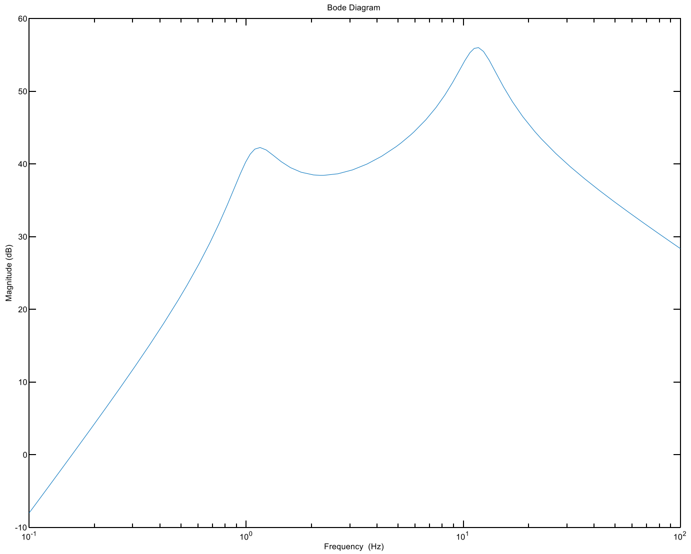
Linearizing Around an equilibrium point

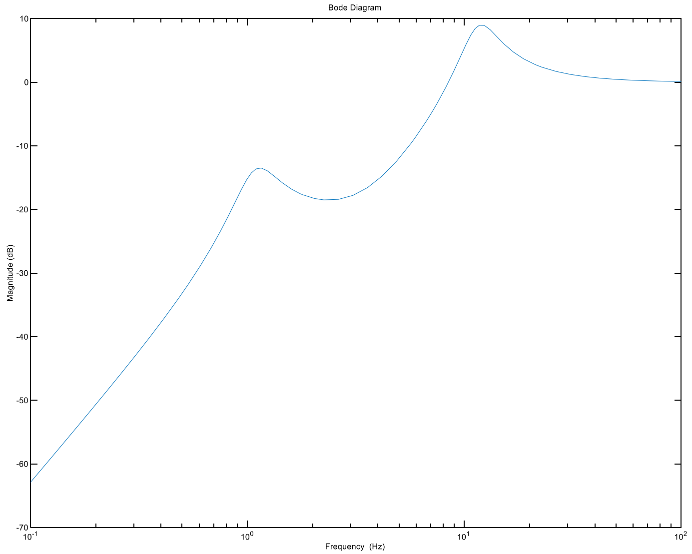
$$x = \begin{bmatrix} \delta z \\ \delta \dot{z} \\ \delta z_t \\ \delta \dot{z}_t \end{bmatrix}, \quad u = [\delta z_r], \quad y = \begin{bmatrix} \delta z \\ \delta z_t \end{bmatrix}$$

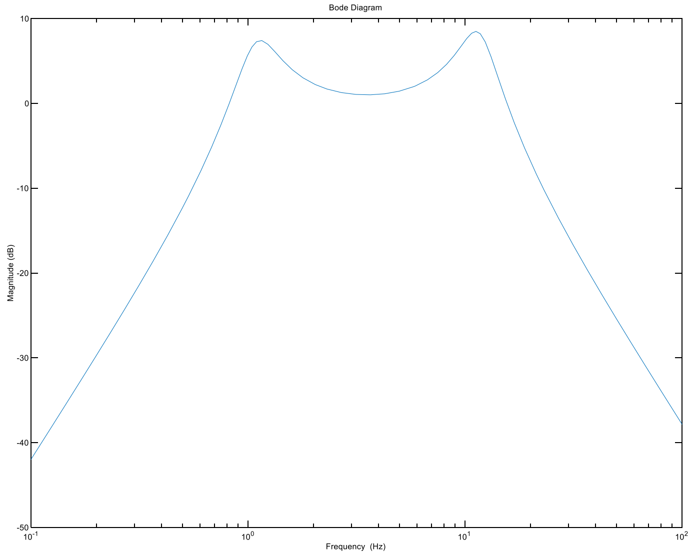
$$\begin{cases} \dot{x}_1 = x_2 \\ \dot{x}_2 = -\frac{k}{M}x_1 - \frac{c}{M}x_2 + \frac{k}{M}x_3 + \frac{c}{M}x_4 \\ \dot{x}_3 = x_4 \\ \dot{x}_4 = \frac{k}{m}x_1 + \frac{c}{m}x_2 - \frac{k+k_t}{m}x_3 - \frac{c}{m}x_4 + \frac{k_t}{m}u \\ y_1 = x_1 \\ y_2 = x_3 \end{cases}$$

From which the transfer functions

$$\begin{cases} \delta Z(s) = F_z(s)U(s) \\ \delta Z_t(s) = F_{z_t}(s)U(s) \end{cases}$$







$$\delta z_r \to \ddot{\delta z} = s^2\, F_z(s)$$

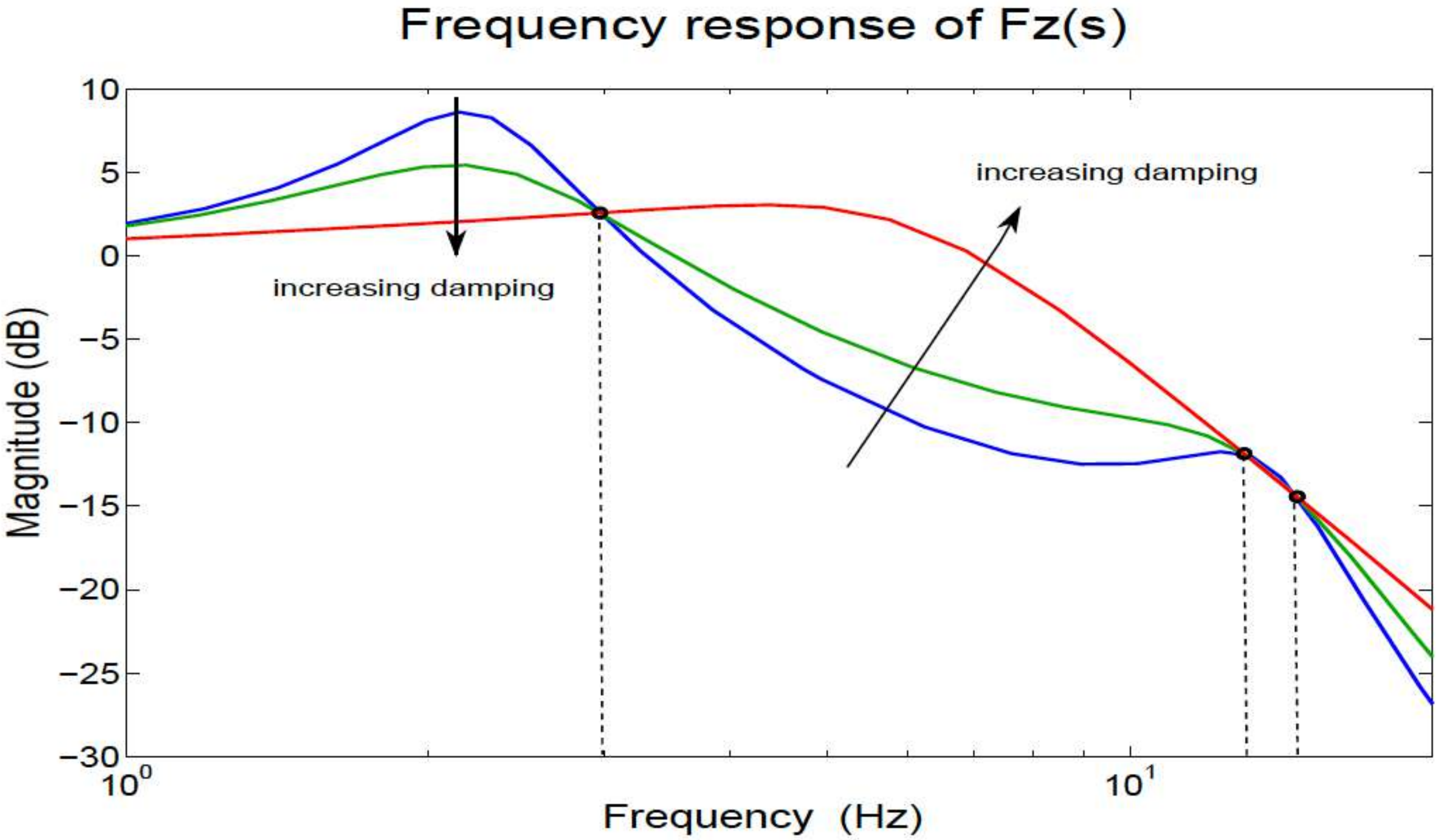
«Comfort» or «acceleration» transfer function

$$\delta z_r \to \delta z_t - \delta z_r = F_{zt}(s) - 1$$

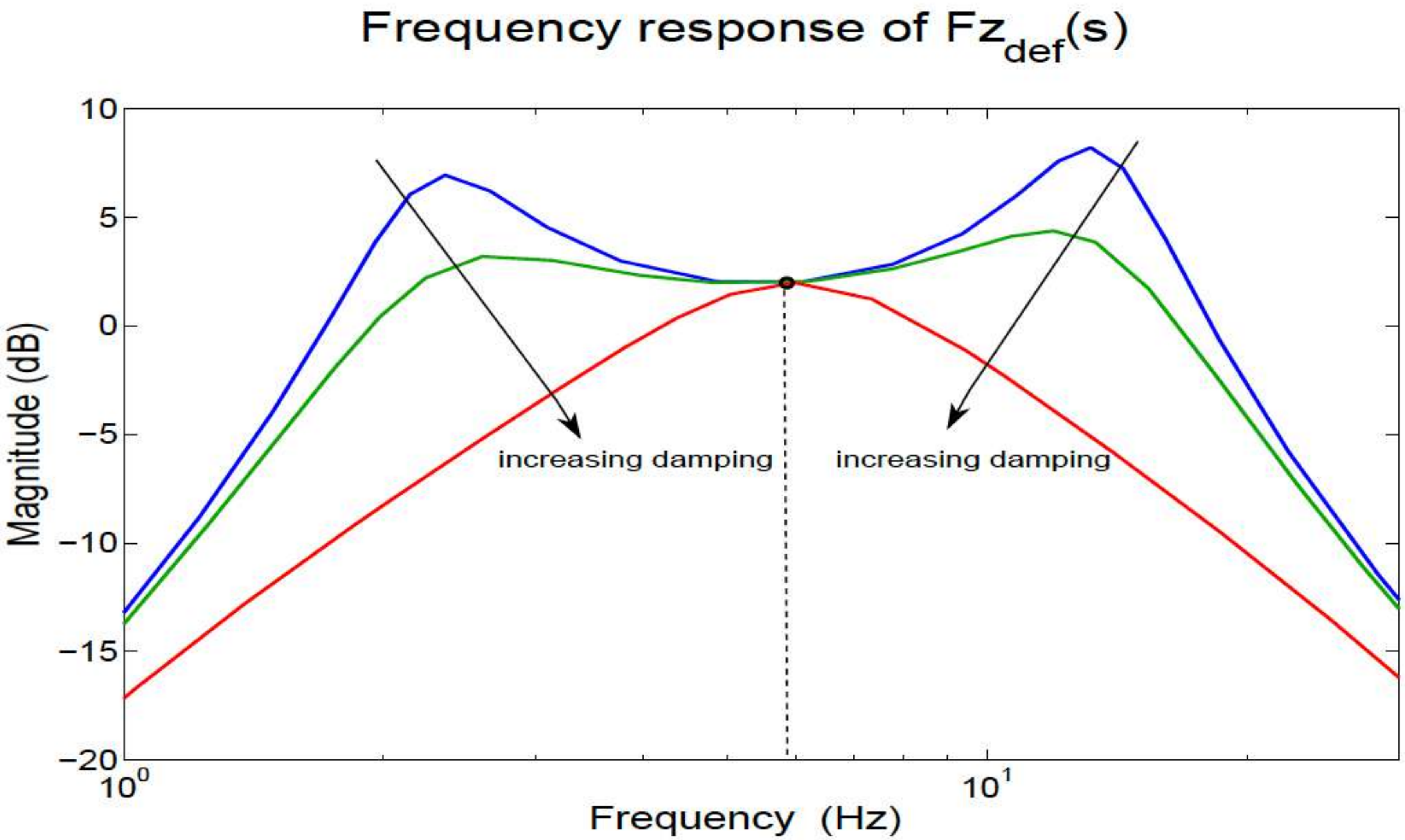
«Road-contact» transfer function

$$\delta z_r \to \delta z - \delta z_t = F_z(s) - F_{zt}(s)$$

«Elongation» transfer function



green: c=2600 Ns/m
blue : c=1300 Ns/m
red: c=750 Ns/m



green: *c*=2600 Ns/m
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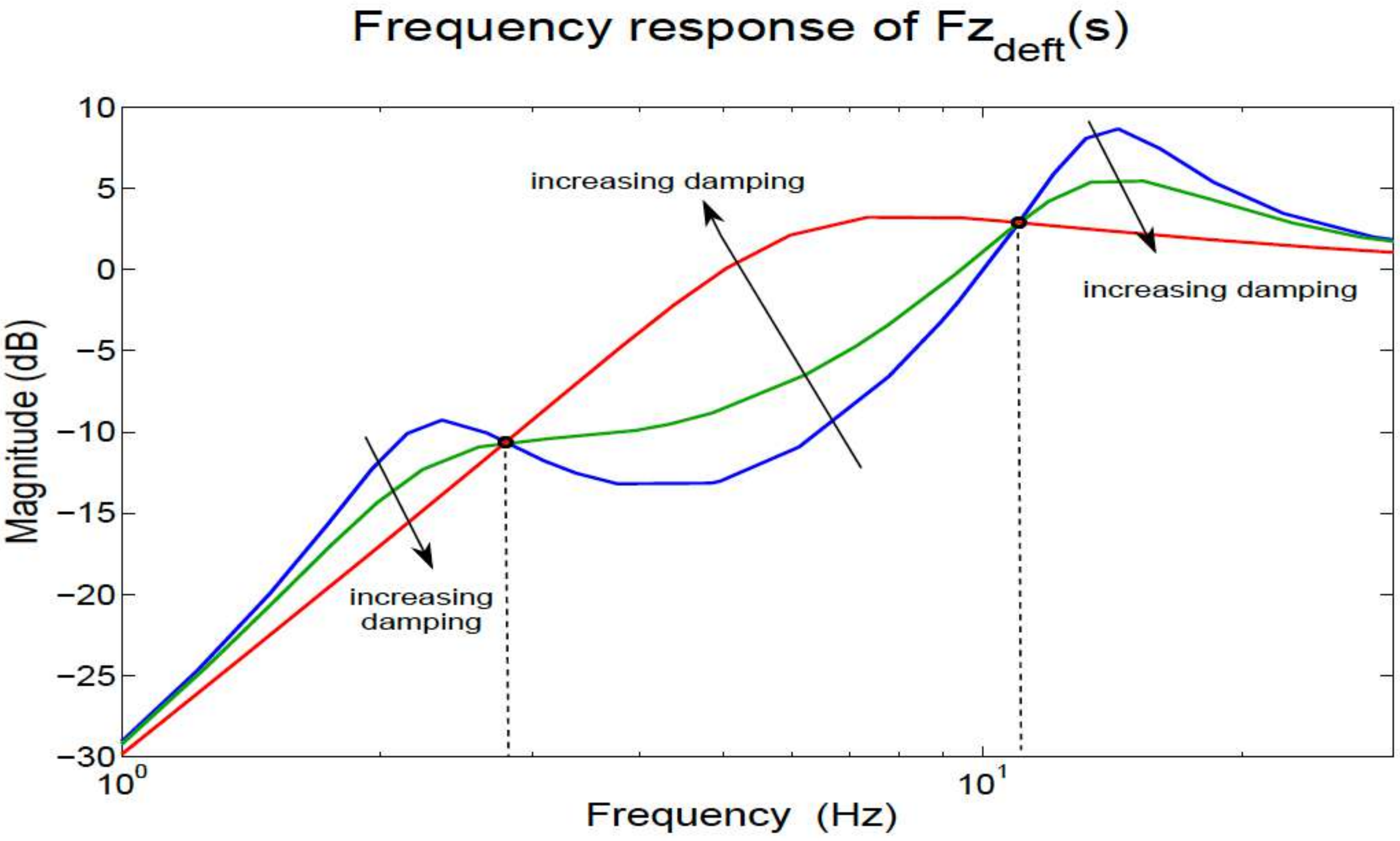
Semi-Active Damping Control

The quarter-car model and its features



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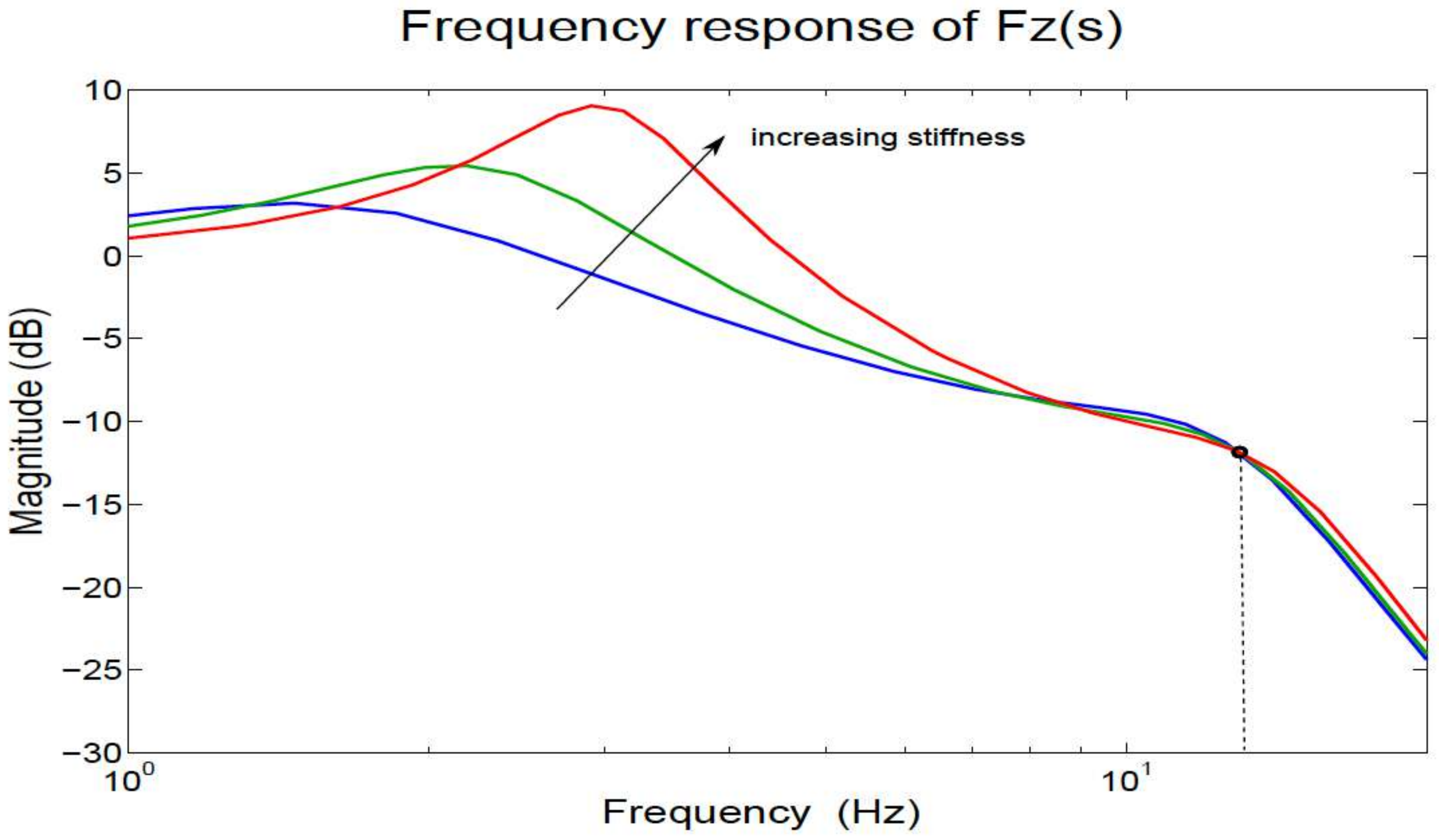
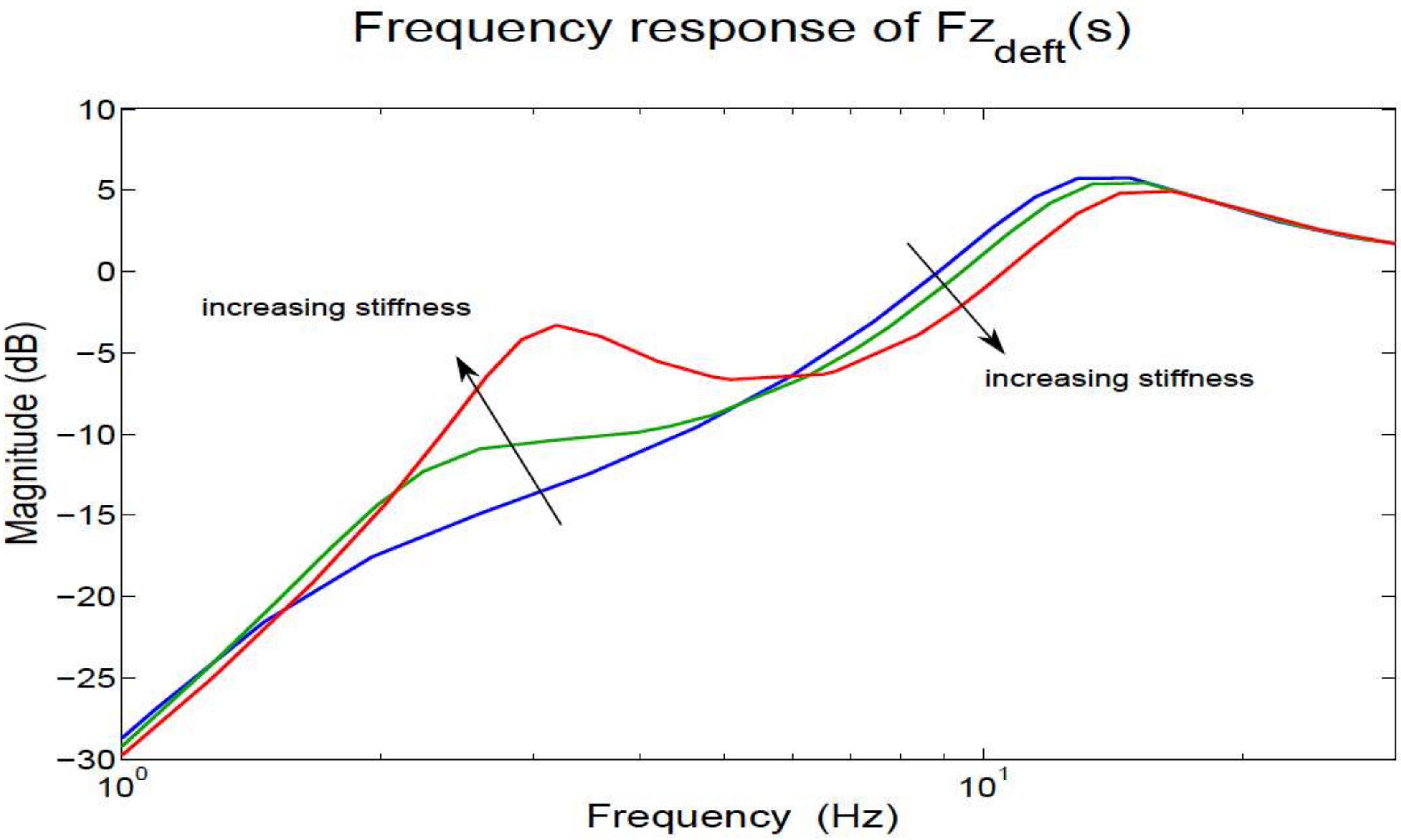


blue : k=20000 N/m
green: k=40000 N/m
red: k=10000 N/m



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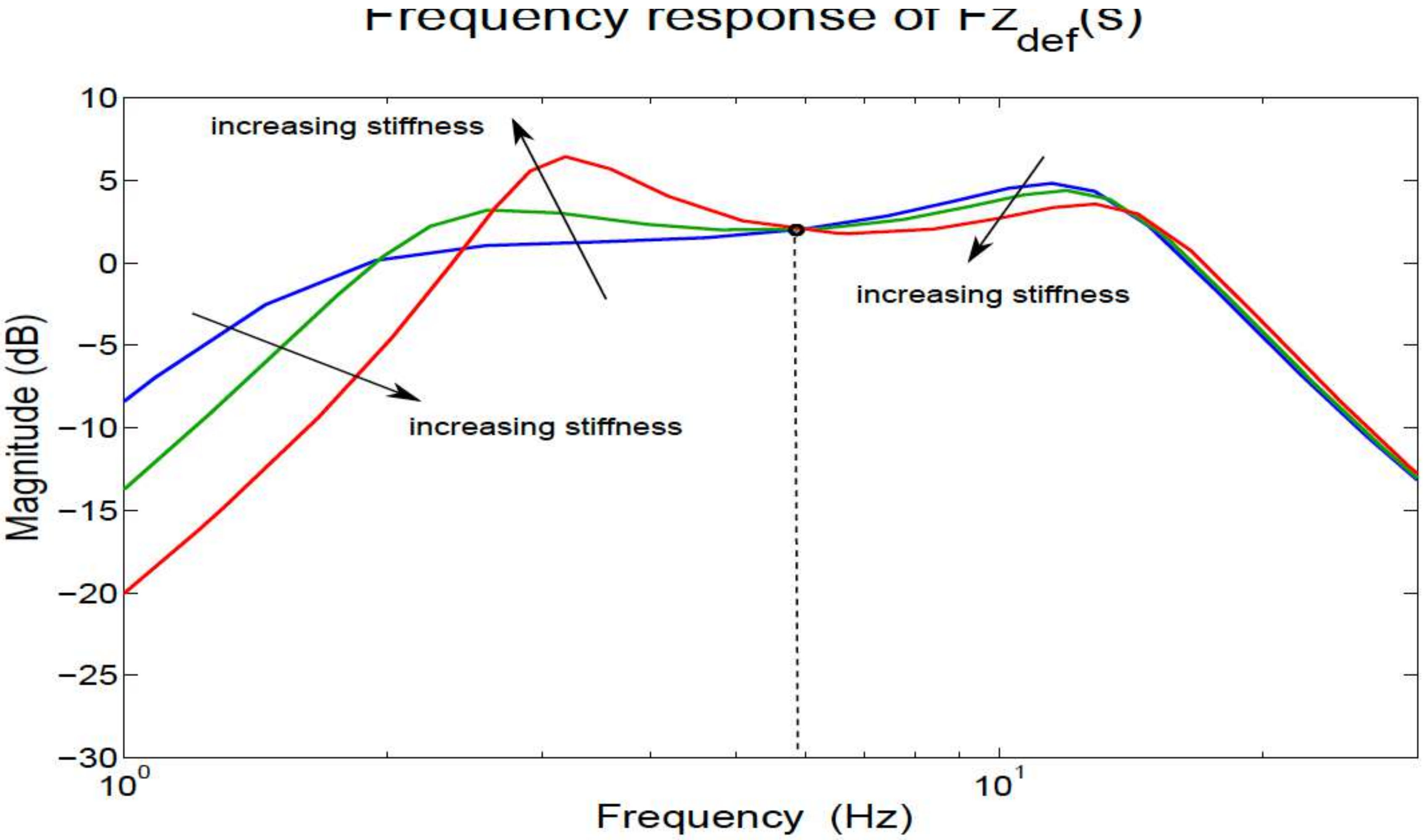

blue : k=20000 N/m
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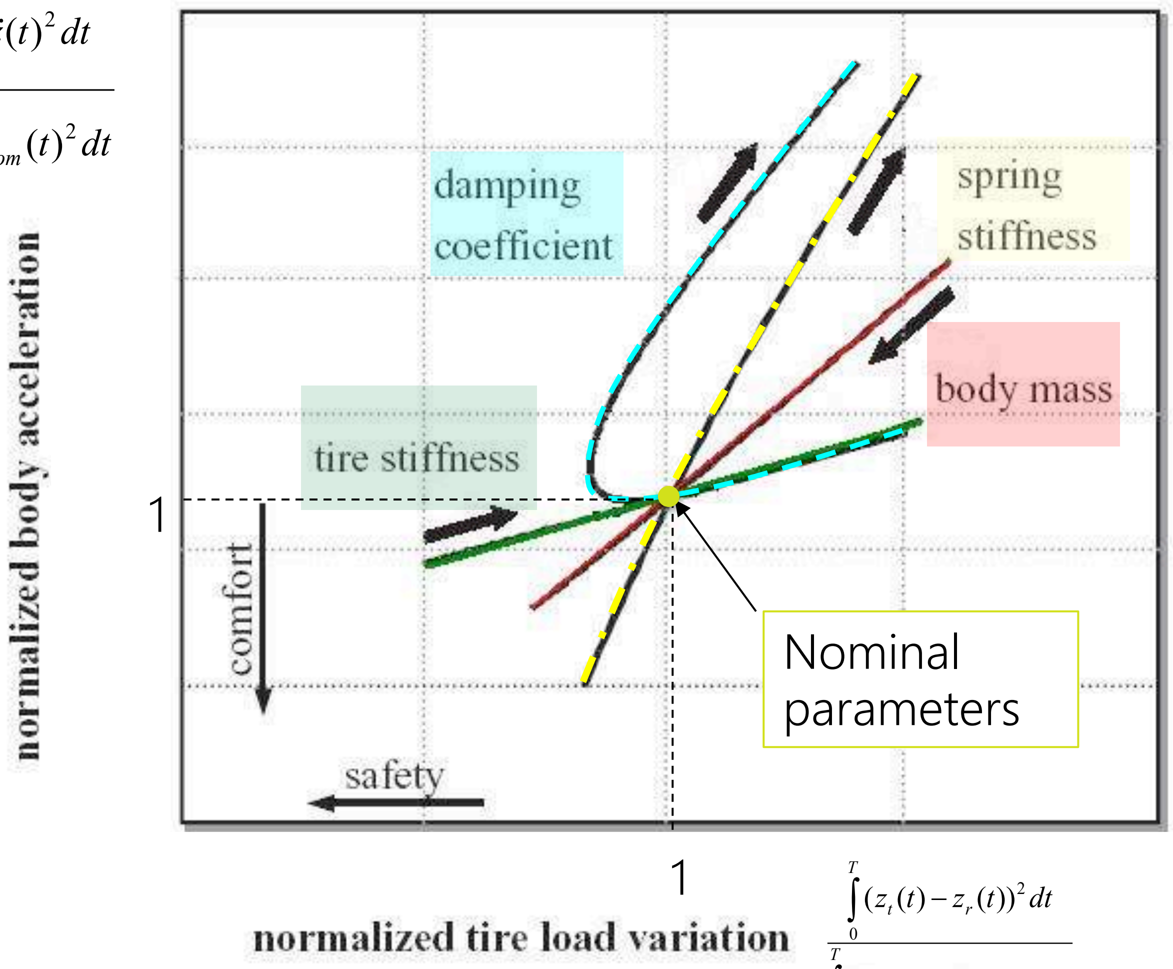
$$\frac{\int_0^T \ddot{z}(t)^2\,dt}{\int_0^T \ddot{z}_{nom}(t)^2\,dt}$$



$$\frac{\int_0^T (z_t(t)-z_r(t))^2\,dt}{\int_0^T (z_{t,nom}(t)-z_r(t))^2\,dt}$$

Consider a specific road profile $z_r(t)$ over a time-window 0-T as «standard» input for the comparison

The experiment is made with all the parameters at their «nominal» value is the (1,1) position

Each point on the trade-off map is obtained by changing a parameter (one only)

Comment on:

- Body mass
- Spring stiffness
- Tire stiffness

Recall that the three objectives are:

$$F_{acceleration}(s)Z_r(s) = s^2 Z(s)$$
$$F_{stroke}(s)Z_r(s) = Z(s) - Z_t(s)$$
$$F_{load}(s)Z_r(s) = (K_t / m)(Z_t(s) - Z_r(s))$$

three objectives with apparently only 2 variables (Z(s) and Z_t(s)).

→ cannot achieve all three objectives

Given:

Z_r
comfort
handling

→

it seems possible to design a control law for the suspension force to achieve those objectives

(2 unknowns 2 equations)

… not quite true. Assume the ideal case where F can be freely controlled

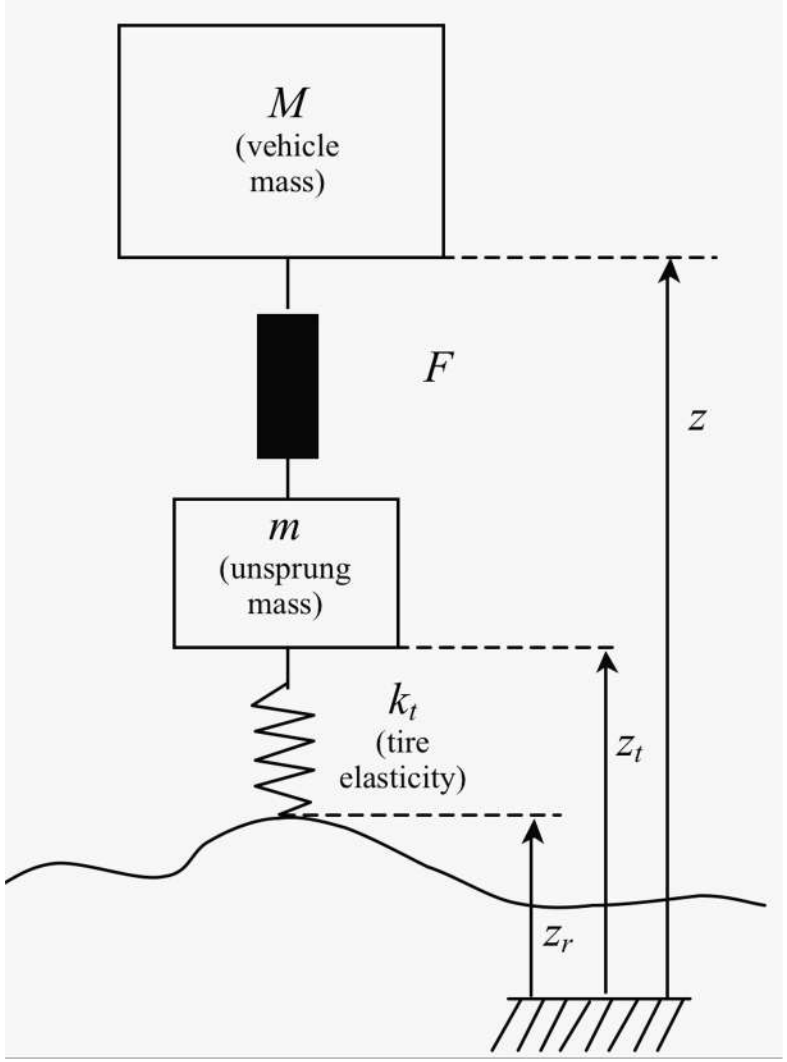
$$\begin{cases} M\delta\ddot{z} = \delta F \\ m\delta\ddot{z}_t = -k_t\left(\delta z_t - \delta z_r\right) - \delta F \end{cases}$$

by eliminating δF:

$$Ms^2Z(s) + ms^2Z_t(s) + k_t\left(Z_t(s) - Z_r(s)\right) = 0$$

there is an additional dynamic constraint:

The two objectives cannot be independently set



Semi-Active Damping Control

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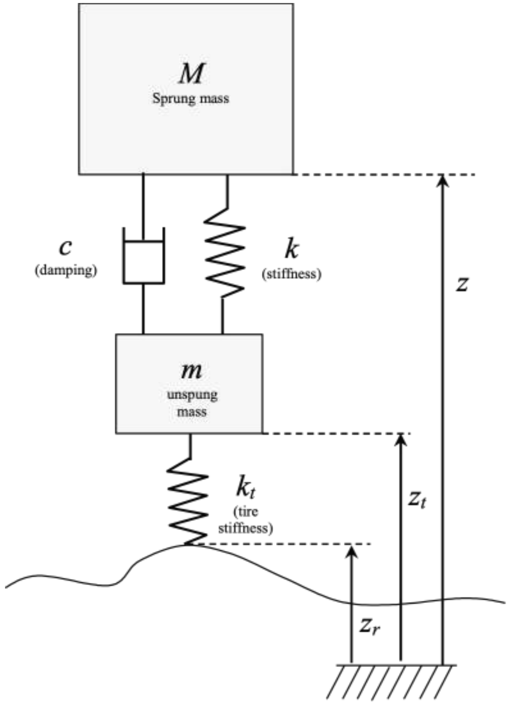

$$x = \begin{bmatrix} z \\ \dot{z} \\ z_t \\ \dot{z}_t \end{bmatrix} \quad u = \begin{bmatrix} z_r \\ c \end{bmatrix} \quad y = \begin{bmatrix} z \\ z_t \end{bmatrix}$$

$$\begin{cases} M\ddot{z}(t) = -c\left(\dot{z}(t) - \dot{z}_t(t)\right) - k\left(z(t) - z_t(t) - \Delta_s\right) - Mg \\ m\ddot{z}_t(t) = +c\left(\dot{z}(t) - \dot{z}_t(t)\right) + k\left(z(t) - z_t(t) - \Delta_s\right) - k_t\left(z_t(t) - z_r(t) - \Delta_t\right) - mg \end{cases}$$

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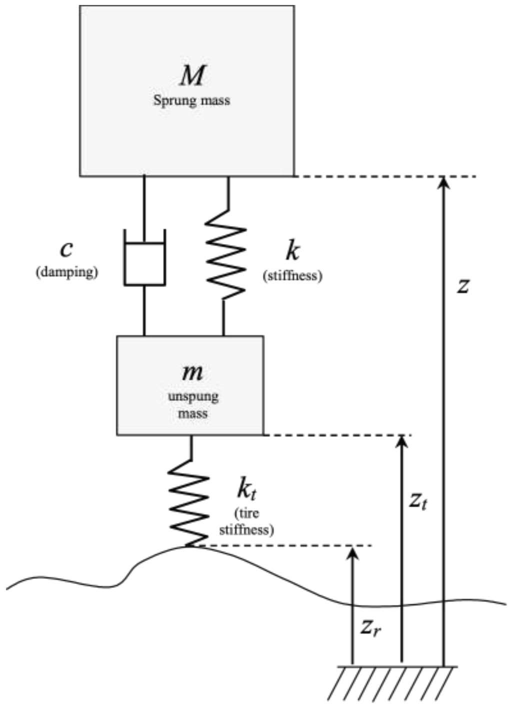

$$x = \begin{bmatrix} z \\ \dot{z} \\ z_t \\ \dot{z}_t \end{bmatrix} \quad u = \begin{bmatrix} z_r \\ c \end{bmatrix} \quad y = \begin{bmatrix} z \\ z_t \end{bmatrix}$$

If we linearize around an equilibrium point we loose the effect of the damping variation

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Furthermore, the suspension response is more complex:

- Hysteresis
- Dynamic response

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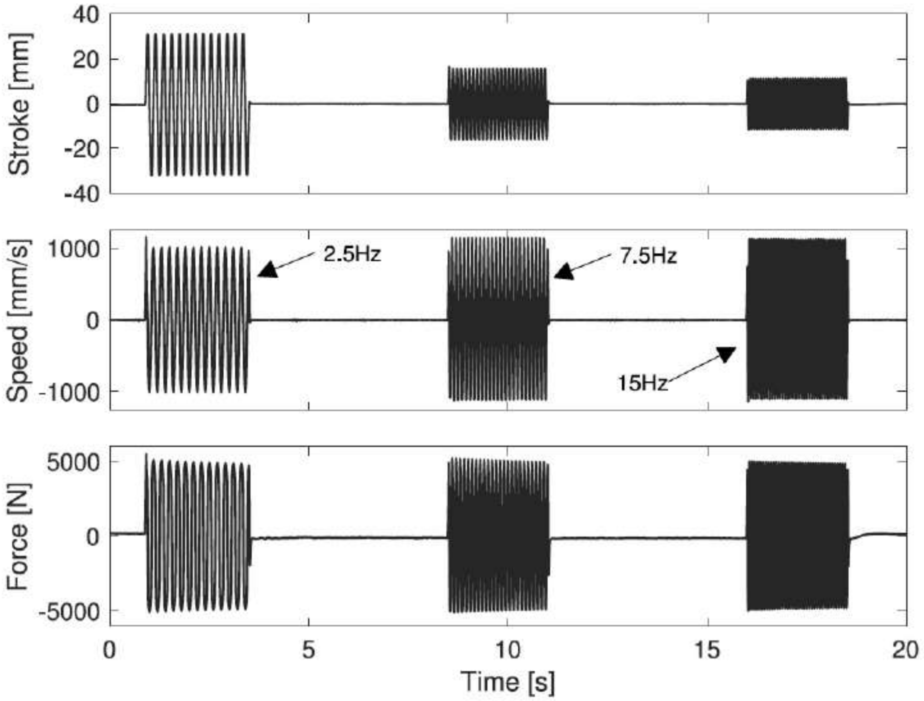

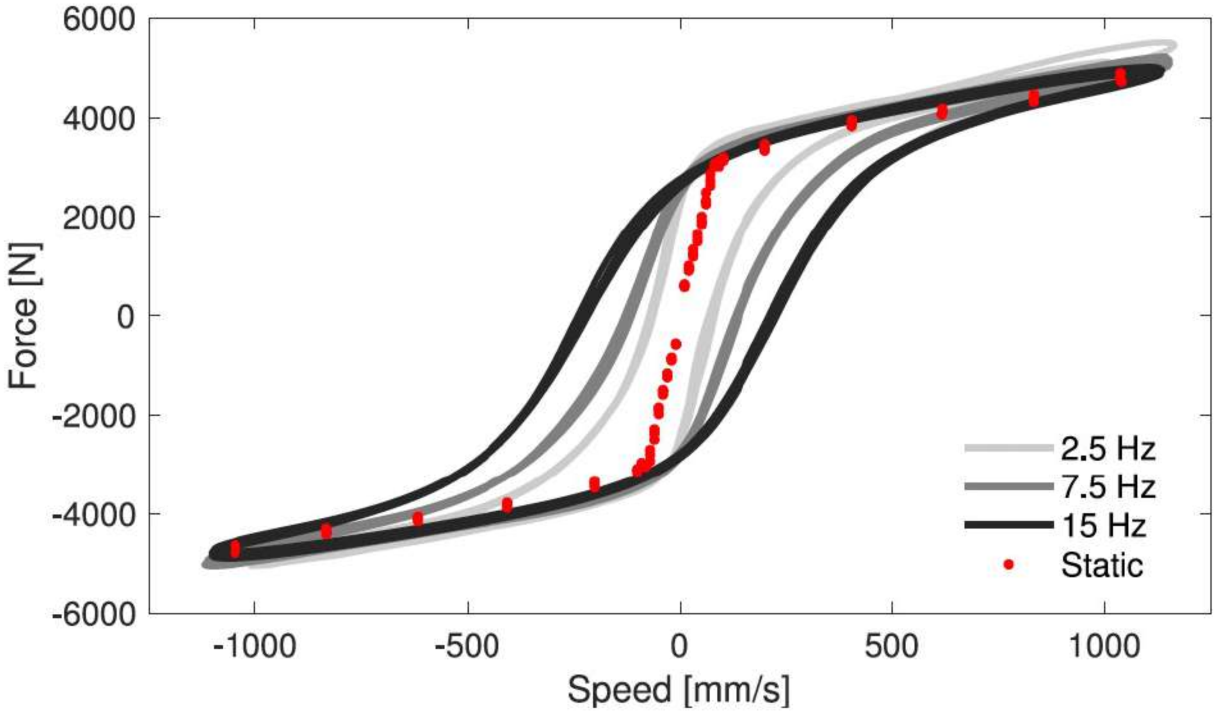

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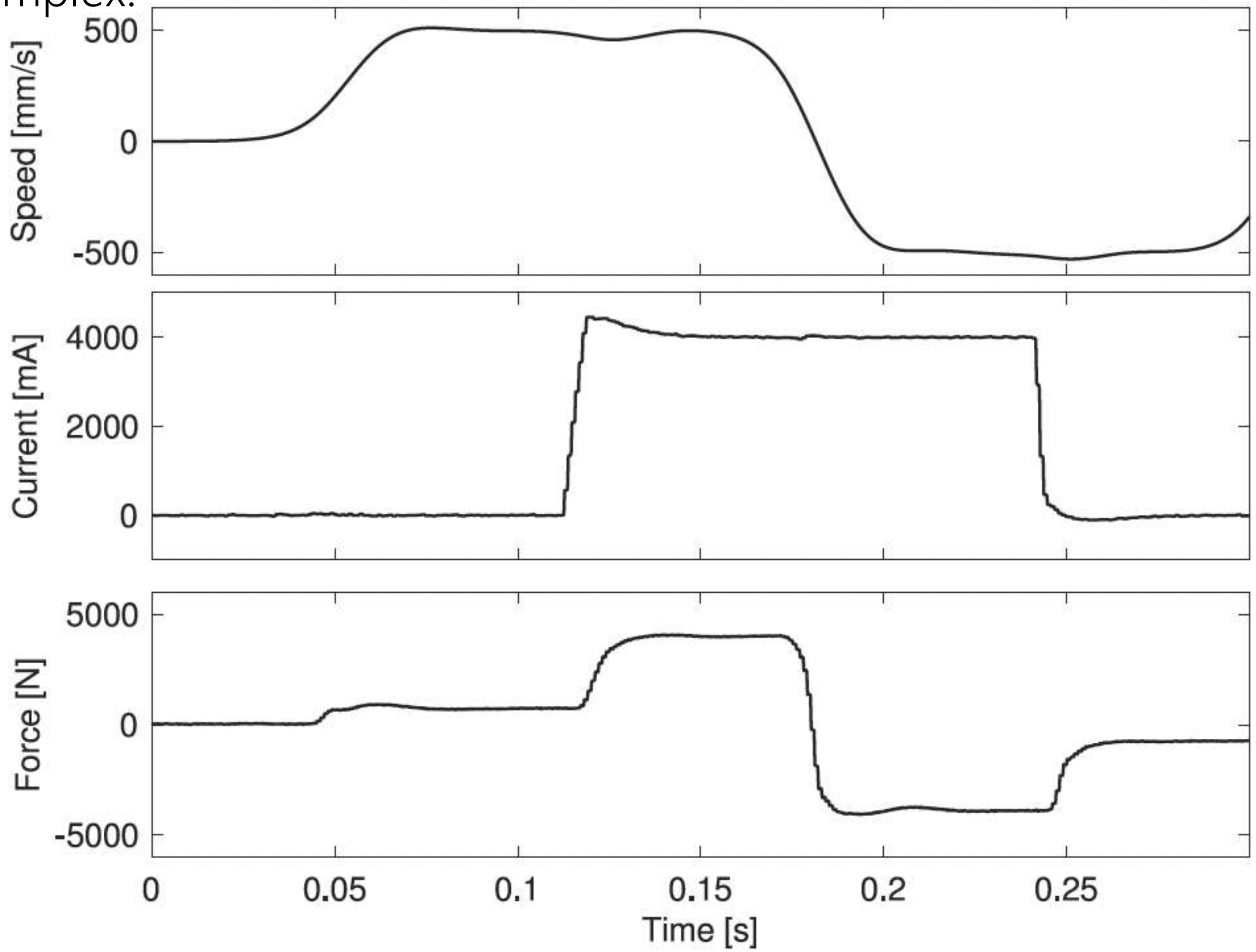

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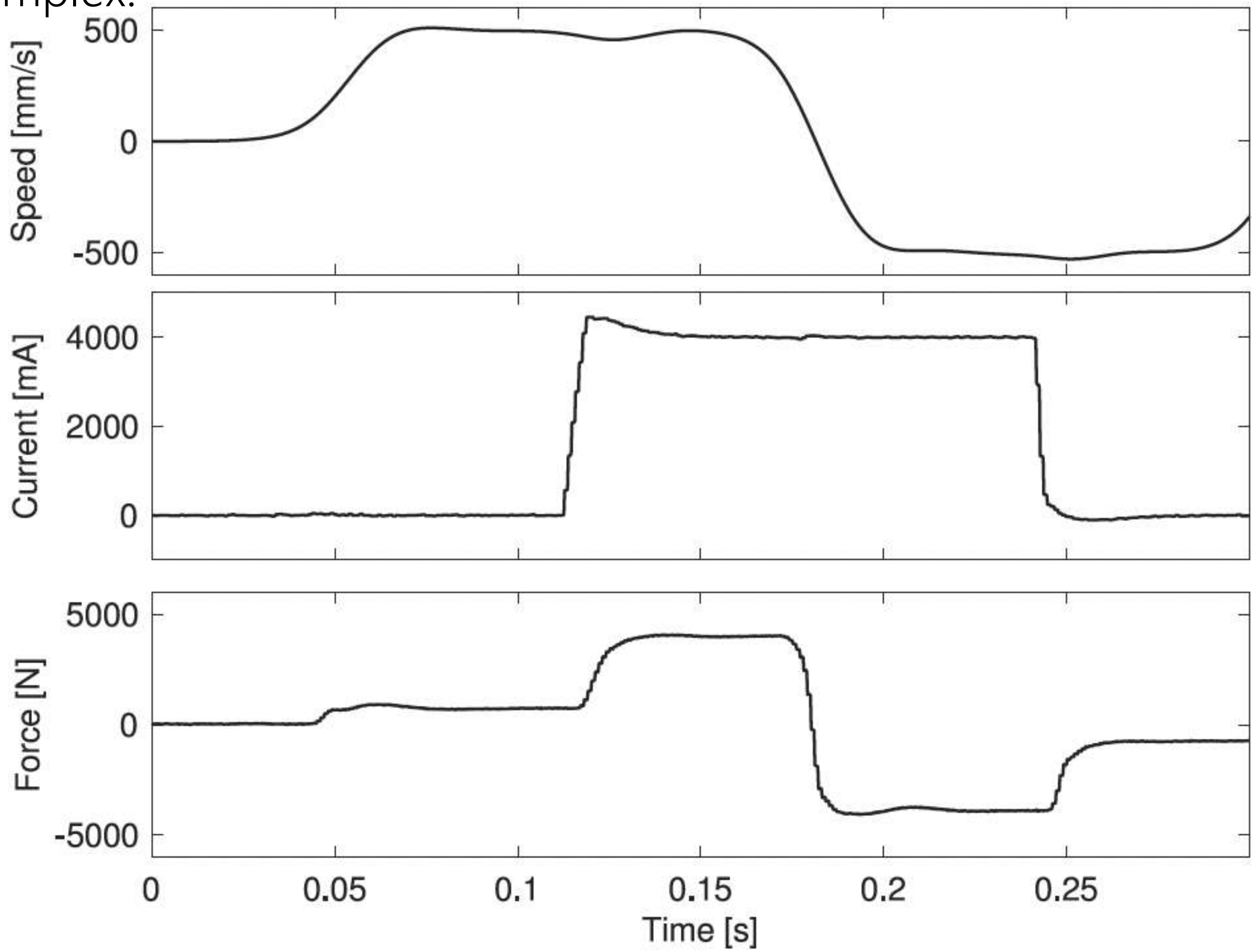
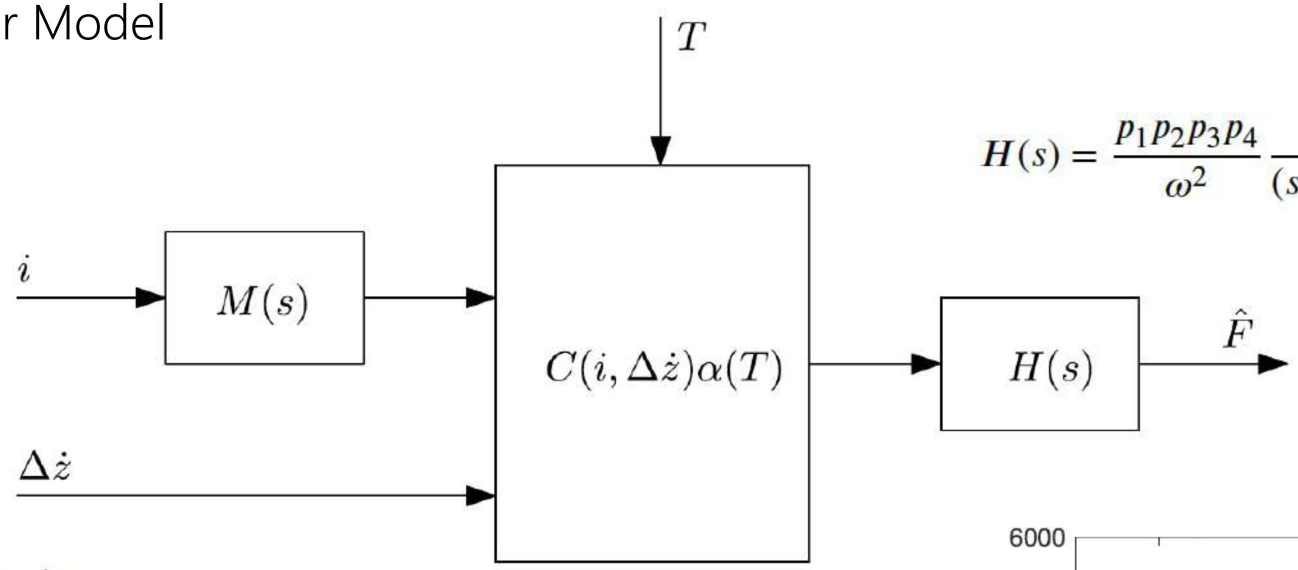


Semi-Active Damping Control

Actuator Technology – Dynamic Properties

Hammerstein-Wiener Model

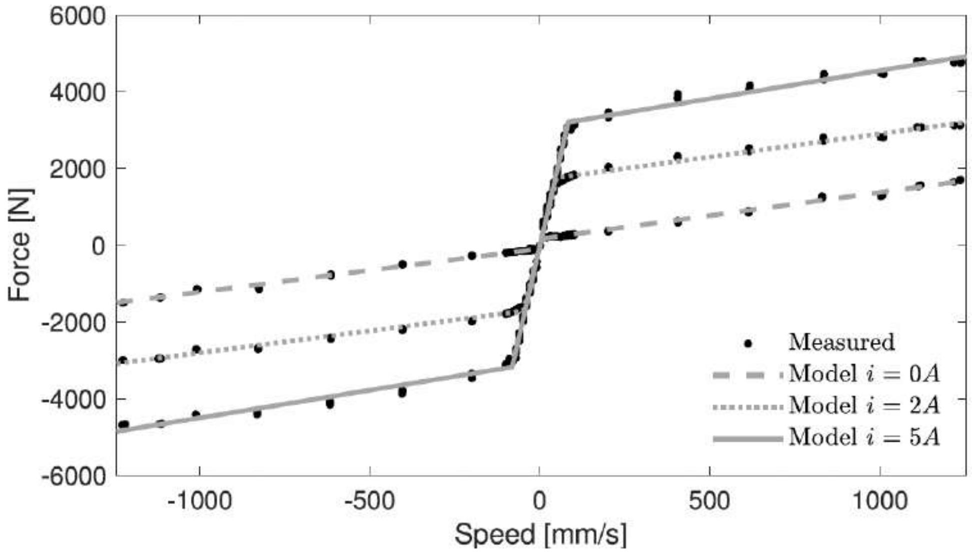


$$H(s) = \frac{p_1 p_2 p_3 p_4}{\omega^2} \frac{s^2 + 2\xi\omega s + \omega^2}{(s + p_1)(s + p_2)(s + p_3)(s + p_4)}$$

$$M(s) = \frac{p_1 p_2}{z} \frac{s + z}{(s + p_1)(s + p_2)} e^{-\tau s}$$

Magnetization dynamic

Static
Damping
Characteristics



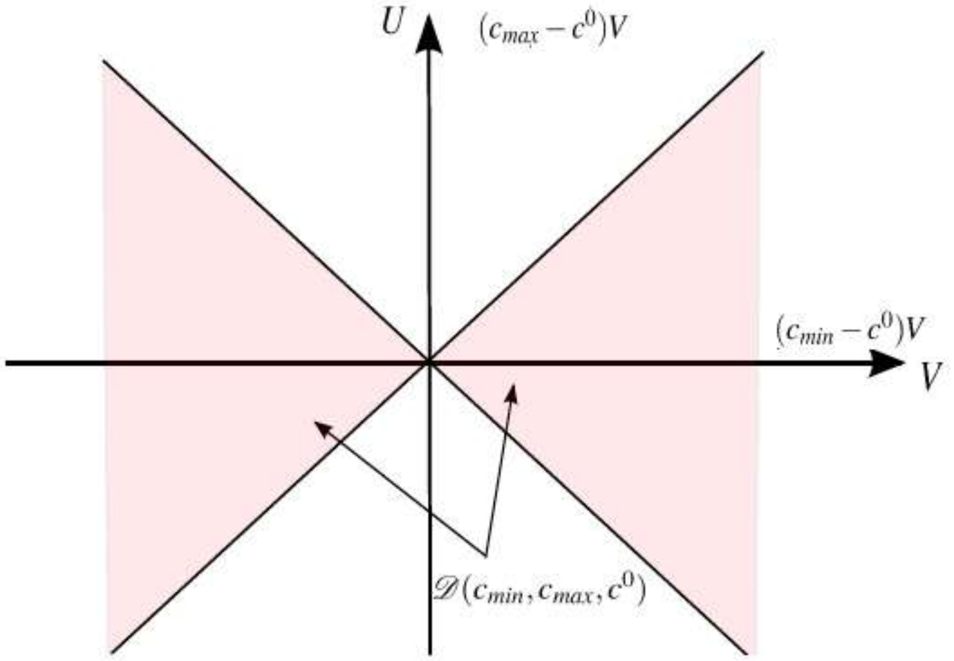
Considers a nominal damping

$$\Sigma_c(c^0) := \begin{cases} M\ddot{z} &= -k(z-z_t) - c^0(\dot{z}-\dot{z}_t) - F_d \\ m\ddot{z}_t &= k(z-z_t) + c^0(\dot{z}-\dot{z}_t) + F_d - k_t(z_t - z_r) \\ \dot{F}_d &= \beta(u - F_d) \end{cases}$$

Models the actuator bandwidth

Is the control variable.
We need to add a dissipative constrain

$$\Sigma_c(c^0) := \begin{cases} M\ddot{z} &= -k(z-z_t) - c^0(\dot{z}-\dot{z}_t) - F_d \\ m\ddot{z}_t &= k(z-z_t) + c^0(\dot{z}-\dot{z}_t) + F_d - k_t(z_t - z_r) \\ \dot{F}_d &= \beta(u - F_d) \end{cases}$$

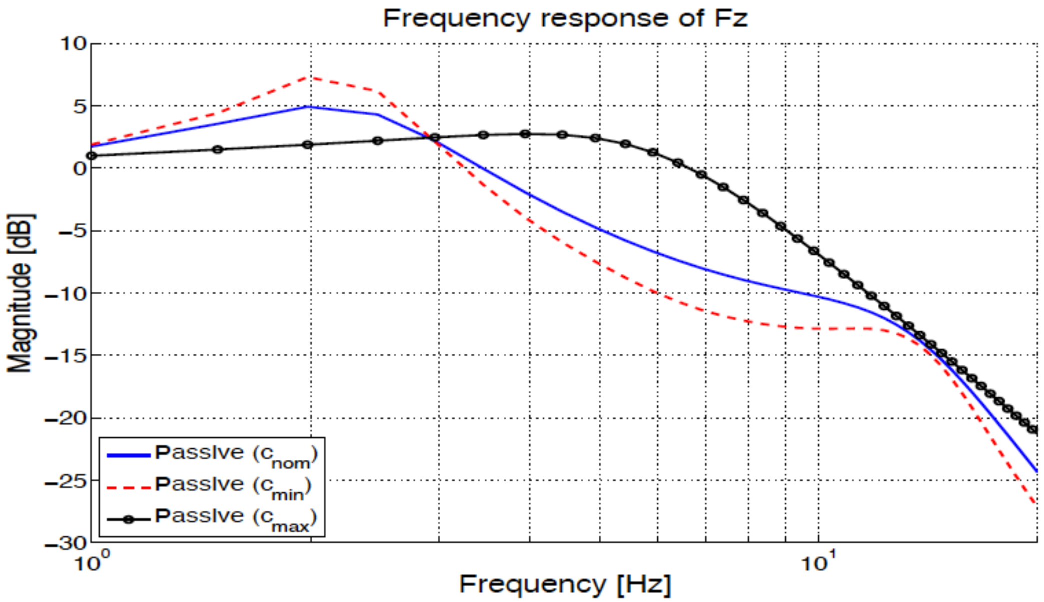


$$u \in \mathscr{D}(c_{min}, c_{max}, c^0) \subseteq \mathbb{R}$$

$$\mathscr{D}(c_{min}, c_{max}, c^0) := \{\ \forall (U,V) \in \mathbb{R} \times \mathbb{R} | \big(U - (c_{max} - c^0)V\big)\big((c_{min} - c^0)V - U\big) \geq 0\ \}$$

Several ways to assess performance:

- Frequency Response.
  - It requires the knowledge of the input.
  - Work well in simulation.
  - Not appicable in many experimental scenarios



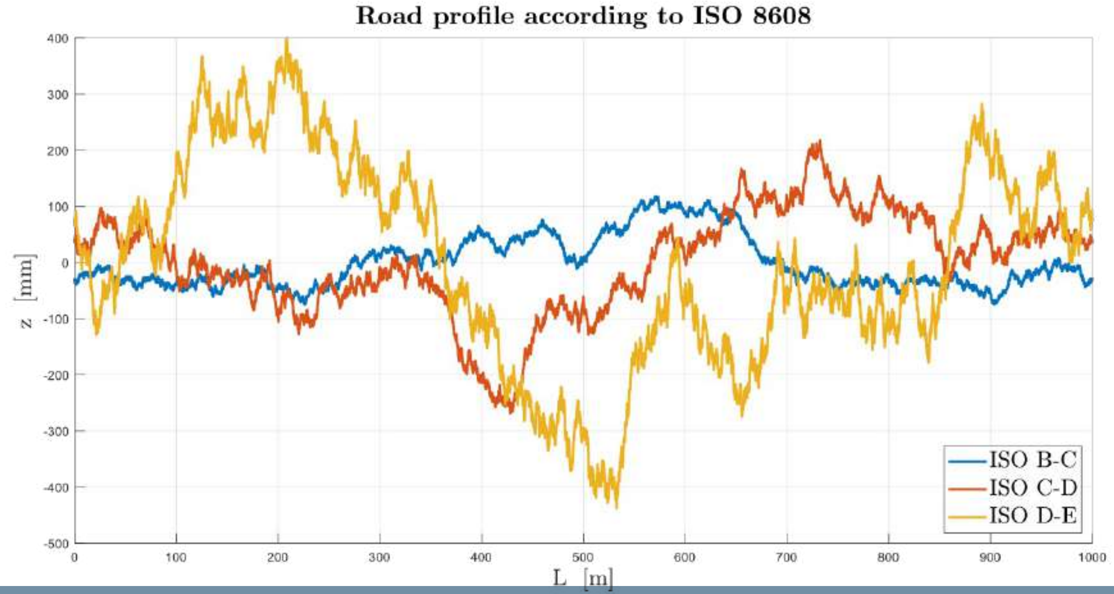
- Integral Performance Index
  - it works experimentally
  - it is a "lumped" approach

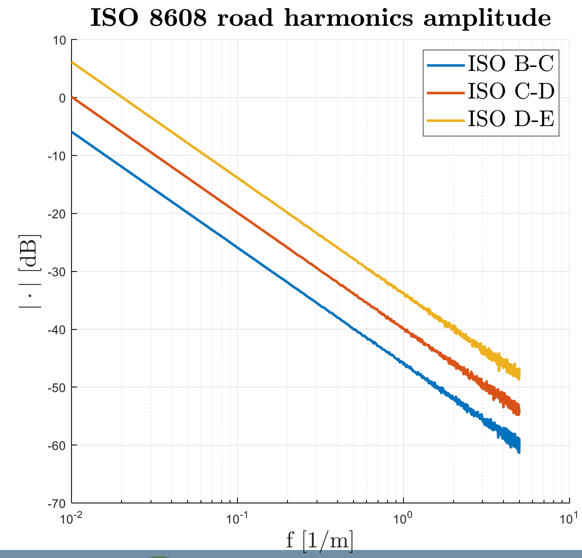
$$J = \frac{1}{t_2 - t_1} \int_{t_1}^{t_2} |x(t)|^2 dt$$

Road classification is made according to ISO 8608 standard
Standard road profile can be mathematically modeled as a sum of sinusoids with decreasing amplitude
Road profile can be approximated with a white noise filtered with a very low-frequency 1st order low-pass filter

$$h(x) = \sum_{i=1}^{N} \sqrt{\Delta_n}\, 2^k \cdot 10^{-3} \frac{n_0}{i\,\Delta_n} \cos(2\pi\, i\, \Delta_n\, x + \phi_i)$$

- k, that allows to build road profiles with different levels of roughness;
- x, that is the longitudinal displacement;
- ϕ_i, that is the phase of each sinusoidal component, randomly chosen to obtain an irregular profile.





Semi-Active Damping Control

Road Profile Generation


Pebble Road A


Cement Road


Belgian Road C1


Pebble Road B


Dislocated Washboard Road C


Belgian Road C2


Long wave road
(Short wavelenght)


Long wave road
(Long wavelenght)

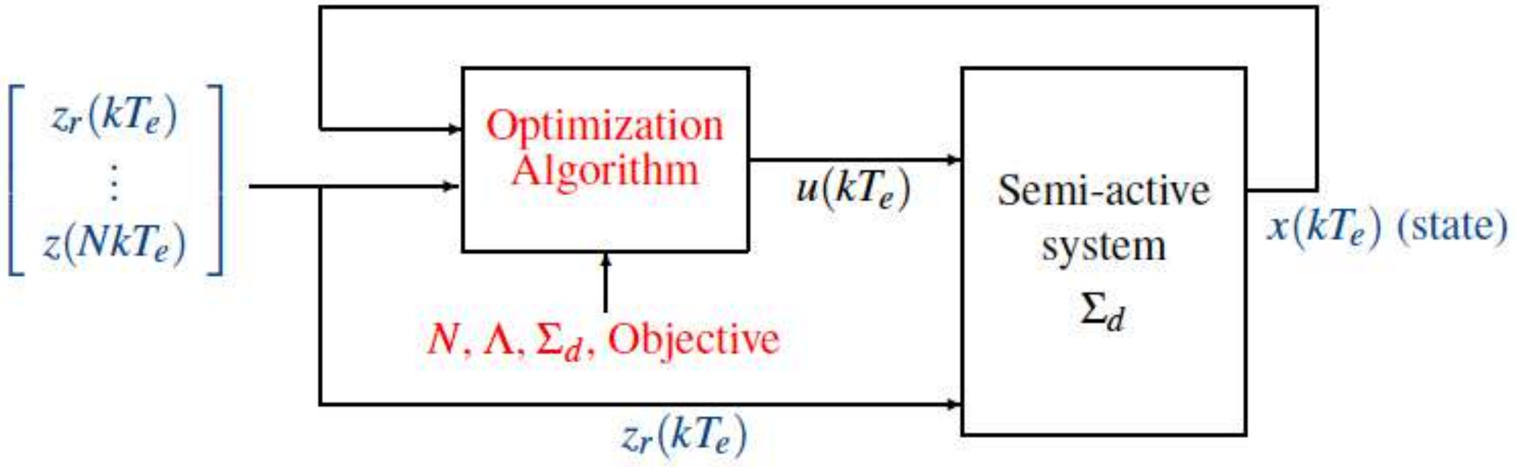
Semi-Active Damping Control

Road Profile Generation

It is useful to evaluate the best performance a given system, subject to actuator and inner nested limitations, can achieve

Assumptions:

1. The road disturbance profile is known
2. The state variables of the system are perfectly measured (i.e. no measurement noise).
3. The semi-active quarter car model is known (no system uncertainty).



Semi-Active Damping Control

Optimal Control and Benchmarking

$$J_i^*(N,u,x,z_r) \quad = \min \; J_\alpha = \alpha J_c(N,u,x,z_r) + (1-\alpha) J_{rh}(N,u,x,z_r)$$

Subject to

$$\Sigma_d(c^0) : x(k+1) = \left(I_n + A(c^0)\right) T_e x(k) + B T_e \left[\; z_r(k) \quad u(k) \;\right]^T$$

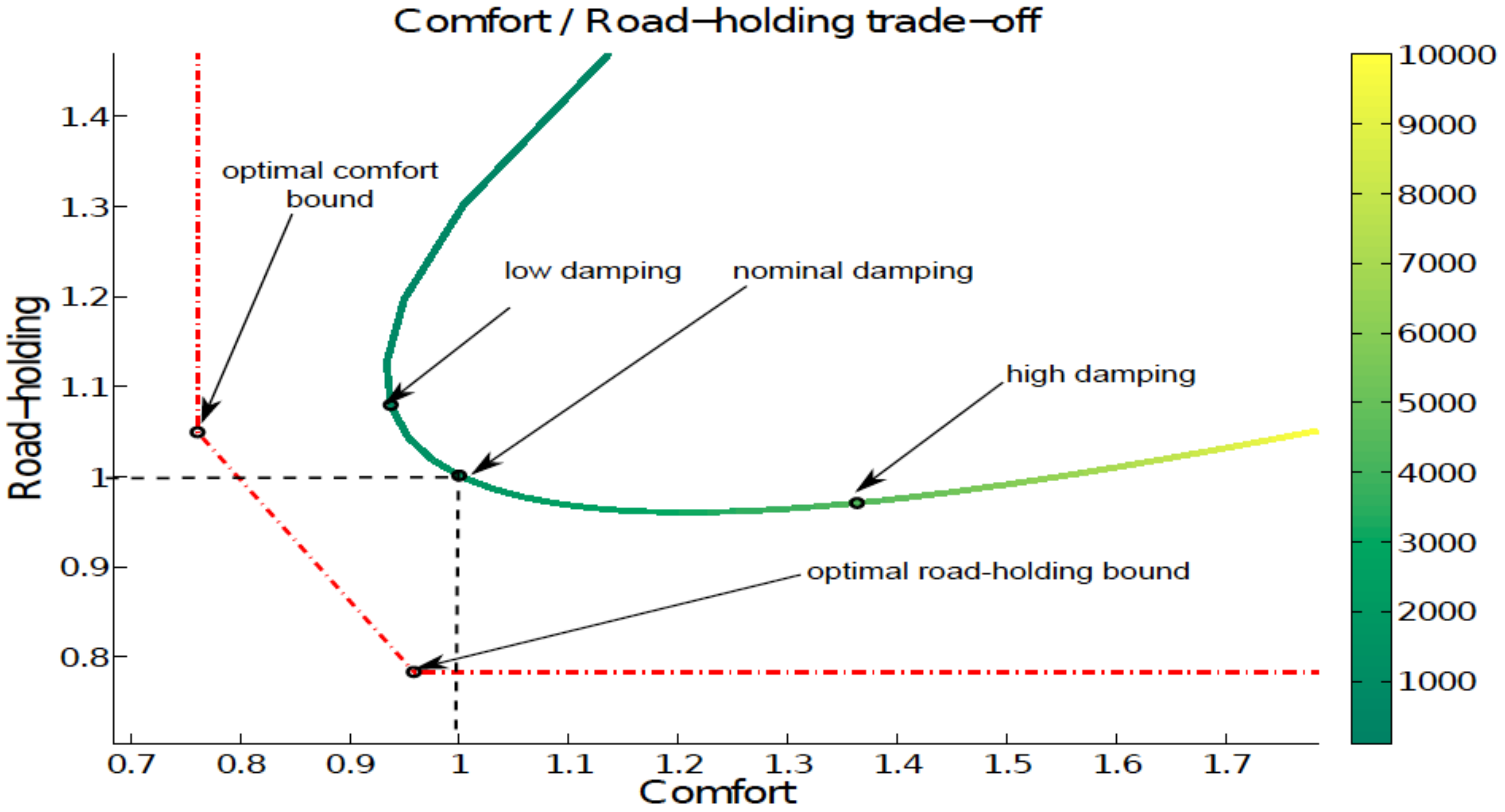
$$\text{if } \dot{z} - \dot{z}_t \geq 0, \Lambda: \quad \begin{cases} u \geq (c_{min} - c^0)(\dot{z} - \dot{z}_t) \\ u \leq (c_{max} - c^0)(\dot{z} - \dot{z}_t) \end{cases}$$

$$\text{if } \dot{z} - \dot{z}_t < 0, \Lambda: \quad \begin{cases} u \leq (c_{min} - c^0)(\dot{z} - \dot{z}_t) \\ u \geq (c_{max} - c^0)(\dot{z} - \dot{z}_t) \end{cases}$$

- It is framed as a nonlinear optimization problem with logical constraints and solved using YALMIP
- α balances the two objective: comfort and road holding
- N is the optimization horizon

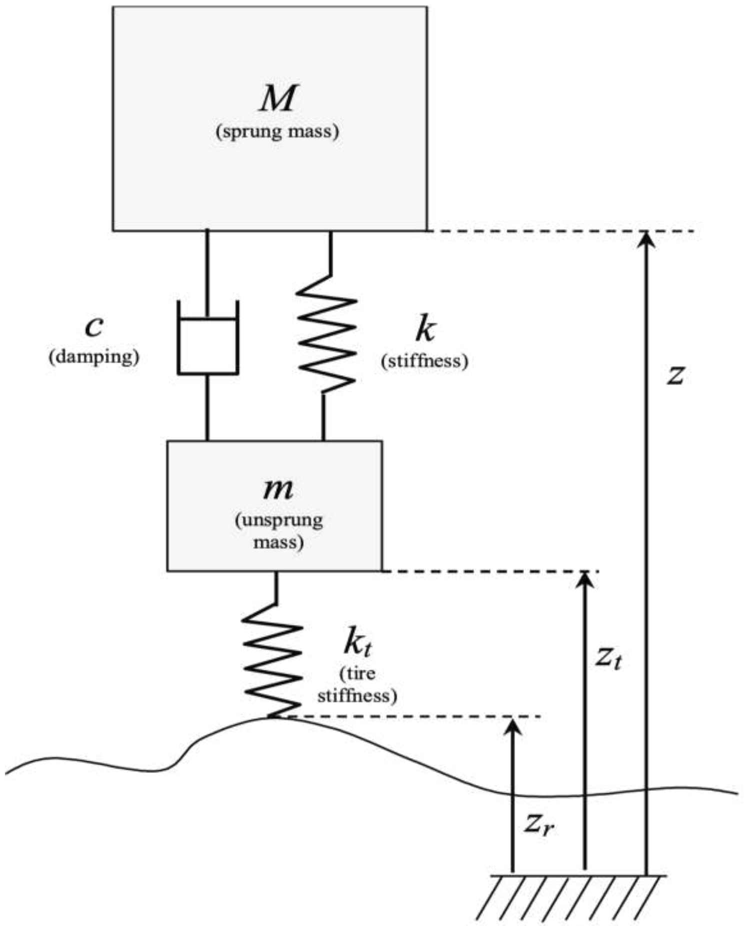
Semi-Active Damping Control

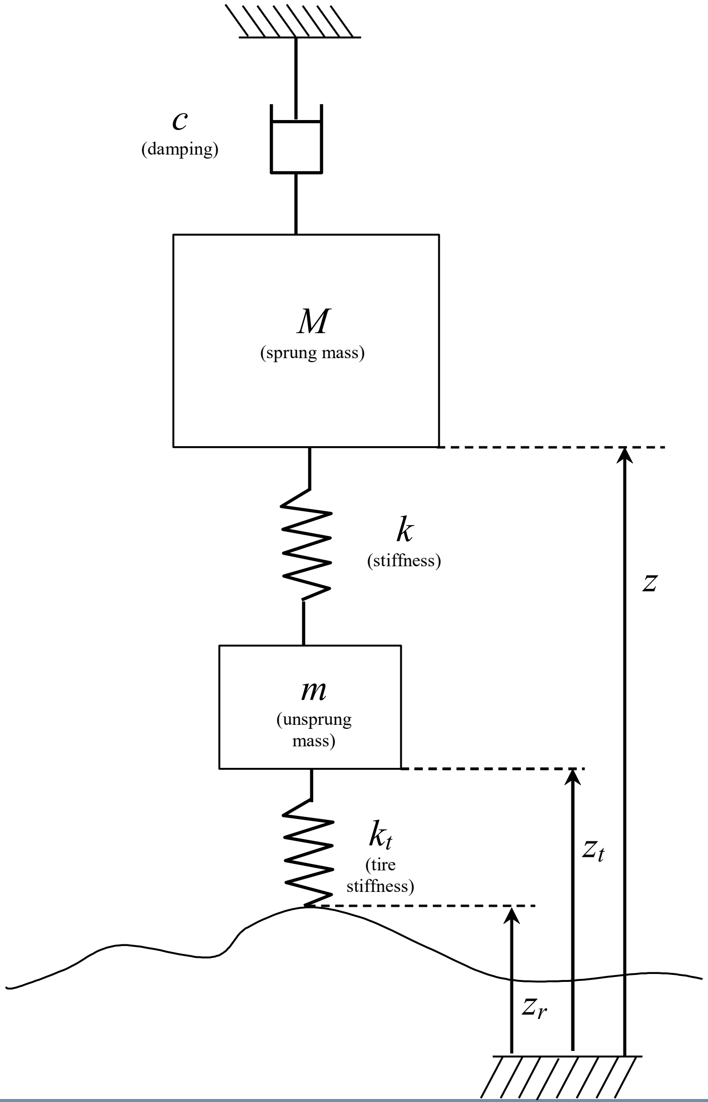
Optimal Control and Benchmarking



Semi-Active Damping Control

Sky-Hook Concept (Ideal Sky-Hook)

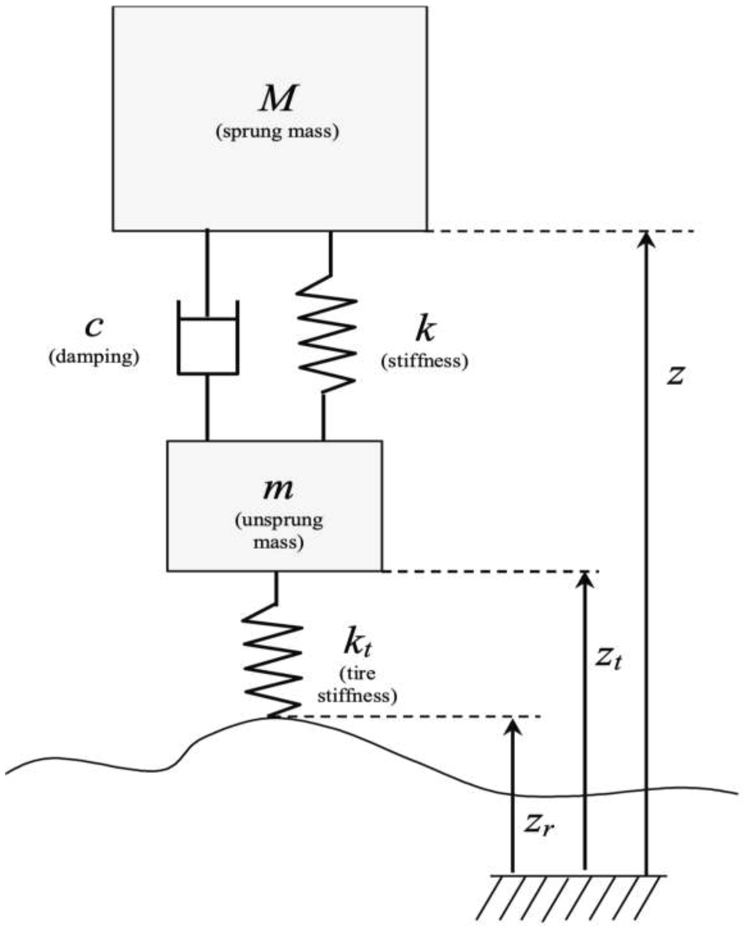


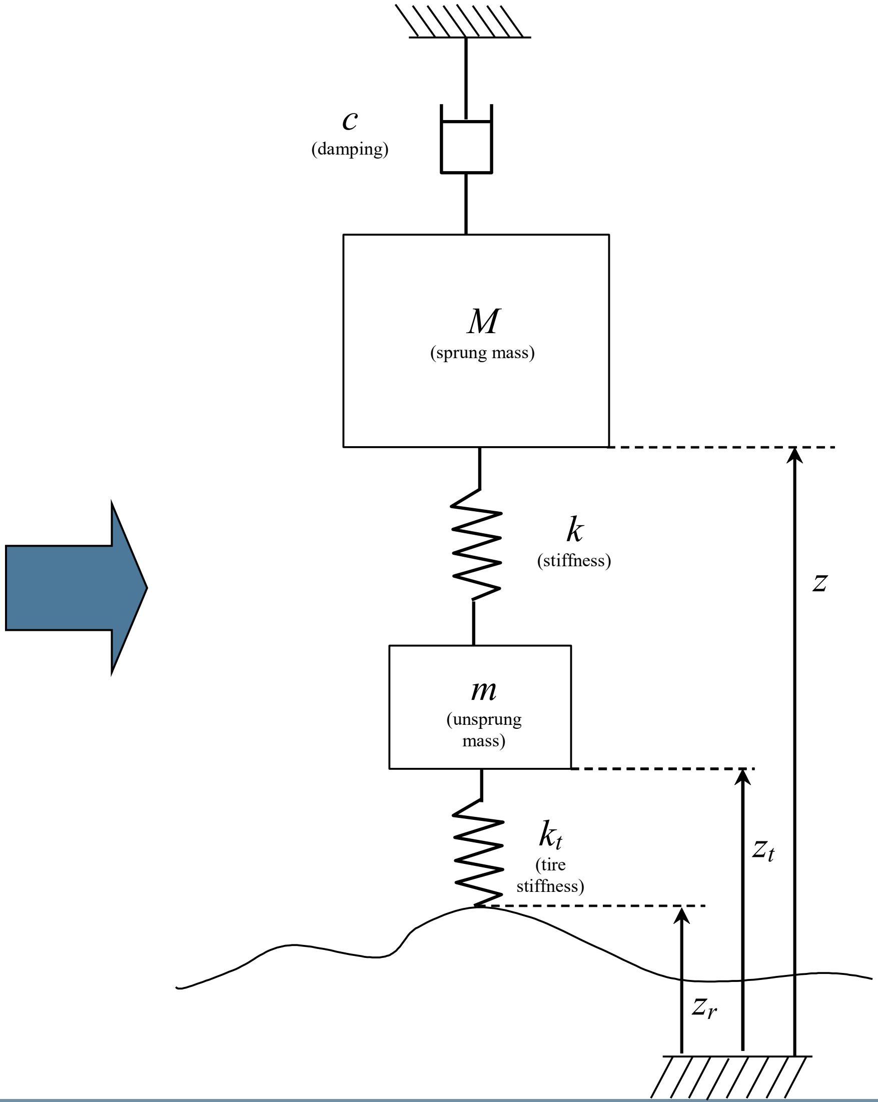


Damping force: proportional to body-speed only

Semi-Active Damping Control

Sky-Hook Concept (Ideal Sky-Hook)



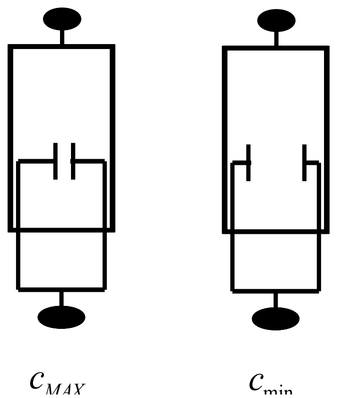


Damping force: proportional to body-speed only

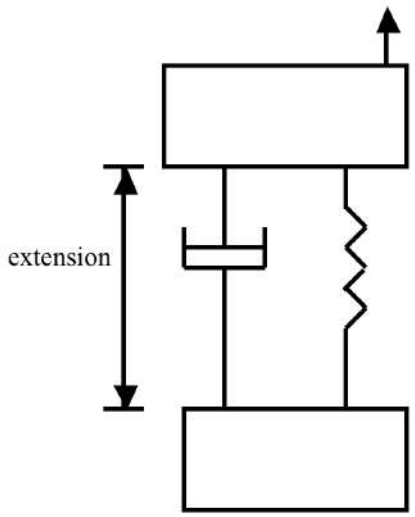
$$\begin{cases} c(t) = c_{MAX} & if \quad \dot{z}(\dot{z} - \dot{z}_t) \geq 0 \\ c(t) = c_{\min} & if \quad \dot{z}(\dot{z} - \dot{z}_t) < 0 \end{cases}$$

Sensors requirement:
- Body speed
- Stroke speed

Actuator requirement: two-states only, Cmin and Cmax



Remark on its intuitive interpretation



if the sprung mass is raising and suspension extending → the damper does what we want → c_{max}

Semi-Active Damping Control

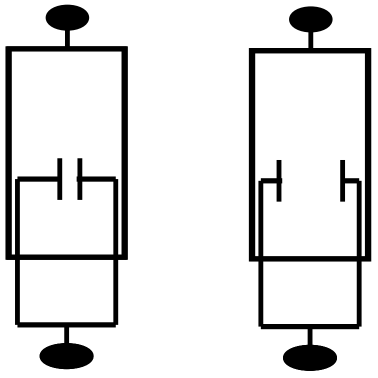
Sky-Hook Concept (Two-State Sky-Hook Control)

$$\begin{cases} c(t) = c_{MAX} & \text{if} \quad \dot{z}(\dot{z} - \dot{z}_t) \geq 0 \\ c(t) = c_{\min} & \text{if} \quad \dot{z}(\dot{z} - \dot{z}_t) < 0 \end{cases}$$

Sensors requirement:

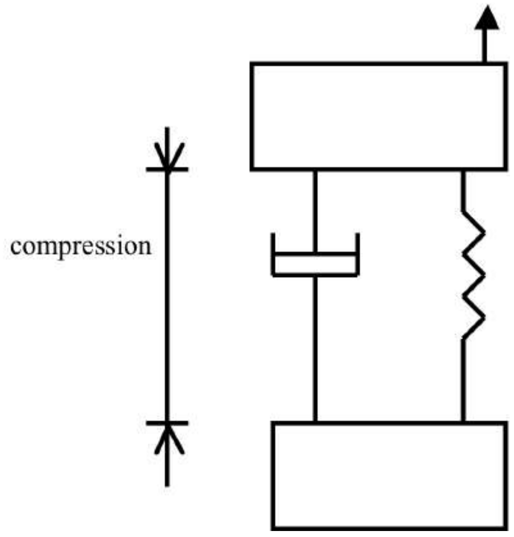
- Body speed
- Stroke speed

Actuator requirement: two-states only, Cmin and Cmax



c_{MAX} $c_{\min}$

Remark on its intuitive interpretation

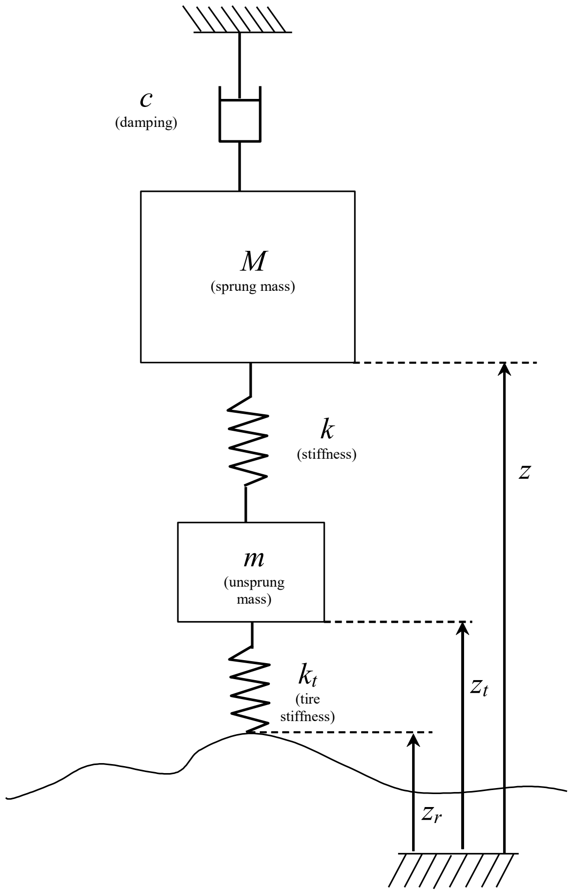


if the sprung mass is raising and suspension compressing → the damper is amplifying the sprung mass movement → $c_{\min}$

Semi-Active Damping Control

Sky-Hook Concept (Classical Linear Sky-Hook Control)

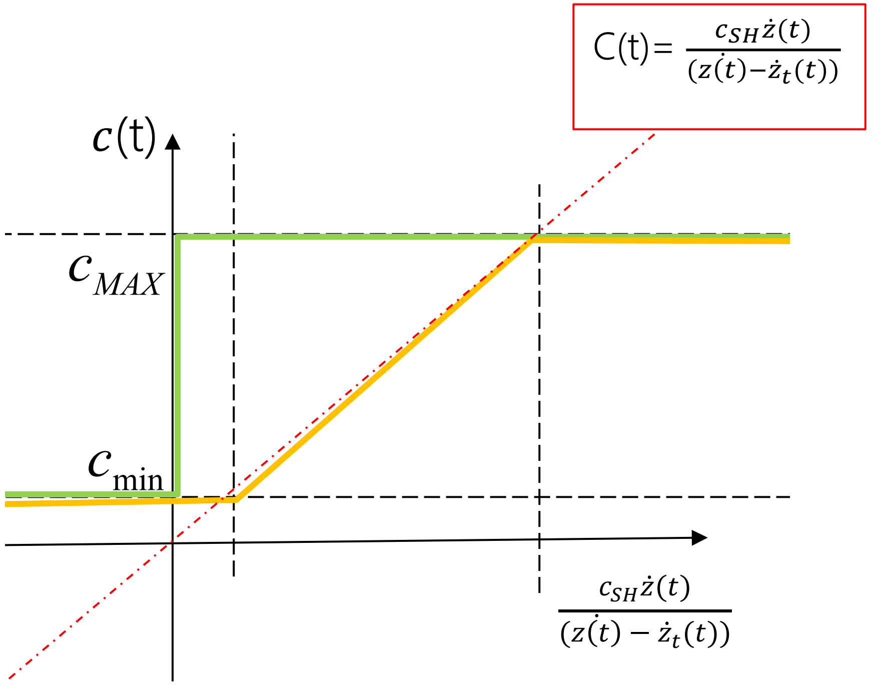
$$-c(t)(\dot{z}-\dot{z}_t) = -c_{SH}\dot{z} \quad \Rightarrow \quad c(t) = sat_{[Cmin,Cmax]}\left\{\frac{c_{SH}\dot{z}}{(\dot{z}-\dot{z}_t)}\right\}$$



Red: ideal

Green: on-off (simple) approximation

Yellow: linear approximation



The two-state SH control law can be applied based on the acceleration:
Acceleration Driven Damper Control

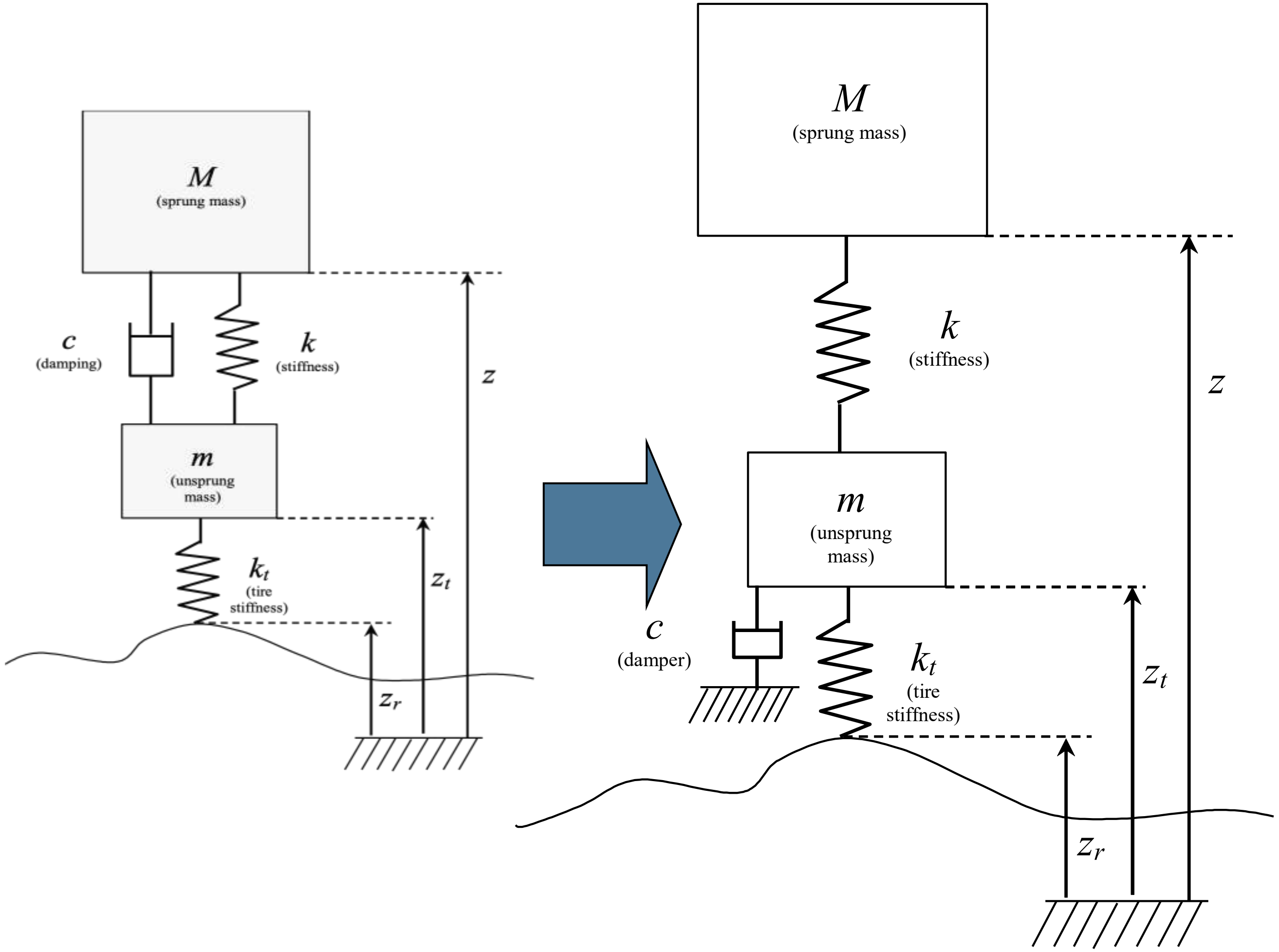
$$\begin{cases} c(t) = c_{MAX} & if \quad \ddot{z}(\dot{z} - \dot{z}_t) \geq 0 \\ c(t) = c_{\min} & if \quad \ddot{z}(\dot{z} - \dot{z}_t) < 0 \end{cases}$$

It is optimal if the road profile is a white noise.

The switching behavior causes high frequency discomfort.

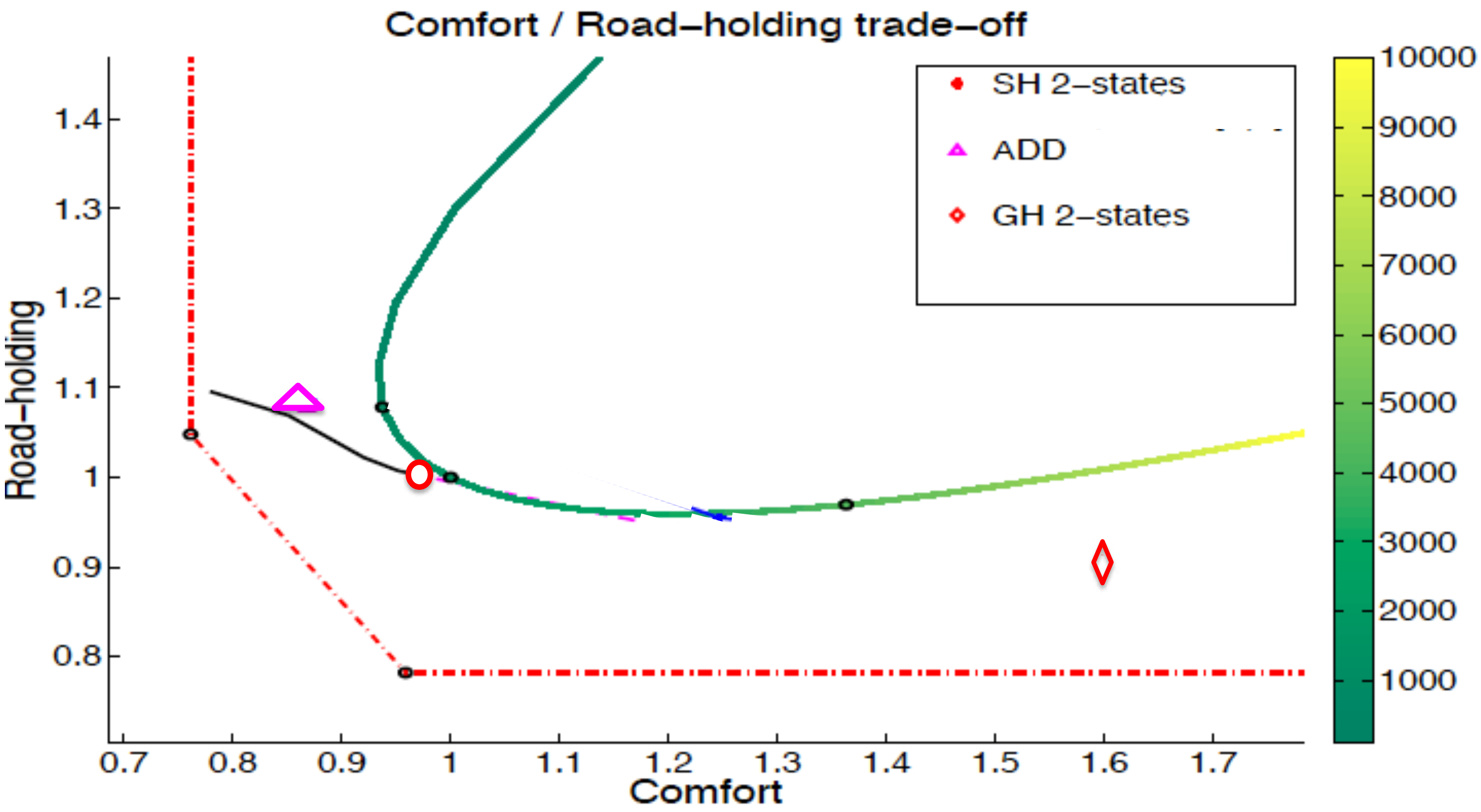
Semi-Active Damping Control

Ground-Hook Concept



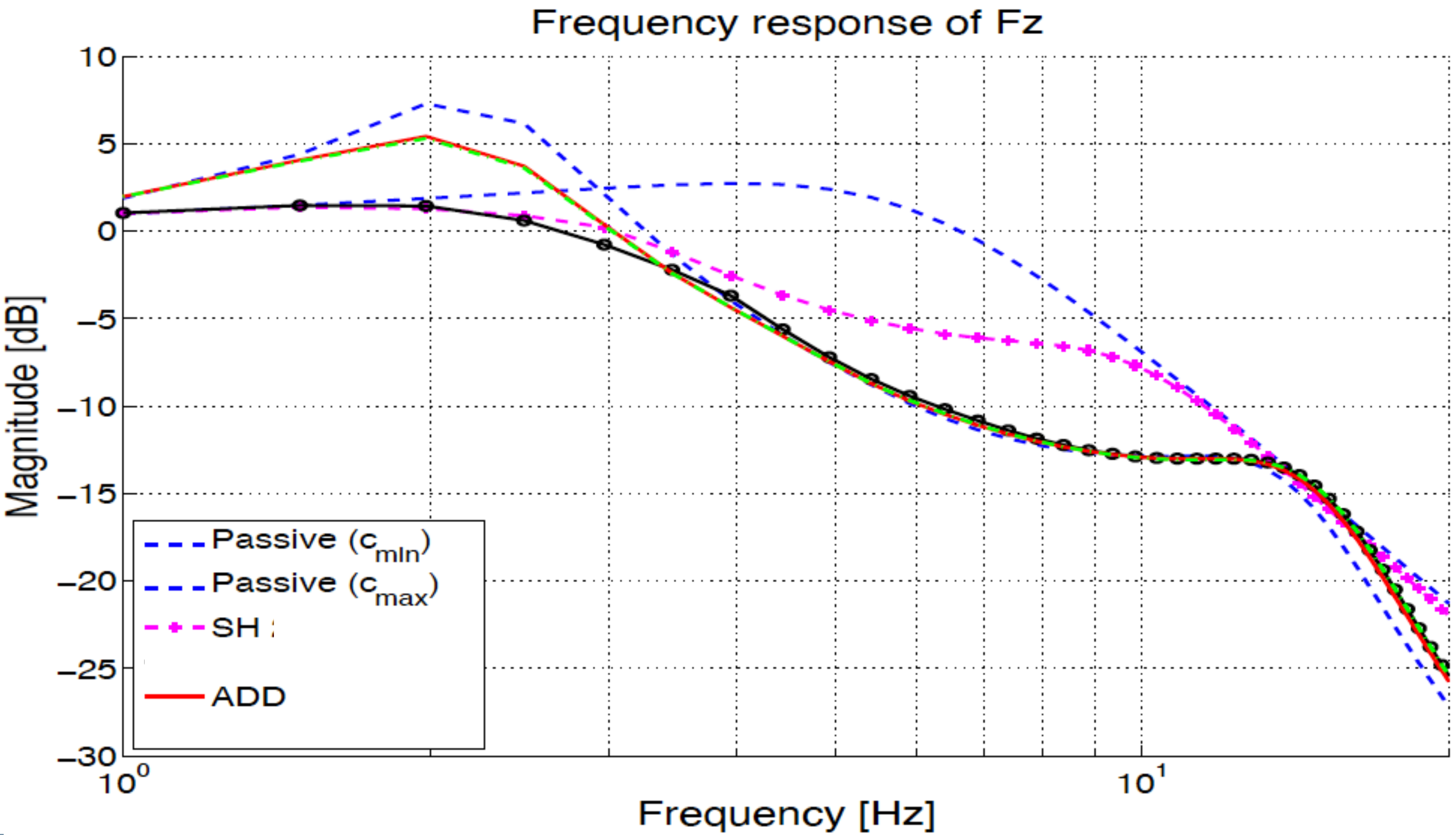
$$\begin{cases} c(t) = c_{MAX} & if \quad -\dot{z}_t(\dot{z} - \dot{z}_t) \geq 0 \\ c(t) = c_{\min} & if \quad -\dot{z}_t(\dot{z} - \dot{z}_t) < 0 \end{cases}$$

Acceleration Driven Damper Control



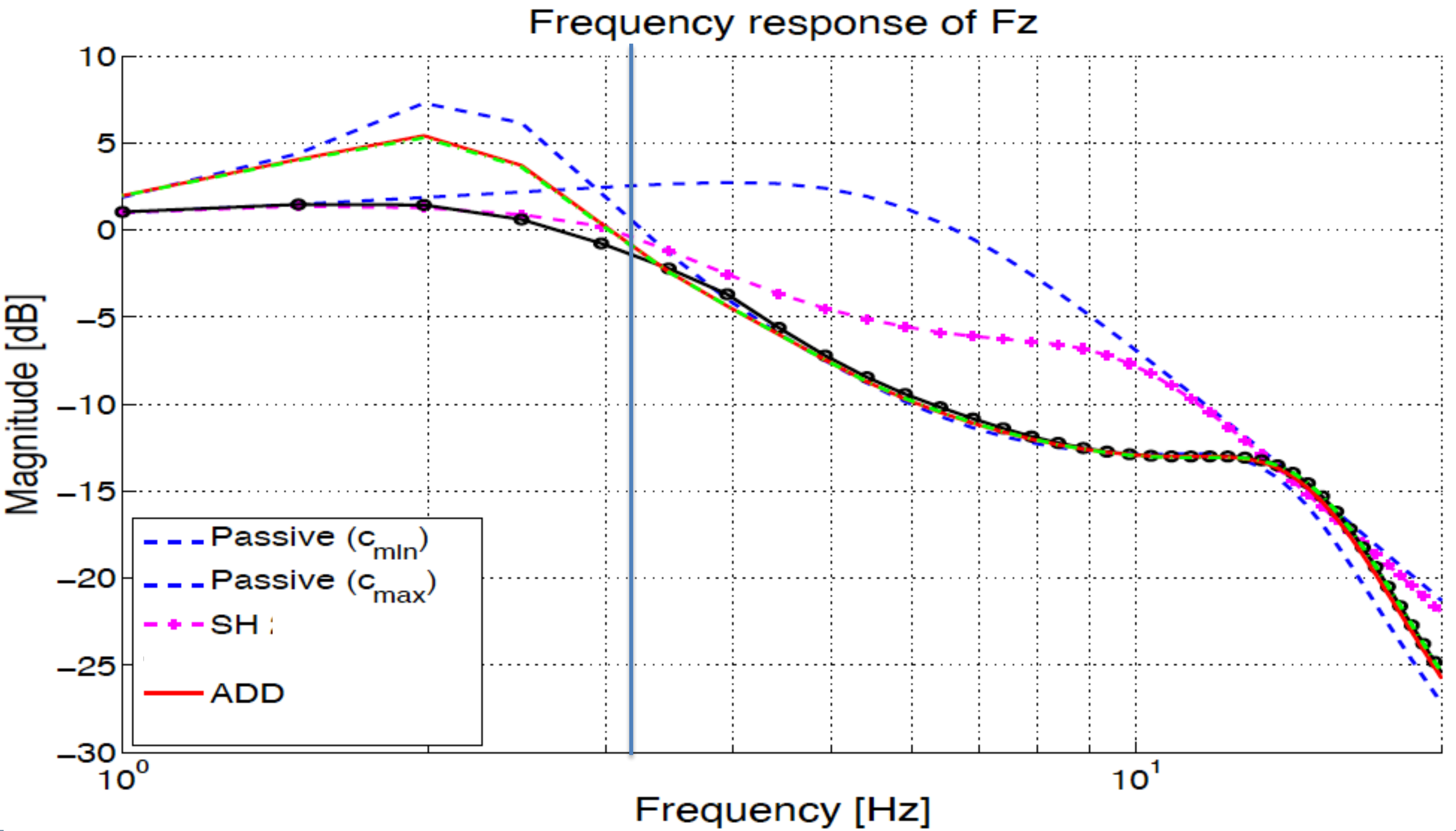
Semi-Active Damping Control

Acceleration Driven Damper Control



Semi-Active Damping Control

Acceleration Driven Damper Control



Idea: distinguish the instantaneous dynamical behavior of the suspension: in case of low frequency dynamic the SH is selected while the ADD is selected otherwise

$$\begin{cases} c_{in}(t) = c_{\max} & if \left[(\ddot{z}^2 - \alpha^2 \dot{z}^2) \le 0 \quad \wedge \quad \dot{z}(\dot{z} - \dot{z}_t) > 0\right] \quad \vee \quad \left[(\ddot{z}^2 - \alpha^2 \dot{z}^2) > 0 \quad \wedge \quad \ddot{z}(\dot{z} - \dot{z}_t) > 0\right] \\ c_{in}(t) = c_{\min} & if \left[(\ddot{z}^2 - \alpha^2 \dot{z}^2) \le 0 \quad \wedge \quad \dot{z}(\dot{z} - \dot{z}_t) \le 0\right] \quad \vee \quad \left[(\ddot{z}^2 - \alpha^2 \dot{z}^2) > 0 \quad \wedge \quad \ddot{z}(\dot{z} - \dot{z}_t) \le 0\right] \end{cases}$$

Frequency Selector — SH — ADD

Consider the single tone $\dot{z}(t) = Asin(\omega t)$

And the frequency selector $f(t) = \ddot{z}(t)^2 - \alpha^2 \dot{z}(t)^2$

$$f(t) = A^2\omega^2 - A^2 \sin^2(\omega t)(\alpha^2\omega^2)$$

We can see that $$f(t) > 0 \quad \Rightarrow \quad \sin^2(\omega t) < \frac{\omega^2}{\omega^2 + \alpha^2}$$

If we call $$D_+(\omega) - \{t : f(t) > 0, 0 \leq t \leq T\}$$

$$|D_+(\omega)| = \frac{2T}{\pi} \arcsin\left(\sqrt{\frac{\omega^2}{\omega^2 + \alpha^2}}\right)$$

Semi-Active Damping Control

Frequency Range Selector

$$\frac{|D_+(\omega)|}{T} \rightarrow 0 \text{ if } \omega \ll \alpha$$

$$\frac{|D_+(\omega)|}{T} \rightarrow 1 \text{ if } \omega \gg \alpha$$

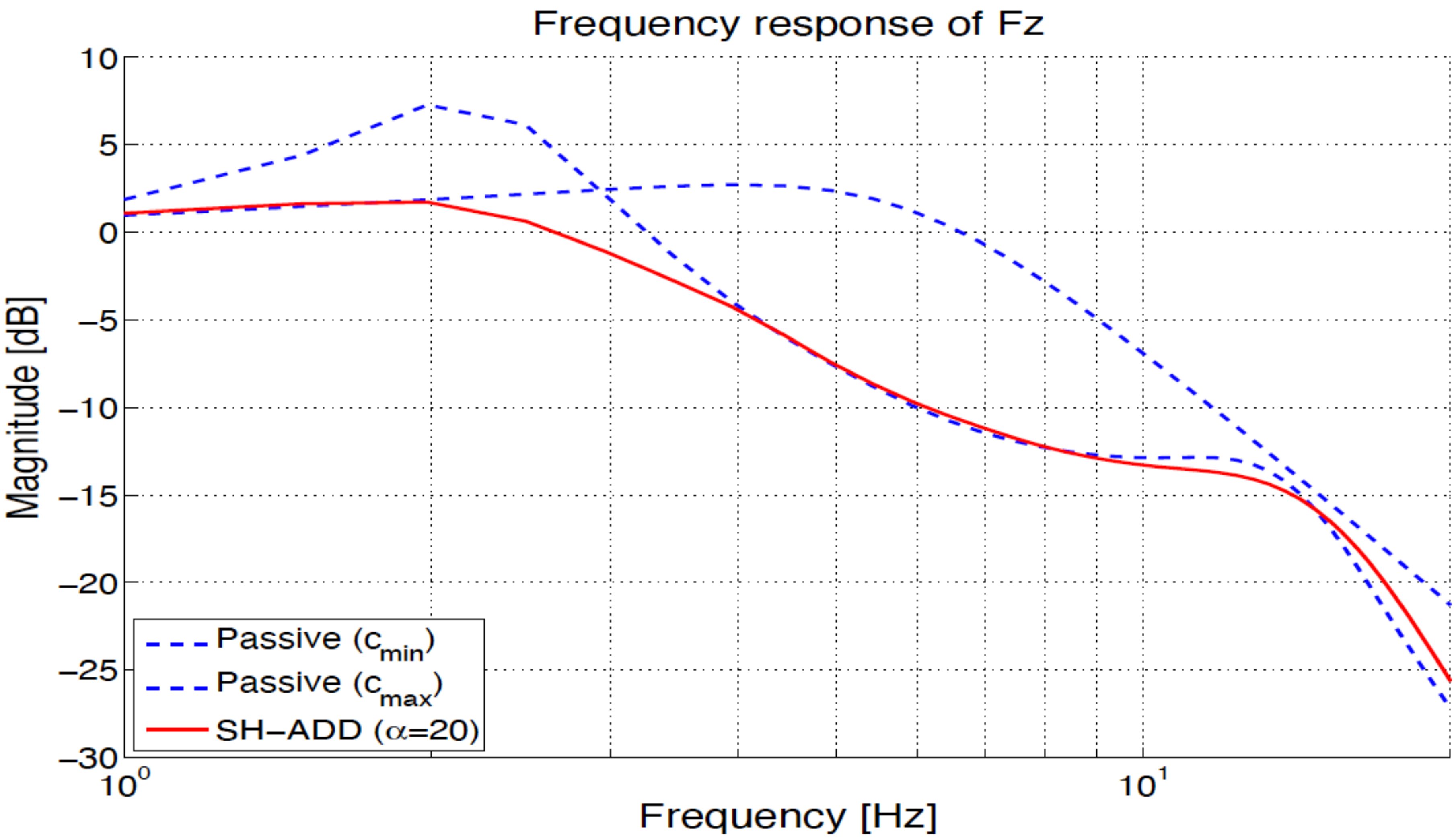
$$\frac{|D_+(\omega)|}{T} = \frac{1}{2} \text{ if } \omega = \alpha$$

Over a period T:

- $f(t)>0$ for more than T/2 if $\omega > \alpha$.
- $f(t)<0$ for more than T/2 if $\omega < \alpha$.

Semi-Active Damping Control

Frequency Range Selector



$$
\begin{cases}
c_{in}(t) = c_{\max} & \text{if } \left[(\ddot{z}^2 - \alpha^2 \dot{z}^2) \le 0 \quad \wedge \quad \dot{z}(\dot{z} - \dot{z}_t) > 0 \right] \vee \left[(\ddot{z}^2 - \alpha^2 \dot{z}^2) > 0 \quad \wedge \quad \ddot{z}(\dot{z} - \dot{z}_t) > 0 \right] \\
c_{in}(t) = c_{\min} & \text{if } \left[(\ddot{z}^2 - \alpha^2 \dot{z}^2) \le 0 \quad \wedge \quad \dot{z}(\dot{z} - \dot{z}_t) \le 0 \right] \vee \left[(\ddot{z}^2 - \alpha^2 \dot{z}^2) > 0 \quad \wedge \quad \ddot{z}(\dot{z} - \dot{z}_t) \le 0 \right]
\end{cases}
$$

The mixed SH-ADD control logic requires:

- Stroke velocity
- Corner acceleration and velocity

Two sensors for each corner

- Potentiometer
- Accelerometer

Semi-Active Damping Control

Single Sensor Mix Algorithm

$$\begin{cases} c_{in}(t) = c_{\max} & if \left[(\ddot{z}^2 - \alpha^2 \dot{z}^2) \le 0 \quad \wedge \quad \dot{z}(\dot{z} - \dot{z}_t) > 0\right] \quad \vee \quad \left[(\ddot{z}^2 - \alpha^2 \dot{z}^2) > 0 \quad \wedge \quad \ddot{z}(\dot{z} - \dot{z}_t) > 0\right] \\ c_{in}(t) = c_{\min} & if \left[(\ddot{z}^2 - \alpha^2 \dot{z}^2) \le 0 \quad \wedge \quad \dot{z}(\dot{z} - \dot{z}_t) \le 0\right] \quad \vee \quad \left[(\ddot{z}^2 - \alpha^2 \dot{z}^2) > 0 \quad \wedge \quad \ddot{z}(\dot{z} - \dot{z}_t) \le 0\right] \end{cases}$$

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Semi-Active Damping Control

Single Sensor Mix Algorithm

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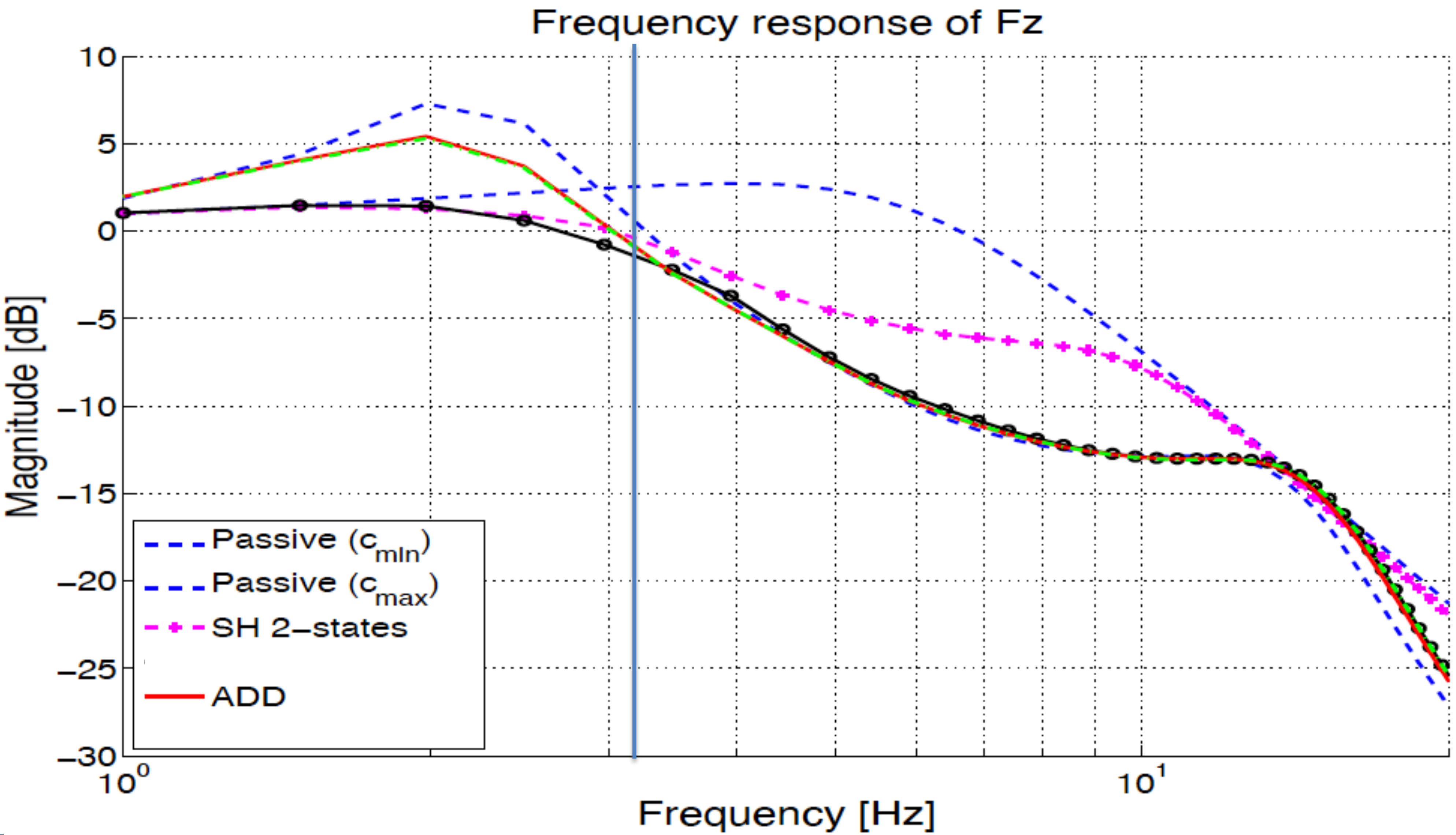
The mixed SH-ADD control logic requires:

- Stroke velocity
- Corner acceleration and velocity

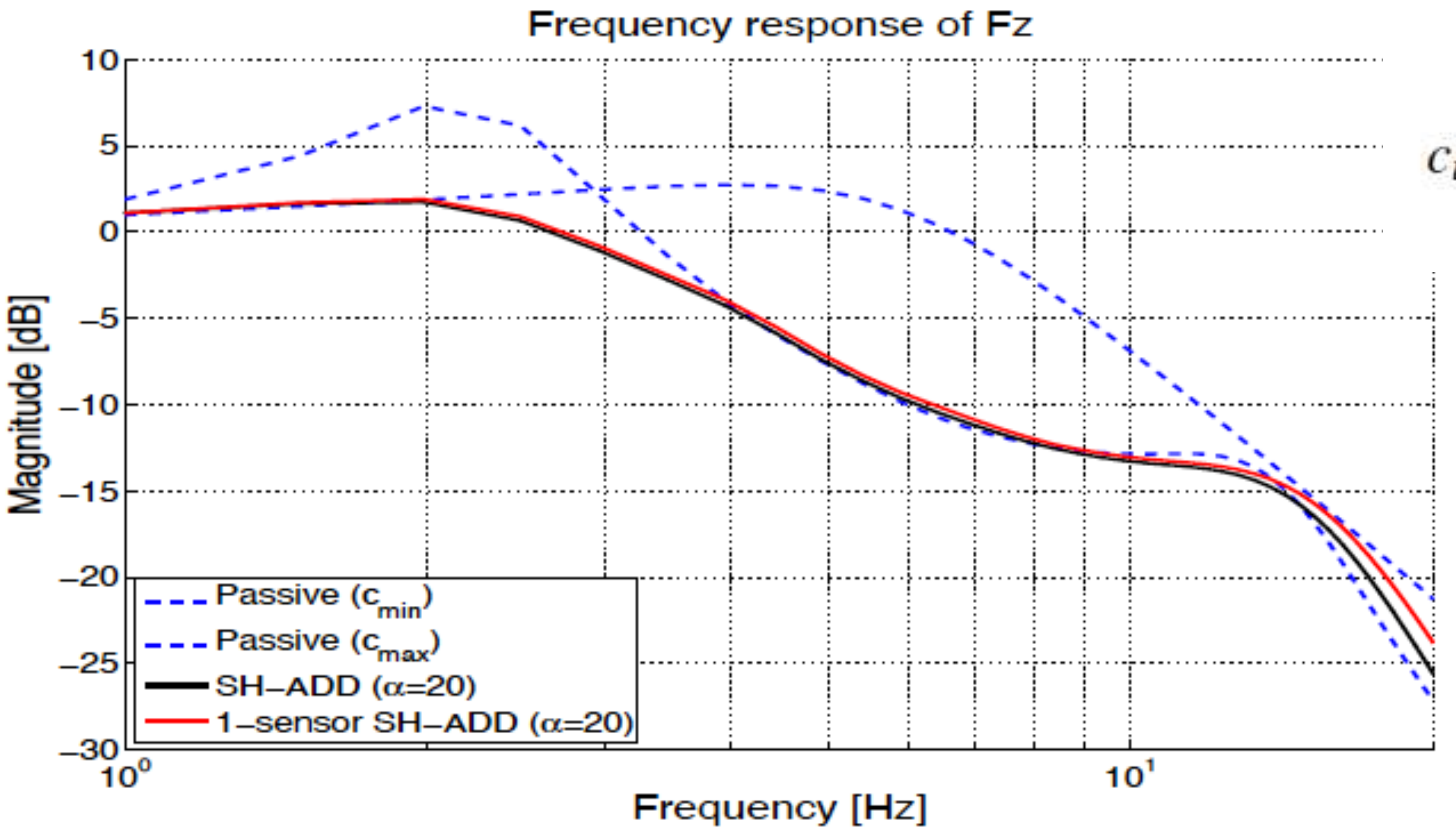
The frequency selector uses only the accelerometer
→ what happens if we use only the frequency selector?

Semi-Active Damping Control

Single Sensor Mix Algorithm

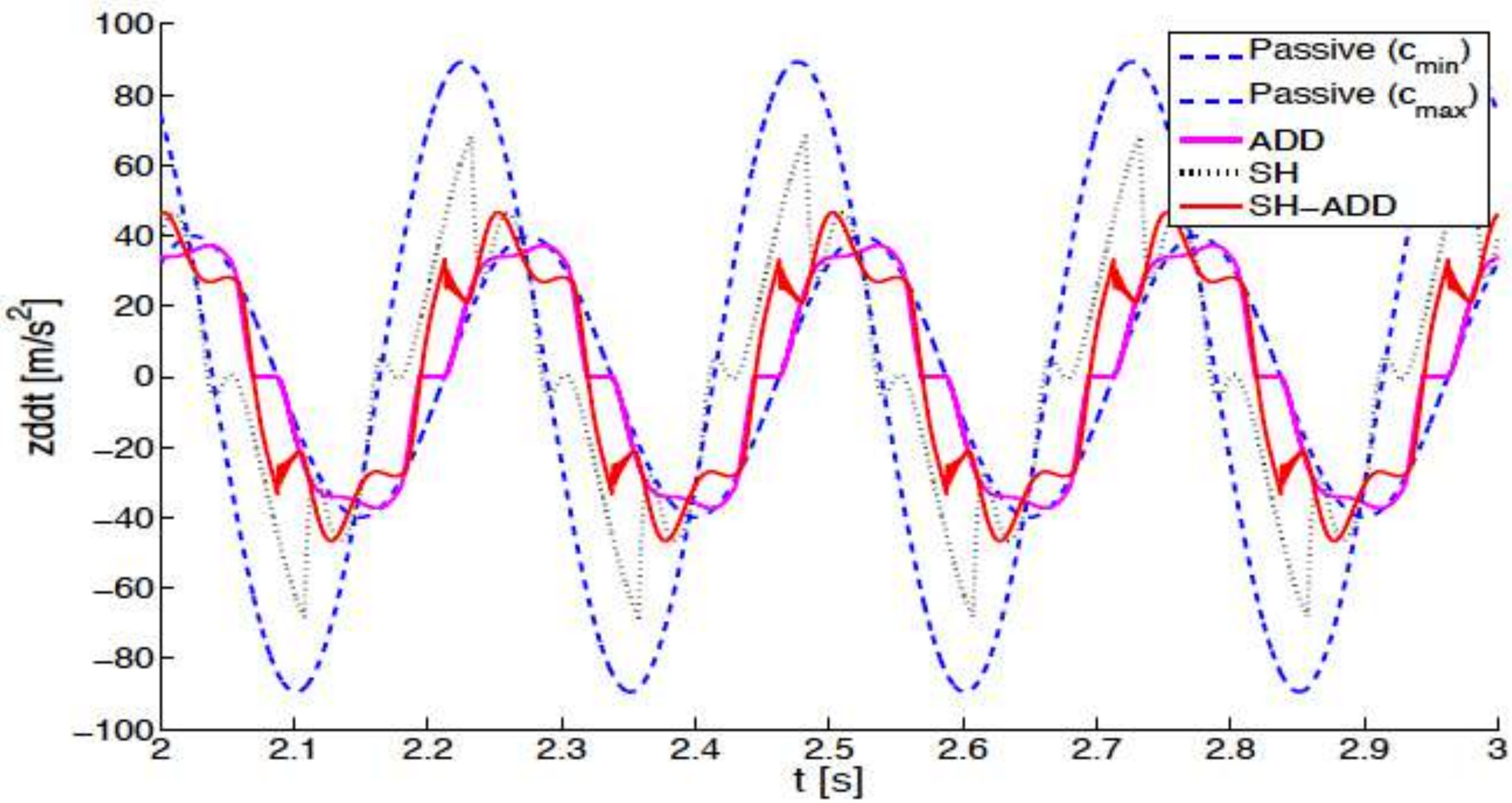


Single sensor Mix Algorithm



$$c_{in} = \begin{cases} c_{min} & \text{if } (\ddot{z}^2 - \alpha^2 \dot{z}^2) \leq 0 \\ c_{max} & \text{if } (\ddot{z}^2 - \alpha^2 \dot{z}^2) > 0 \end{cases}$$

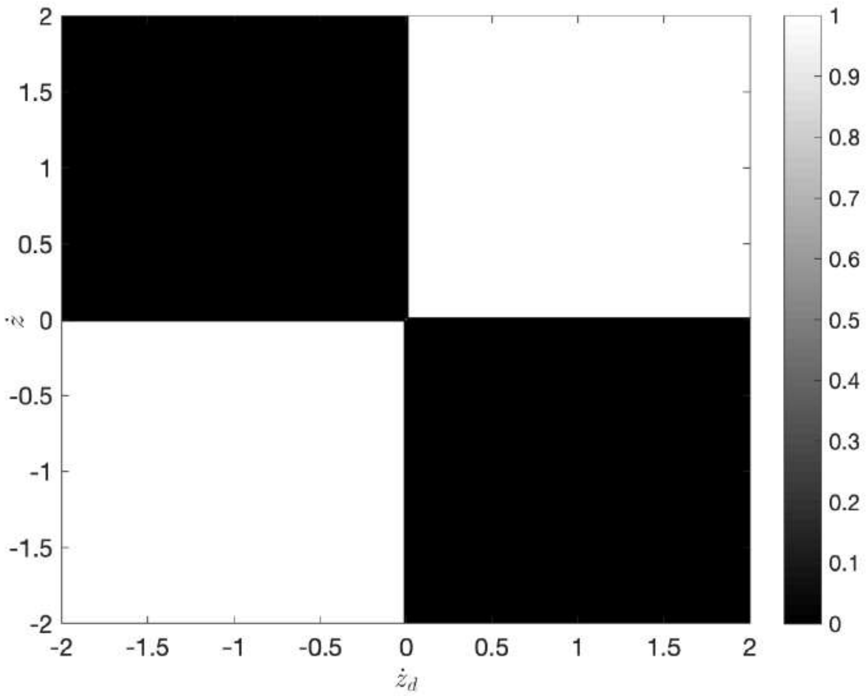
Both versions of the algorithm are switching algorithms:

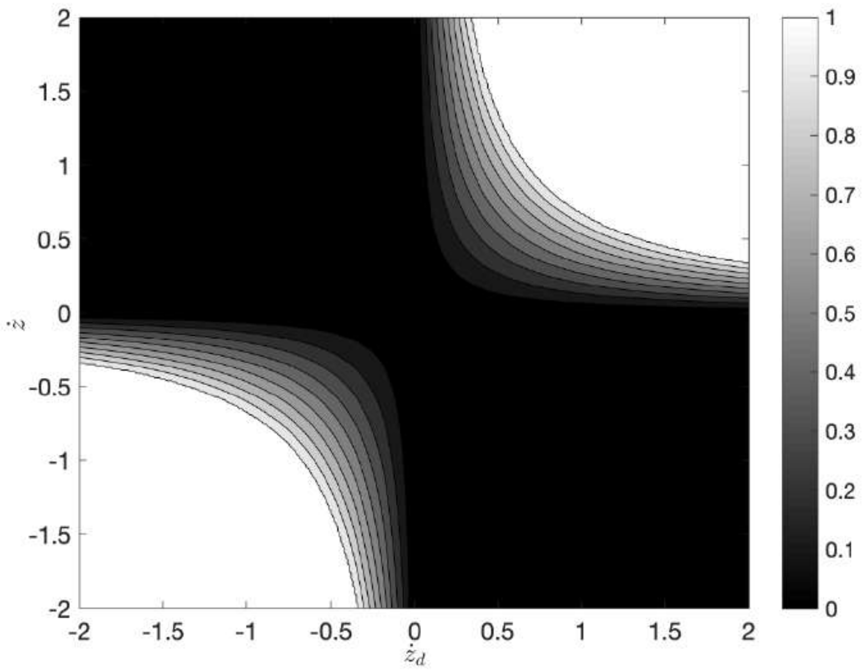


Idea: propose a continuously modulating version of the SH and ADD and combine the two.

Continuously modulating SH:

$$c_{ref} = \underset{c_{ref} \in [c_{min}; c_{max}]}{\text{sat}} (k_{sky} \dot{z} \dot{z}_d + c_{nom})$$

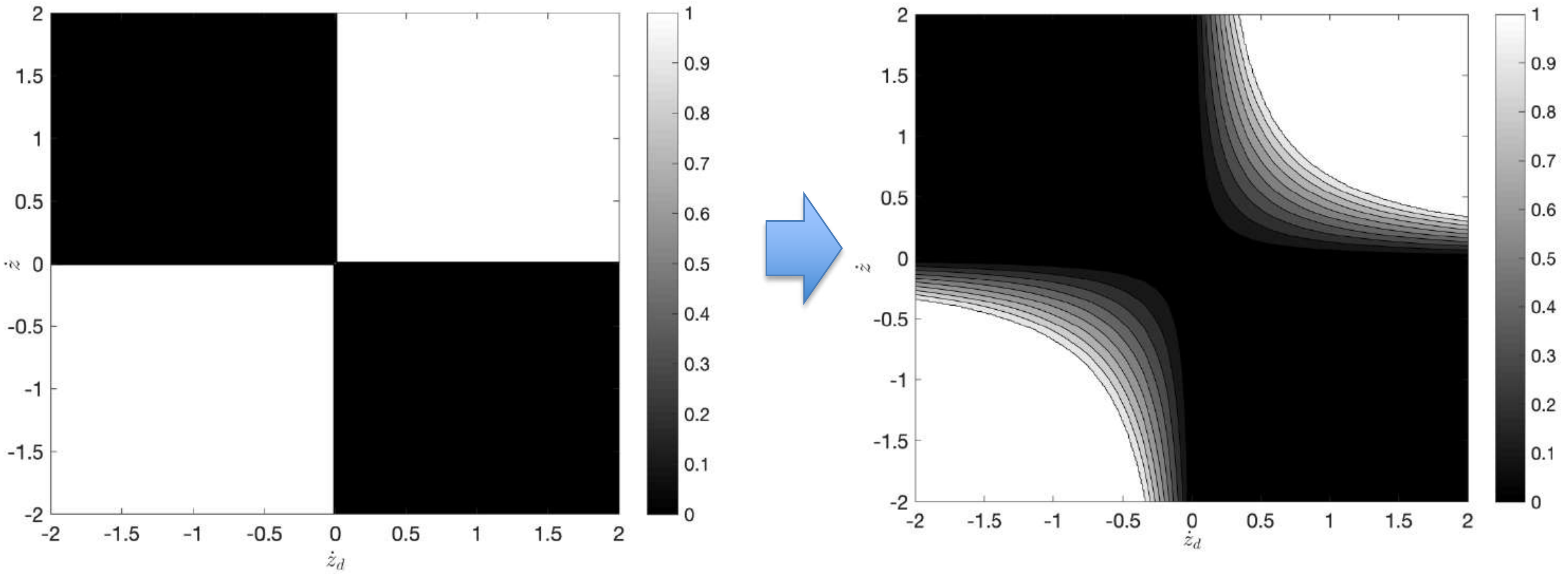




- Smooth
- Easily parametrizable
- It converges to the switching algorithm when k_{sky} increases

Idea: propose a continuously modulating version of the SH and ADD and combine the two.

Continuously modulating ADD: $c_{ref} = sat_{[c_{min},c_{max}]}(k_{ADD}\ddot{z}_b\Delta\dot{z})$



Idea: propose a continuously modulating version of the SH and ADD and combine the two.

Continuously mixed SH- ADD: $c_{ref} = sat_{[c_{min},c_{max}]}(c_{nom} + k_{SH}\dot{z}_b\Delta z + k_{ADD}\ddot{z}_b\Delta\dot{z})$

Idea: propose a continuously modulating version of the SH and ADD and combine the two.

Continuously mixed SH- ADD: $c_{ref} = sat_{[c_{min},c_{max}]}(c_{nom} + k_{SH}\dot{z}_b\Delta z + k_{ADD}\ddot{z}_b\Delta\dot{z})$

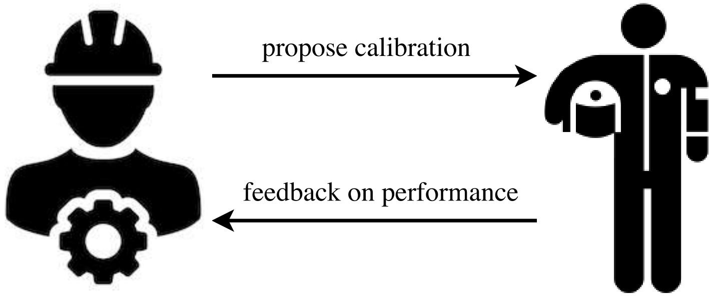
We can extend the approach to the single-sensor philosophy

$$\begin{cases} c_{ref} = c_{min}, & if\left(\ddot{z}_b^2 - \alpha^2\dot{z}_b^2\right) \leq 0 \\ c_{ref} = c_{max}, & if\left(\ddot{z}_b^2 - \alpha^2\dot{z}_b^2\right) > 0 \end{cases}$$

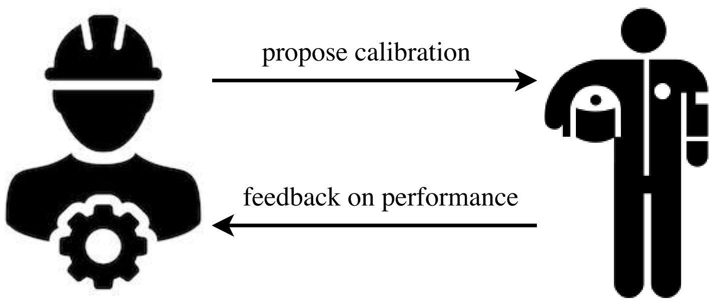
$$\Rightarrow \quad c_{ref} = sat_{[c_{min},c_{max}]}(k_{M1S}|sat_{[-\infty,0]}\left(\ddot{z}_b^2 - \alpha^2\dot{z}_b^2\right)|)$$

- Continuously increase the damping at low frequency.
- Keep minimum damping at high frequency.

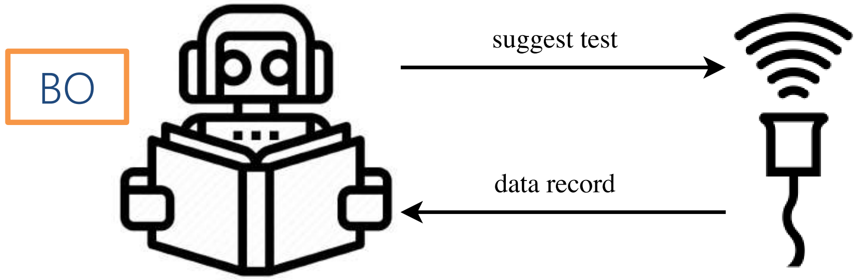
(A) traditional calibration



(A) traditional calibration



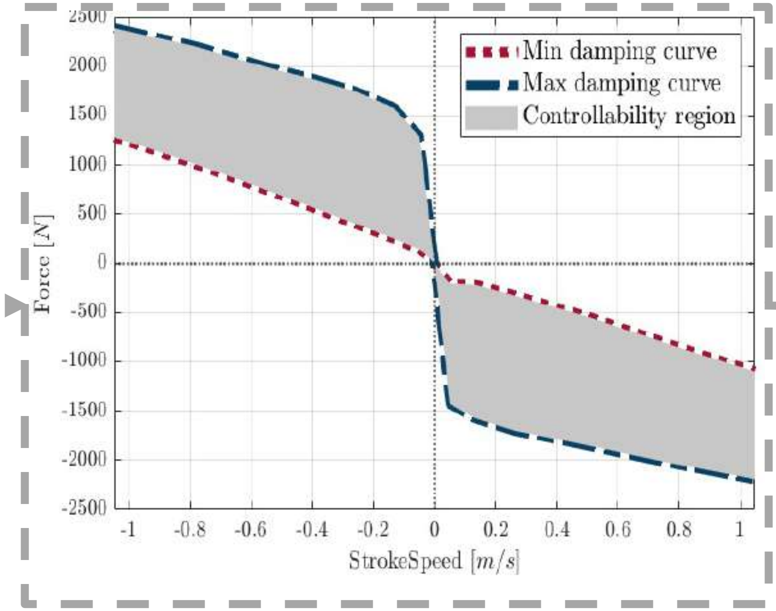
(B) automatic performance-based paradigm



Semi-Active Damping Control

Calibration

Experimental MR damper curves



VI-GRADE

Damping reference command (x4)

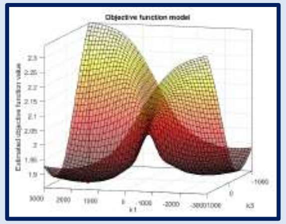
Control strategy

Corner accelerations (x4)
Stroke velocities (x4)

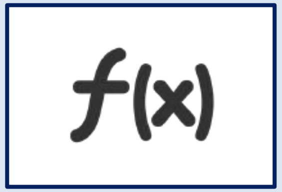
Bayesian Optimization

Data-driven optimization technique suitable for **cost-to-evaluate objective function.**

At each optimization step:

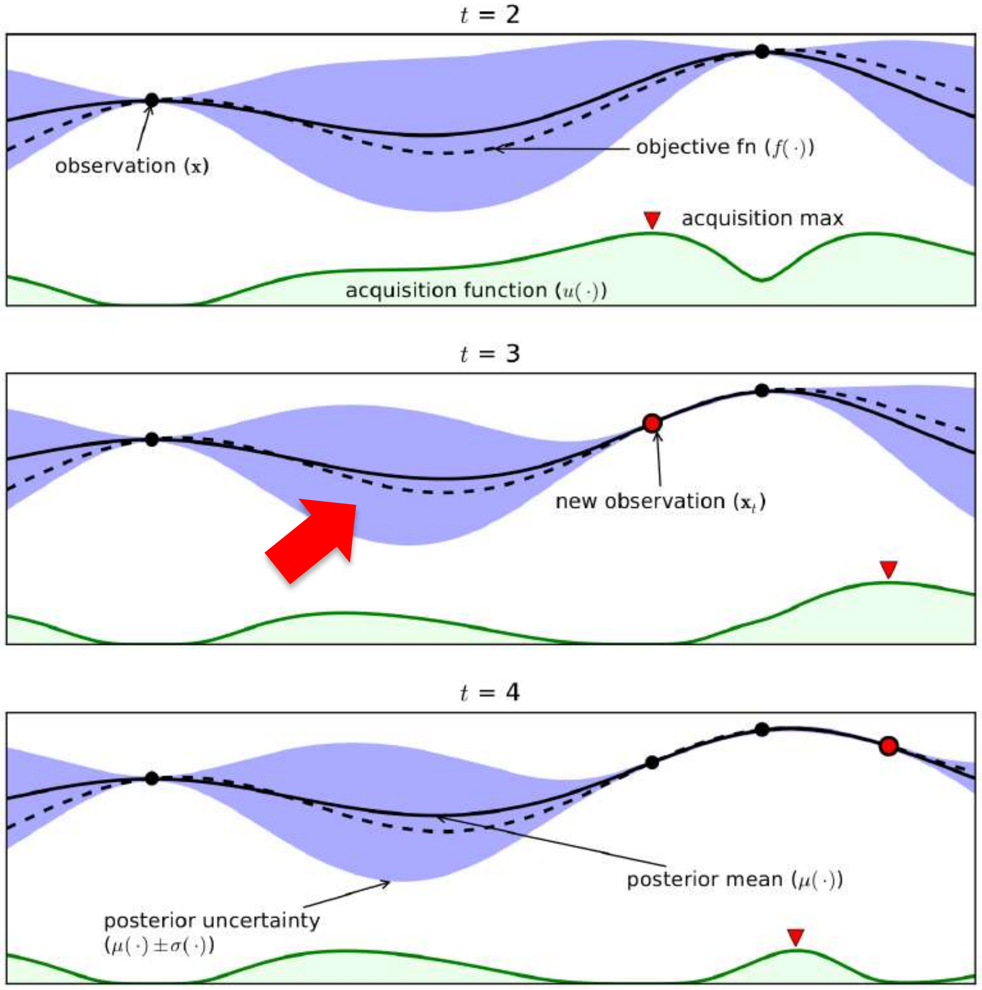


Objective function is modeled as a realization of a Gaussian Process



An **acquisition function** determines where to sample the parameters space next.

Frazier, P.I. (2018). A tutorial on bayesian optimization. arXiv preprint arXiv:1807.02811.



The objective function is not explicitly known.

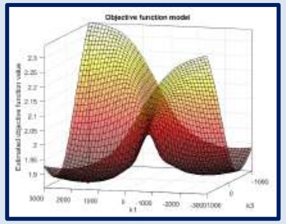
It can be considered a **stationary gaussian process.**

A known surrogate of the objective function (**Acquisition Function**) is optimized at each iteration.

Bayesian Optimization

Data-driven optimization technique suitable for **cost-to-evaluate objective function.**

At each optimization step:



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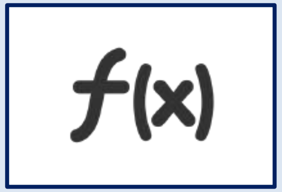


An **acquisition function** determines where to sample the parameters space next.

Frazier, P.I. (2018). A tutorial on bayesian optimization. arXiv preprint arXiv:1807.02811.

Several acquisition functions:

Expected Improvement: The assumption is to return only explored values. We maximize the a posteriori expected improvement

$$\mathrm{EI}_n(x) := E_n\left[[f(x) - f_n^*]^+\right]$$

EI is efficient to compute and to maximize

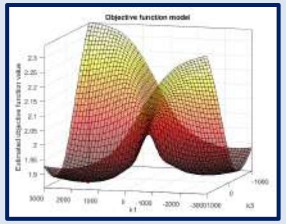
Knowledge Gradient: We allow the decision-maker to return any solution she likes,

Entropy Search: acquisition function values the information we have about the location of the global maximum according to its differential entropy

Bayesian Optimization

Data-driven optimization technique suitable for **hard-to-evaluate objective function.**

At each optimization step:



Objective function is modeled as a realization of a Gaussian Process

f(x)

An **acquisition function** determines where to sample the parameters space next.

Frazier, P.I. (2018). A tutorial on bayesian optimization. arXiv preprint arXiv:1807.02811.

Objective function

Typical quantitative performance index for ride comfort:

$$min_{\Theta}\left[\frac{1}{T}\int_0^T A_z(t,\Theta)^2 dt\right]$$

Where:

- $\Theta = control\ algorithm\ parameters$
- $A_z = chassis\ CoG\ vertical\ acceleration$

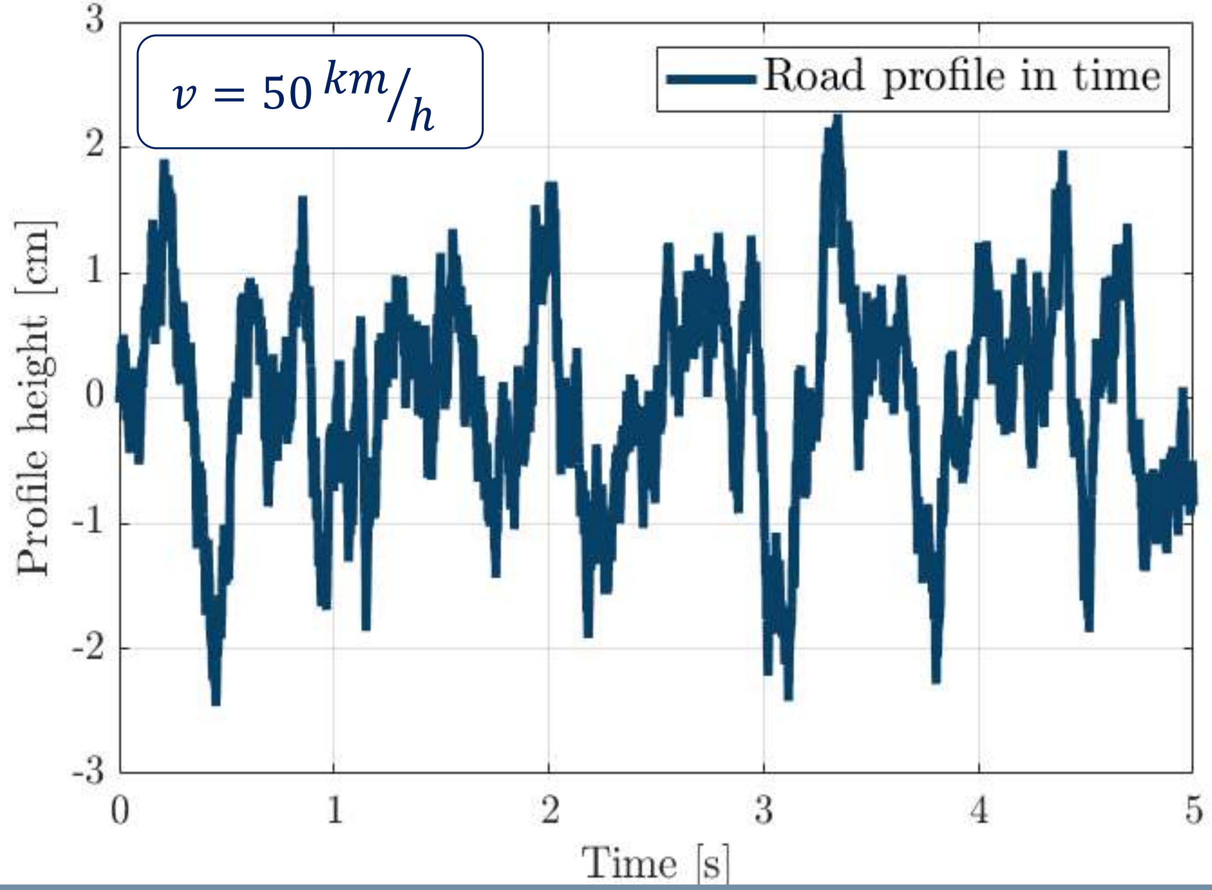
Optimization settings

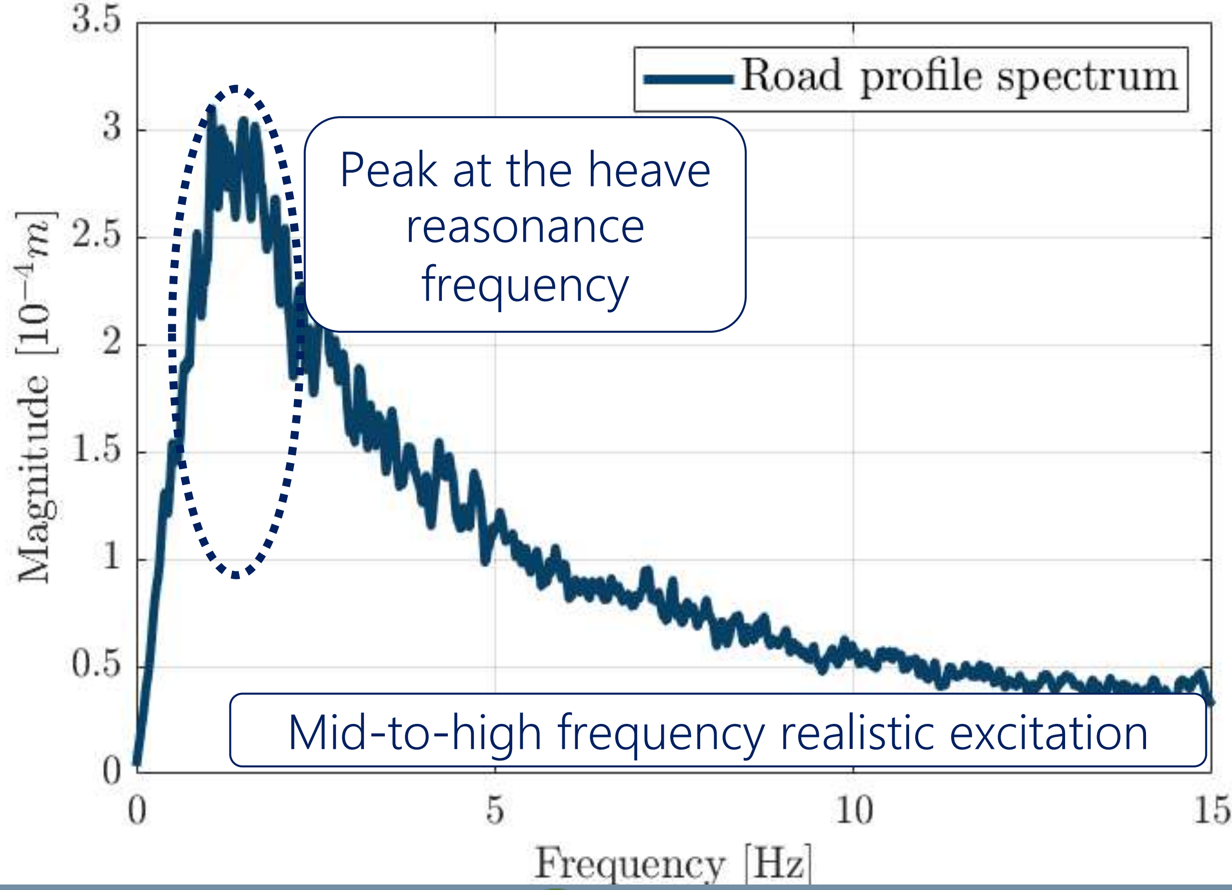
Range of parameters: obtained by sensitivity analysis

Number of iterations: 100 ~ 150

Standard ISO – 8608 C-D road profile: regular-to-poor road scenario

$$h(x) = \sum_{i=0}^{N} \sqrt{\Delta n} 2^k 10^{-3} \left(\frac{n_0}{i\Delta n}\right) \cos(2\pi i \Delta n x + \phi_i)$$





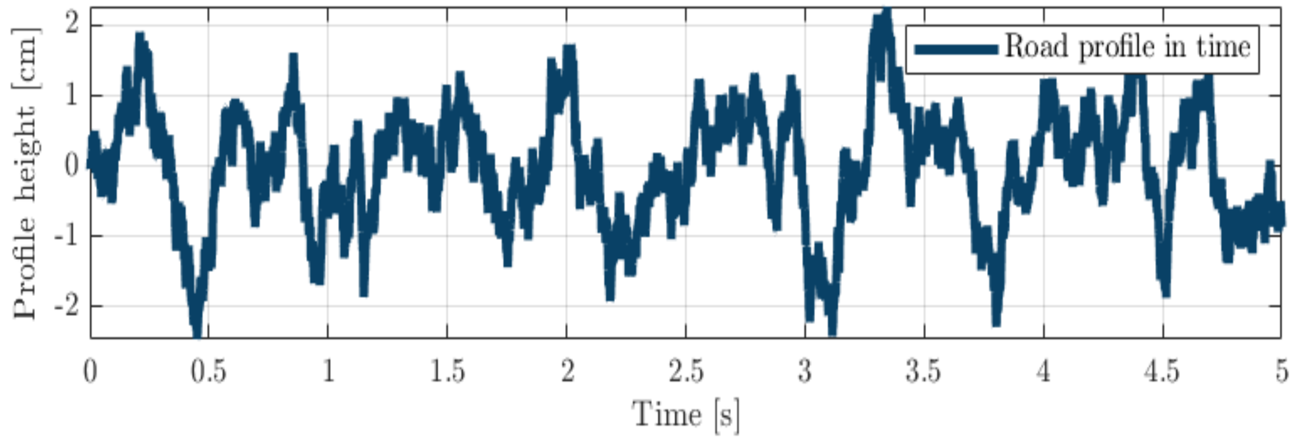
Road profile

20 realizations of the ISO road profile

$$h(x) = \boxed{\sum_{i=0}^{N} \sqrt{\Delta n} 2^k 10^{-3}} \left(\frac{n_0}{i\Delta n}\right) \cos\boxed{(2\pi i \Delta n x + \phi_i)}$$

Amplitude fixed by the standard

Phase lag randomly generated



Performance indexes

- Acceleration index:

$$J_{A_z} = \frac{1}{T}\int_0^T A_z(t)^2 dt$$

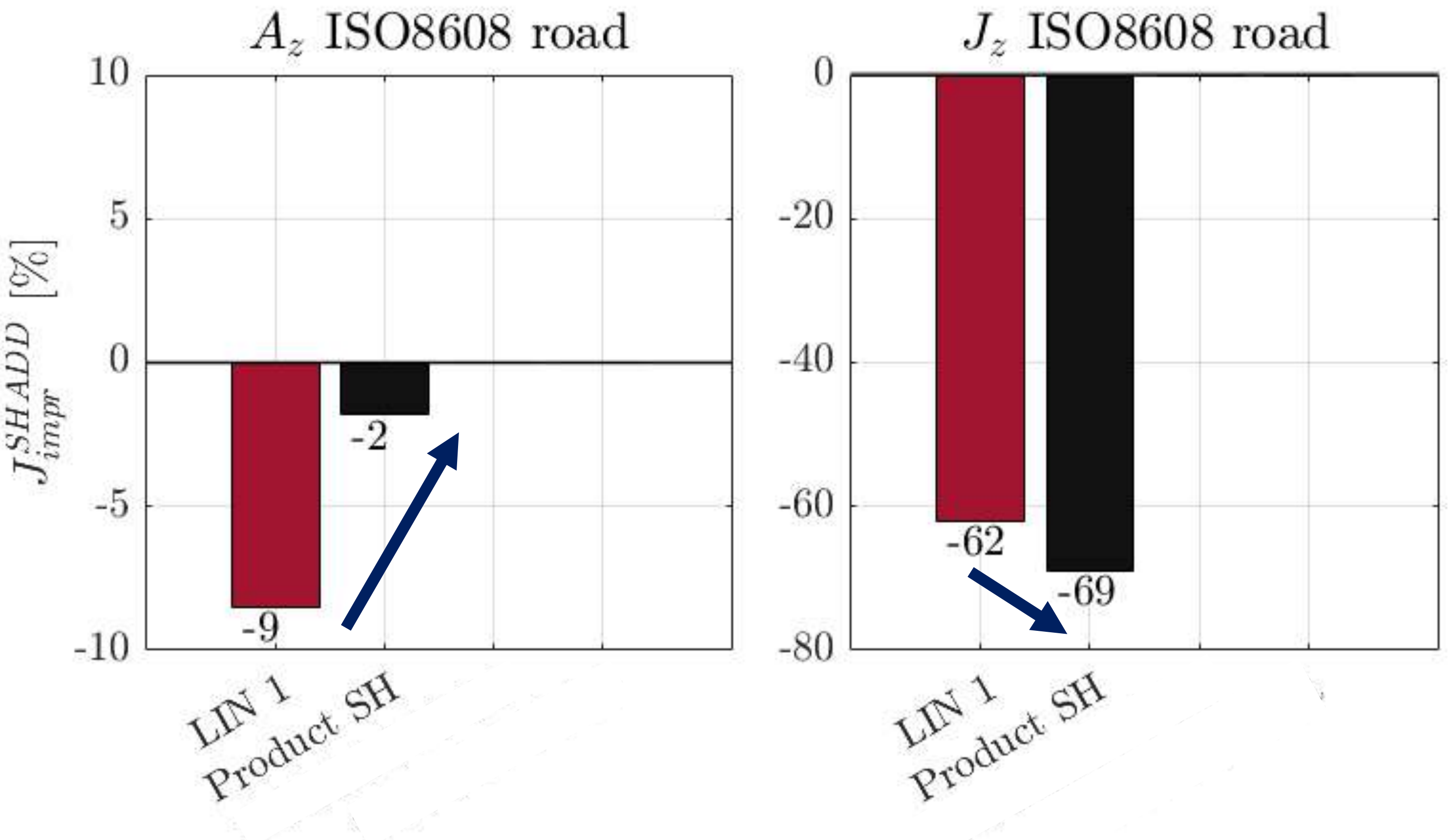
- Vertical jerk index

$$J_{J_z} = \frac{1}{T}\int_0^T J_z(t)^2 dt$$

Indexes are reported as percentage improvement with respect to the original Mix SH-ADD:

$$J_{impr}^{A_z,J_z} = \frac{J_{A_z,J_z} - J_{A_z,J_z}^{SHADD}}{J_{A_z,J_z}^{SHADD}} \times 100$$

The continuously modulating Mix SH-ADD is benchmarked against the Product SkyHook.
Index values are the average over the 20 experiments.



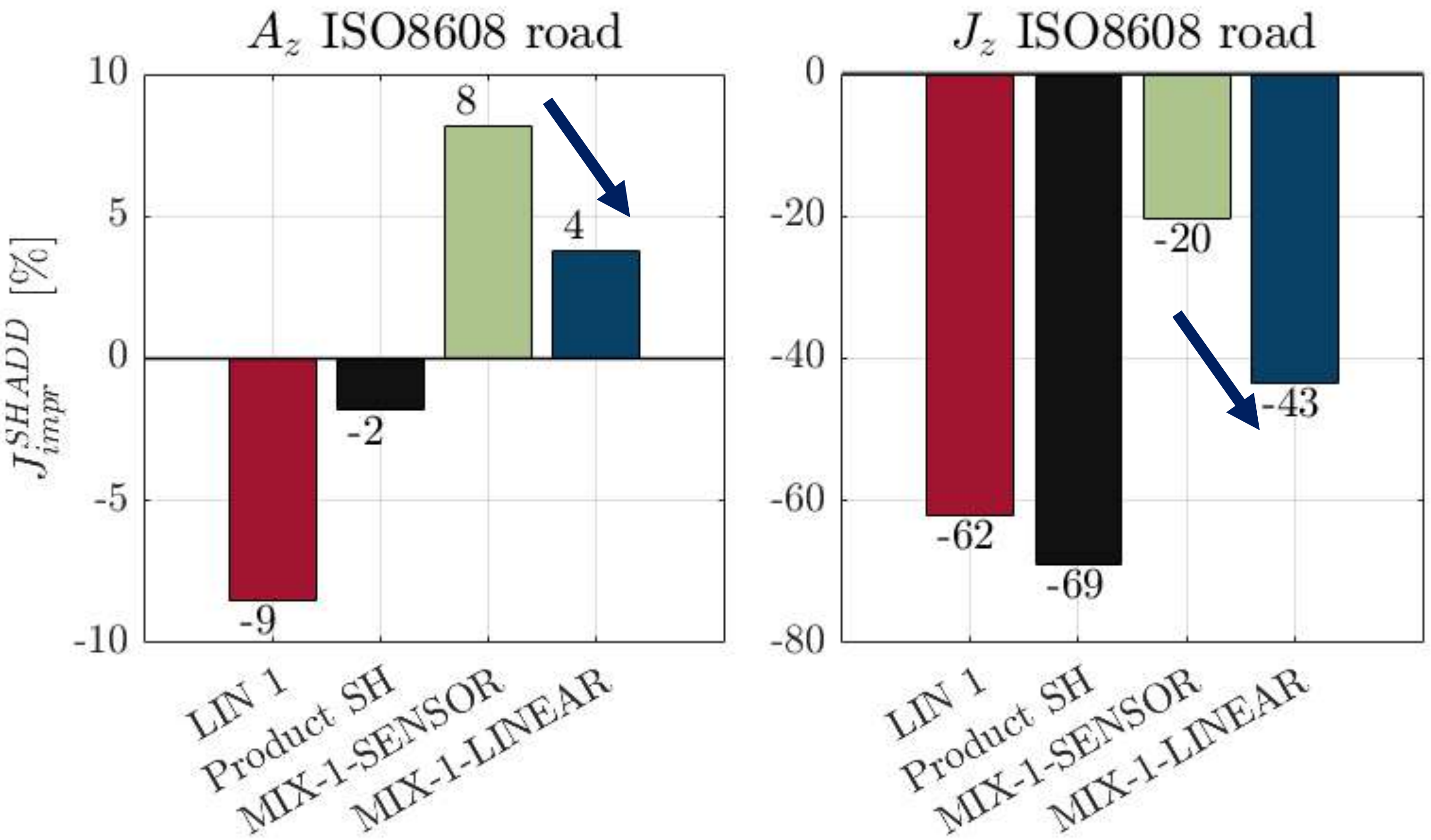
Benchmark with switching Mix SH-ADD:

- $J_{impr}^{A_z} = 9\%$
- $J_{impr}^{j_z} = 62\%$

Benchmark with Product SH:

- Better filtering of road excitation
- Slightly higher vertical jerk.

The Mix-1-Linear is benchmarked against the Mix-1-Sensor algorithm.
Index values are the average over the 20 experiments.

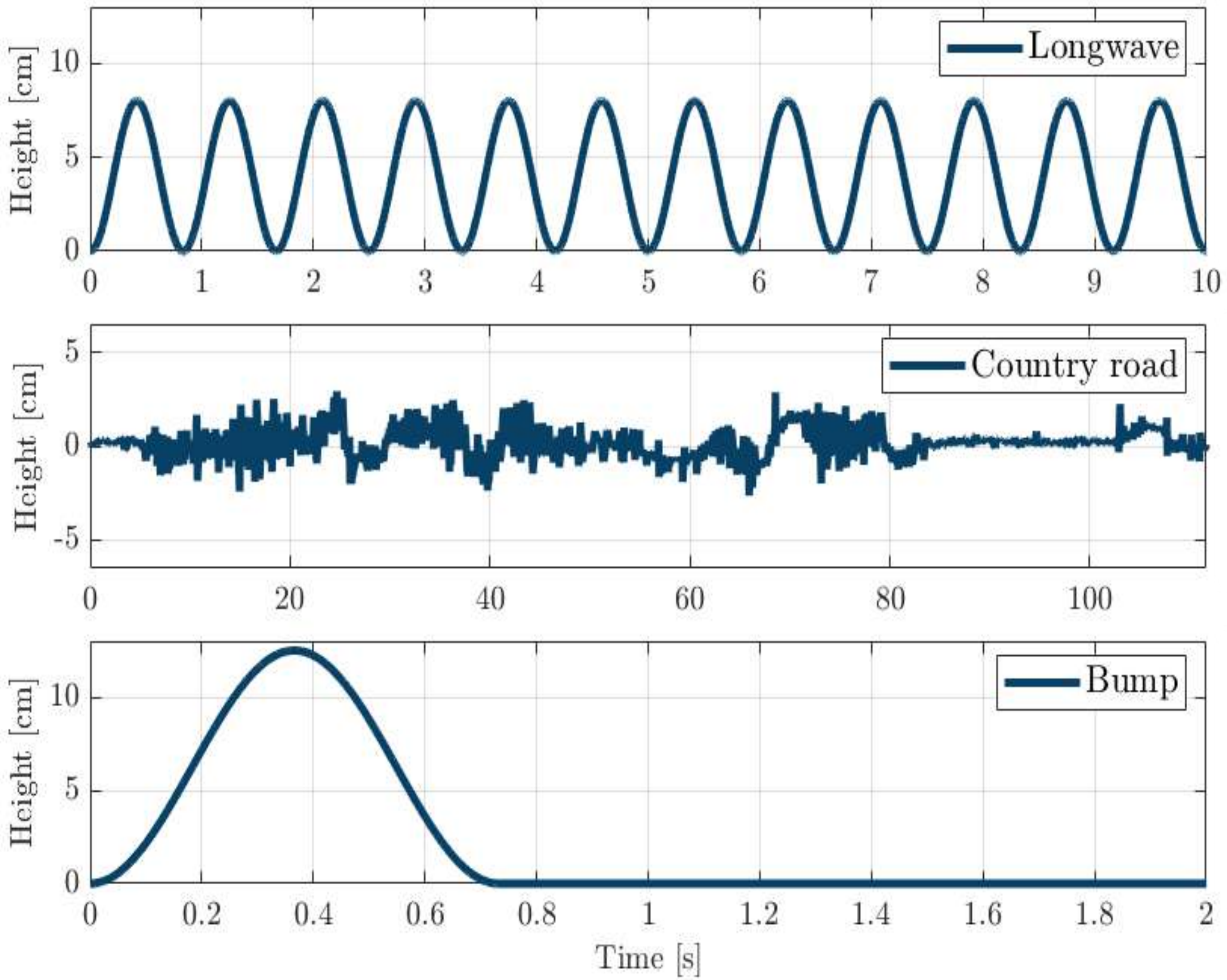


Benchmark with switching Mix SH-ADD:

- $J_{impr}^{A_z} = -4\%$ ∽ due to reduced setup
- $J_{impr}^{jz} = 43\%$

Benchmark with Mix-1-Sensor:

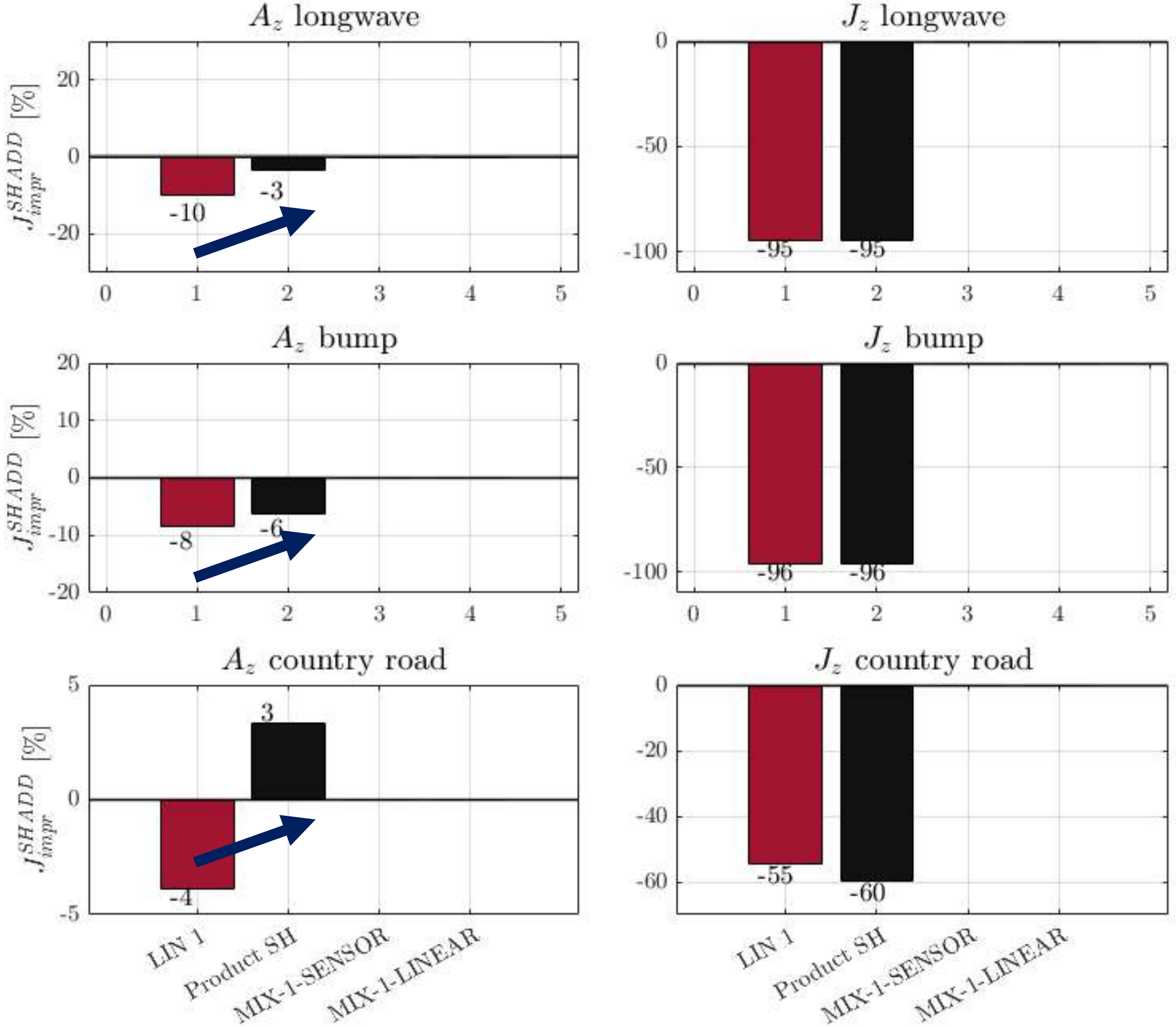
- Better filtering of road excitation
- Better reduction of vertical jerk



Performance indexes are the ones introduced for the validation on the ISO road profile.

Semi-Active Damping Control

Validation

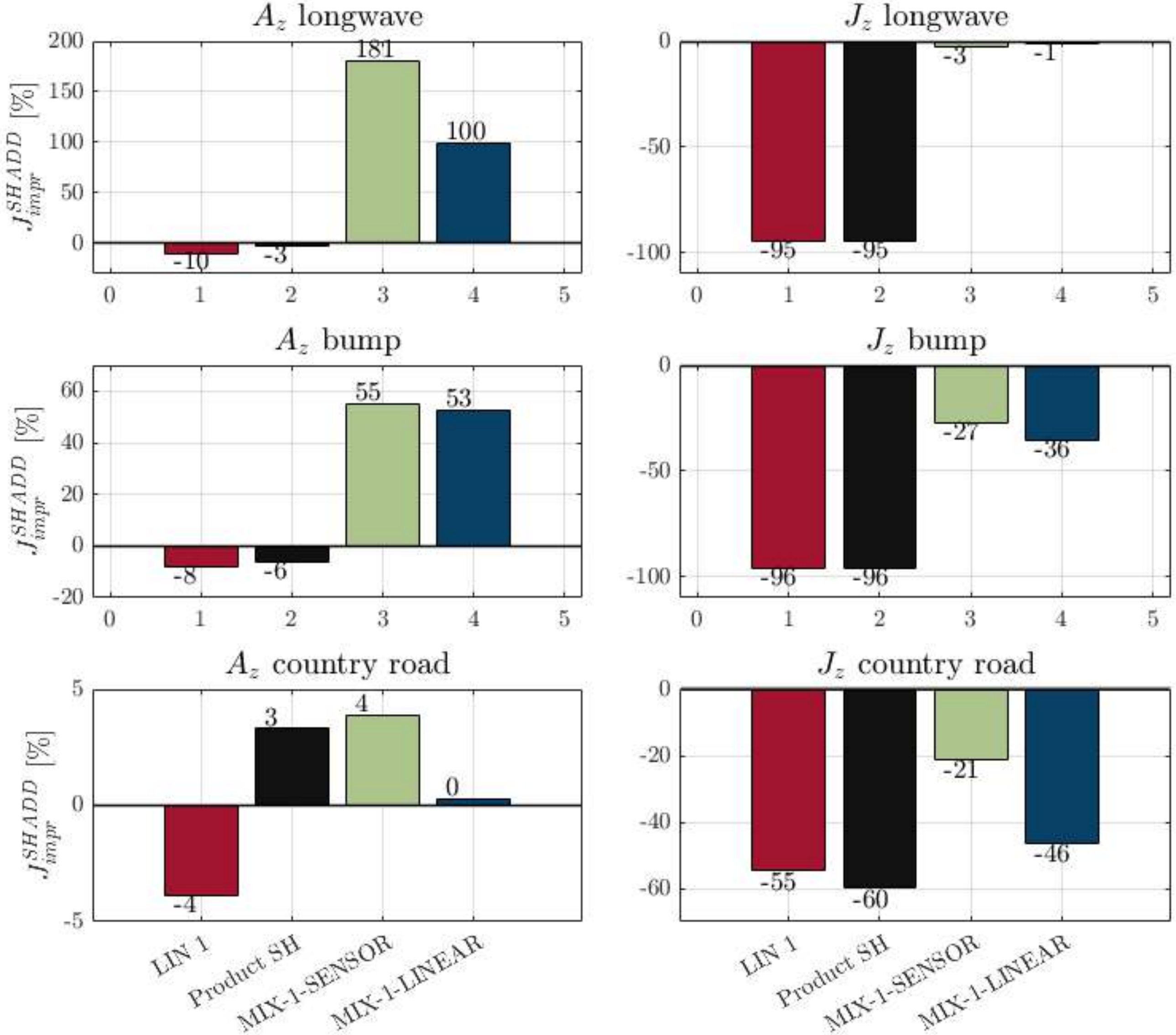


- Improvement in terms of A_z filtering on all validation profiles (up to 10%).
- Reduction of J_z on all validation profiles (up to 96%).

- Better filtering of road excitation on validation profiles.
- Comparable vertical jerk on all validation profiles.

Semi-Active Damping Control

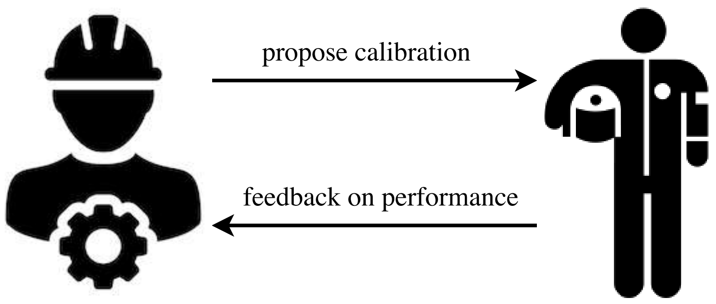
Validation



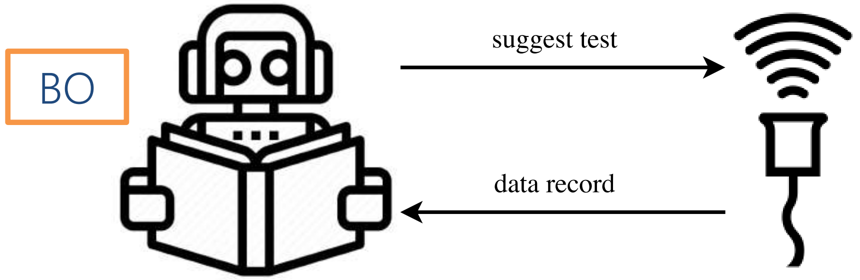
- Expected degradation of performance in terms of A_z filtering, due to reduced setup.
- Comparable or lower J_z on all validation profiles (up to 46% improvement on *country*).

- Better filtering of road excitation on *longwave* and *bump*, comparable on *country road*.
- Better reduction of vertical jerk on *bump* and *country road*, comparable on *longwave.*

(A) traditional calibration

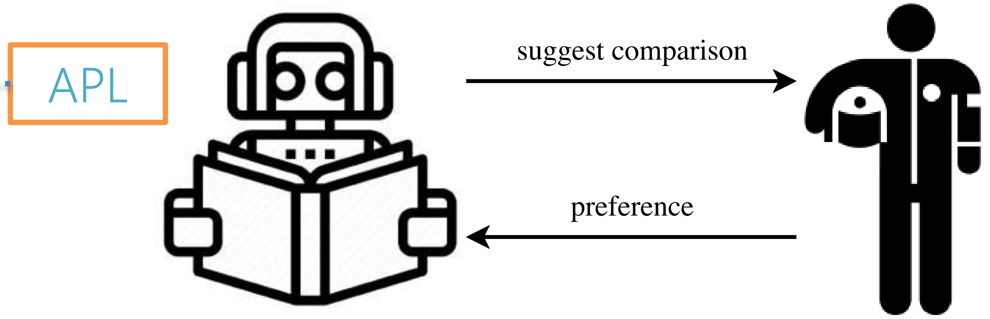


(B) automatic performance-based paradigm



Savaia, Sohn, Formentin, Panzani, Corno, Savaresi –
Experimental Automatic Calibration of a Semi-Active Suspension Controller via Bayesian Optimization,
Journal of Systems and Control, 2021 [in press]

(C) semi-automatic preference-based paradigm



[Bemporad, 2020] – Active preference learning based on radial basis functions.

- Advantages w.r.t. (A)
  - ➢ time/cost of experiments
- Advantages w.r.t. (B)
  - ➢ **model-free**
  - ➢ optimization **tailored to** subjective **preference**

- $x \in \mathbb{R}^n$ decision vector ($\mathbb{R}^n$ decision variable space).

$x = \begin{bmatrix} \vartheta_F \\ \vartheta_R \end{bmatrix} \in \mathbb{R}^2$

- π: $\mathbb{R}^n \times \mathbb{R}^n \to \{-1,0,1\}$ preference function defined as:

$$\pi(x_1, x_2) = \begin{cases} -1 & \text{if } x_1 \text{ is better than } x_2 \\ 0 & \text{if } x_1 \text{ is as good as } x_2 \\ 1 & \text{if } x_1 \text{ is worst than } x_2 \end{cases}$$

Assumption: properties of π.

- reflexivity
  $\pi(x_1, x_1) = 0 \ \forall x_1 \in \mathbb{R}^n$
- anticommutativity
  $\pi(x_1, x_2) = -\pi(x_2, x_1) \ \forall x_1, x_2 \in \mathbb{R}^n$
- transitivity
  $\pi(x_1, x_2) = \pi(x_2, x_3) = -1$
  $\Rightarrow \pi(x_1, x_3) = -1 \ \forall x_1, x_2, x_3 \in \mathbb{R}^n$

Find **best preference vector**, inside **the feasible space**.

$$\text{find } x^* \text{ s.t. } \pi(x^*, x) \leq 0, \ \forall x \in \mathbb{R}^n, \ l \leq x \leq u$$

$l, u \in \mathbb{R}^n$: lower and upper bound on x.

$l = \begin{bmatrix} 0 \\ 0 \end{bmatrix}, u = \begin{bmatrix} 166 \\ 166 \end{bmatrix}$

APL Methodology

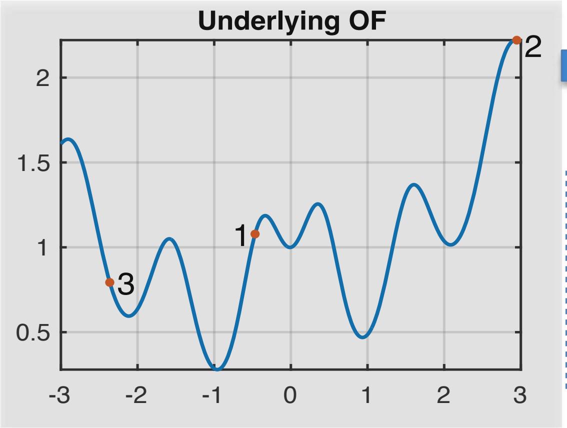
APL: general scheme

Initialization + scaling

1) Learn the **surrogate function** → $\hat{f}(x)$

2) Define the **acquisition function** → $a(x)$

3) Generate the **next sample** to test → x_{N+1}



$$\pi(x_1, x_2) = \begin{cases} -1 & \text{if } f(x_1) - f(x_2) < -\sigma_f \\ 0 & \text{if } |f(x_1) - f(x_2)| \leq \sigma_f \\ 1 & \text{if } f(x_1) - f(x_2) > \sigma_f \end{cases}$$

σ_f: comparison tolerance

Generate 3 samples with LHS.

- It. 1: observe $\pi(x_1, x_2) = -1$ $(x_1^* = x_1)$
- It. 2: observe $\pi(x_1, x_3) = 1$ $(x_2^* = x_3)$

APL Methodology

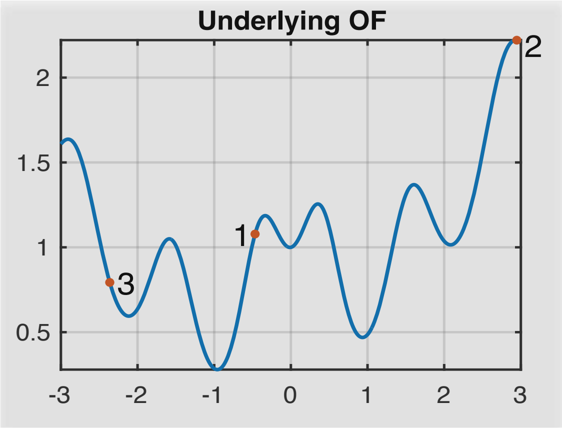
APL: general scheme

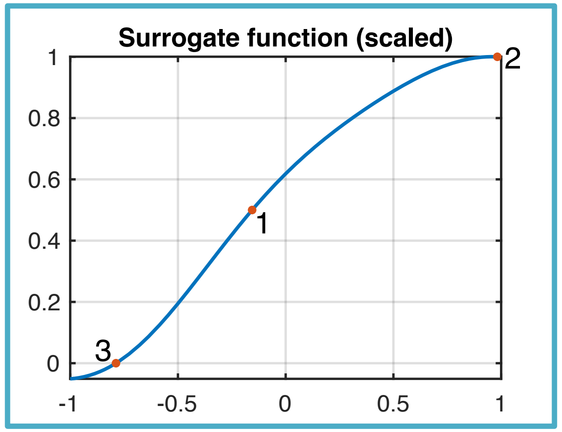
Initialization + scaling

1) Learn the surrogate function → $\hat{f}(x)$

2) Define the **acquisition function** → $a(x)$

3) Generate the **next sample** to test → x_{N+1}





$$
\begin{aligned}
\underset{\beta,\varepsilon}{\text{minimize}} \quad & \frac{\gamma}{2}\beta^T\beta + c^T\varepsilon \\
\text{subject to} \quad & (\Psi^{i(h)} - \Psi^{j(h)})\beta \leq -\sigma + \varepsilon_h \quad && \forall h : b_h = -1, \\
& (\Psi^{i(h)} - \Psi^{j(h)})\beta \geq \sigma - \varepsilon_h \quad && \forall h : b_h = 1, \\
& (\Psi^{i(h)} - \Psi^{j(h)})\beta \leq \sigma + \varepsilon_h \quad && \forall h : b_h = 0, \\
& (\Psi^{i(h)} - \Psi^{j(h)})\beta \geq -\sigma - \varepsilon_h \quad && \forall h : b_h = 0, \\
& \varepsilon_h \geq 0 \quad && \forall h
\end{aligned}
$$

↓ β

$$\hat{f}(x) = \sum_{i=1}^{N} \beta_i \phi(\epsilon d(x, x_i))$$

RBF-interpolant

APL Methodology

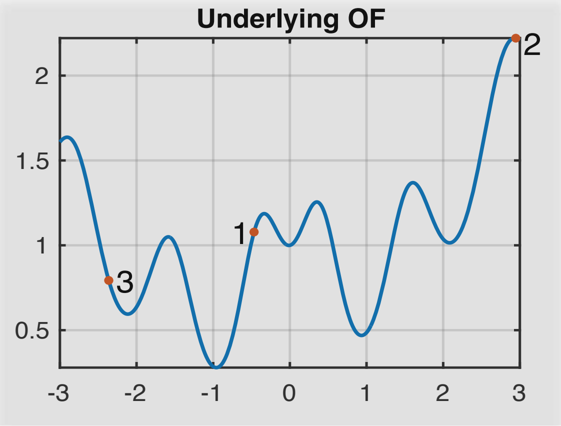
APL: general scheme

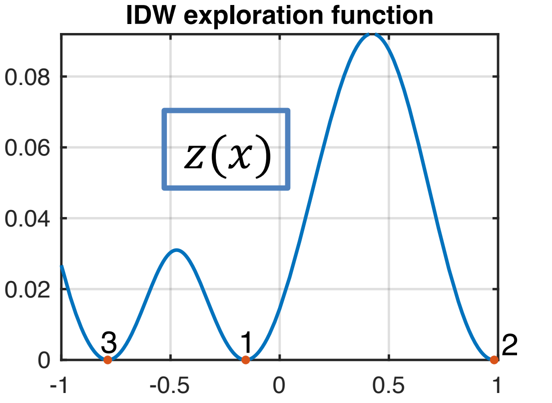
Initialization + scaling

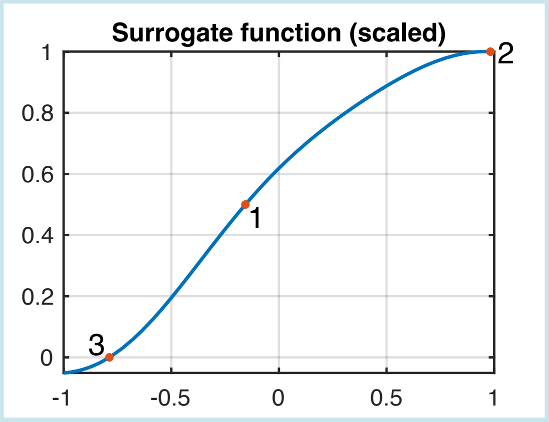
1) Learn the **surrogate function** → $\hat{f}(x)$

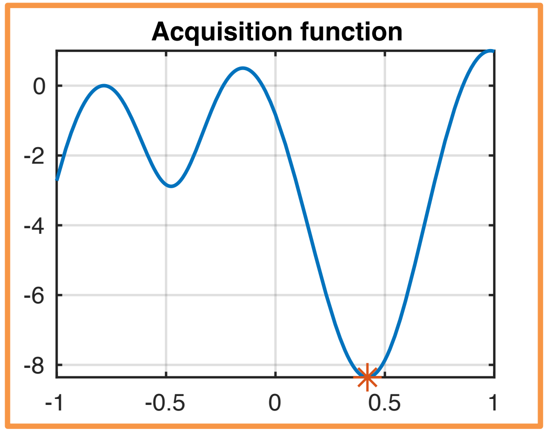
2) Define the **acquisition function** → $a(x)$

3) Generate the **next sample** to test → x_{N+1}









Exploration parameter $\delta \geq 0$

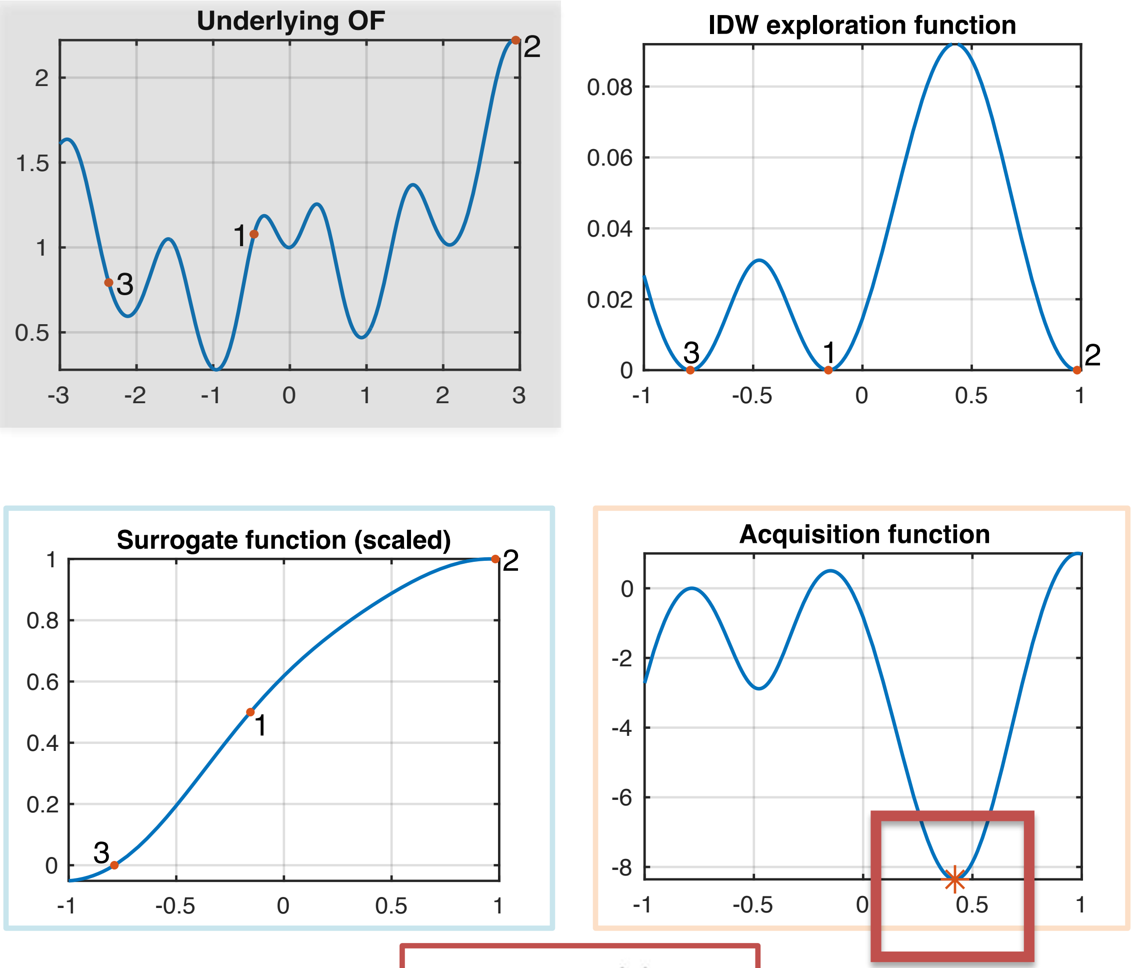
$$a(x) = \hat{f}(x) - \delta z(x)$$

Initialization + scaling

1) Learn the **surrogate function** → $\hat{f}(x)$

2) Define the **acquisition function** → $a(x)$

3) Generate the **next sample** to test → x_{N+1}



$$\begin{array}{ll} \underset{x}{\text{minimize}} & a(x) \\ \text{subject to} & l \leq x \leq u \end{array}$$

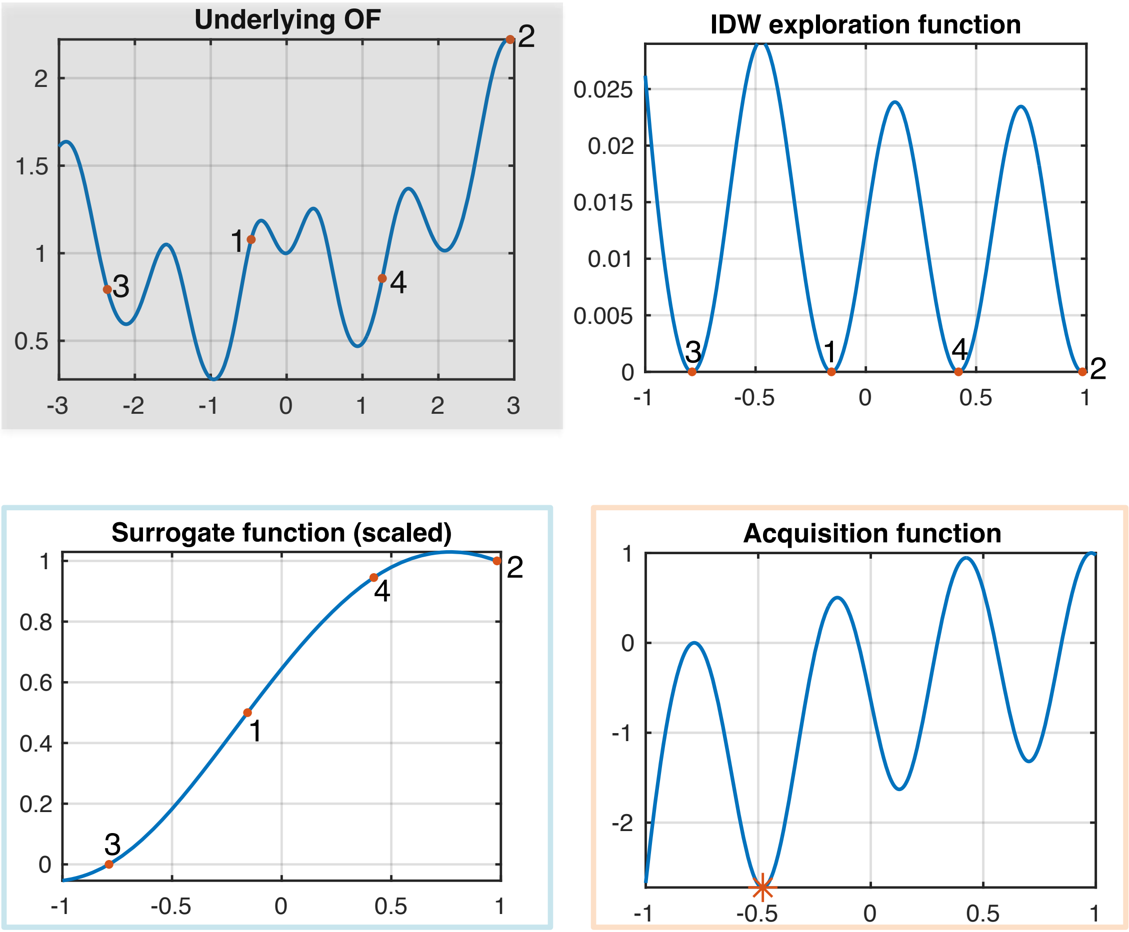
Initialization + scaling

1) Learn the **surrogate function** → $\hat{f}(x)$

2) Define the **acquisition function** → $a(x)$

3) Generate the **next sample** to test → x_{N+1}

Observe $\pi(x_{i^*}, x_{N+1})$



APL Methodology

APL: general scheme

Initialization + scaling

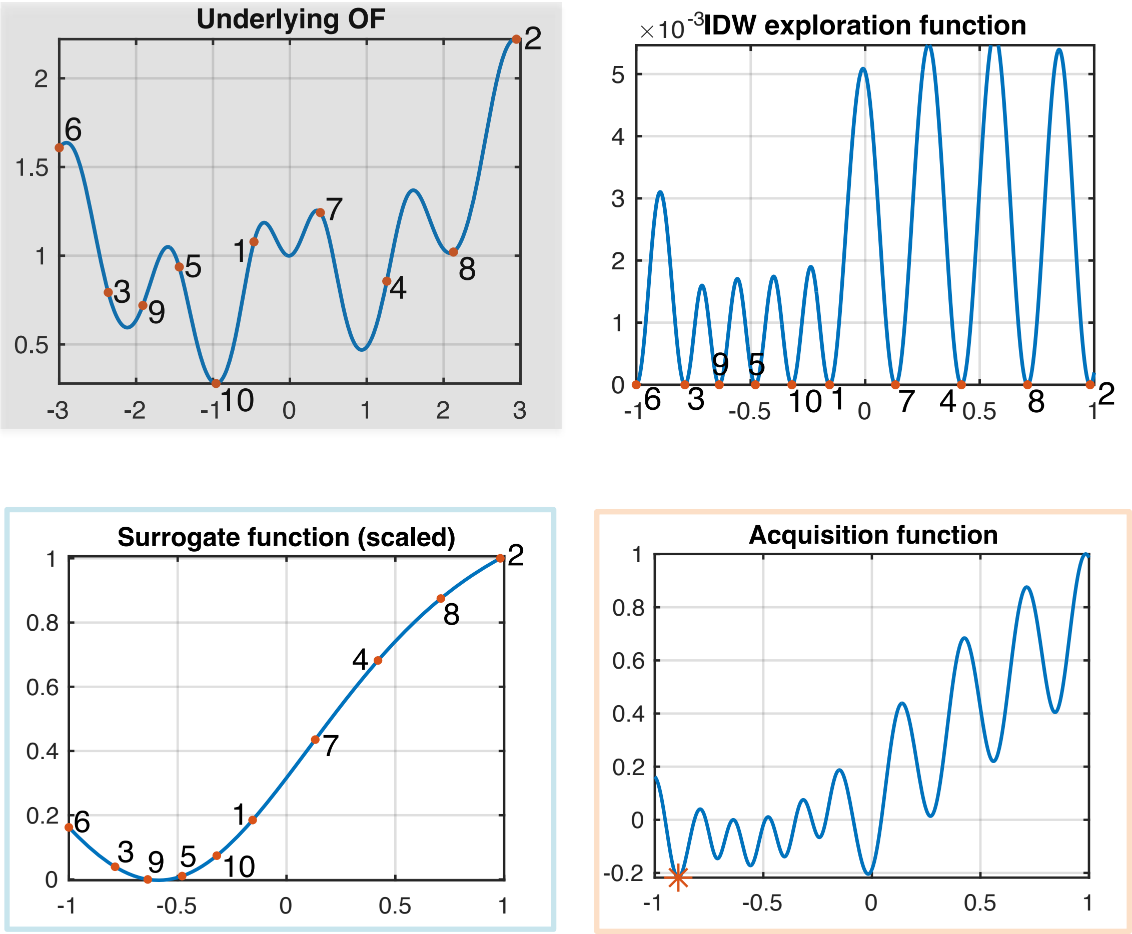
1) Learn the **surrogate function** → $\hat{f}(x)$

2) Define the **acquisition function** → $a(x)$

3) Generate the **next sample** to test → x_{N+1}

Observe $\pi(x_{i^*}, x_{N+1})$

x_N^* s.t. $x_N^* \to x^*$ as $N \to \infty$



APL Methodology

Simulation study

Param	Description
N_{init}	**Number of initial samples.**
δ	**Exploration parameter** of acquisition function.
ϵ	**Shape parameter** of RBF.
σ	**Tolerance** of (QP) learning problem.
…	…

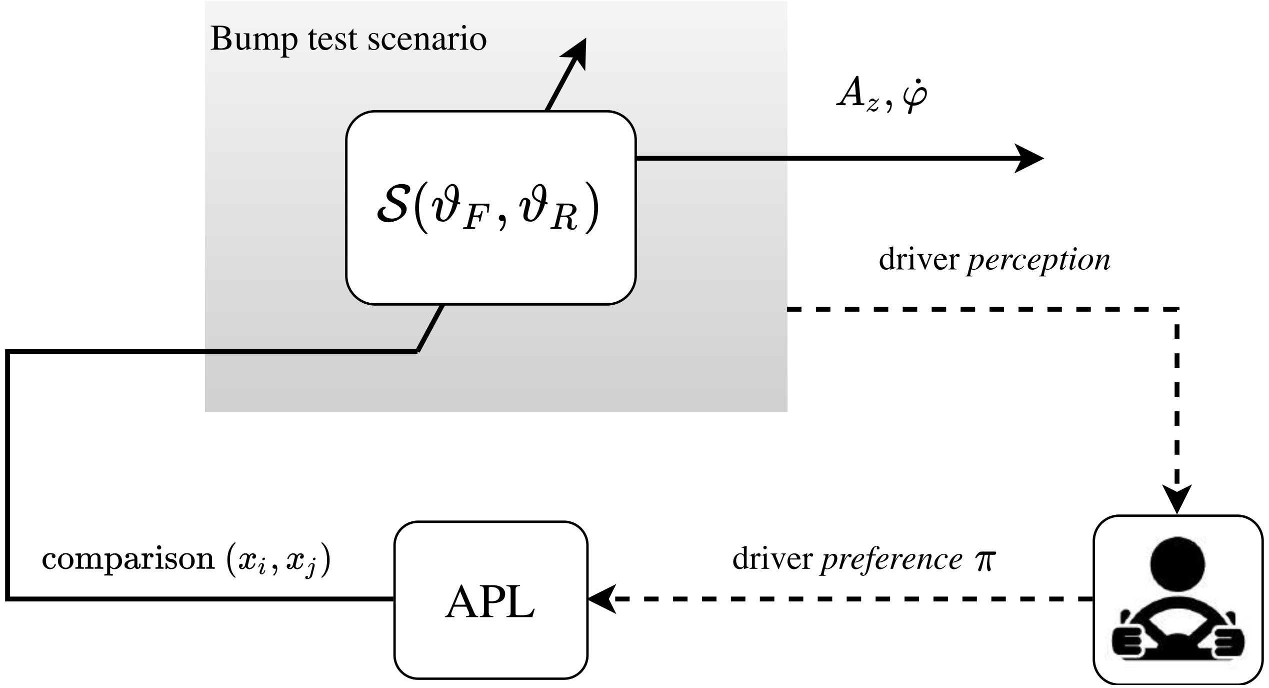
$$a(x) = \hat{f}(x) - \delta z(x)$$

Exploration-exploitation trade-off:

- $x_N^* \to x^*$ **only for δ sufficiently large**
- too high δ shows slower **convergence**

APL has many degrees of freedom → Sensitivity analysis (via simulation) → Conclusion

- δ is the **most important hyperparameter.**
- Fine-tuning the others gives small benefit (once δ is tuned).

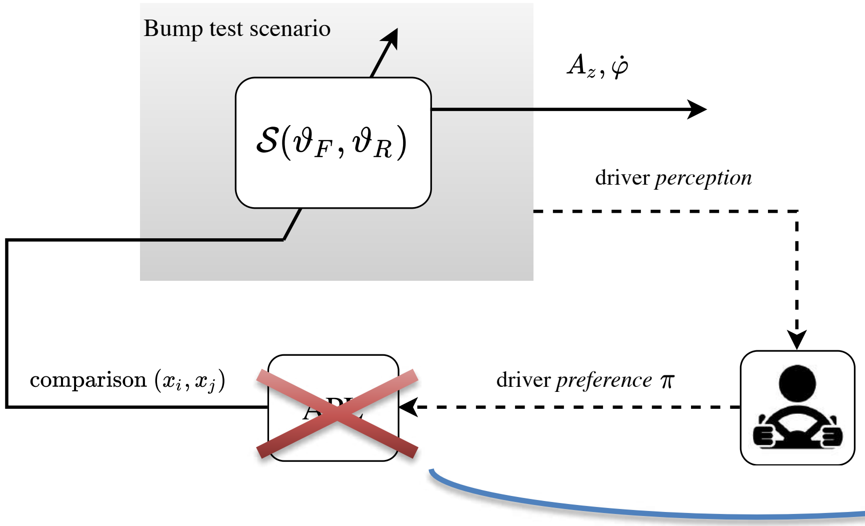


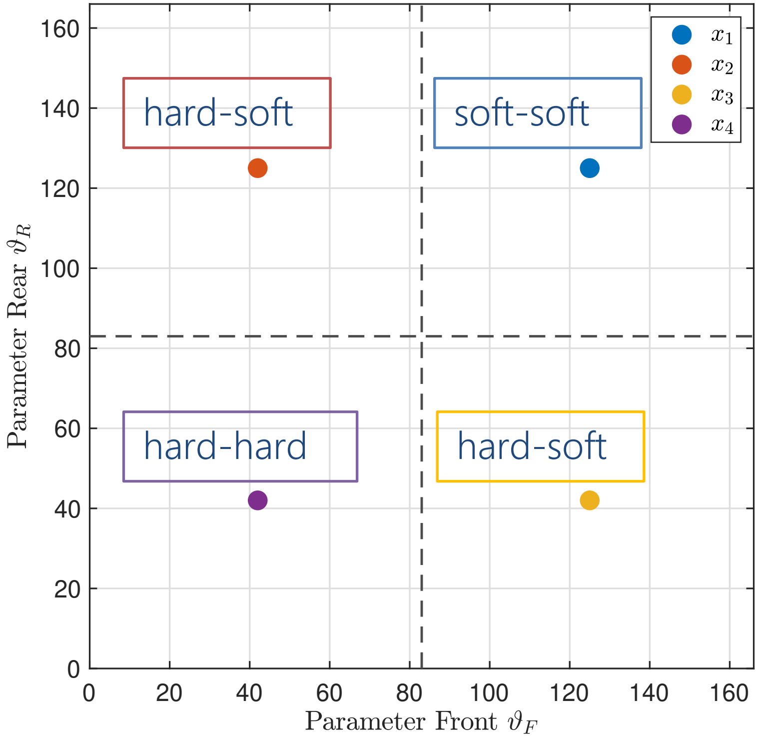
Bump test scenario
Negotiate a **speed bump** at constant speed.
(30 km/h using CC system)

Suspension in a car influence (mainly):
- Vertical movement → A_z
- Pitch → $\dot{\varphi}$
- Roll (negligible in this case)

Preliminary Experiment

1) Understand our **capability to perceive** different behaviors of the car.
2) Fit rough model of underlying OF.





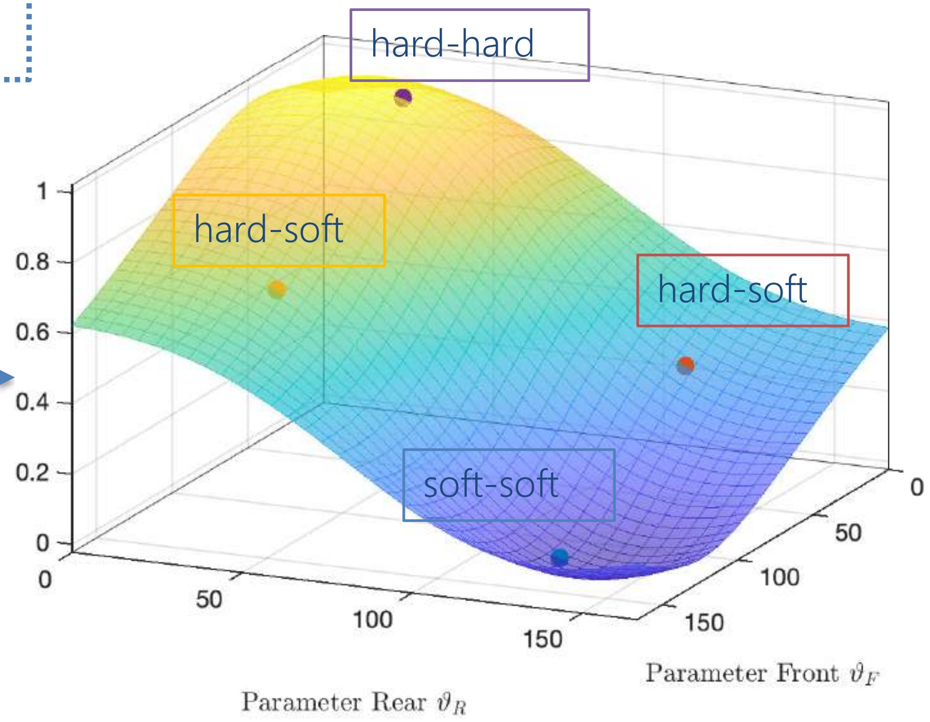
4 benchmark settings in the parameters space:

x_1, x_2, x_3, x_4

Same procedure as in APL to learn the surrogate.

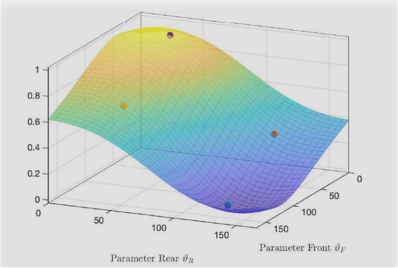
Test #	1	2	3	4	5	6
x_i	x_2	x_1	x_1	x_3	x_4	x_3
x_j	x_1	x_3	x_4	x_2	x_2	x_4
best	x_1	x_1	x_1	x_2	x_2	x_3

- Driver is able to express committed preference.
- **Transitive property** satisfied → ranking: s_s, h_s, s_h, h_h.



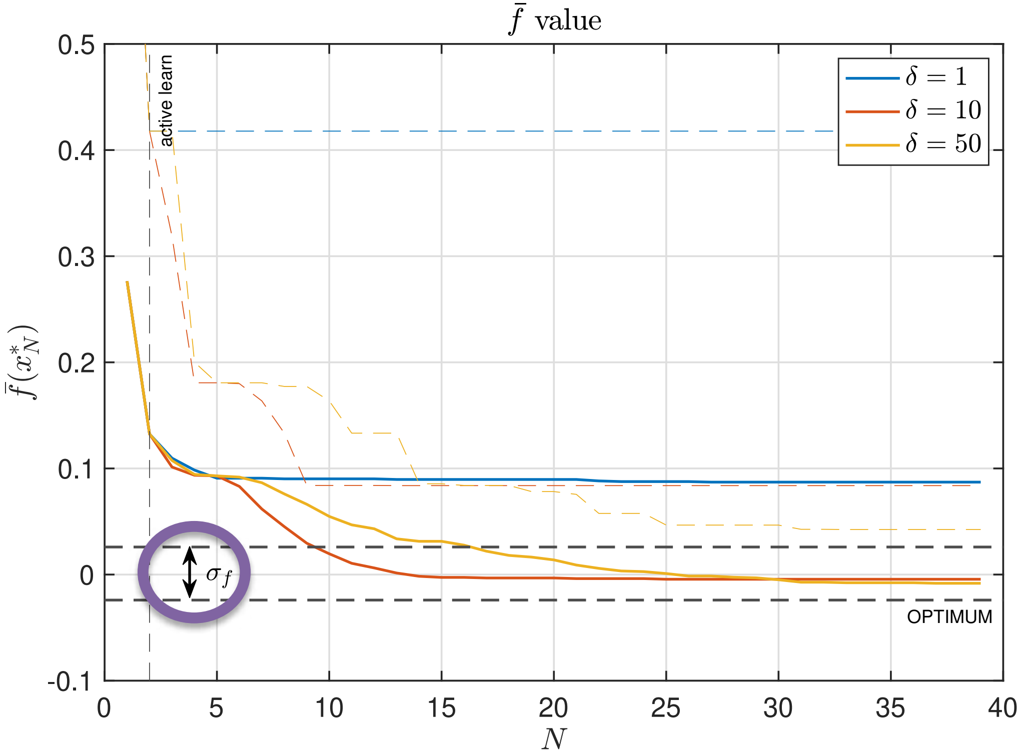
Preference-based identification of the underlying OF.

Tuning hyperparameter δ via simulation



$\sigma_f = 0.05$

heuristics: equivalent to 20 steps of “**resolution**”, expressing our preference



Best $\delta = 10$

	$\delta = 1$	$\delta = 10$	$\delta = 50$
N_{conv}	6	15	36

Stopping criterion

The APL procedure converges when:

- **3 consecutive “zeros”**

OR

- at least 4 “zeros” in 5 consecutive iterations

Bridging-the-gap from theory to practice

Preliminary Experiment

Experimental protocol

- Driver: express preference.
- Co-driver: update parameters.

Step#	Task description
1	APL suggest a pair-wise comparison: x_i VS x_j.
2	Update ϑ_F and ϑ_R according to x_i.
3	Perform first **bump test**.
4	Update ϑ_F and ϑ_R according to x_j.
5	Perform second **bump test**.
6	Driver expresses his preference $\pi(x_i, x_j)$.

Remarks:

- Driver must be **well-focused on his perception** (and familiar with the setup).
- The 2 bump tests should happen **close in time**.
- The test must be informative enough (eventually repeat).
- **Driver must not know** value of ϑ_F and ϑ_R.

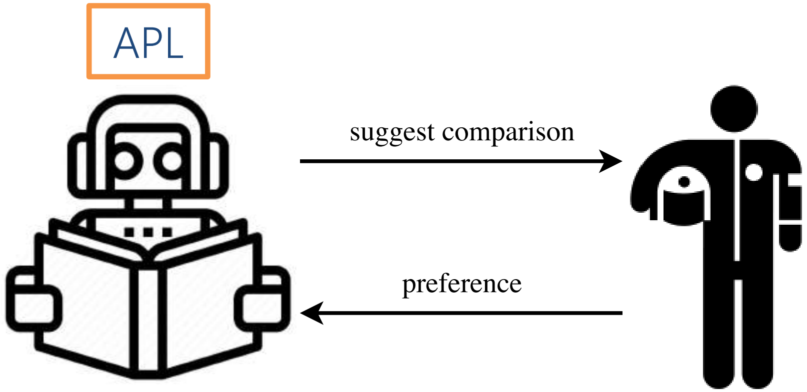
APL Experiment

1) **Semi-automatic preference-based calibration via APL.**
2) **Sensitivity analysis** w.r.t. δ (validate simulation results).

- $\delta = 1$ (3 repetitions) → $\delta 1A$, $\delta 1B$, $\delta 1C$
  Too **low exploration** expected.

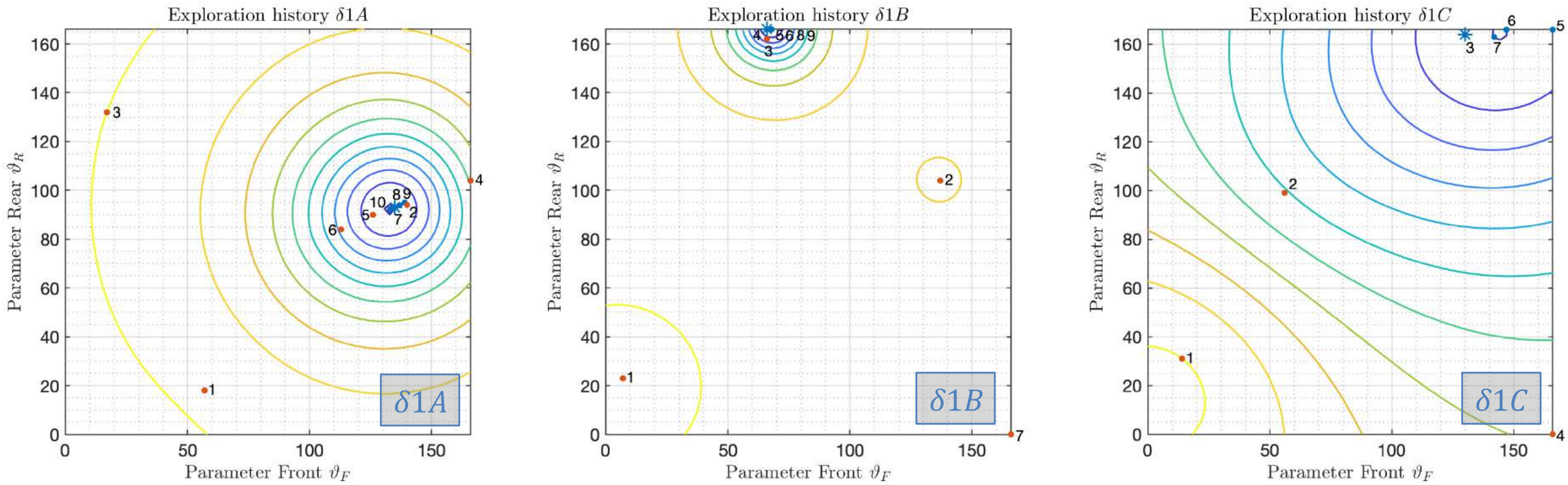
- $\delta = 10$ (2 repetitions) → $\delta 10A$, $\delta 10B$
  Best compromise.

- $\delta = 50$ (1 repetition) → $\delta 50$
  High exploration (too slow convergence) is expected, but most accurate result.



Experimental results

APL Experiment: comparison $\delta = 1$

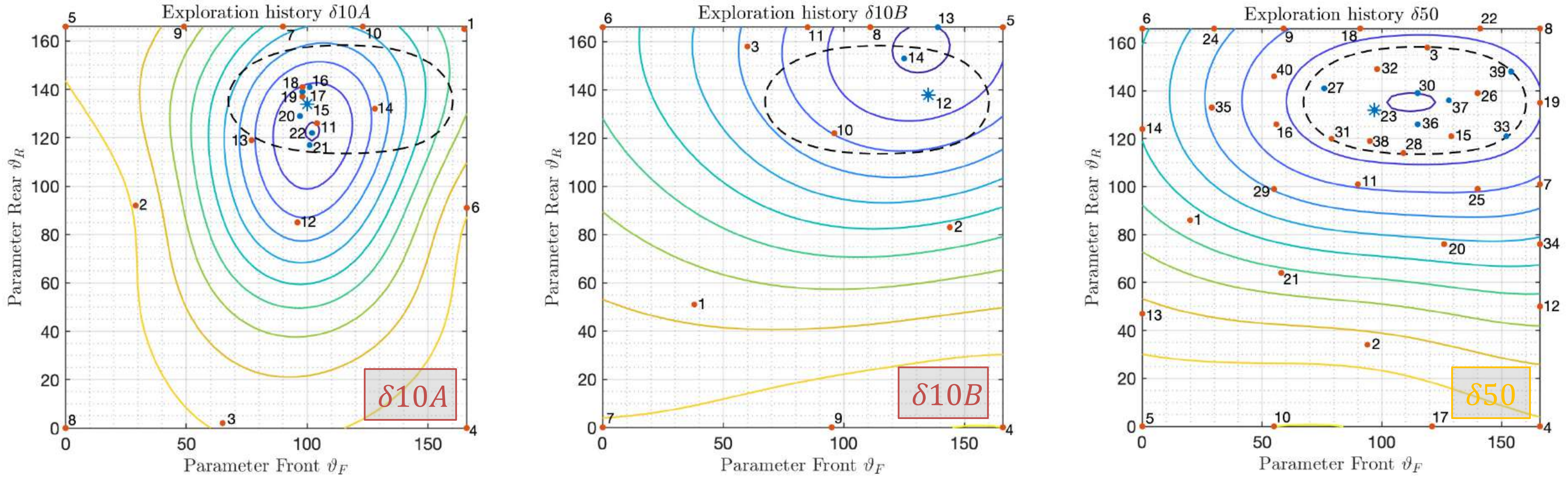


- APL $\delta = 1$ shows poor exploration of parameters space.
- Final result strongly depends on the initialization phase (first 3 samples).

Legend
- Red dots: all samples $x_1, \ldots, x_N$
- ★ Blue star: best preference in-sample x_N^*
- Blue dots: equal-optimum outcomes
- Contour plot is the surrogate function

Experimental results

APL Experiment: comparison $\delta = 10$ / $\delta = 50$



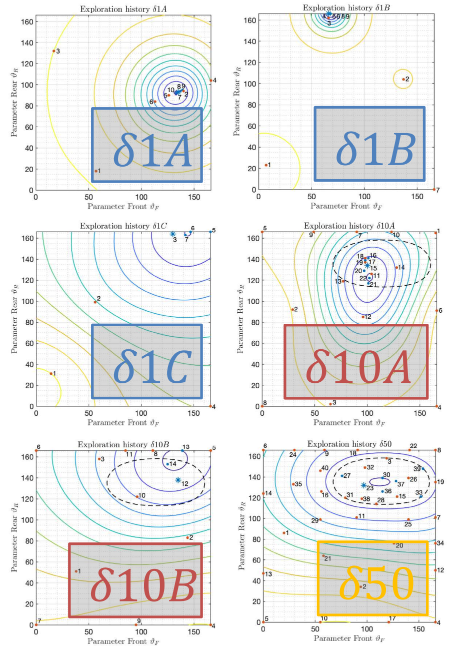
Exploration pattern

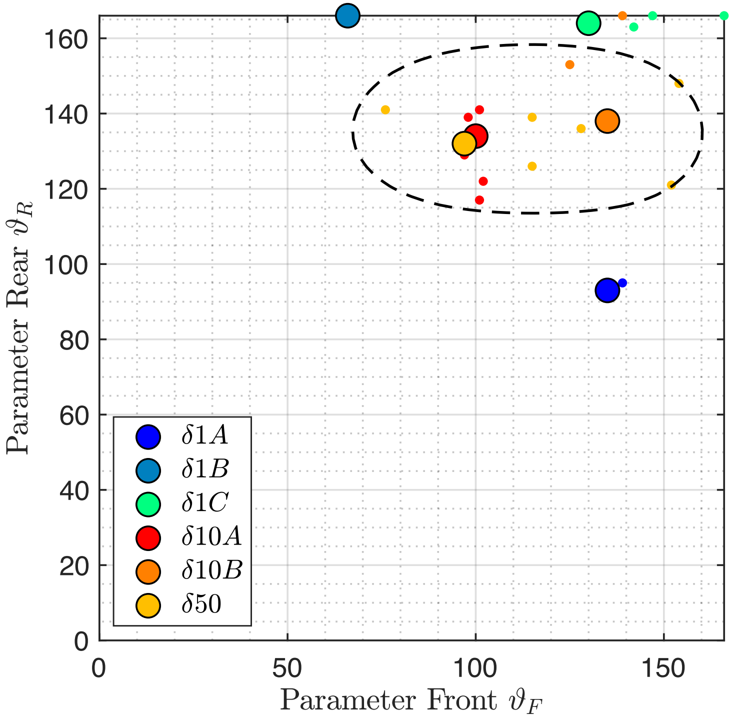
- first rule out “bad points” (exploration)
- then surround optimal point (exploitation)

Definition of **equal-optimum area** from $\delta 50$: smallest-height contour-line enclosing all equal-optimum outcomes ($\sigma_f = 0.07$)

Experimental results

APL Experiment





- Confirm poor exploration of $\delta = 1$
- Equal-optimum points with $\delta = 10$ are inside **equal-optimum area**
- $\delta = 10$ best compromise (considering N_{conv})
- Exploration-exploitation trade-off in agreement with simulation

How to **validate/explain** this result?

N_{conv}	Simulation	(A)	(B)	(C)	
$\delta = 1$	**6**	9	8	6	**8**
$\delta = 10$	**15**	21	13		**17**
$\delta = 50$	**36**	> 39*			/

*budget cap

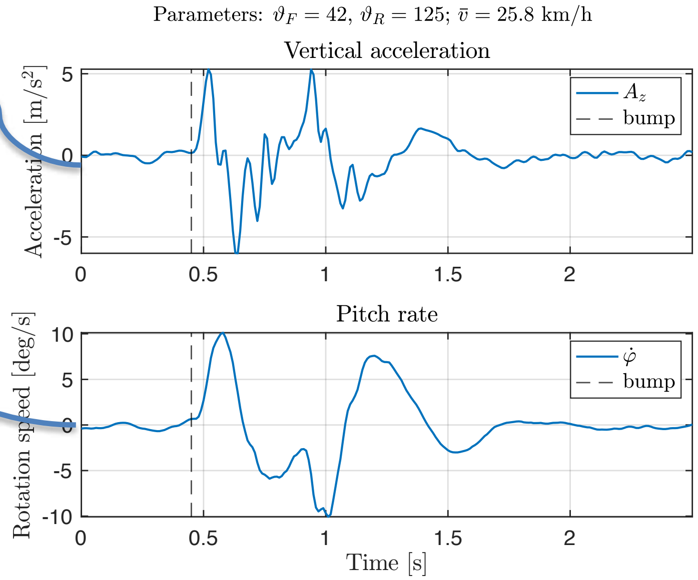
$$J^\lambda = J^V + \lambda J^P$$

$$J^V = \sqrt{\frac{1}{T}\int_0^T A_z^2 dt}$$

$$J^P = \sqrt{\frac{1}{T}\int_0^T \dot{\varphi}^2 dt}$$

Vertical acceleration RMS

Pitch rate RMS



Learn weighting coefficient λ from preference

Supervised multiclass classification problem

- $u = [J^V_{hi} \quad J^P_{hi} \quad J^V_{hj} \quad J^P_{hj}]$ input
- $y \in \{-1,0,1\}$ output

  $\Rightarrow D = \{(u_1, y_1), \ldots, (u_K, y_K)\}$ dataset

- $\tilde{\pi}: U \rightarrow Y$ interpretation function

$$\tilde{\pi}(u) = \begin{cases} -1 & \text{if } J_i^\lambda - J_j^\lambda < -\sigma_J \\ 0 & \text{if } |J_i^\lambda - J_j^\lambda| \leq \sigma_J \\ 1 & \text{if } J_i^\lambda - J_j^\lambda > \sigma_J \end{cases}$$

Experimental results

A preference-based comfort index

Learning procedure

Slack-variable **minimization problem**, which constraints imposes:

$$\tilde{\pi}(x_h) = y_h, \forall h = 1, \dots, K$$

$$\begin{aligned}
\underset{\lambda,\sigma_J,\varepsilon}{\text{minimize}} \quad & \varepsilon \\
\text{subject to} \quad & J^V_{hi} + \lambda J^P_{hi} - J^V_{hj} - \lambda J^P_{hj} \leq -\sigma_J + \varepsilon_h \quad \forall h : y_h = -1, \\
& J^V_{hi} + \lambda J^P_{hi} - J^V_{hj} - \lambda J^P_{hj} \geq \sigma_J - \varepsilon_h \quad \forall h : y_h = 1, \\
& J^V_{hi} + \lambda J^P_{hi} - J^V_{hj} - \lambda J^P_{hj} \leq \sigma_J + \varepsilon_h \quad \forall h : y_h = 0, \\
& J^V_{hi} + \lambda J^P_{hi} - J^V_{hj} - \lambda J^P_{hj} \geq -\sigma_J - \varepsilon_h \quad \forall h : y_h = 0, \\
& \lambda \geq 0, \ \sigma_J \geq 10^{-6}, \ \varepsilon \geq 0
\end{aligned}$$

→ λ (and σ_J)

Cross-validation procedure

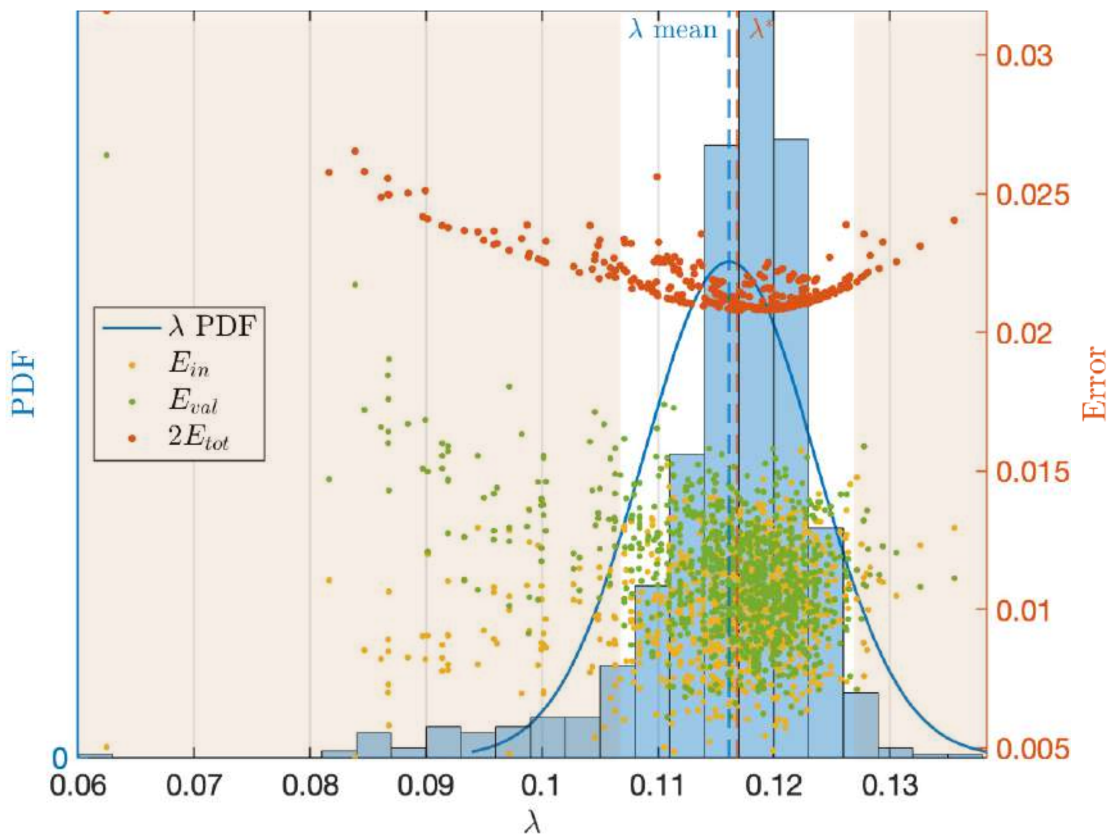
- **Training set** → to train the model solving optimization pb.
- **Validation set** → to detect overfitting (E_{val}).

Mean prediction error: measure how far is the model from correct label prediction

Experimental results

A preference-based comfort index

J^λ from dataset Driver1
(113 preference data)



- E_{tot} has a convex **quadratic-like shape**.
  $\Rightarrow$ best $\lambda^* = 0.117$.
- λ far from λ^* are **outliers** (big E_{val} → overfitting)
- Model J^λ cannot make $E_{tot} = 0$ because of **noise**
  - regressors (sensors measurements)
  - labels (human preference)

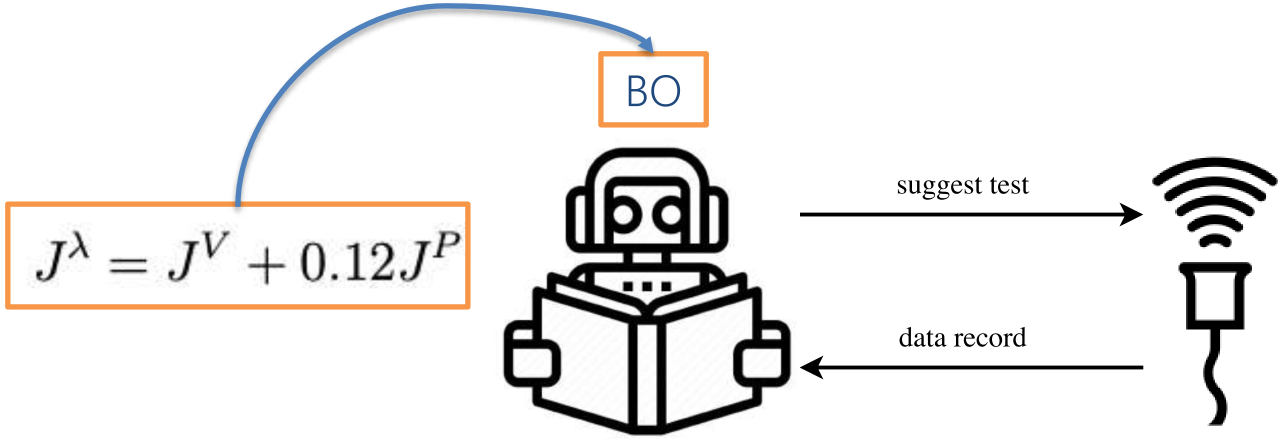
$\lambda \approx 0.12$

BO with J_{λ} Experiment:

1) **Automatic calibration via BO** with J^{λ}.
2) Check if BO optimum is similar to APL→ results **validation.**

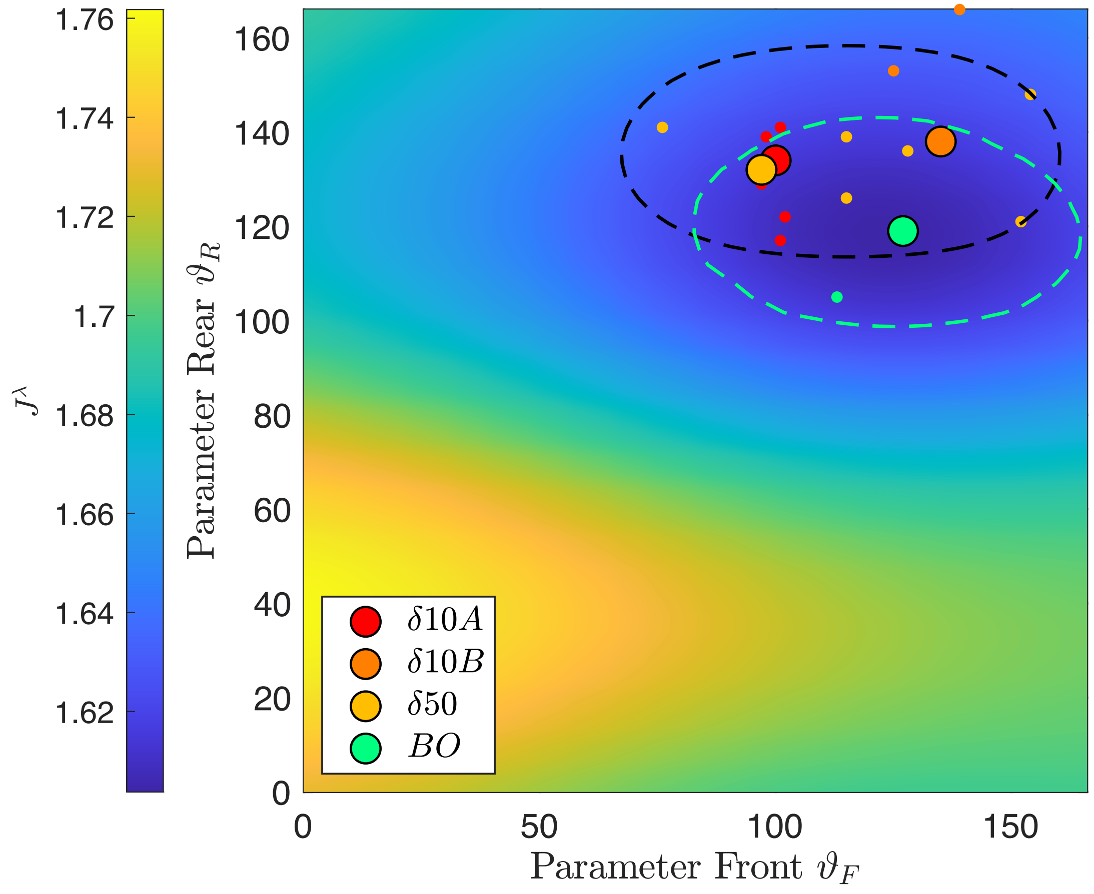
Same experimental setup.

Same scenario: bump test at 30 km/h.



Experimental results

APL Vs BO



- equal-optimum area from APL
- equal-optimum area from BO

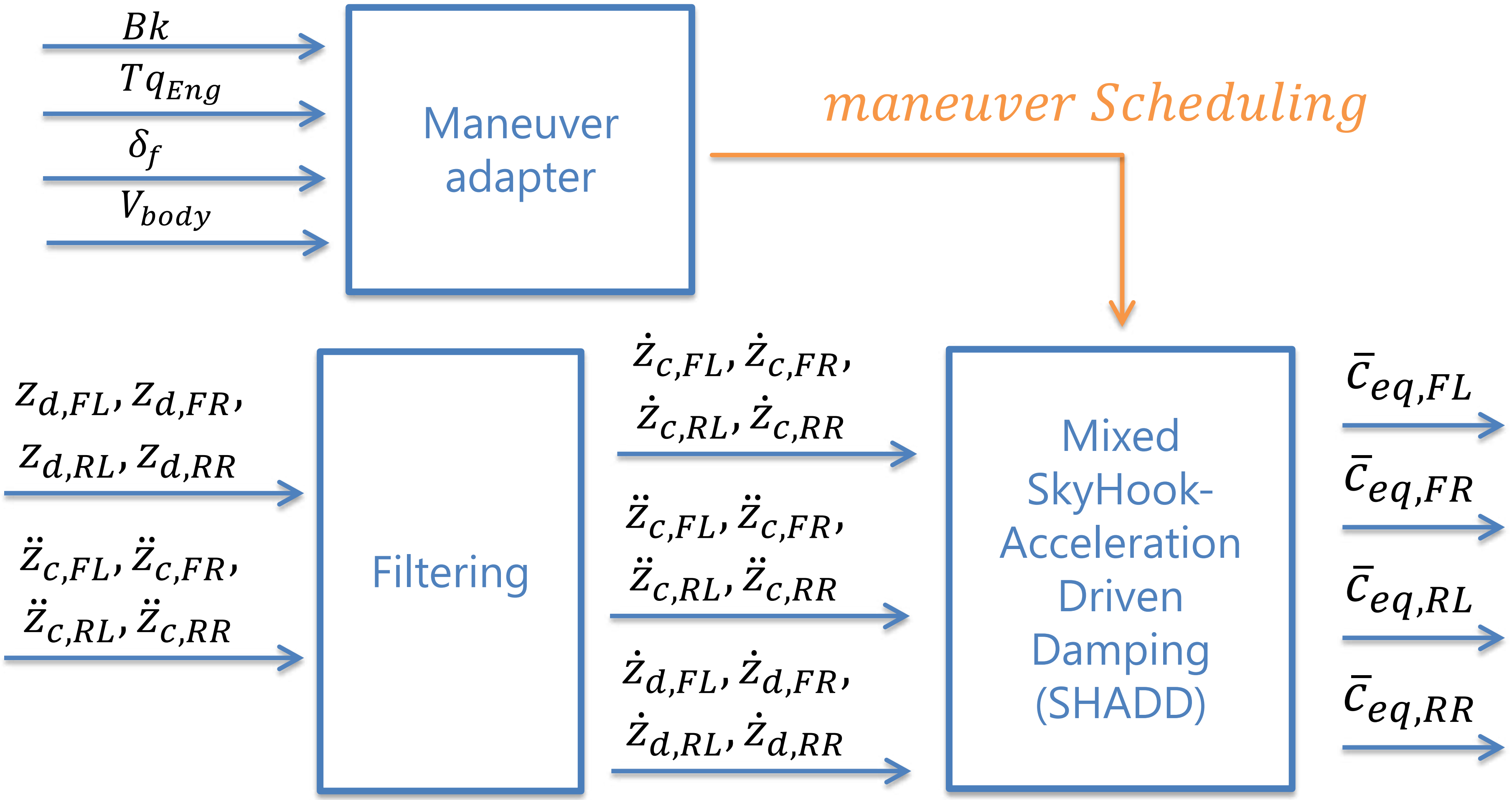
- J^λ gives **interpretation** of APL result → model of driver preference
- APL with $\delta \geq 10$ retrieve optimal solution according to J^λ

APL is **time/cost effective**

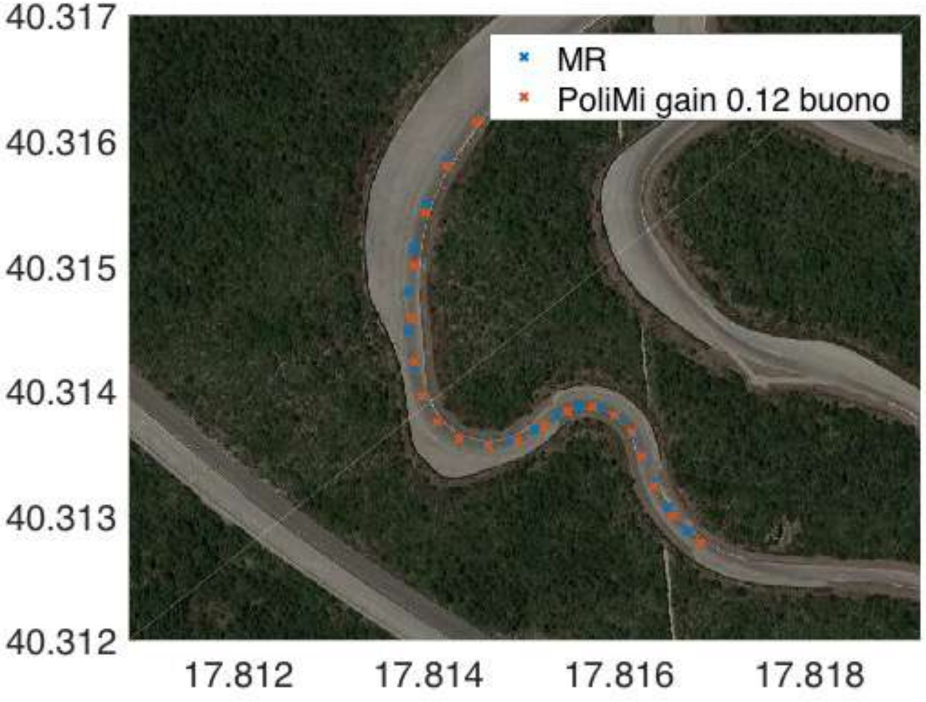
- BO ~40 min Vs
- APL ~50 min (but…)

Semi-Active Damping Control

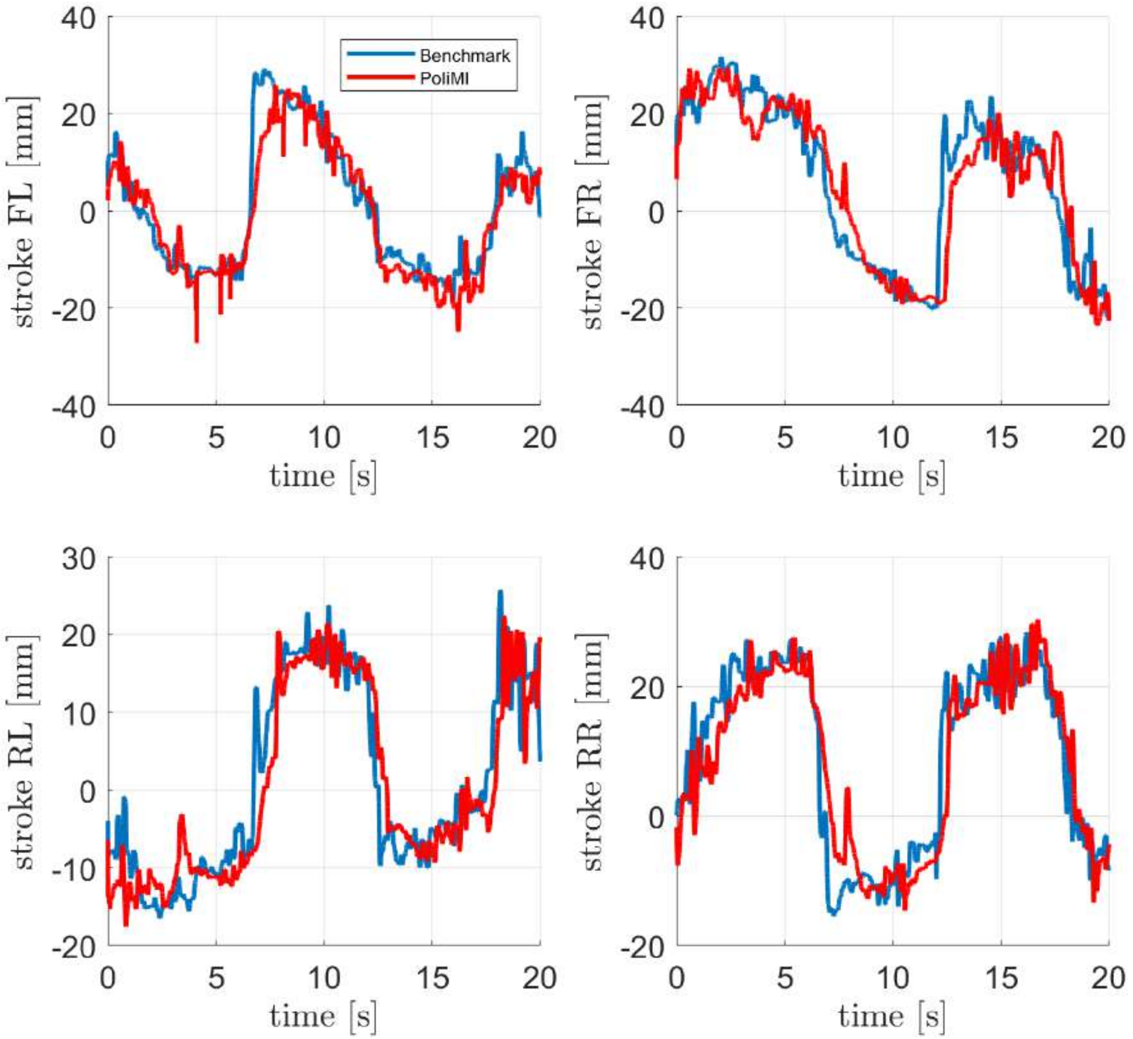
Full Body Control



$$c_{ref} = sat_{[c_{min}, c_{max}]}(c_{nom} + k_{SH}\dot{z}_b\Delta z + k_{ADD}\ddot{z}_b\Delta\dot{z})$$

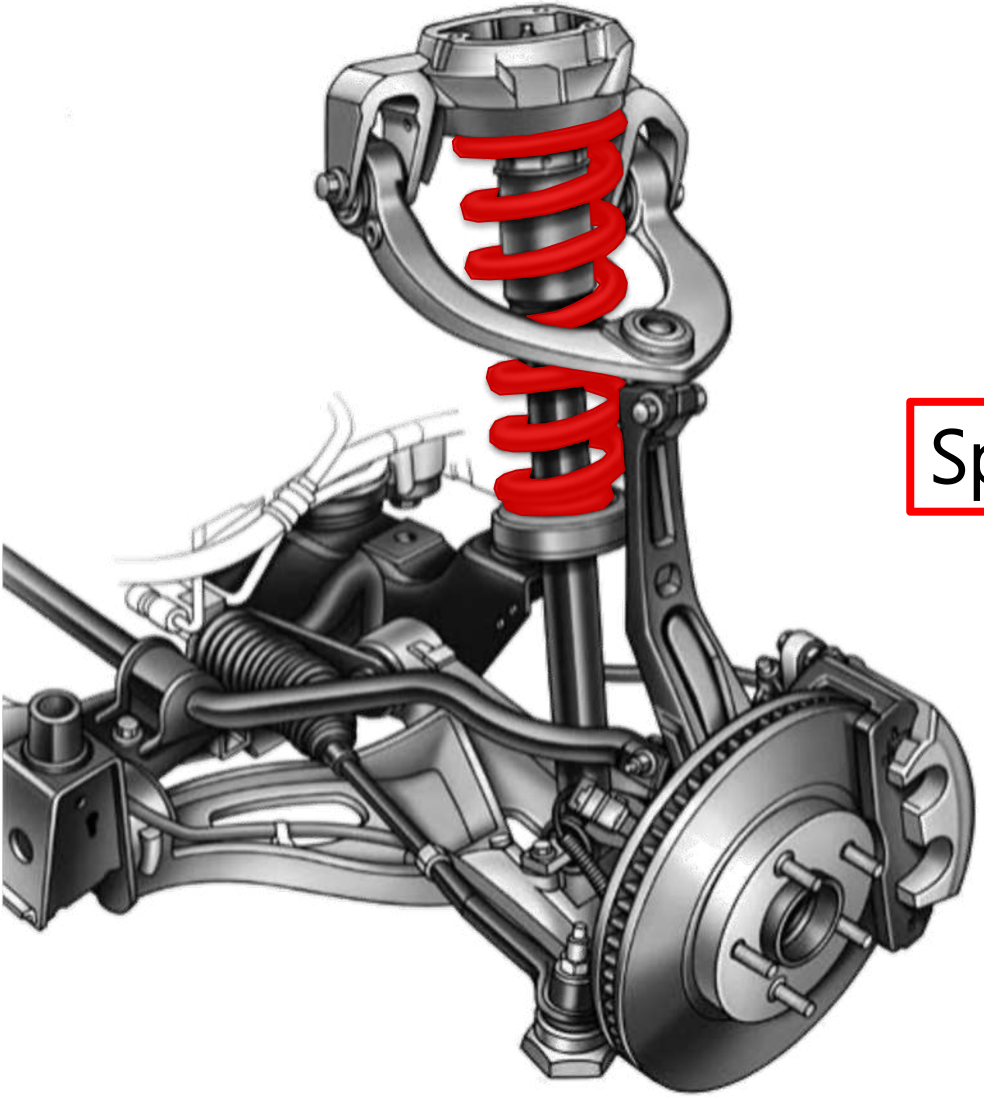


Thanks to the use of the driver scheduling, it is possible to slow down the load transfer and thus yield a more stable feeling while negotiating corners.

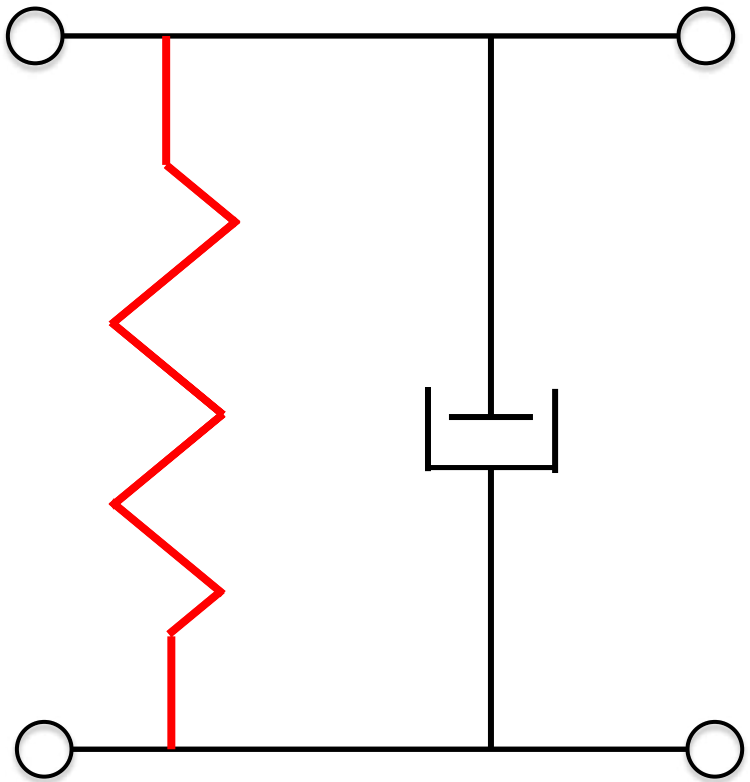


Outline

- Introduction
- Semi-Active Damping Control
    - Actuators
    - Models
    - Benchmark
    - Causal Control
- **Semi-Active Stiffness Control**
    - Actuators
    - Benchmark
    - Causal Control
- Sensing Preliminaries
- A look at the future
- Conclusions



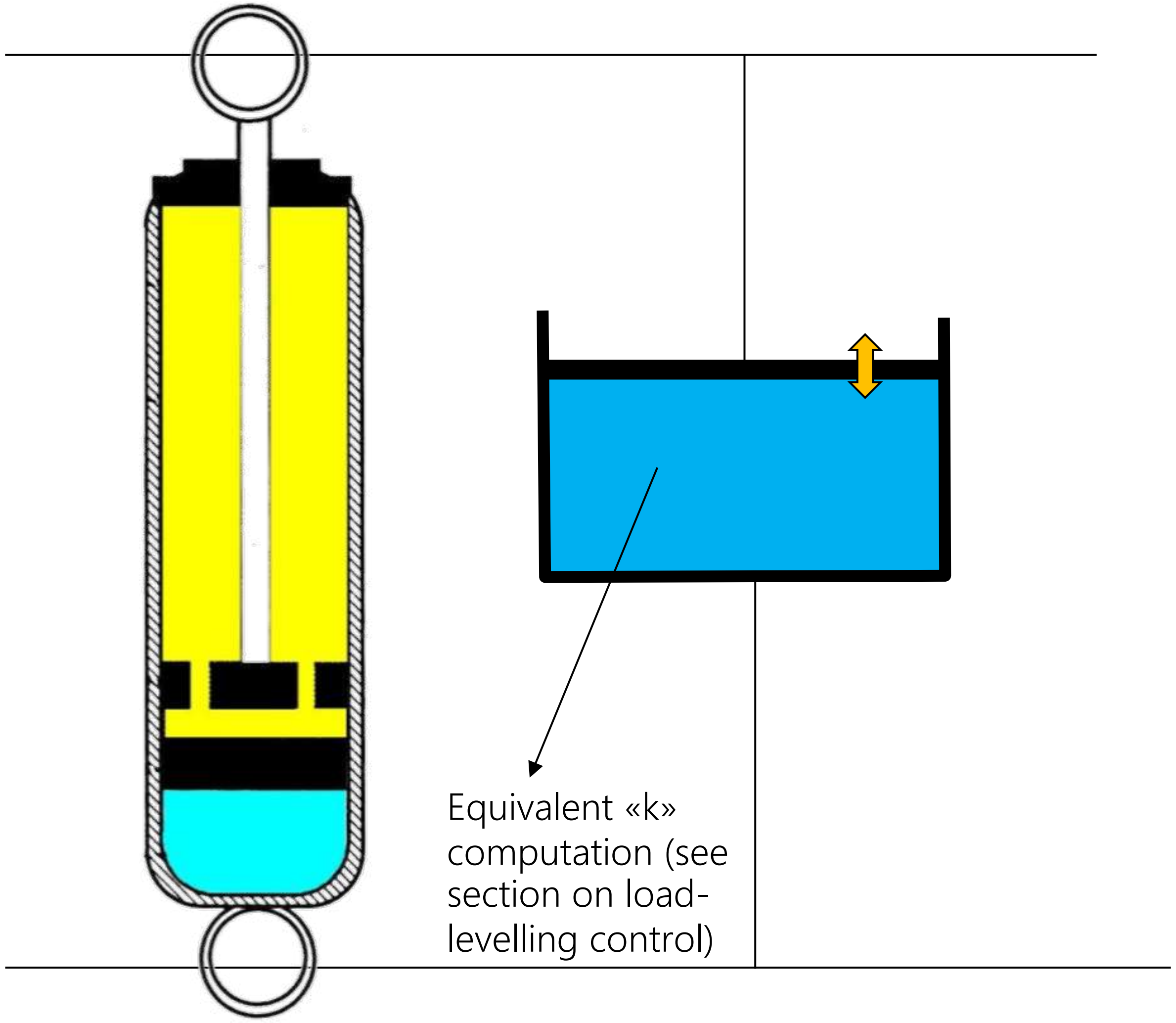
Spring (k)

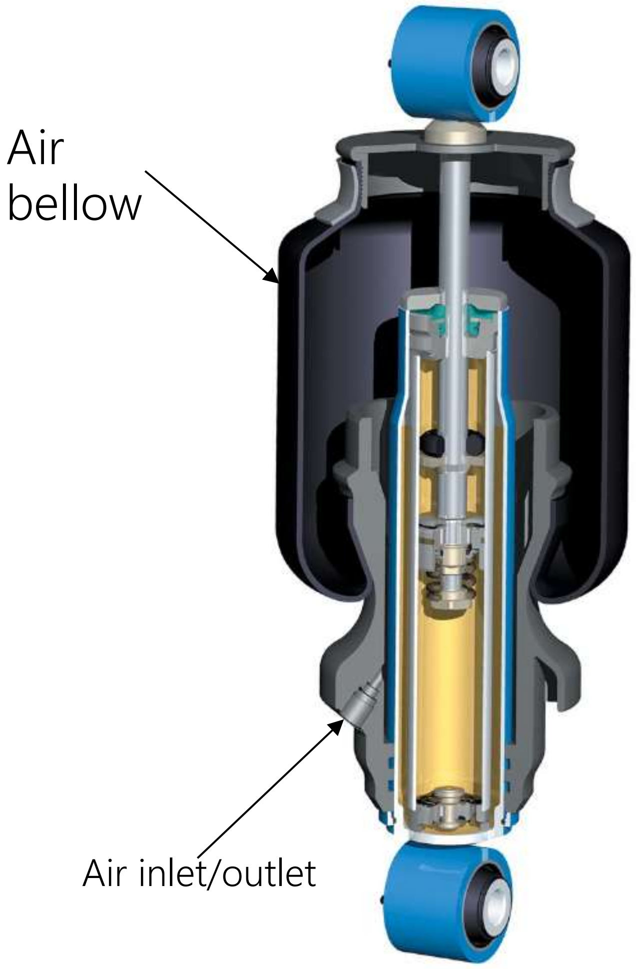


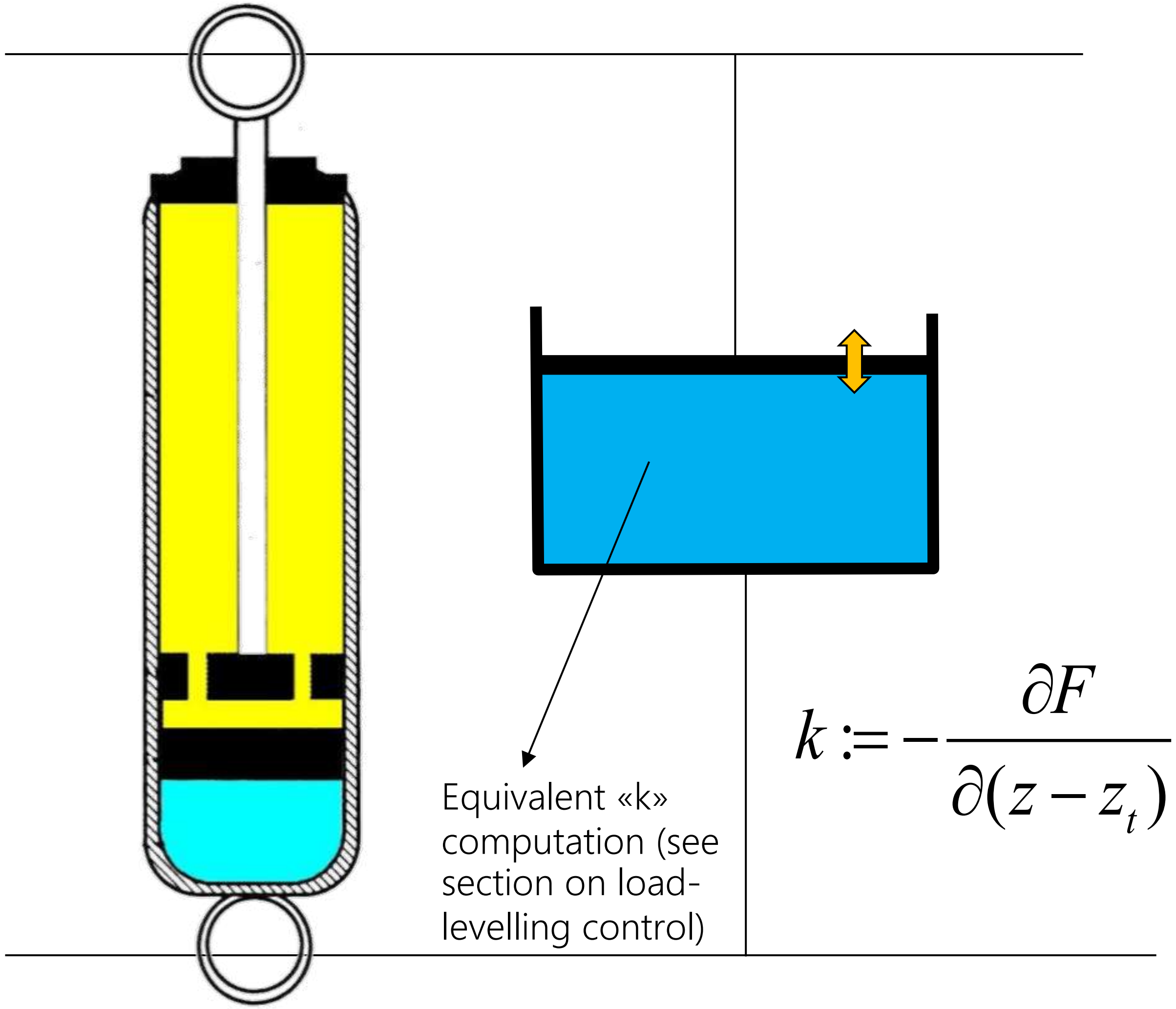
A mechanical spring does not allow for any kind of modulation

Semi-Active Stiffness Control

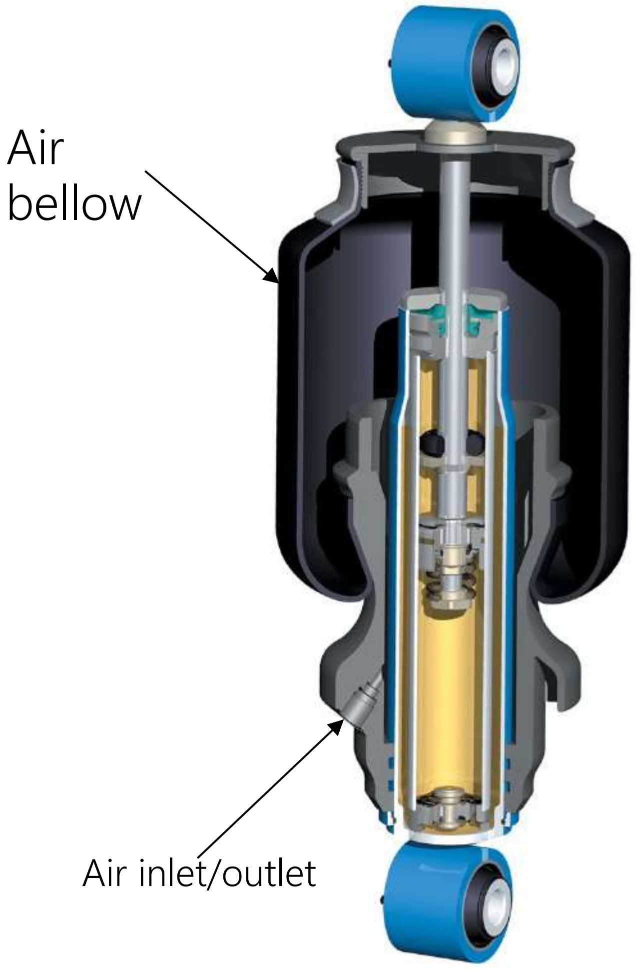
Air Spring – Pneumatic Spring





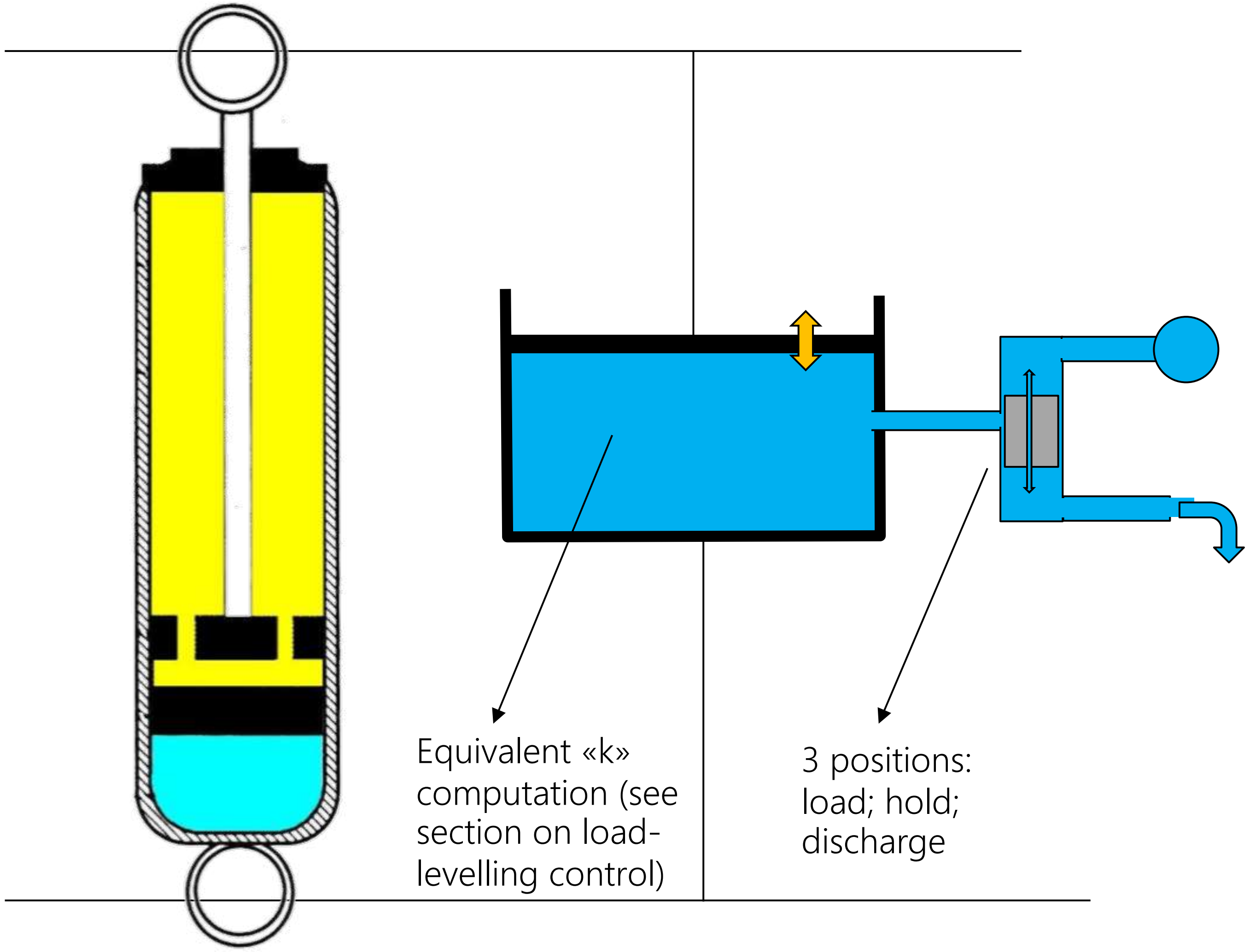


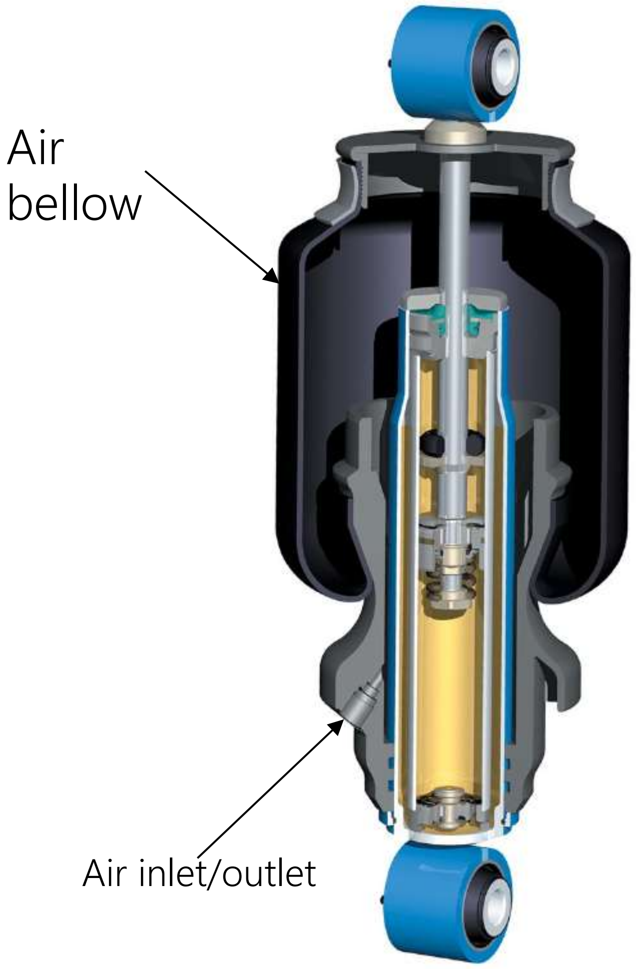
$$k := -\frac{\partial F}{\partial (z - z_t)} = \frac{p\gamma A^2}{V}$$



Semi-Active Stiffness Control

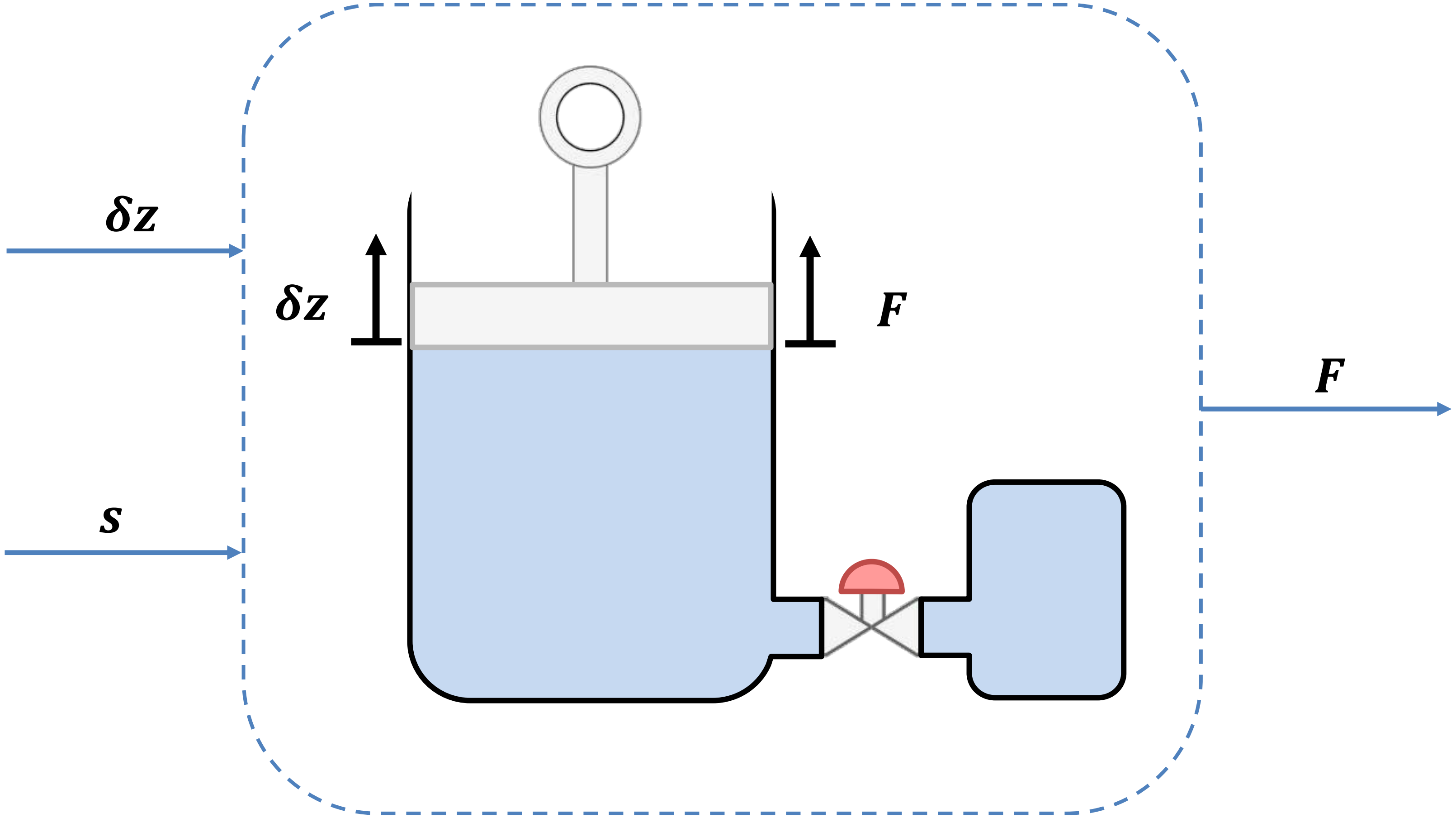
Air Spring – Pneumatic Spring – Slow Active





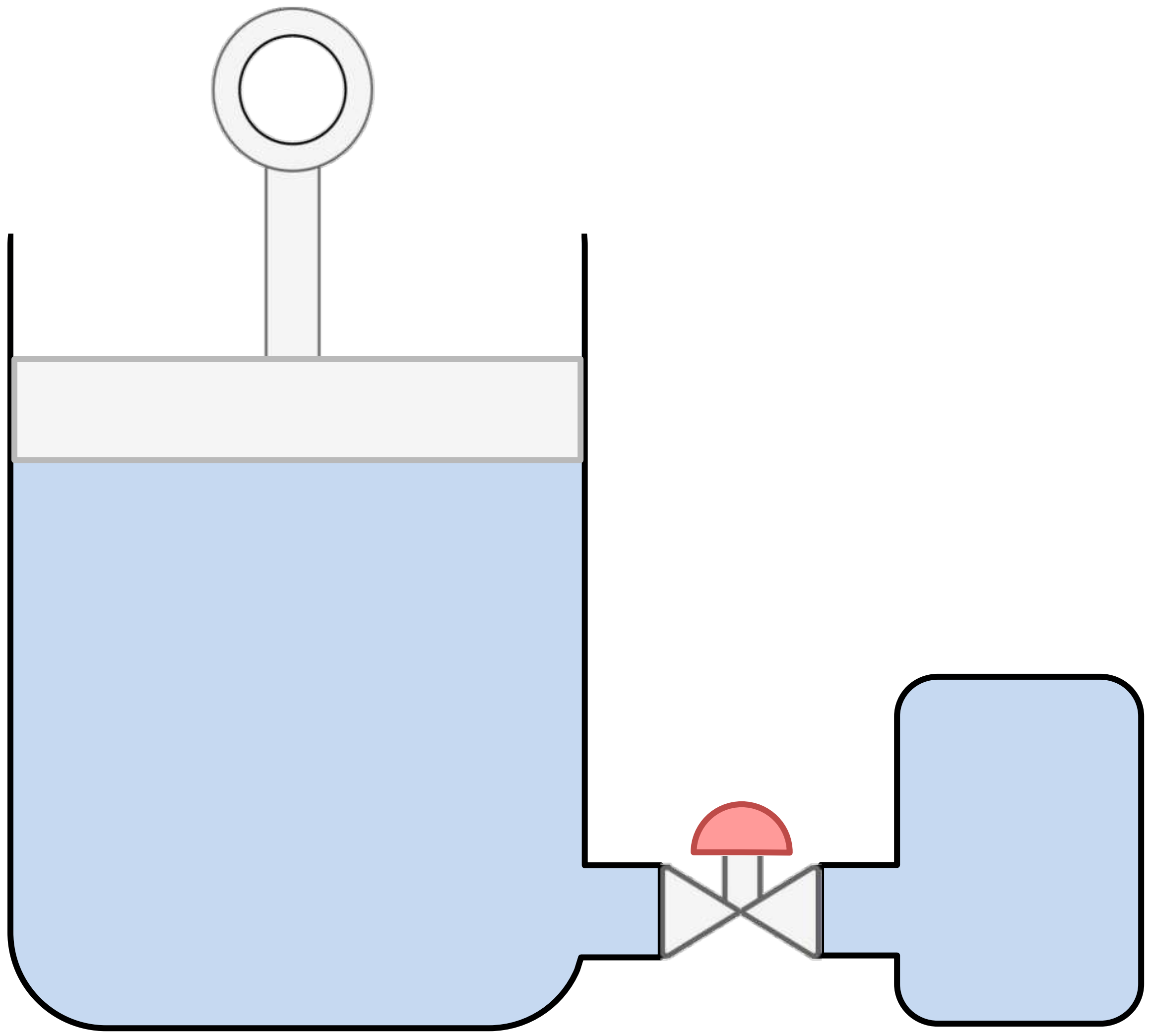
Semi-Active Stiffness Control

Air Spring – Pneumatic Spring – Semi-Active

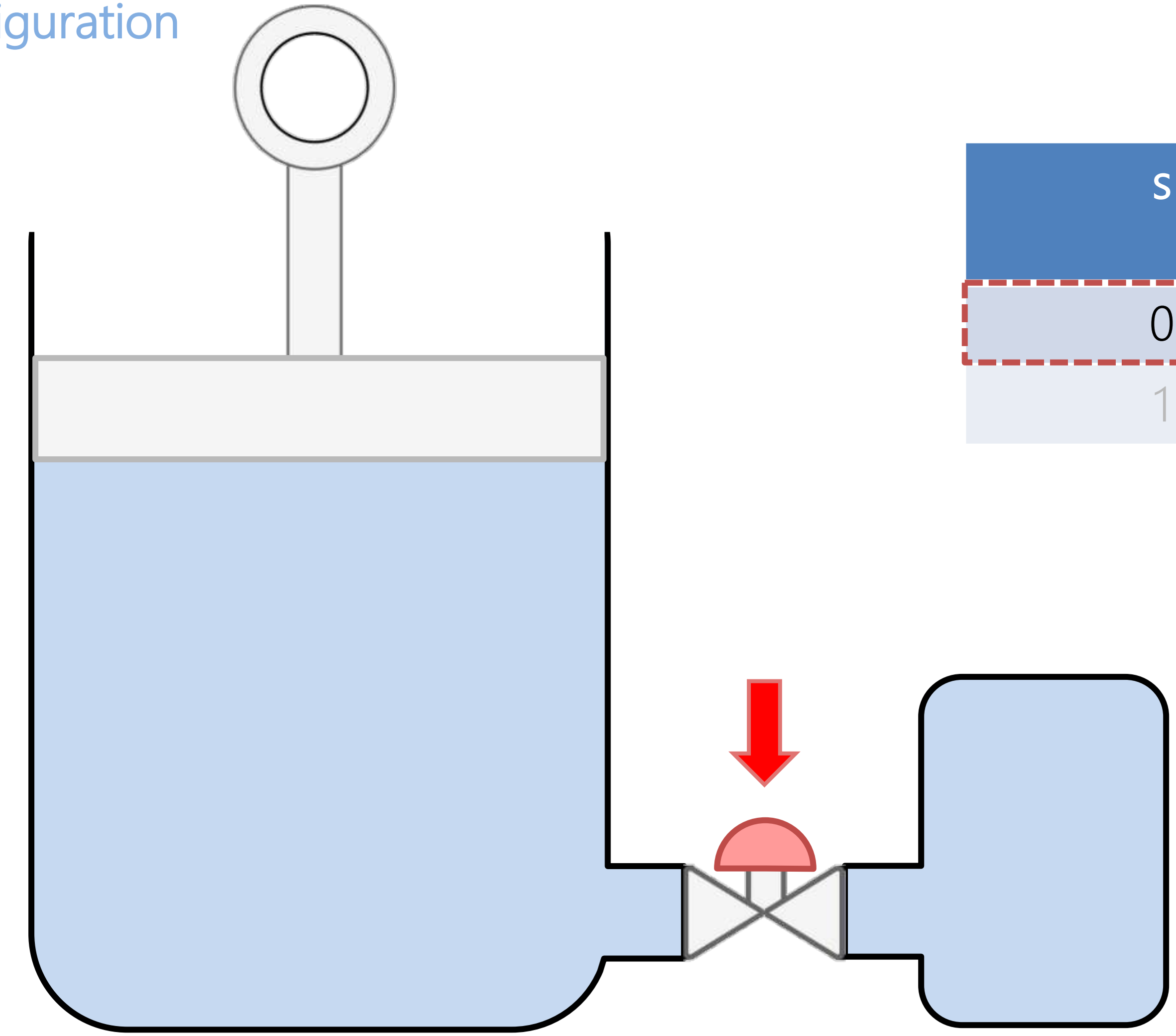


Semi-Active Stiffness Control

Air Spring – Pneumatic Spring – Semi-Active

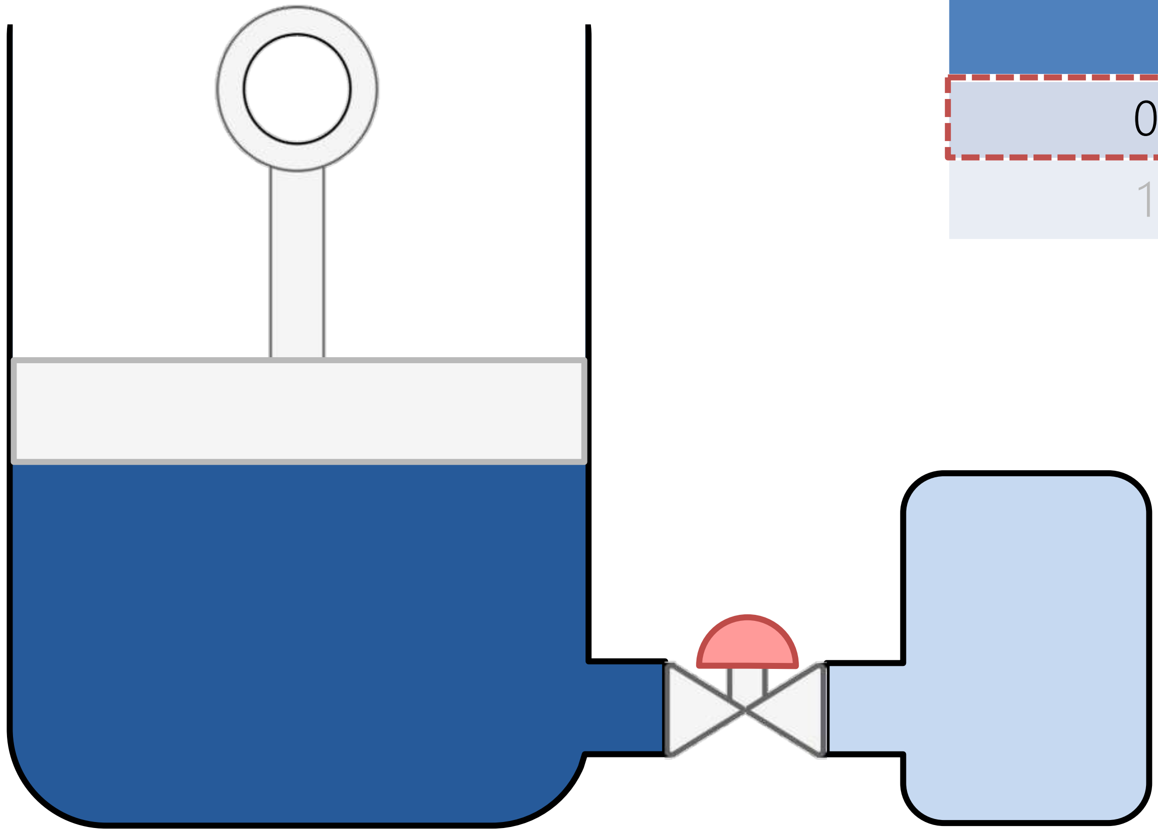


Hard configuration



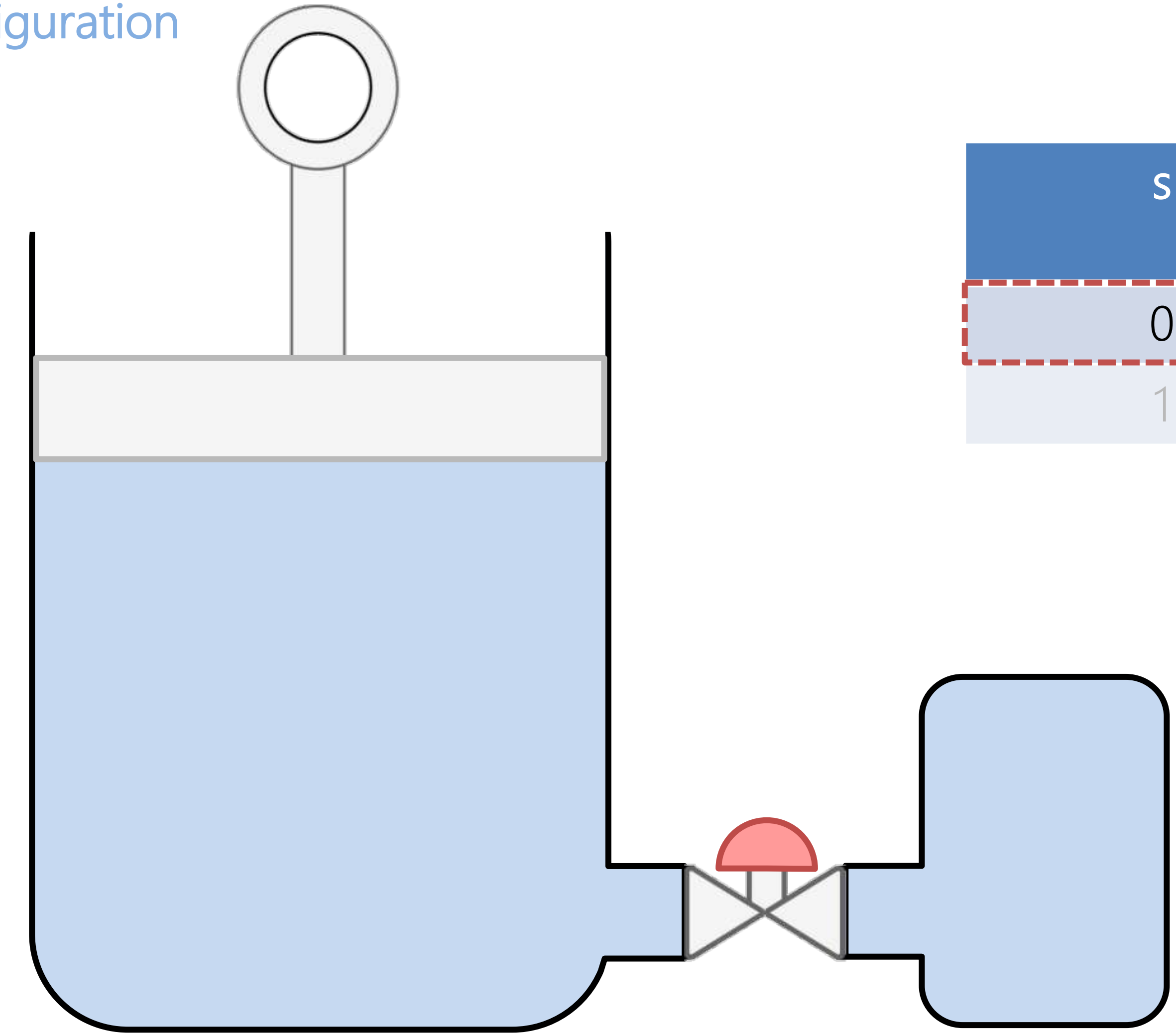
s	Valve configuration	System configuration
0	Closed	Hard
1	Open	Soft

Hard configuration



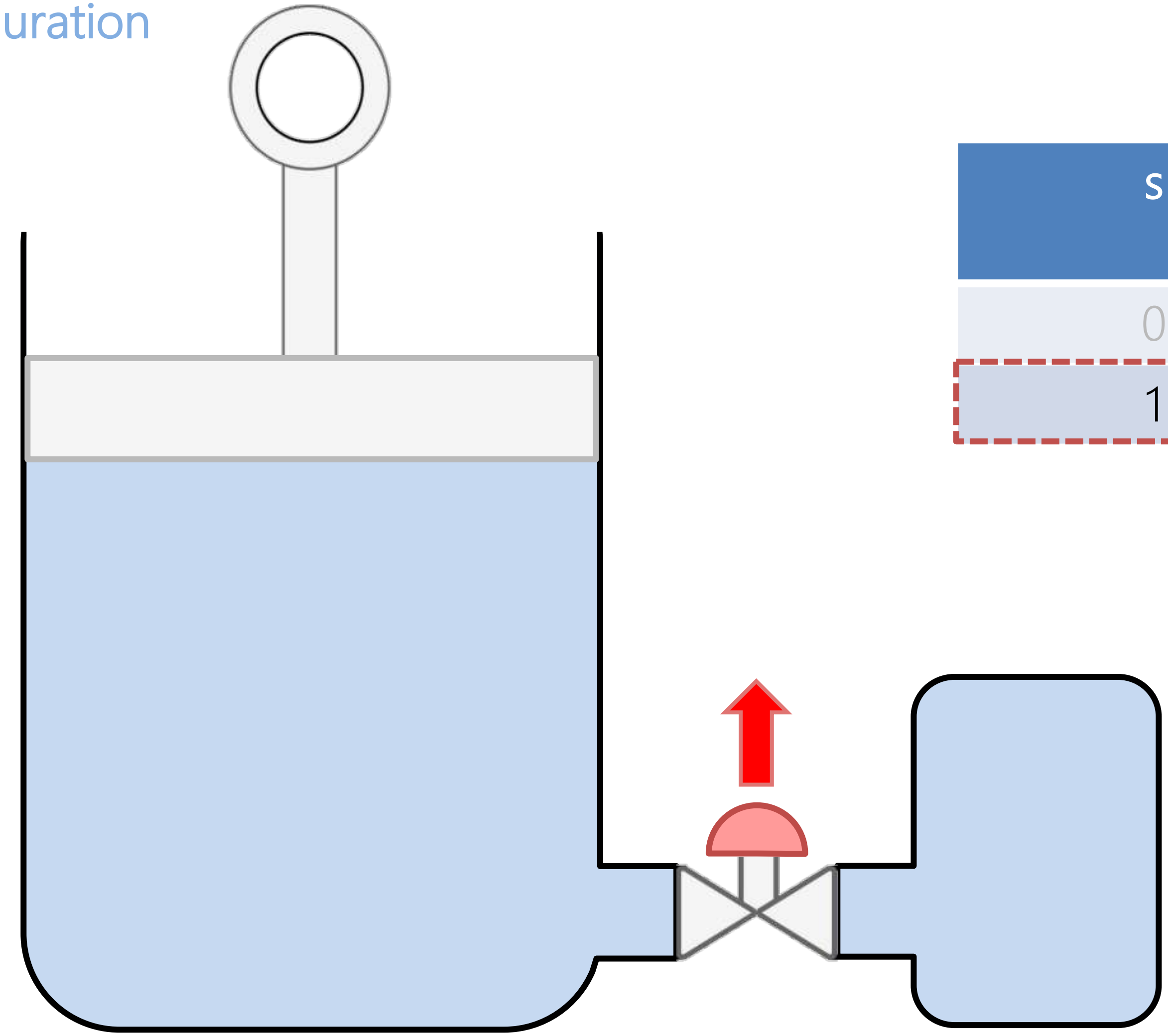
s	Valve configuration	System configuration
0	Closed	Hard
1	Open	Soft

Hard configuration



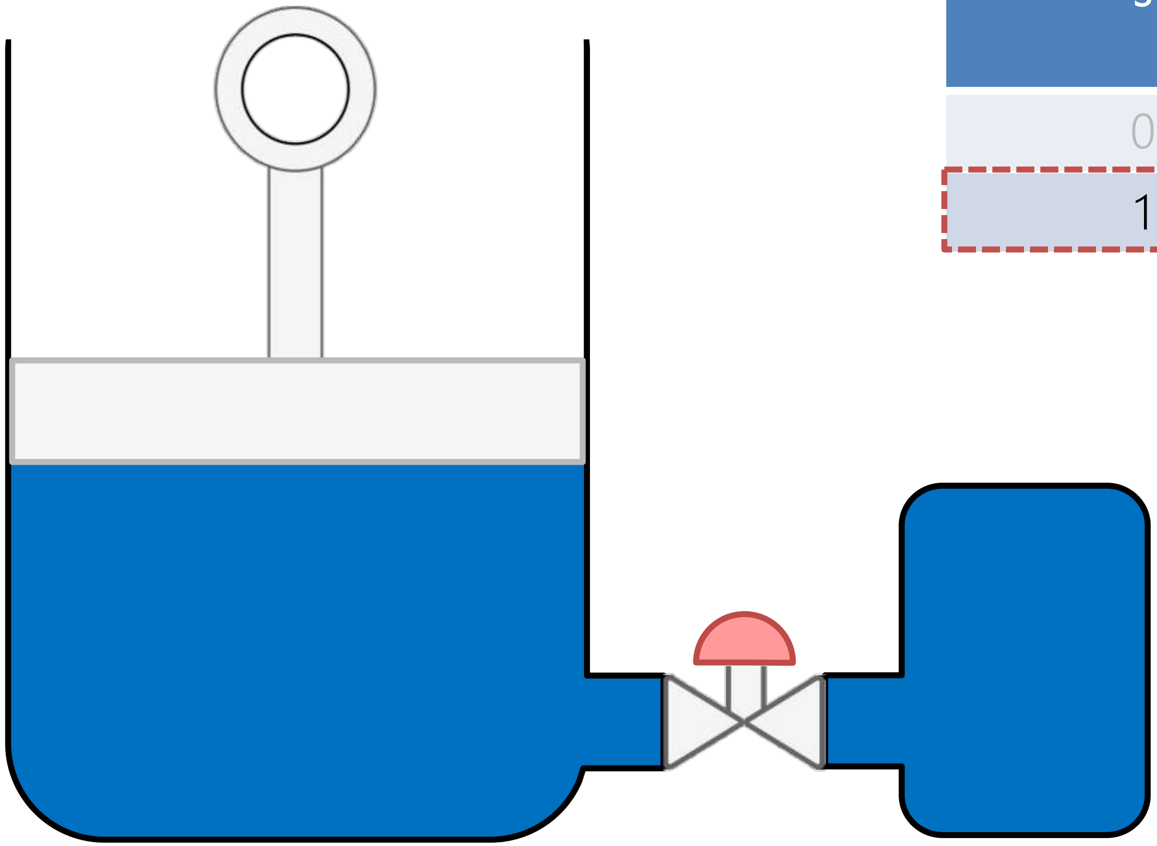
s	Valve configuration	System configuration
0	Closed	Hard
1	Open	Soft

Soft configuration



s	Valve configuration	System configuration
0	Closed	Hard
1	Open	Soft

Soft configuration

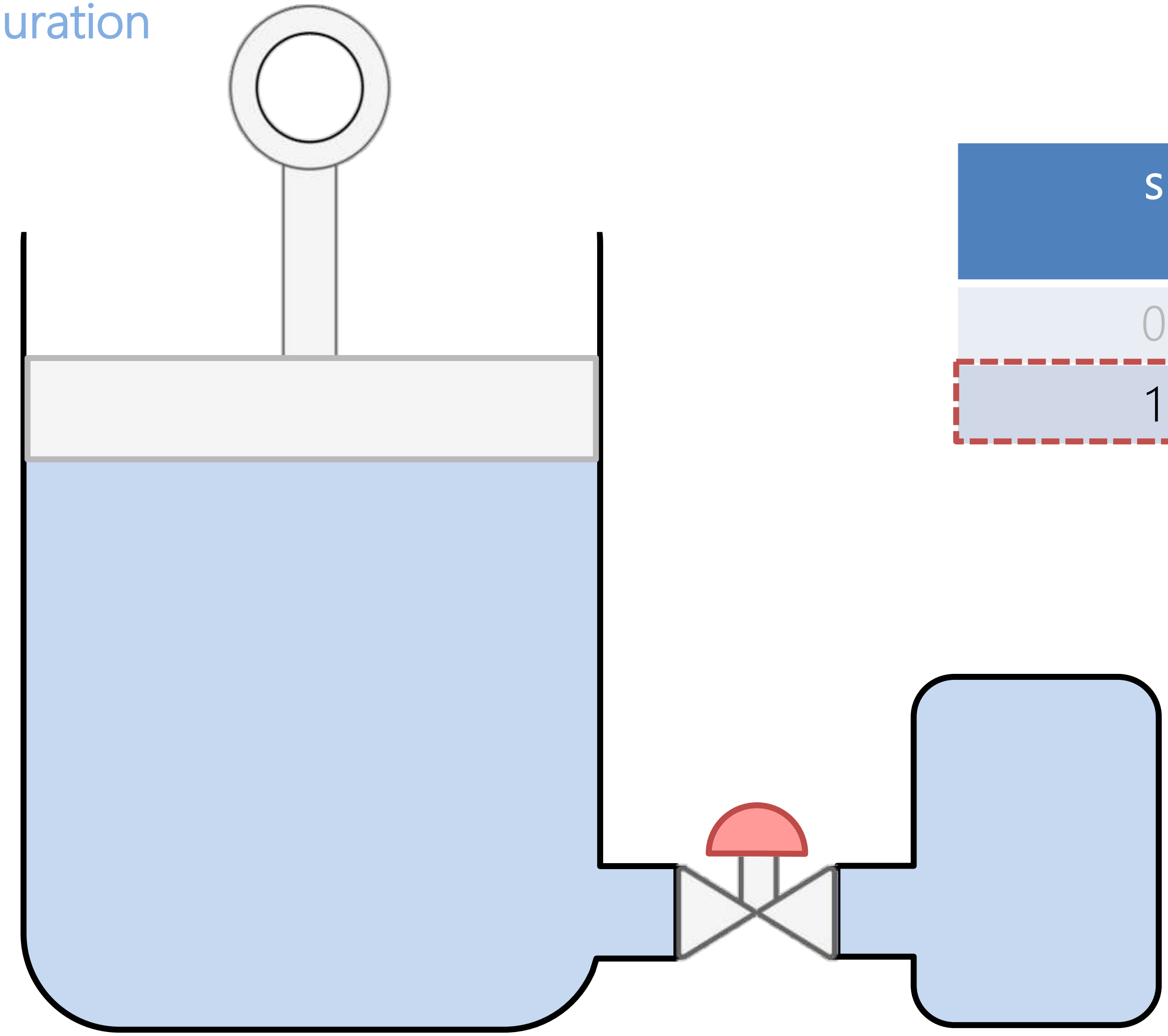


s	Valve configuration	System configuration
0	Closed	Hard
1	Open	Soft

Semi-Active Stiffness Control

Air Spring – Pneumatic Spring – Semi-Active

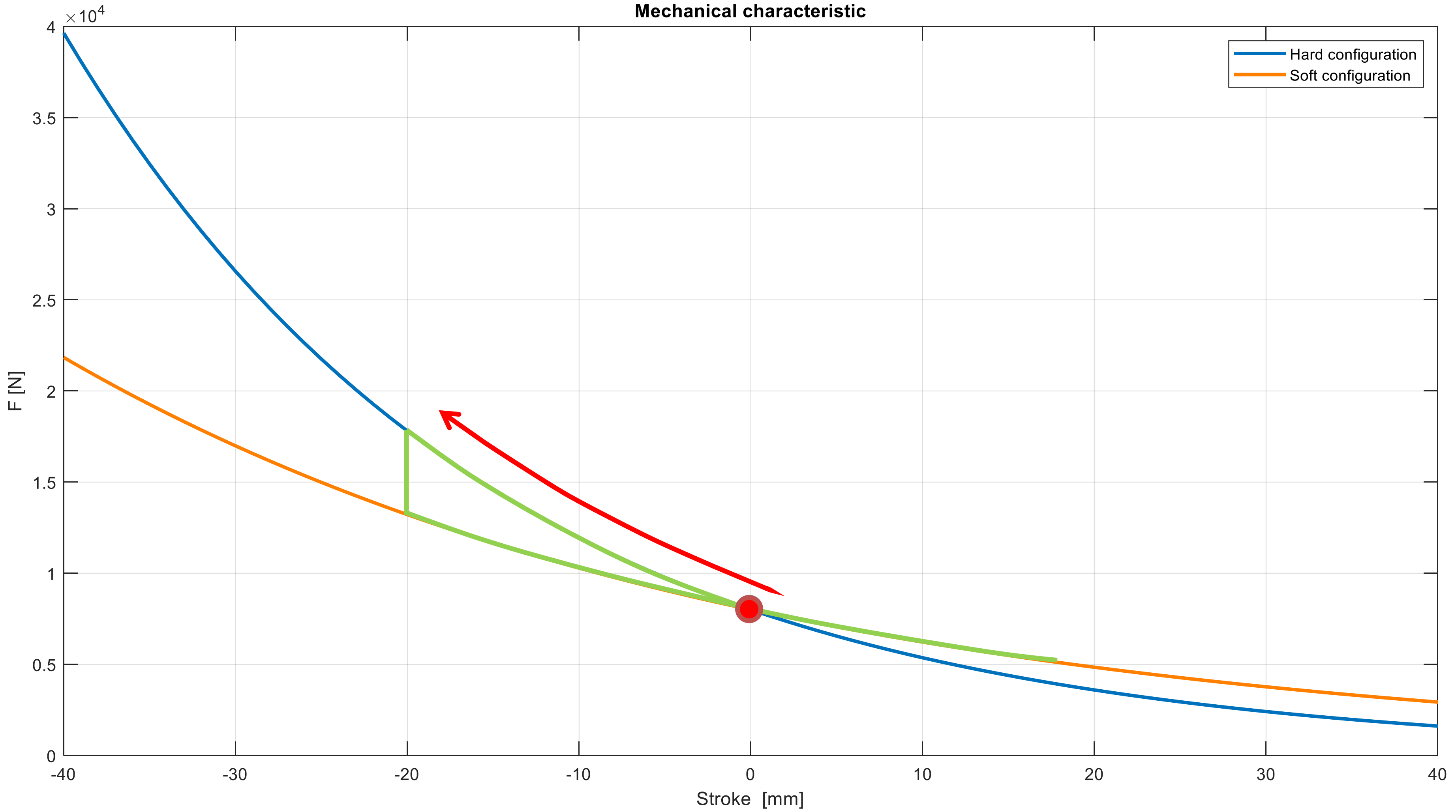
Soft configuration

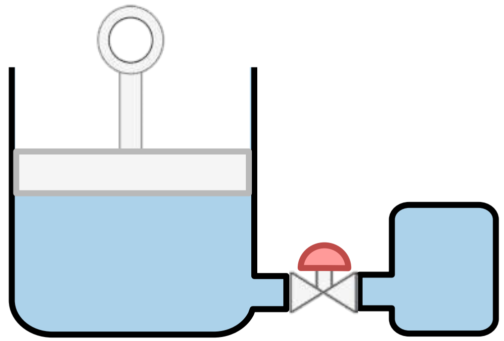


s	Valve configuration	System configuration
0	Closed	Hard
1	Open	Soft

Semi-Active Stiffness Control

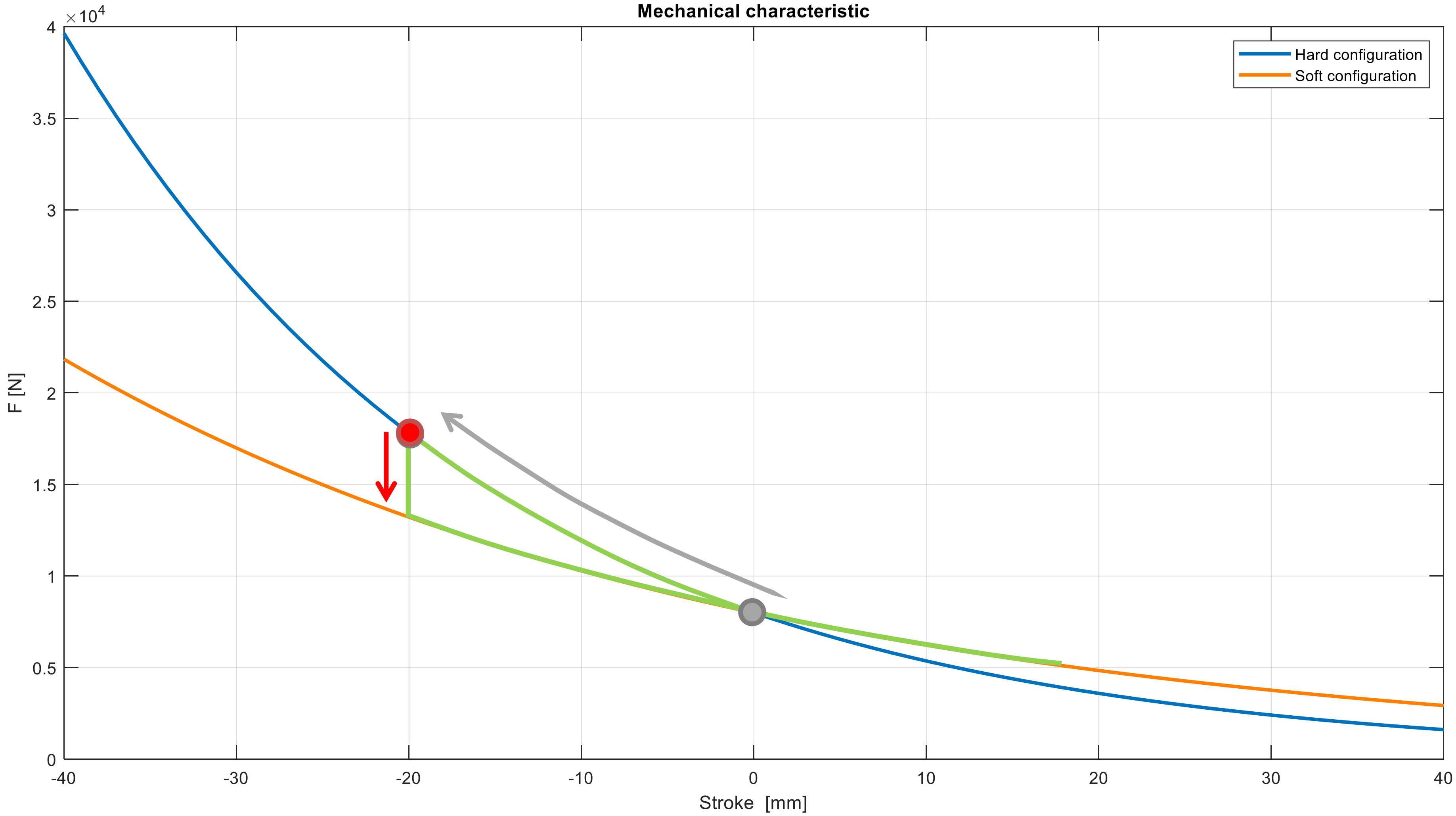
Kick-back

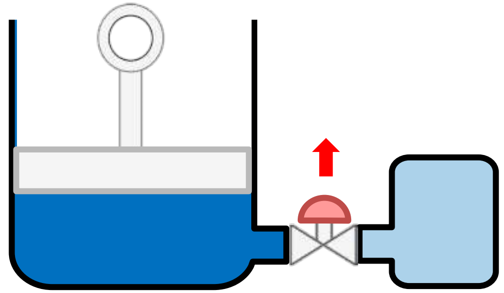




Semi-Active Stiffness Control

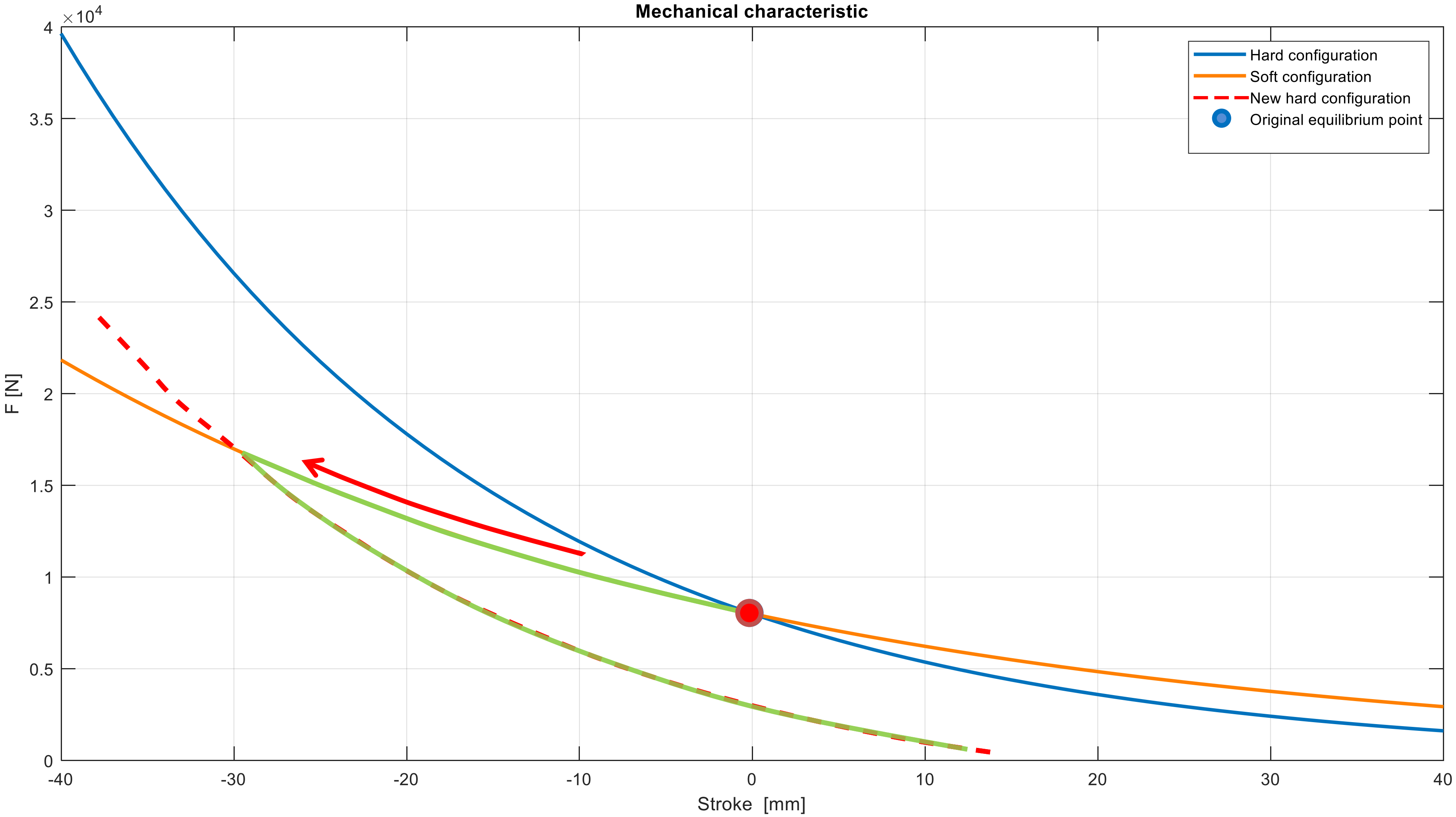
Kick-back

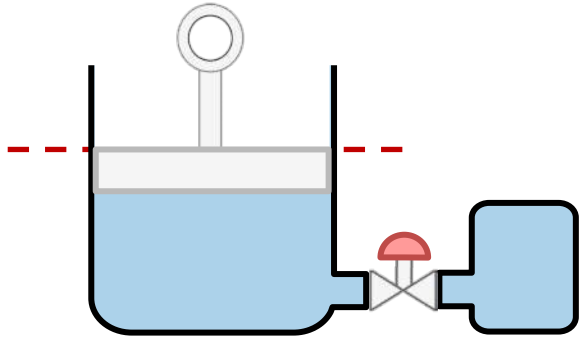




Semi-Active Stiffness Control

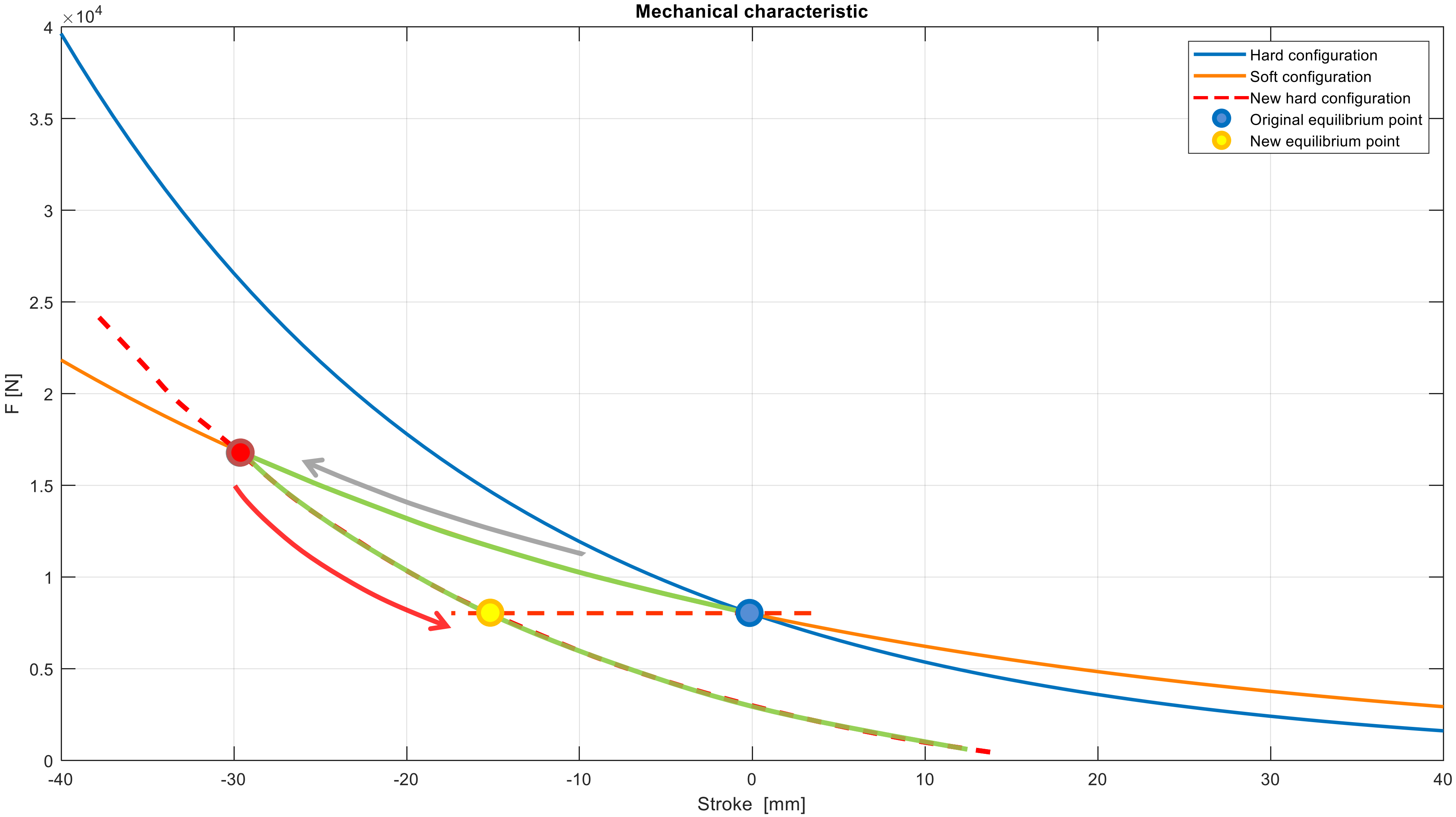
Kick-back

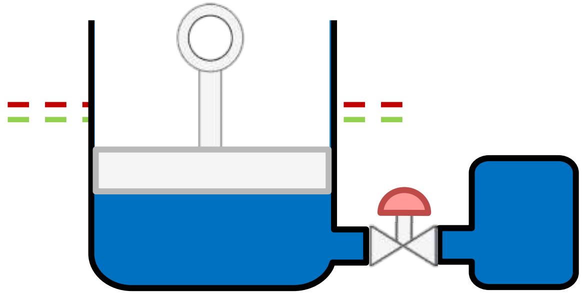


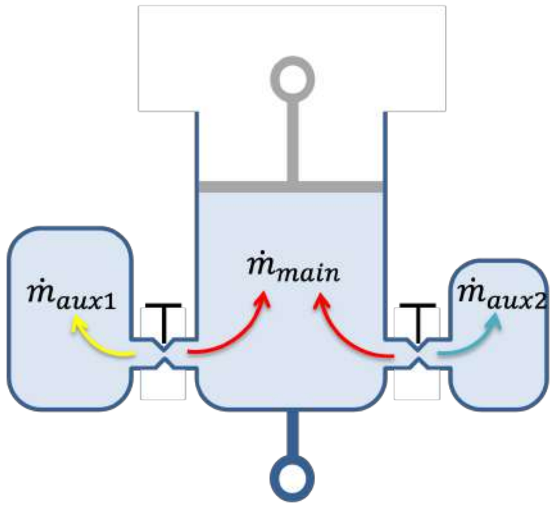


Semi-Active Stiffness Control

Kick-back







Law of ideal gases

$$pV = mRT$$

Law of conservation of energy

$$\delta U = \delta Q + \delta H - \delta W$$

Law of conservation of mass

$$m_{main} + m_{aux1} + m_{aux2} = const.$$

Flow trought valves

$$q_{m,i}^{sub} = s_i A_v C_v p_{max} \sqrt{\frac{2\gamma}{RT_{up}(\gamma - 1)} \left[\left(\frac{p_{min}}{p_{max}}\right)^{\frac{2}{\gamma}} - \left(\frac{p_{min}}{p_{max}}\right)^{\frac{\gamma+1}{\gamma}} \right]}$$

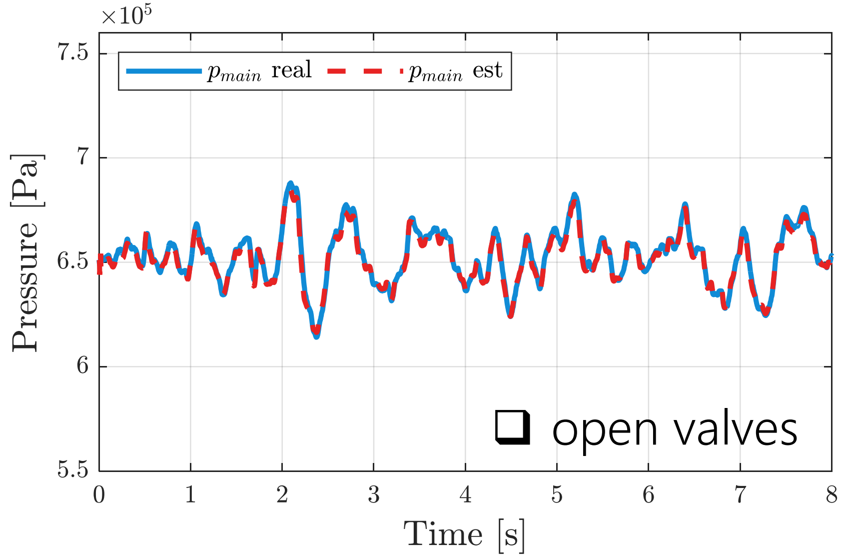
Semi-Active Stiffness Control

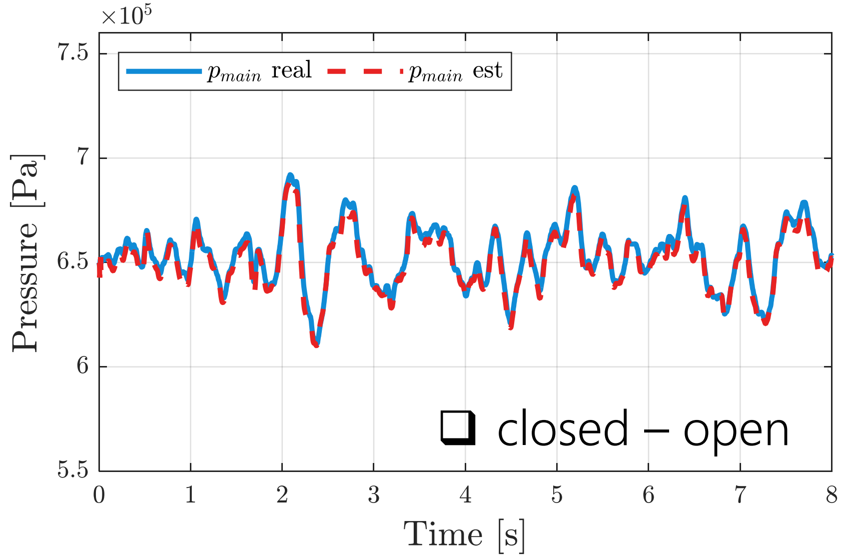
Model Identification

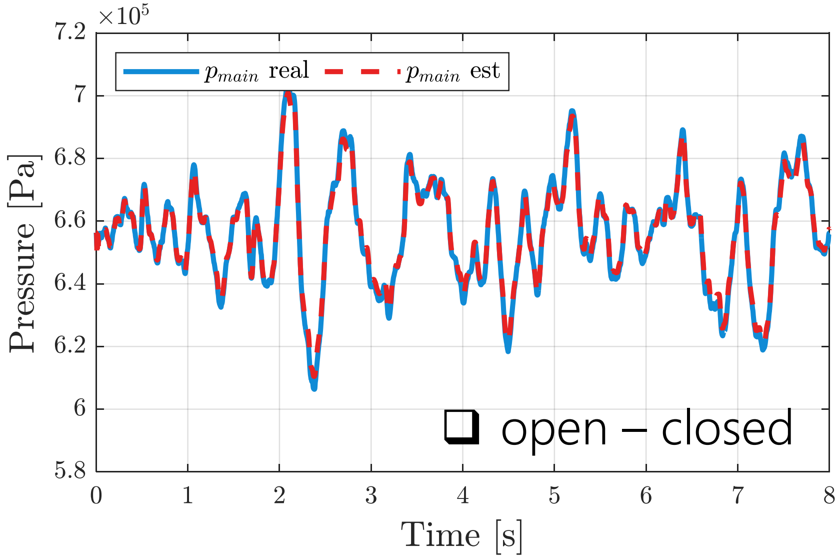
$$
\begin{cases}
\dot p_{main} = -\frac{\gamma \cdot p_{main}\dot V_{main}}{V_{main}} + \frac{\gamma R(T_{main}\cdot \dot m_{main} - T_{aux,1}\cdot \dot m_{aux,1} - T_{aux,2}\cdot \dot m_{aux,2})}{V_{main}} \\
\dot p_{aux,1} = -\frac{\gamma R(T_{main}\dot m_{aux,1} + T_{aux,1}\dot m_{aux,1})}{V_{aux,1}} \\
\dot p_{aux,2} = -\frac{\gamma R(T_{main}\dot m_{aux,2} + T_{aux,2}\dot m_{aux,2})}{V_{aux,2}} \\
\dot T_{main} = \frac{(1-\gamma)\cdot T_{main}\cdot \dot V_{main}}{V_{main}} + \frac{(\gamma-1)\cdot R\cdot T^2_{main}\cdot \dot m_{main}}{V_{main}\cdot p_{main}} - \frac{\gamma\cdot R\cdot T_{main}\cdot (T_{aux,1}\cdot \dot m_{aux,1} + T_{aux,2}\cdot \dot m_{aux,2})}{V_{main}\cdot p_{main}} \\
\dot T_{aux,1} = \frac{(\gamma-1)\cdot R\cdot T^2_{aux,1}\cdot \dot m_{aux,1}}{V_{aux,1}\cdot p_{aux,1}} + \frac{\gamma\cdot R\cdot T_{main}\cdot T_{aux,1}\cdot \dot m_{aux,1}}{V_{aux,1}\cdot p_{aux,1}} \\
\dot T_{aux,2} = \frac{(\gamma-1)\cdot R\cdot T^2_{aux,2}\cdot \dot m_{aux,2}}{V_{aux,2}\cdot p_{aux,2}} + \frac{\gamma\cdot R\cdot T_{main}\cdot T_{aux,2}\cdot \dot m_{aux,2}}{V_{aux,2}\cdot p_{aux,2}} \\
\dot m_{main} = s_1 \cdot A_{v,max}C_{v1} \cdot p_{max}\sqrt{\frac{2\gamma}{RT_{up}(\gamma-1)}\left[\left(\frac{p_{min}}{p_{max}}\right)^{\frac{2}{\gamma}} - \left(\frac{p_{min}}{p_{max}}\right)^{\frac{\gamma+1}{\gamma}}\right]} sign(p_{aux,1} - p_{main}) + \\
+ s_2 \cdot A_{v,max}C_{v2} \cdot p_{max,2}\sqrt{\frac{2\gamma}{RT_{up,2}(\gamma-1)}\left[\left(\frac{p_{min,2}}{p_{max,2}}\right)^{\frac{2}{\gamma}} - \left(\frac{p_{min,2}}{p_{max,2}}\right)^{\frac{\gamma+1}{\gamma}}\right]} sign(p_{aux,2} - p_{main}) \\
\dot m_{aux,1} = s_1 \cdot A_{v,max}C_{v1} \cdot p_{max}\sqrt{\frac{2\gamma}{RT_{up}(\gamma-1)}\left[\left(\frac{p_{min}}{p_{max}}\right)^{\frac{2}{\gamma}} - \left(\frac{p_{min}}{p_{max}}\right)^{\frac{\gamma+1}{\gamma}}\right]} sign(p_{main} - (p_{aux,1}) \\
\dot m_{aux,2} = s_2 \cdot A_{v,max}C_{v2} \cdot p_{max,2}\sqrt{\frac{2\gamma}{RT_{up,2}(\gamma-1)}\left[\left(\frac{p_{min,2}}{p_{max,2}}\right)^{\frac{2}{\gamma}} - \left(\frac{p_{min,2}}{p_{max,2}}\right)^{\frac{\gamma+1}{\gamma}}\right]} sign(p_{main} - (p_{aux,2}) \\
F_k = (p_{main} - p_{atm}) \cdot A
\end{cases}
$$

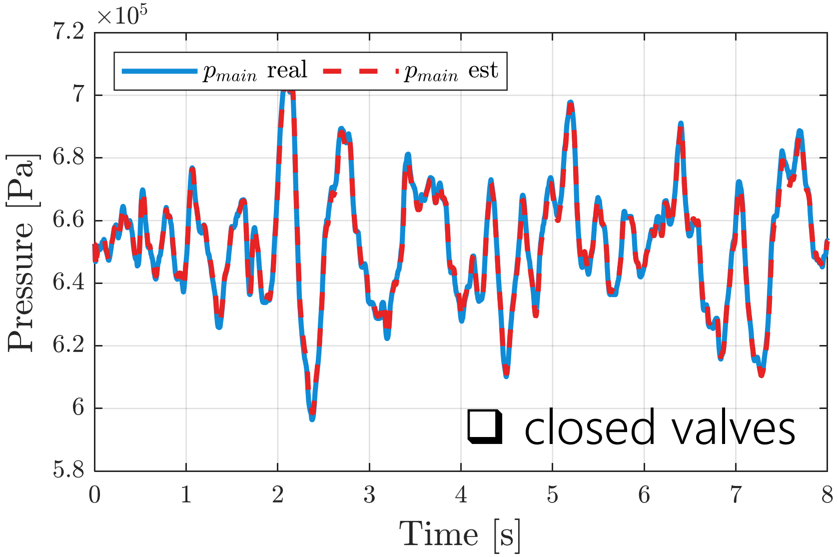
Semi-Active Stiffness Control

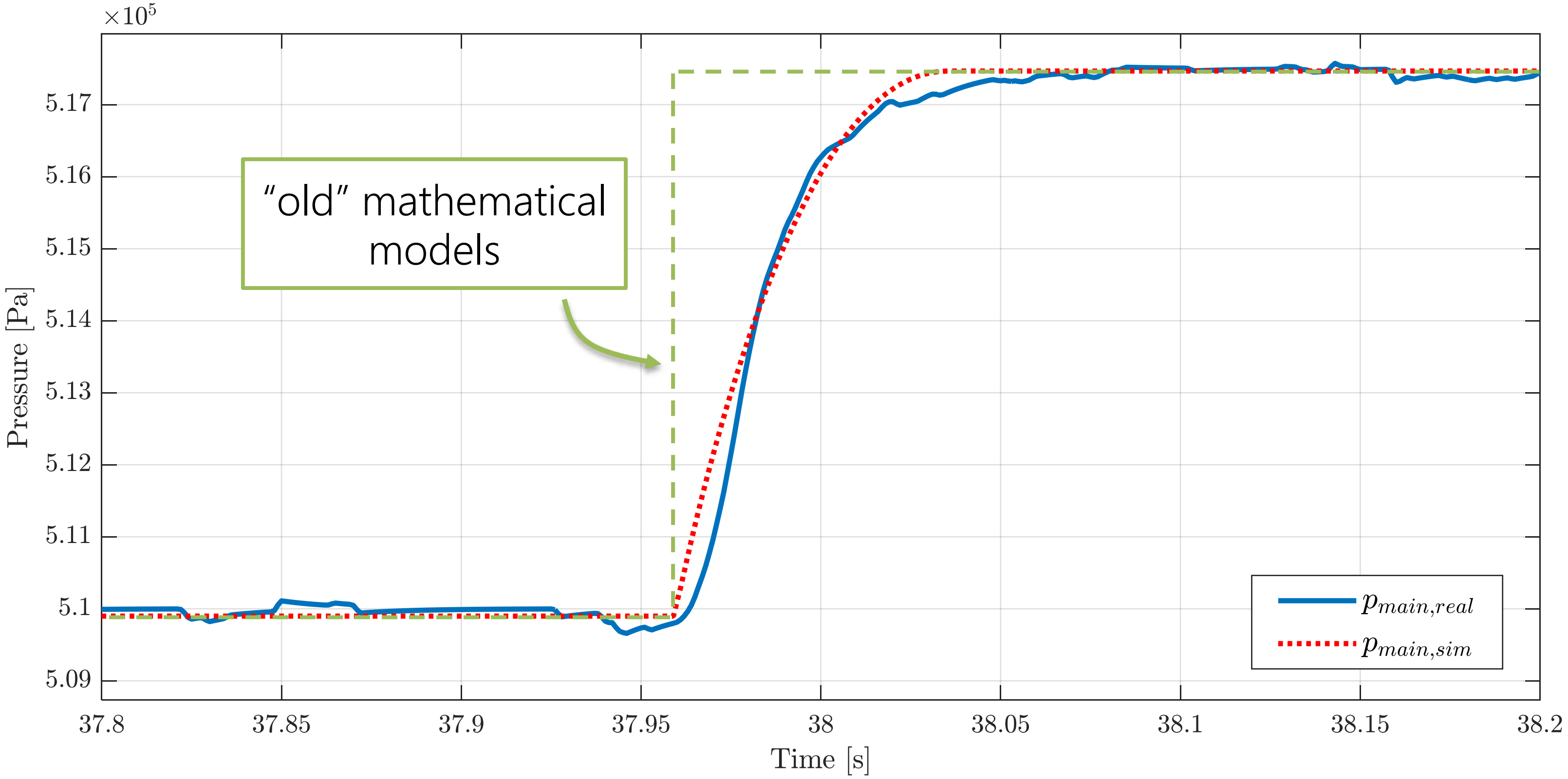
Model Identification











Opening of the valve

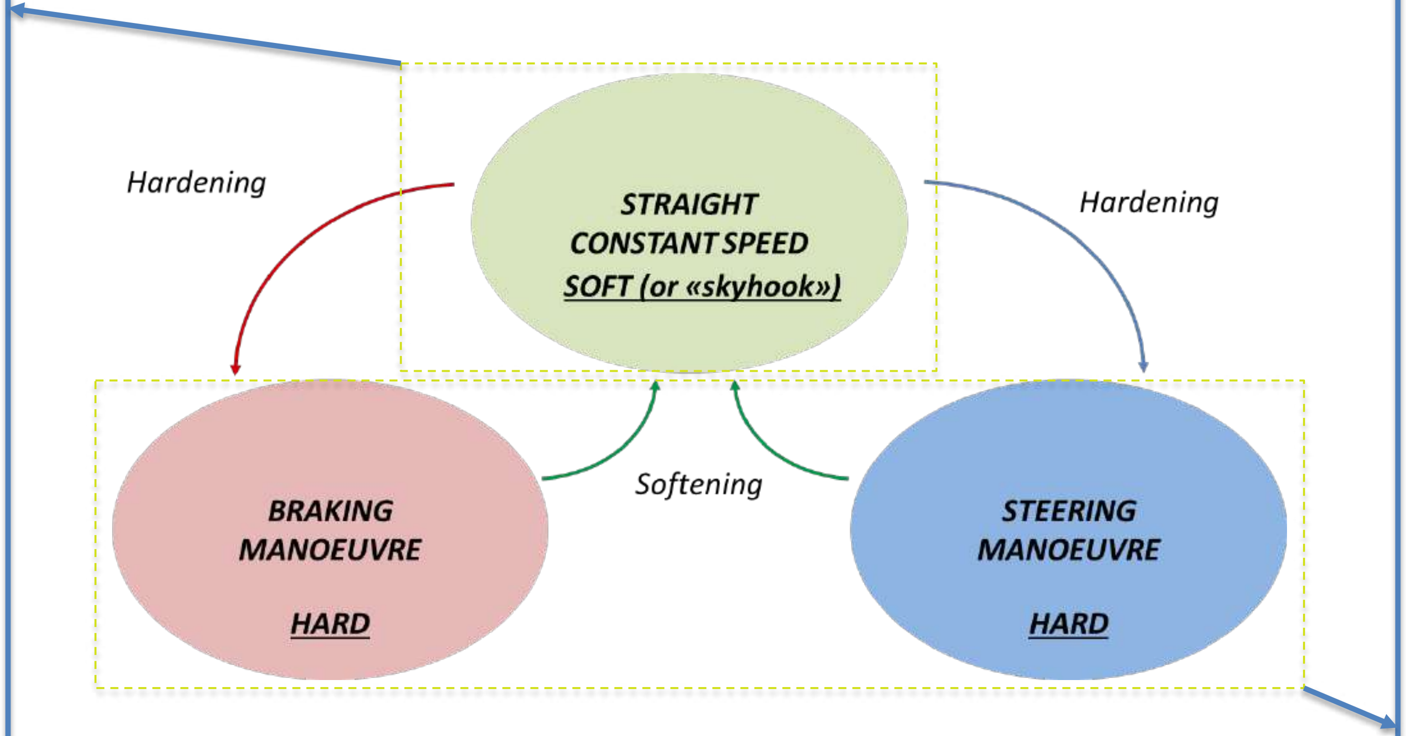
- When a valve is opened, the pressure (and consequently the elastic force) has a jump. The mathematical model is able to describe the pressure dynamics at the valve opening.
- The old models do not capture the real behaviour.

Semi-Active Stiffness Control

General Control Scheme

Car designed to be very comfortable on straight road; FIXED low-stiffness and FIXED low-damping

Good-Comfort - Poor handling

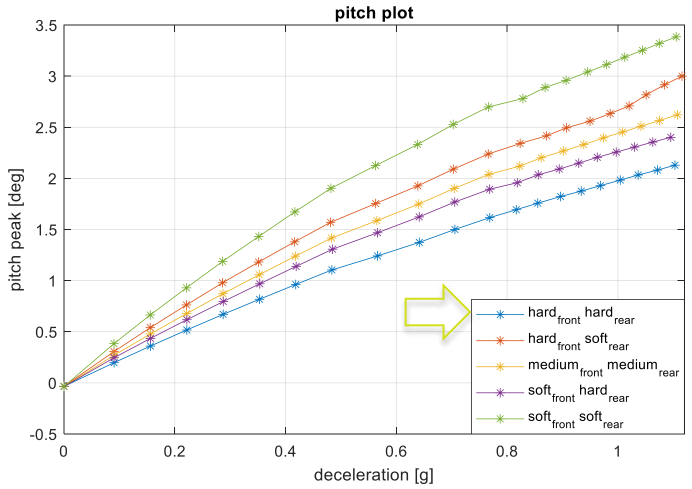


Car designed to have a good handling on curvy-roads; FIXED high-stiffness and FIXED high-damping

Good-Handling – Poor-comfort

Semi-Active Stiffness Control

Longitudinal Control Example

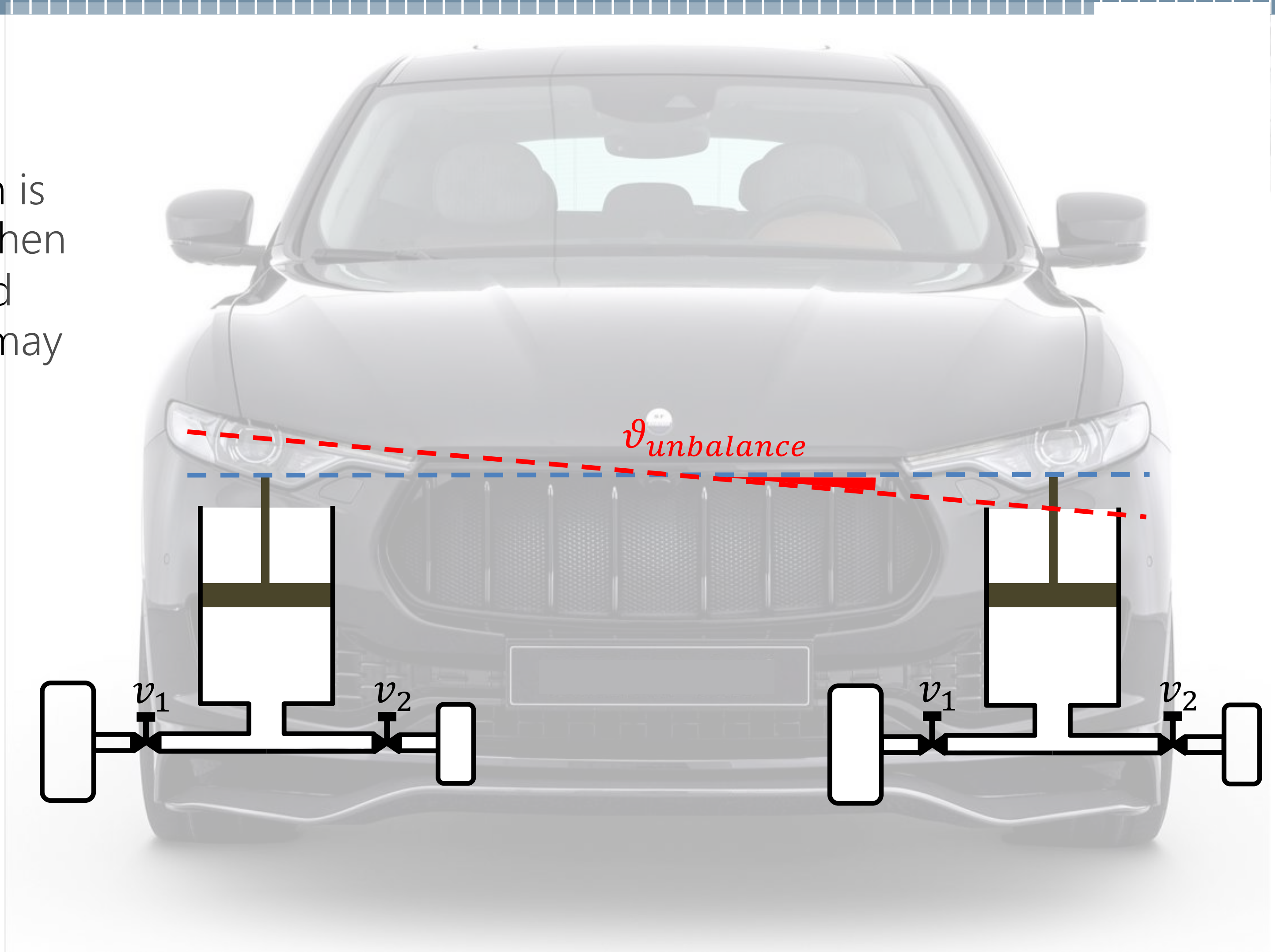


The «all-hard» K configuration guarantees the best «anti-dive» effect in braking (and «anti-squat» in acceleration)

Semi-Active Stiffness Control

Longitudinal Control Example

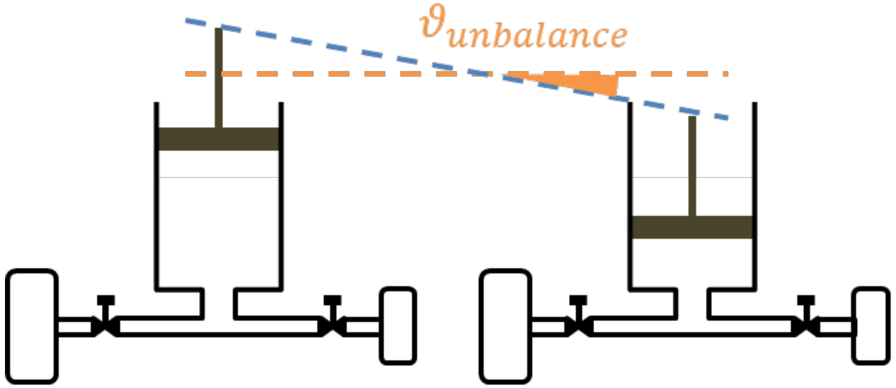
If the hardening-switch is immediately applied when braking, an unbalanced equilibrium roll angle may arise



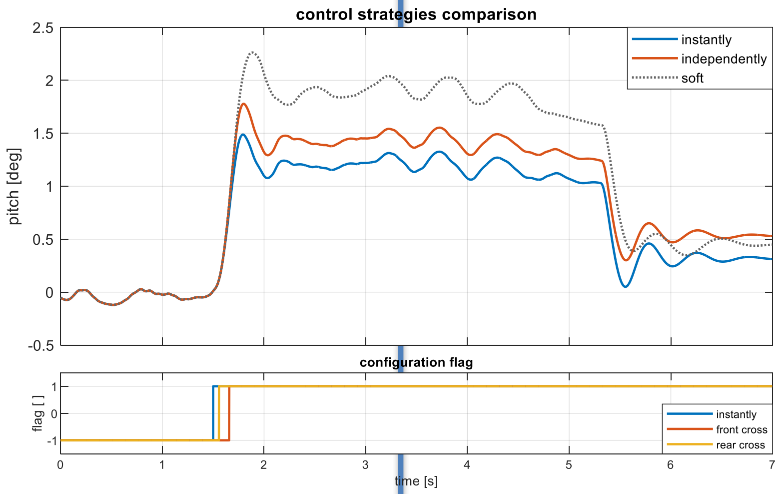
Semi-Active Stiffness Control

Hardening suspensions stiffness *as soon as starts braking manoeuvre*

PRO	CONS
Minimized control response time	*Effects given by suspensions unbalancing*

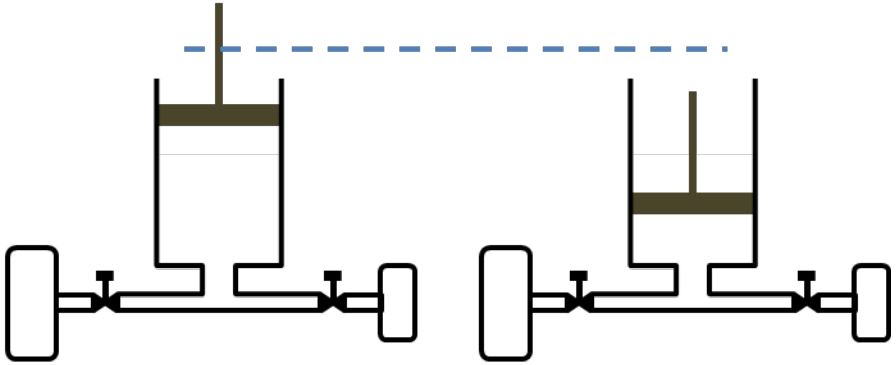


$$K_{soft} \rightarrow K_{hard}$$



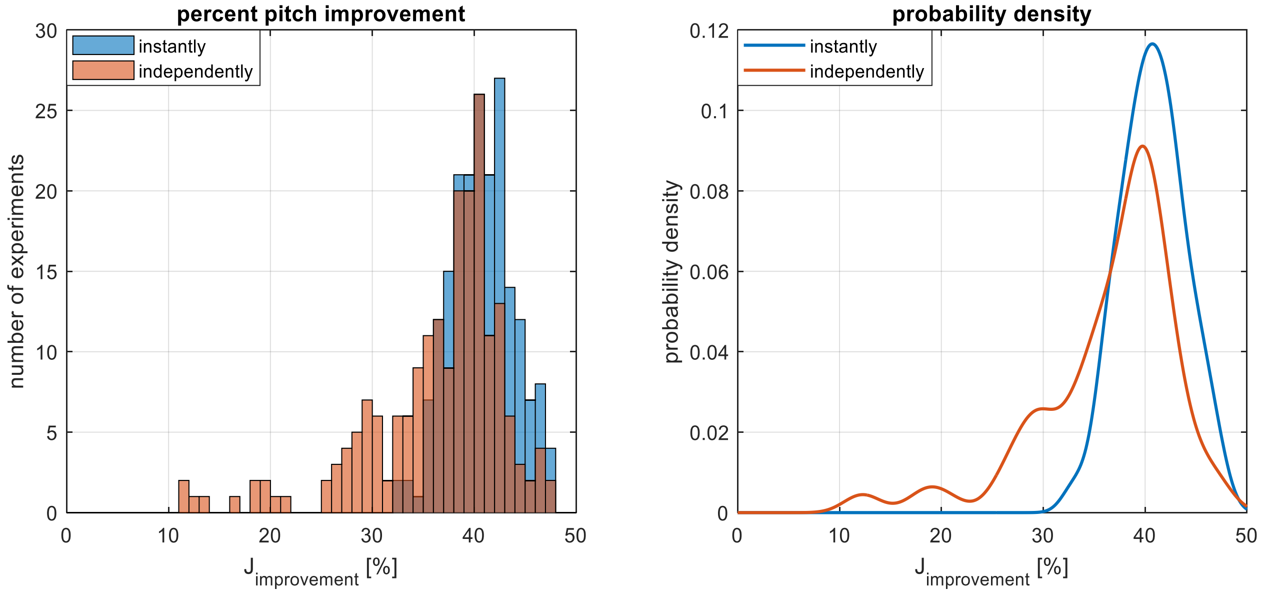
Hardening independently front and rear suspensions stiffness *when braking* manoeuvre *is started* and *left and right suspensions are at the same stroke*

PRO	CONS
Left and right suspensions balanced for each side	*Pitch improvement delayed*

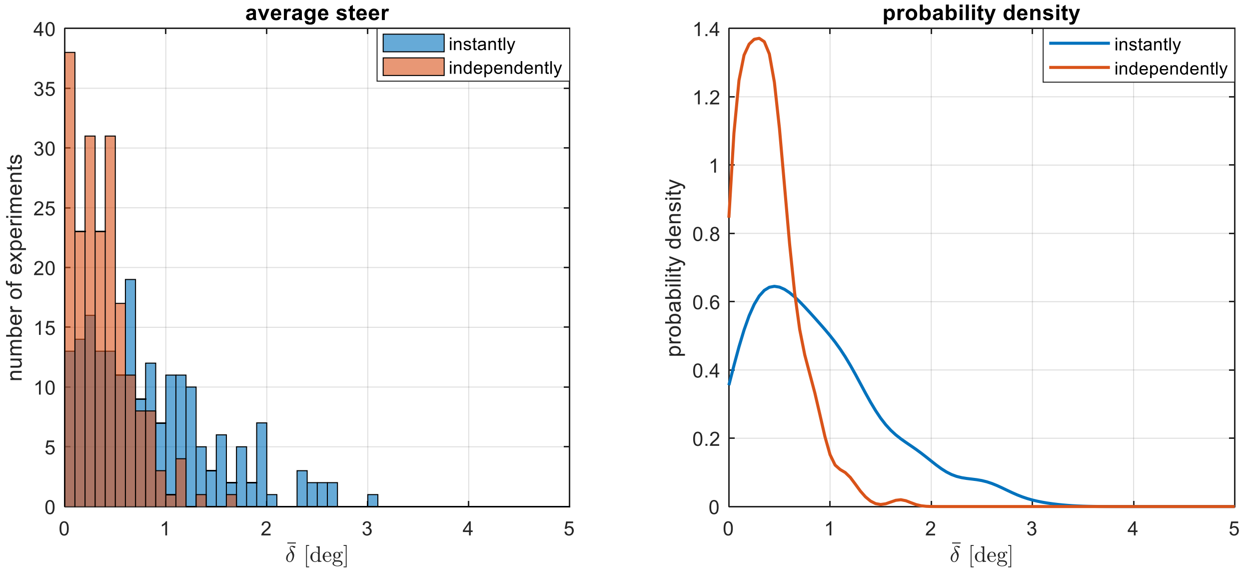


$$K_{soft} \rightarrow K_{hard}$$

Semi-Active Stiffness Control

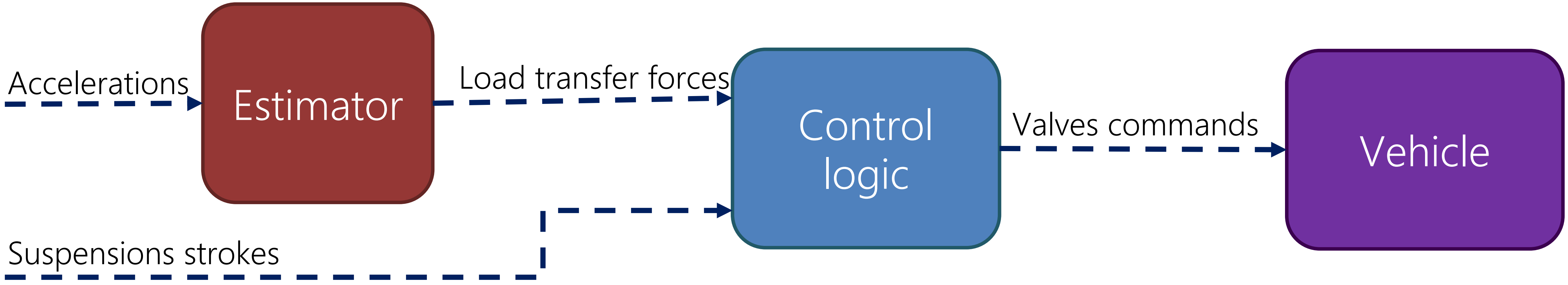


Pitch-unbalancing effect: the «instantly» control approach guarantees (slightly) better performance

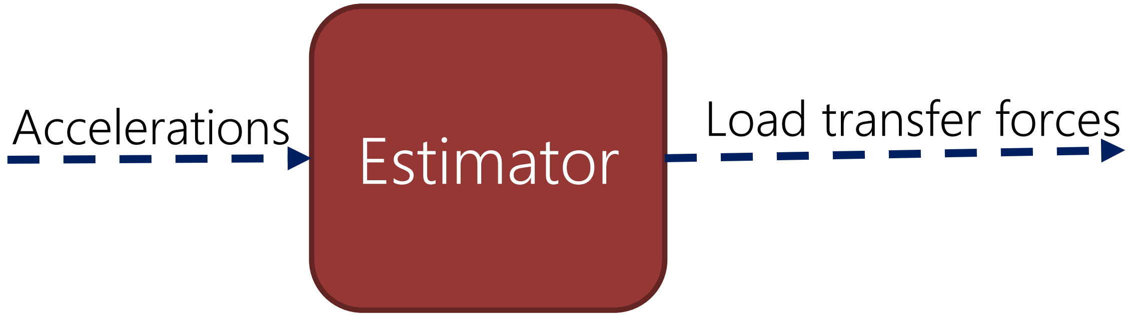


Pitch-unbalancing negative effect: can be seen with the steer-angle correction needed to keep a straight line

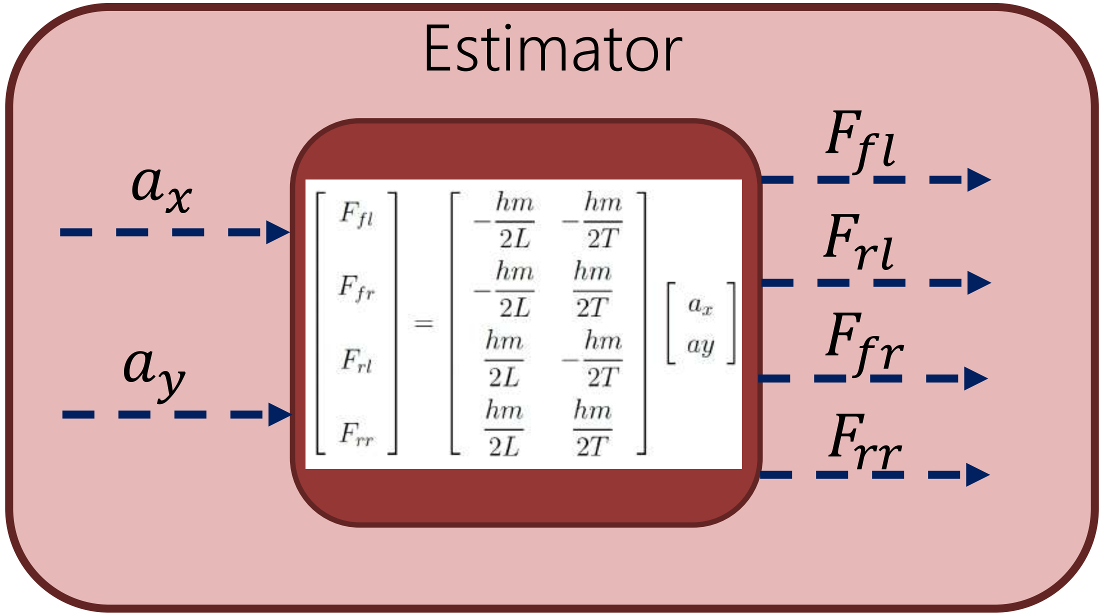
Semi-Active Stiffness Control

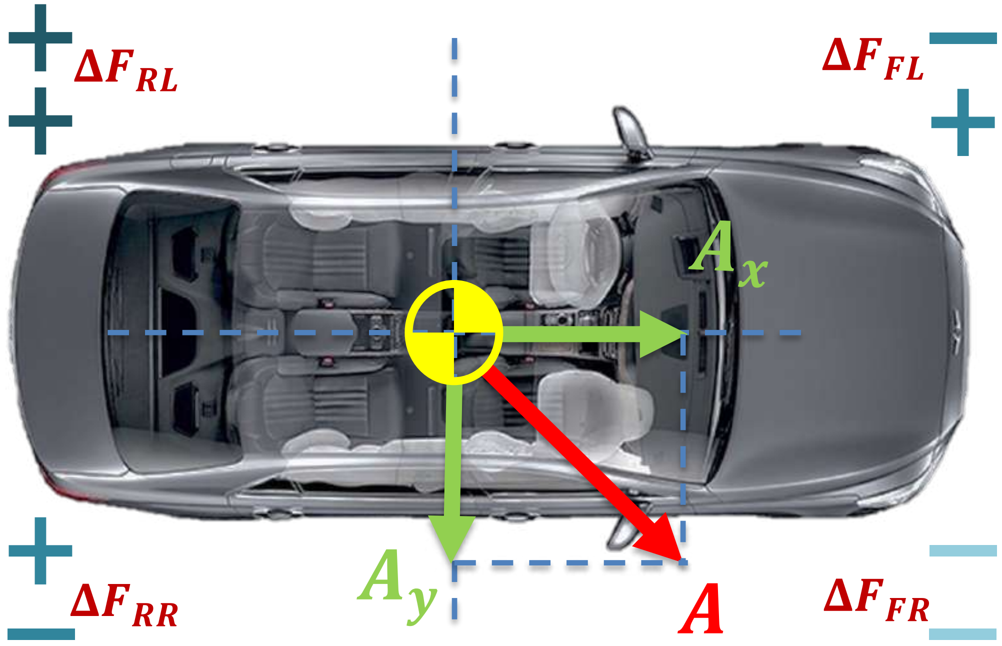


Semi-Active Stiffness Control

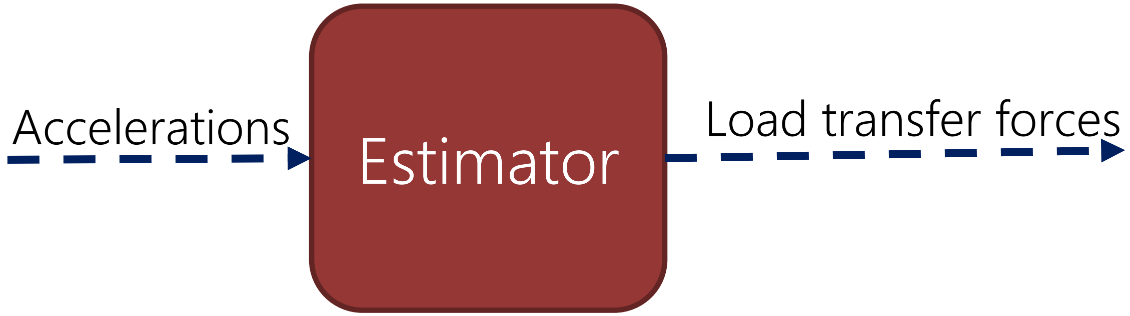


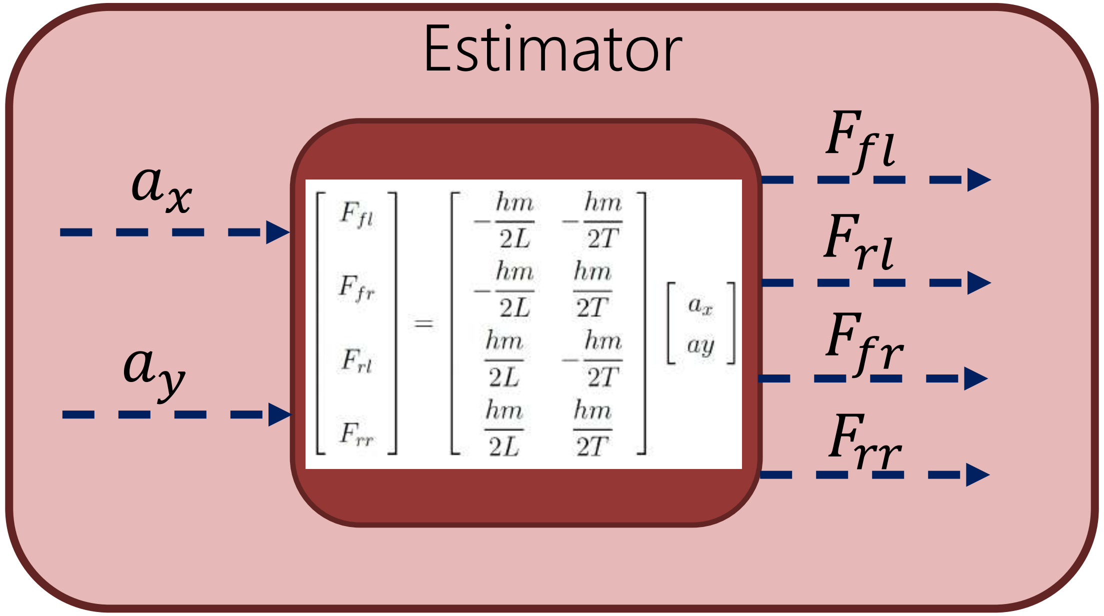
The **load transfer force** of each corner is estimated using a linear system that takes as input the **longitudinal** and **lateral acceleration** of the vehicle's COG.



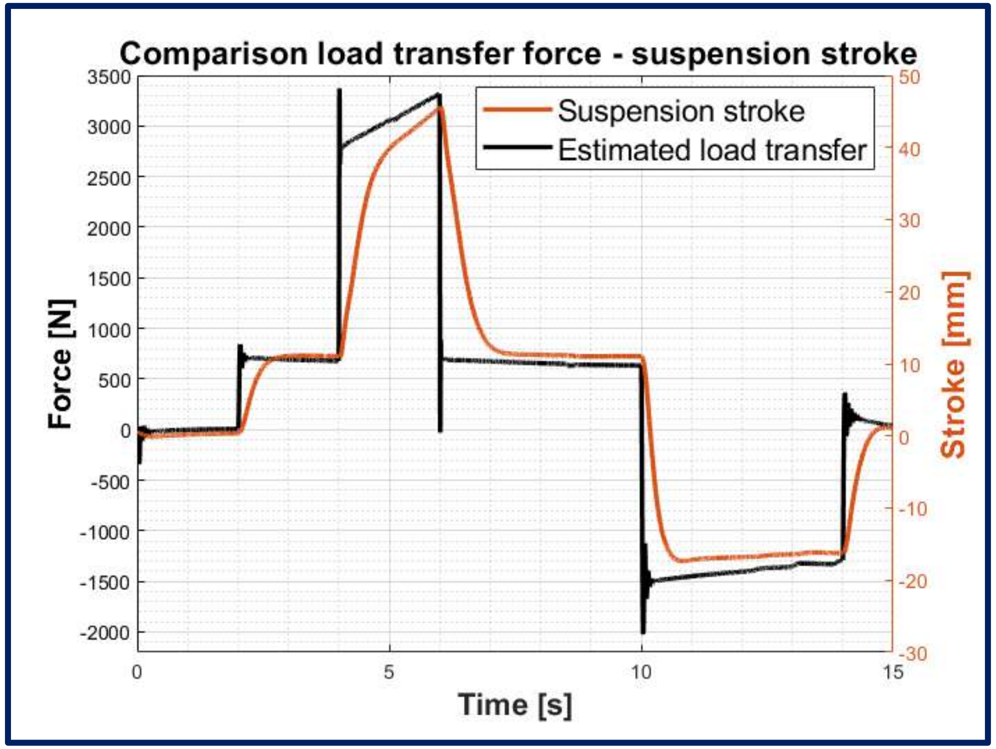


Semi-Active Stiffness Control



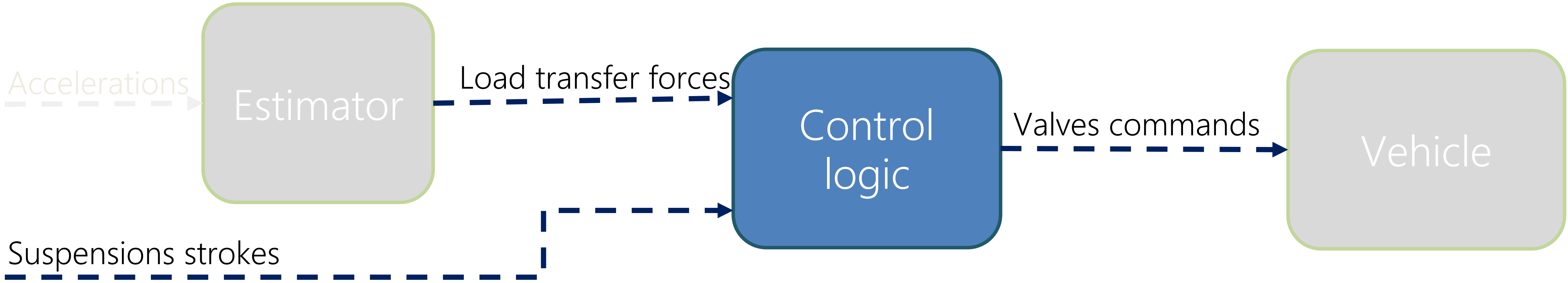


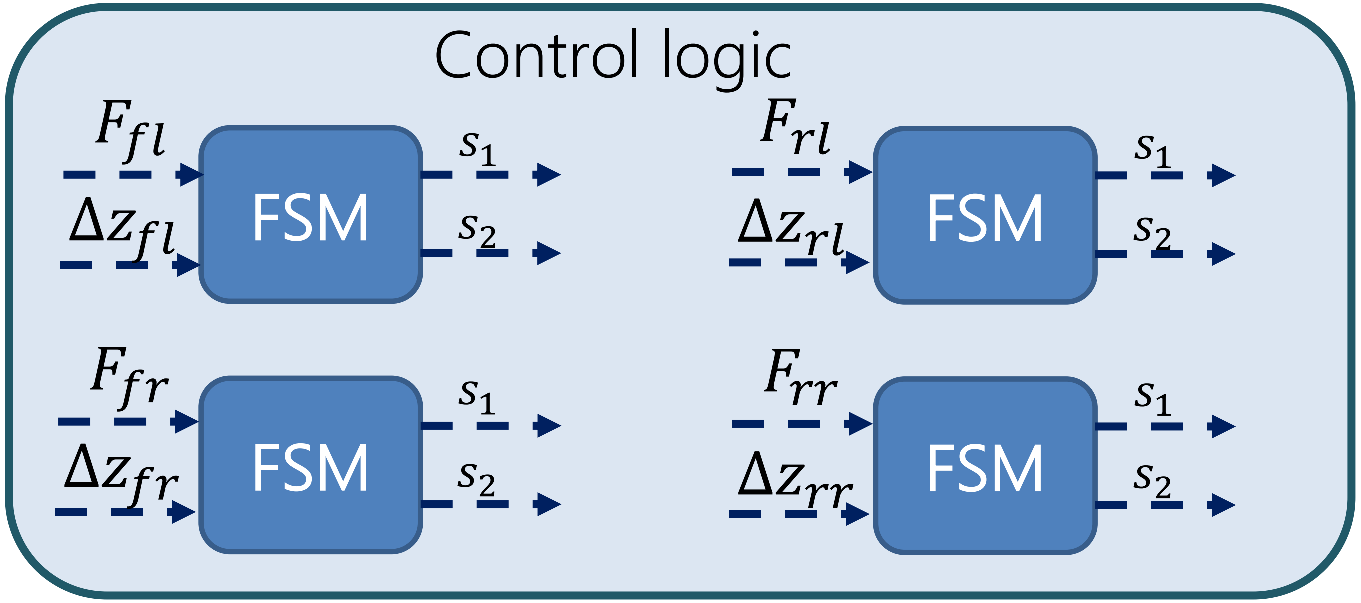
$$\begin{bmatrix} F_{fl} \\ F_{fr} \\ F_{rl} \\ F_{rr} \end{bmatrix} = \begin{bmatrix} -\frac{hm}{2L} & -\frac{hm}{2T} \\ -\frac{hm}{2L} & \frac{hm}{2T} \\ \frac{hm}{2L} & -\frac{hm}{2T} \\ \frac{hm}{2L} & \frac{hm}{2T} \end{bmatrix} \begin{bmatrix} a_x \\ ay \end{bmatrix}$$



- It recognizes and manages **mixed** maneuvers
- It **predicts** suspension behavior
- Unique input for each corner

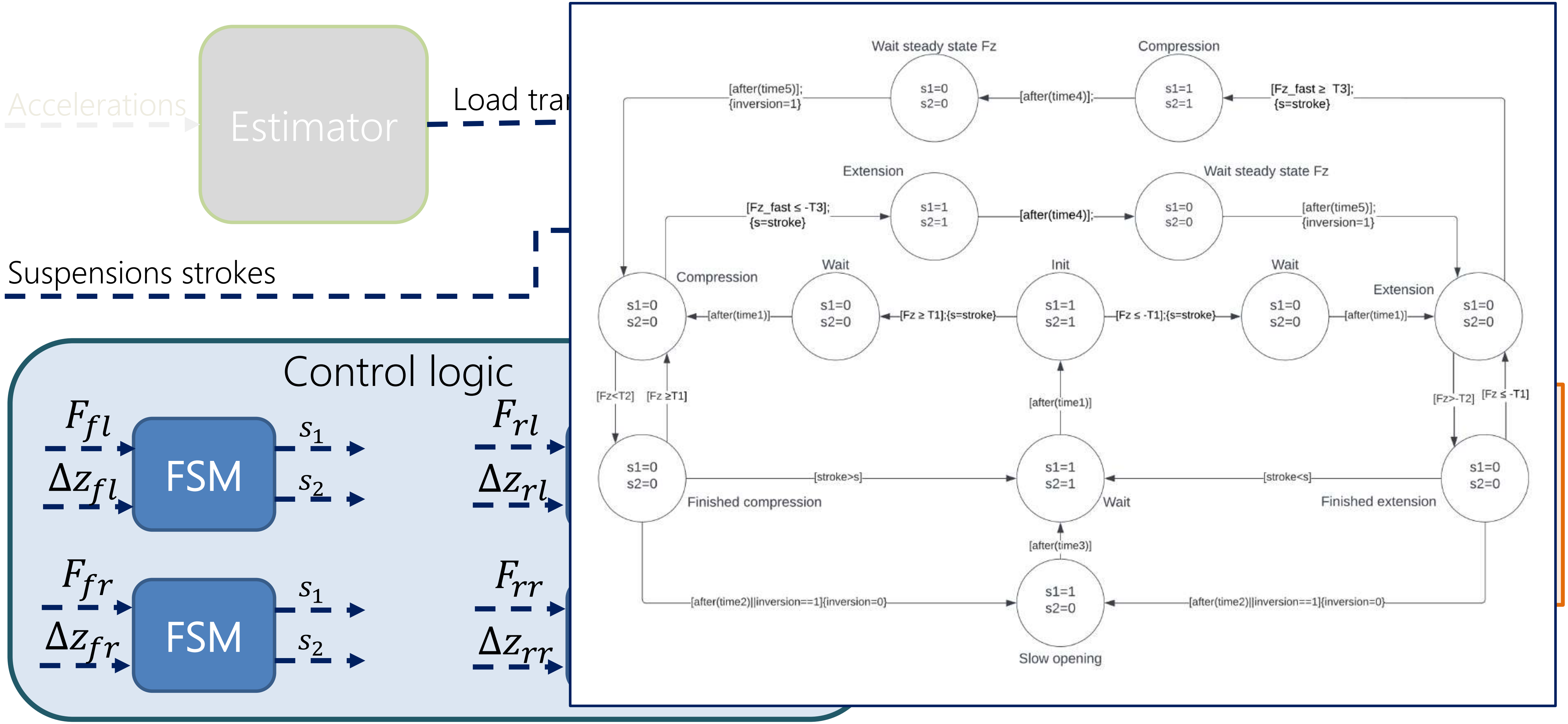
Semi-Active Stiffness Control





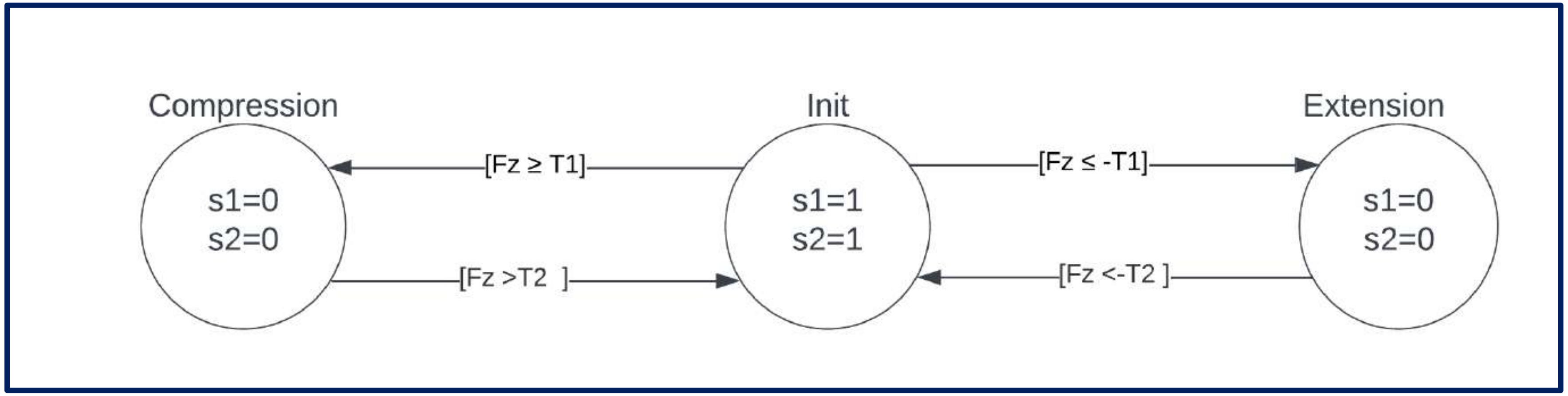
The control logic is made of **four identical finite state machine**, one for each car corner. The inputs are the **estimated load transfer** and the **suspension stroke** and the outputs are the **valves commands**.

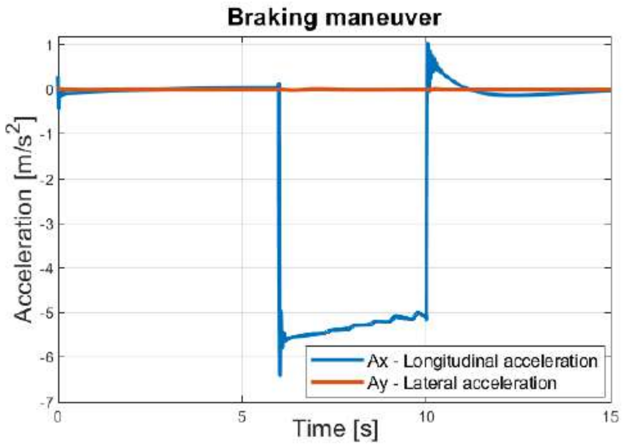
Semi-Active Stiffness Control

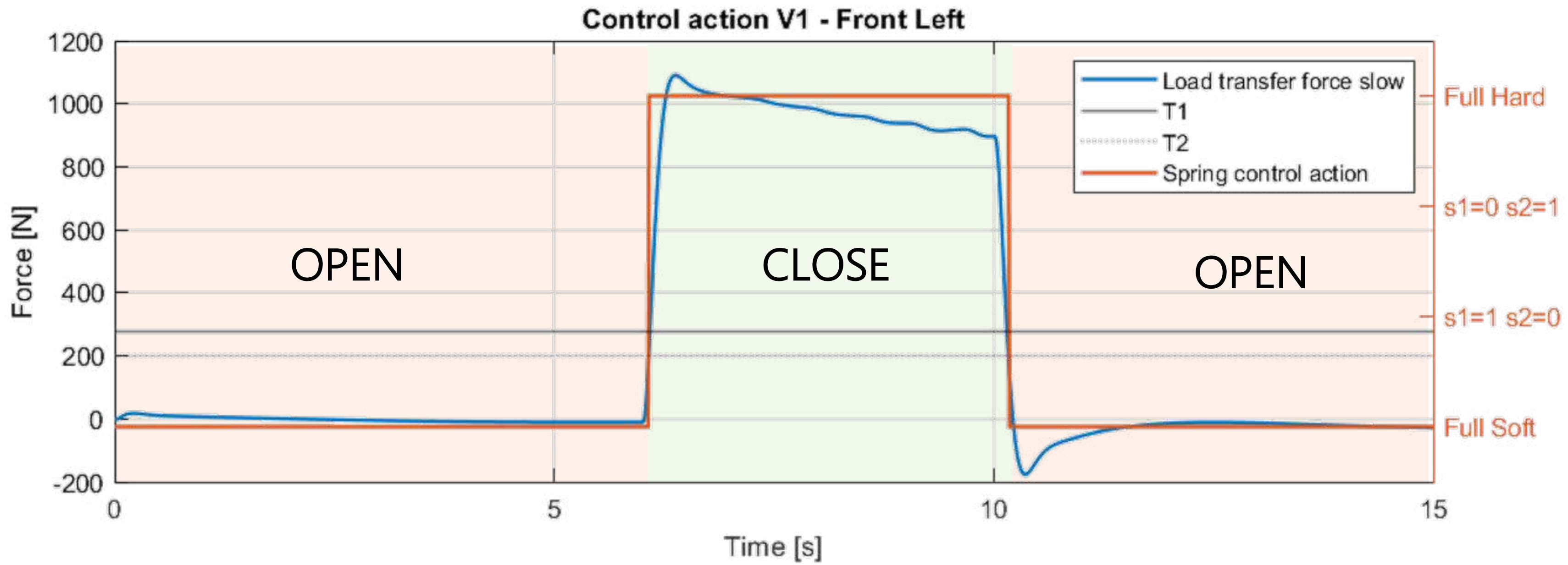


Semi-Active Stiffness Control

As soon as the estimated load transfer force is greater than **T1**, valves get closed. Then if the force is lower than **T2** valves get opened again.

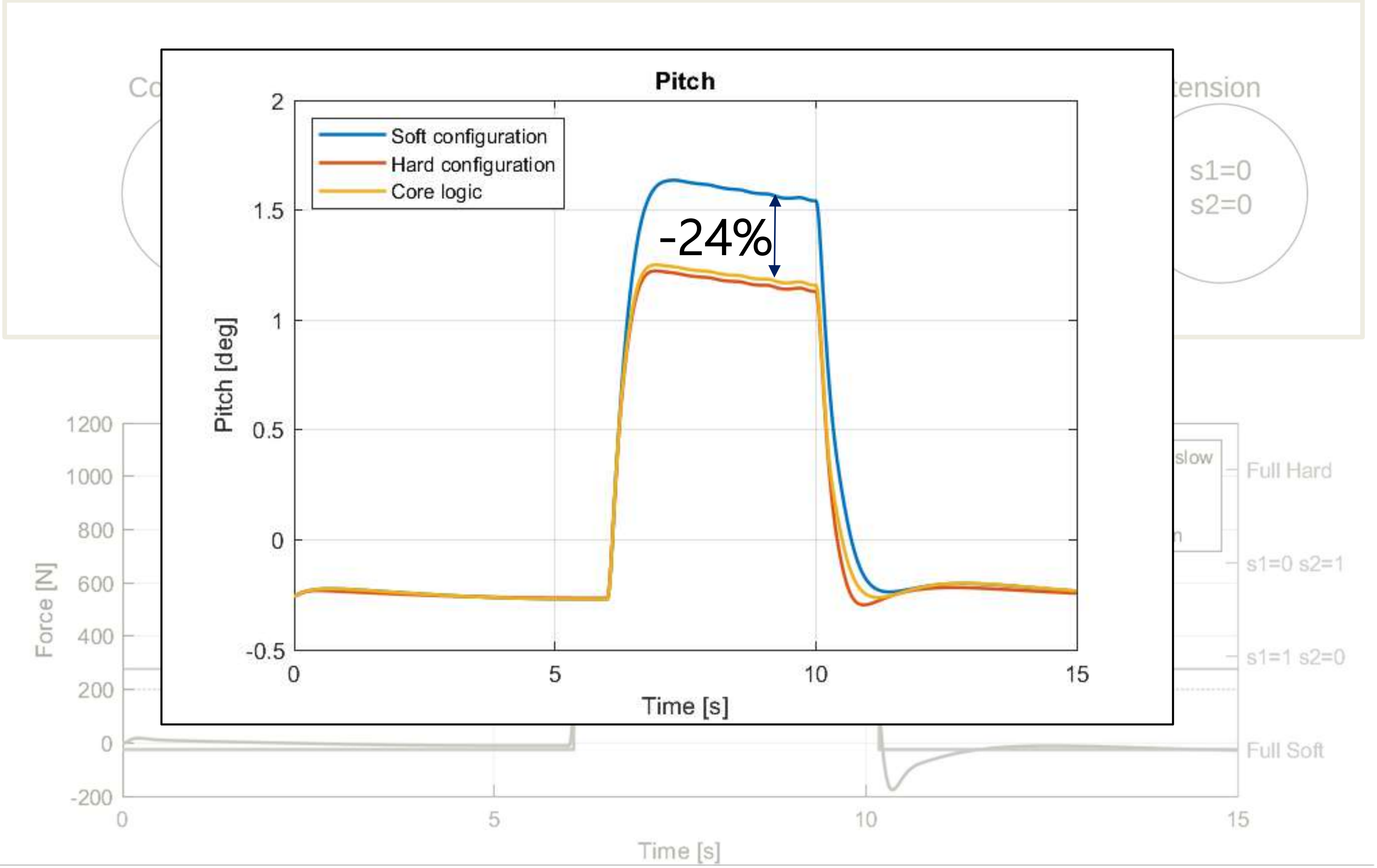


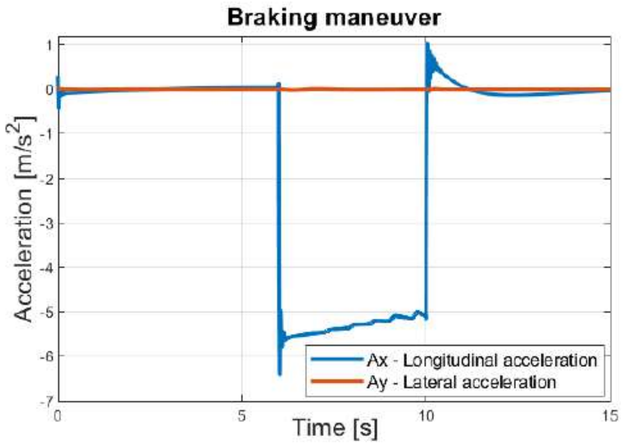




Semi-Active Stiffness Control

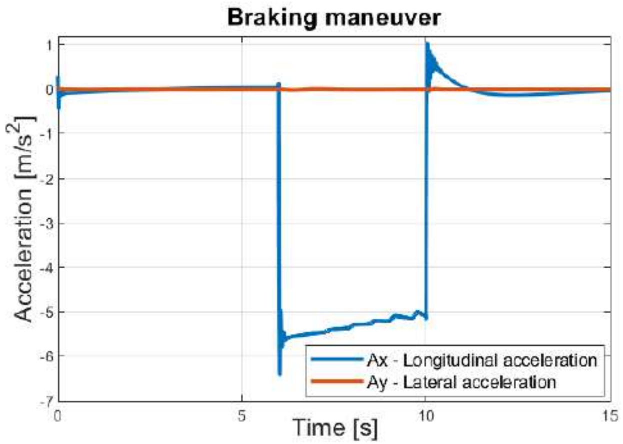
As soon as the estimated load transfer force is greater than **T1**, valves get closed. Then if the force is lower than **T2** valves get opened again.

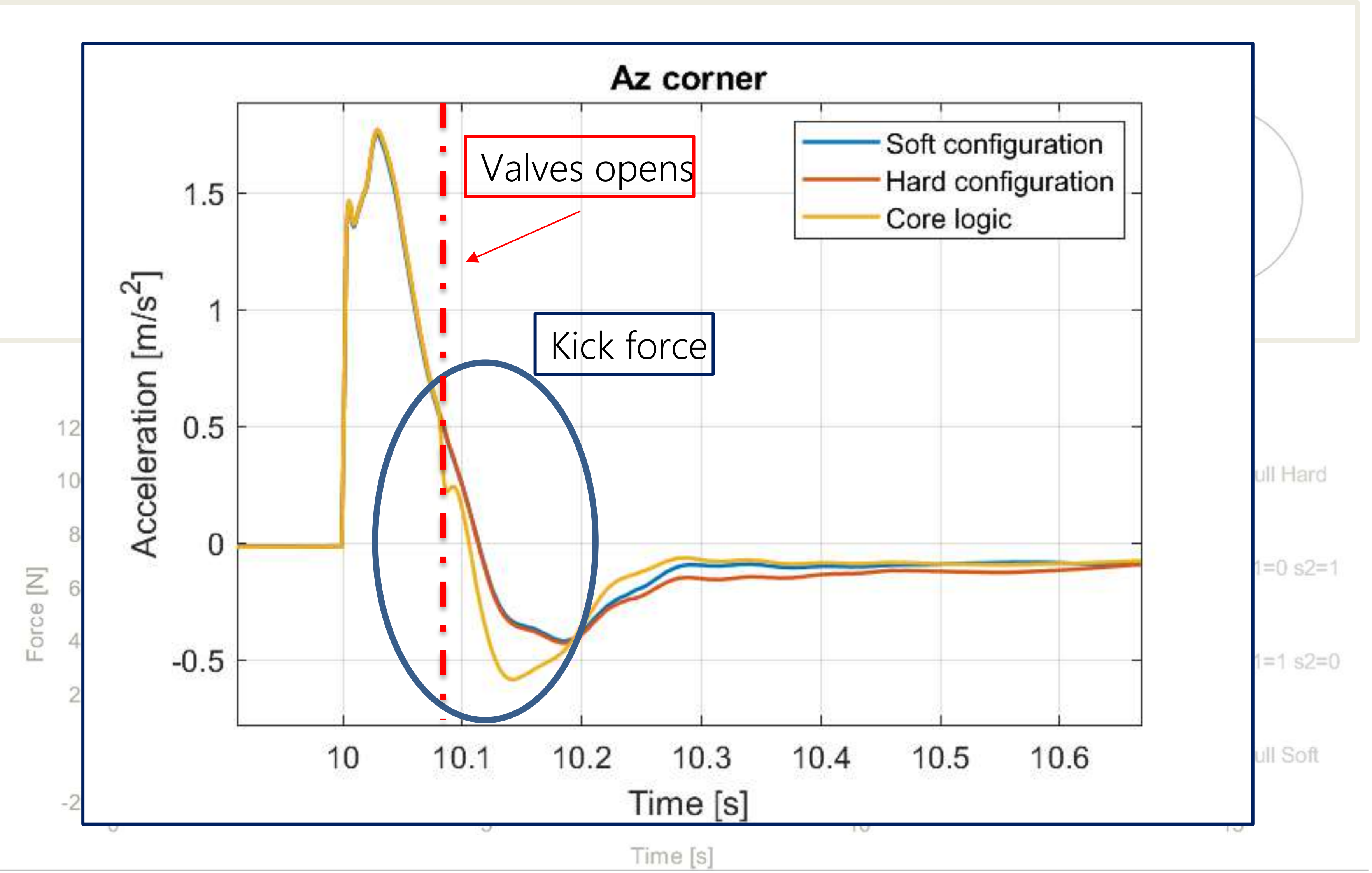




Semi-Active Stiffness Control

Kick force occurs if the valves are opened when the pressure of the **auxiliary** chambers is **different** with respect to the pressure of the **main** chamber.
This phenomenon worsens the **peak** of **vertical acceleration** by **38%**.



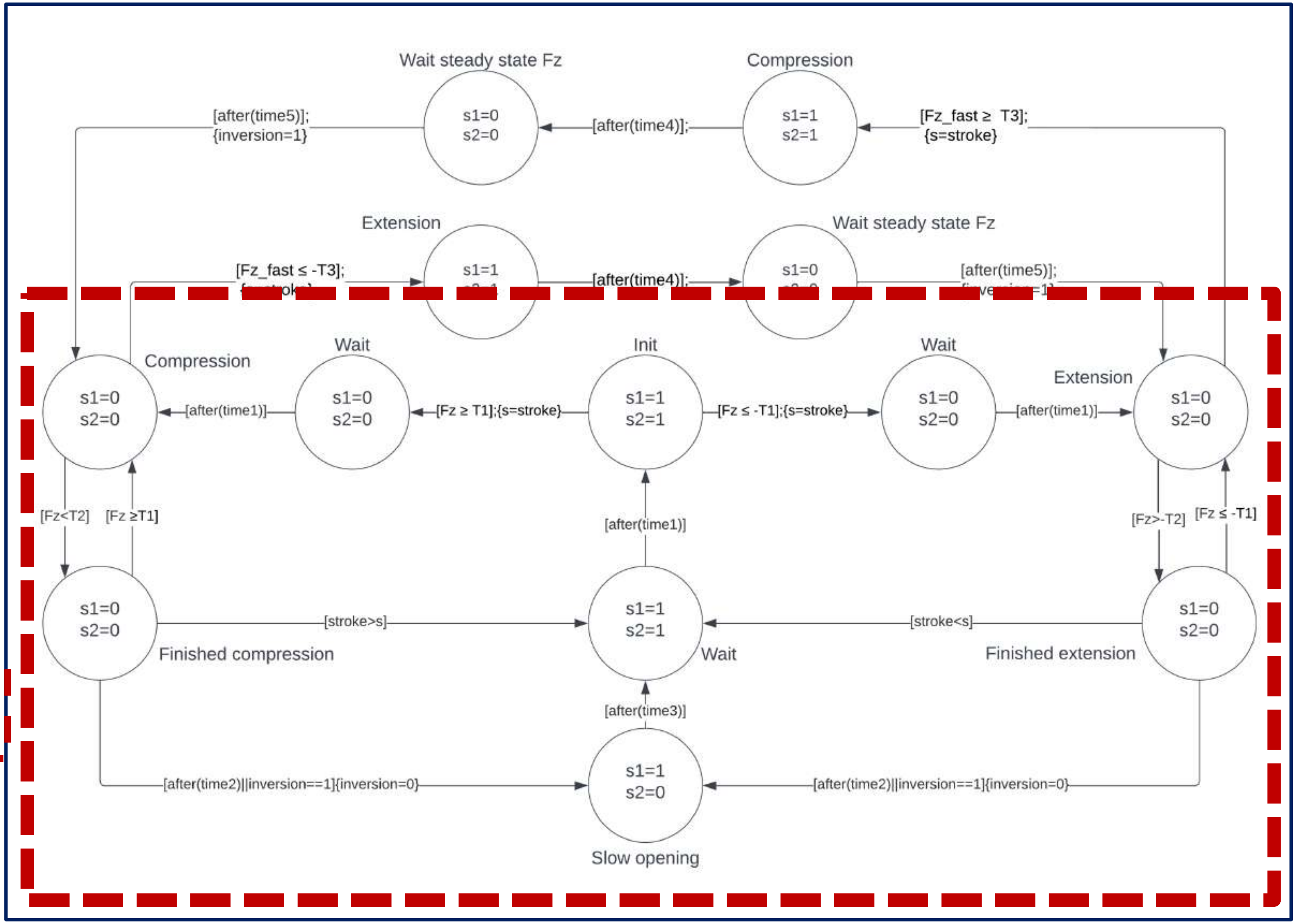


Semi-Active Stiffness Control

The controller has a **stroke-based** opening logic to avoid the kick-force.

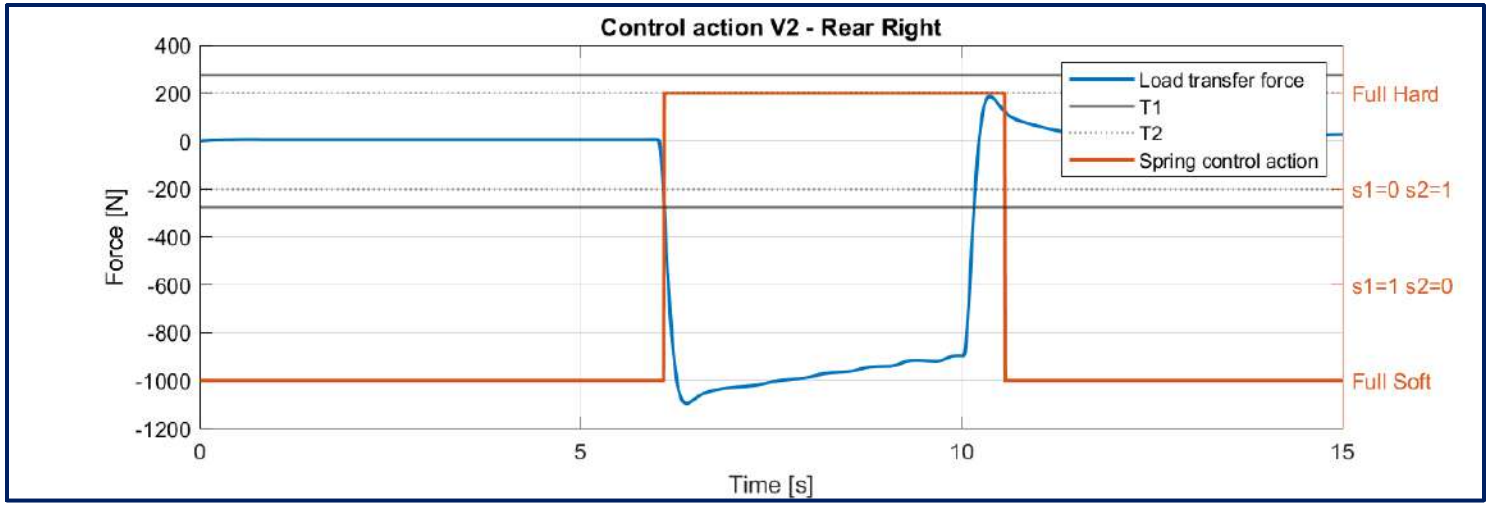
Valves get opened if they reach the **same stroke** value of the **closing instant**.

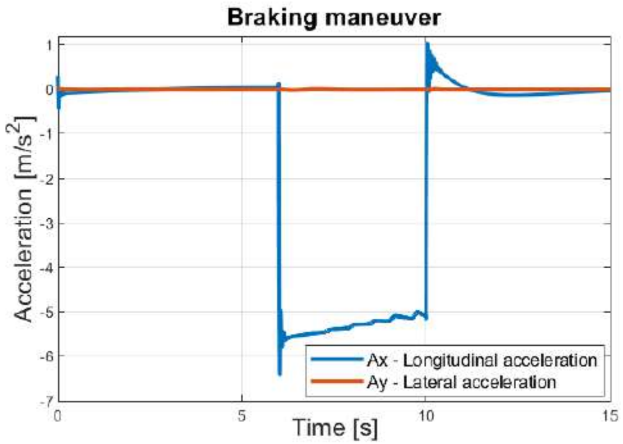
Kick-force avoidance logic

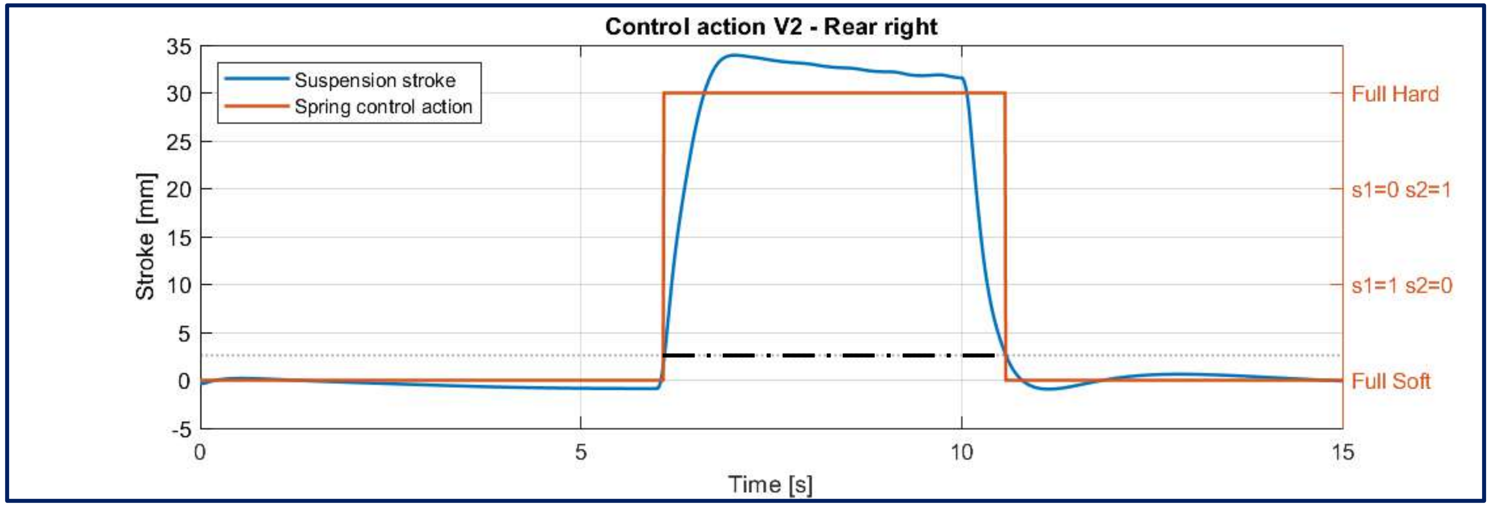


Semi-Active Stiffness Control

Valves get opened if the load transfer force is lower than the threshold **T2** and the **stroke is equal to the closing one.**

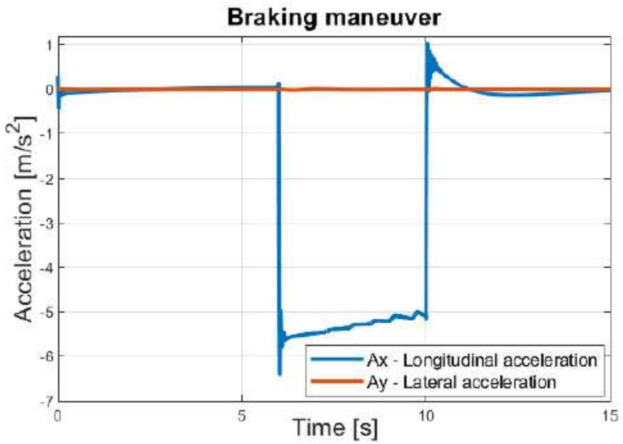


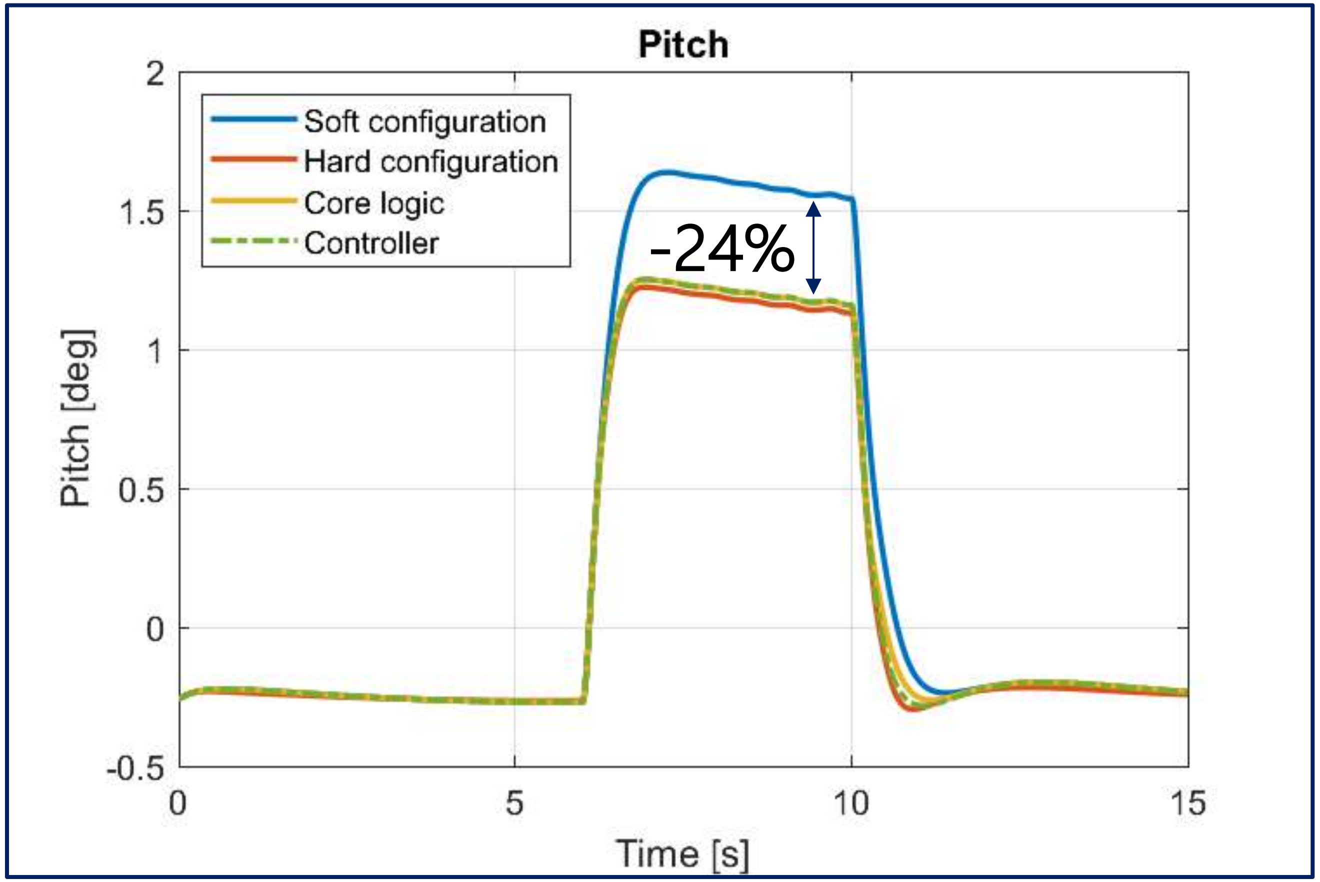




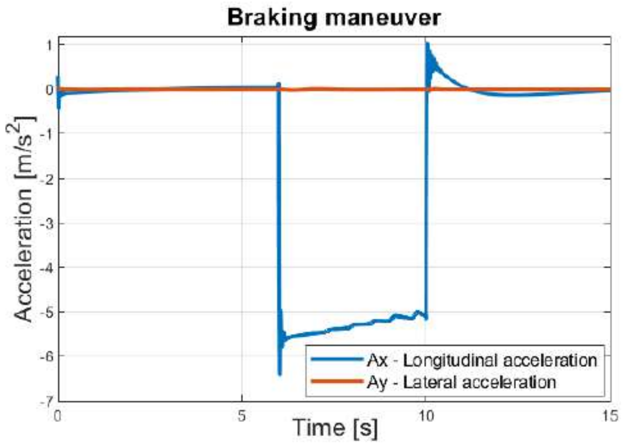
Semi-Active Stiffness Control

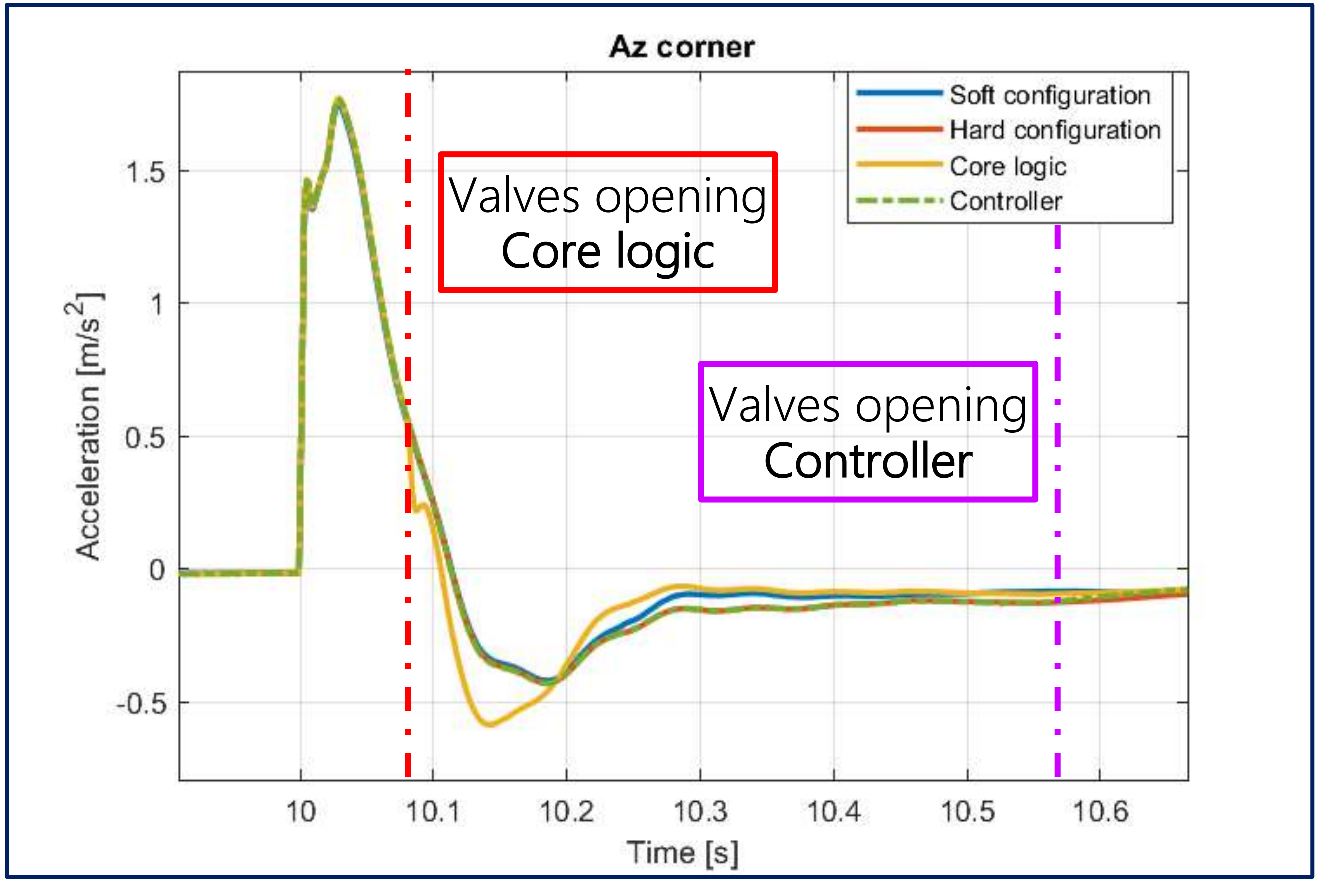
The **core logic** and the **controller** bring to the same improvement because the closing strategy is the same.





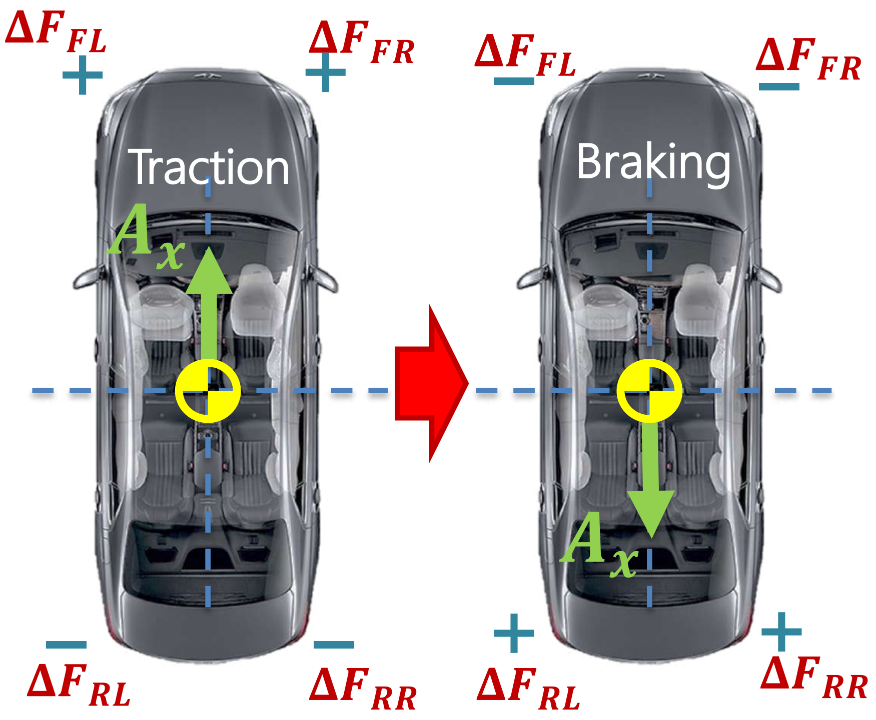
The new condition leads to a **delay** in the opening that solves the kick-force problem.

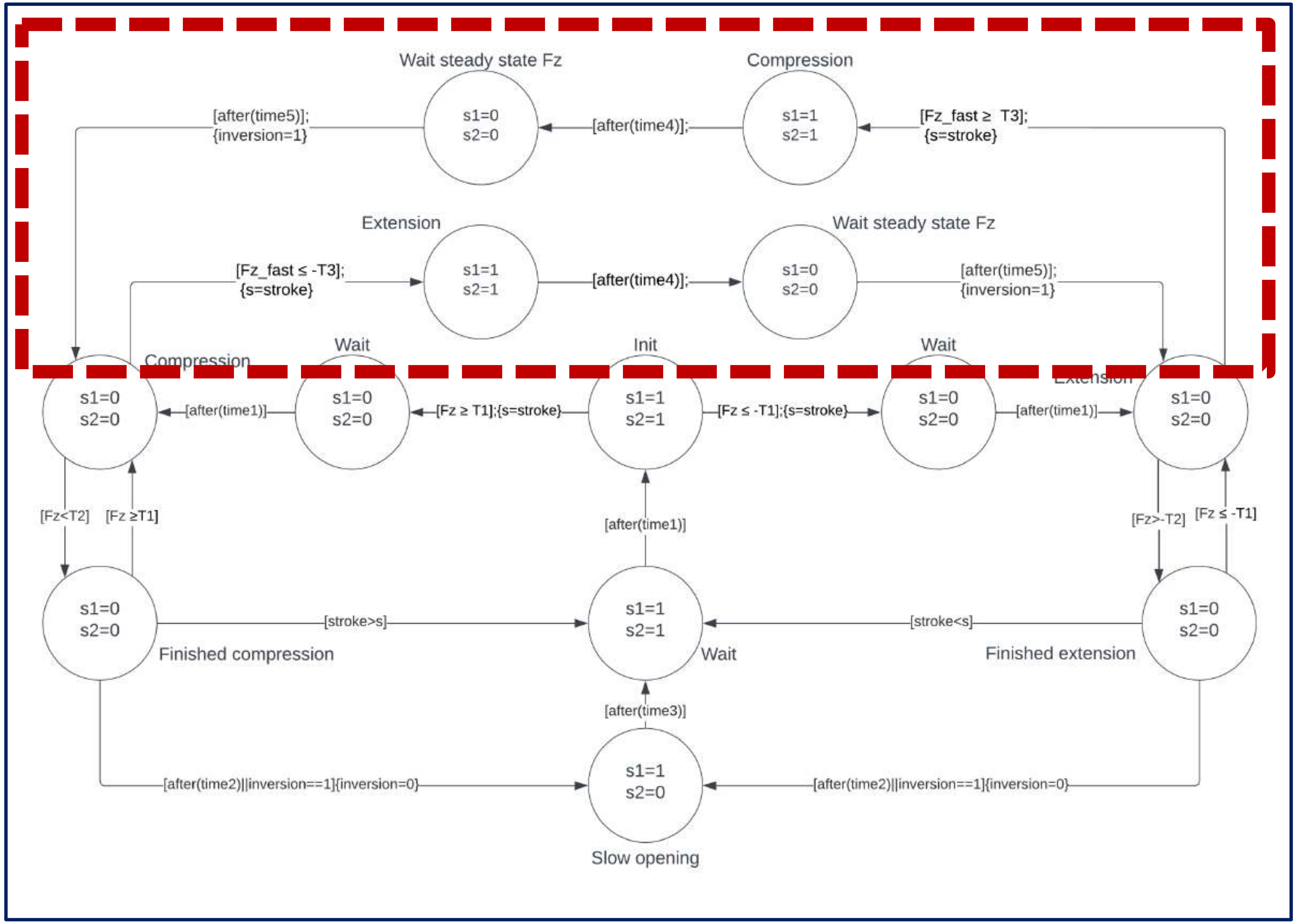




Semi-Active Stiffness Control

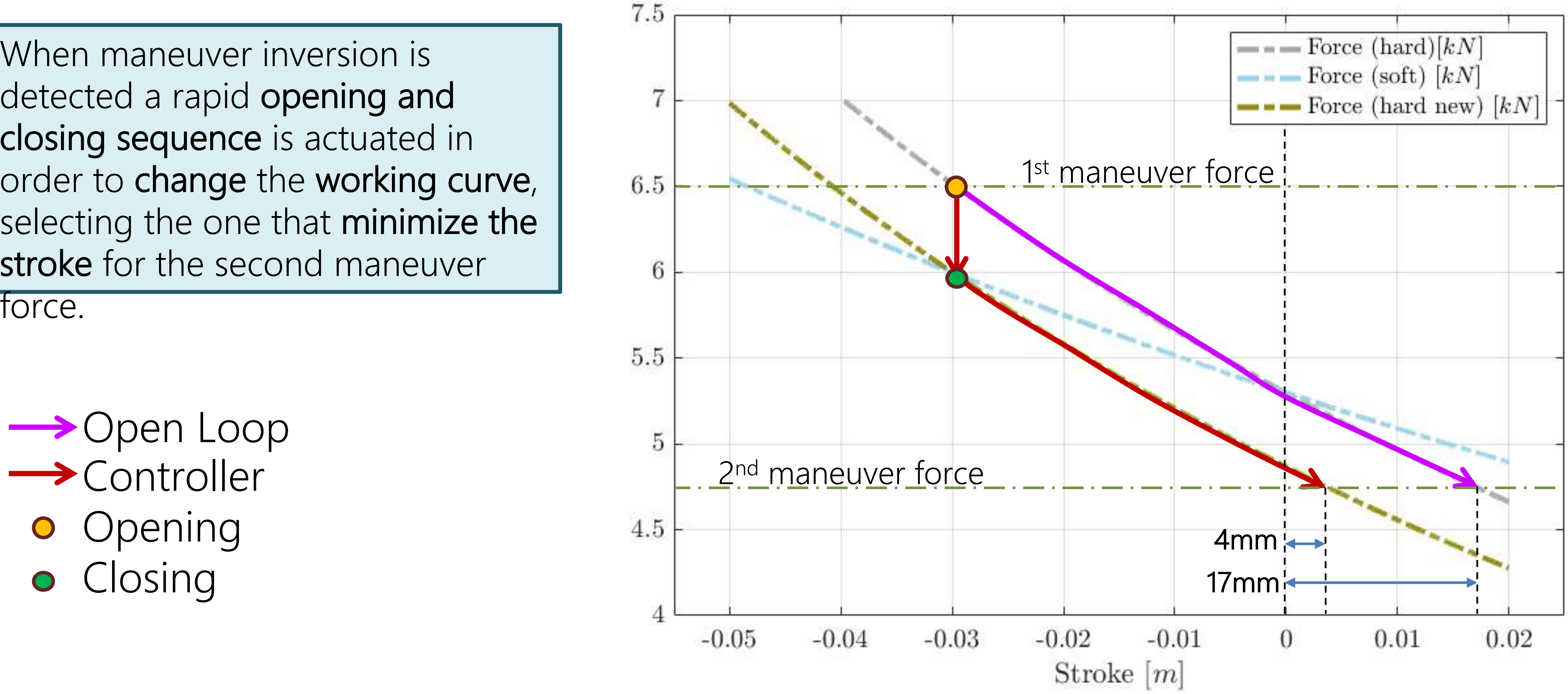
The controller includes an **Inversion maneuver management**, that **improves** the pitch and roll angles if **maneuver inversion** has occurred.





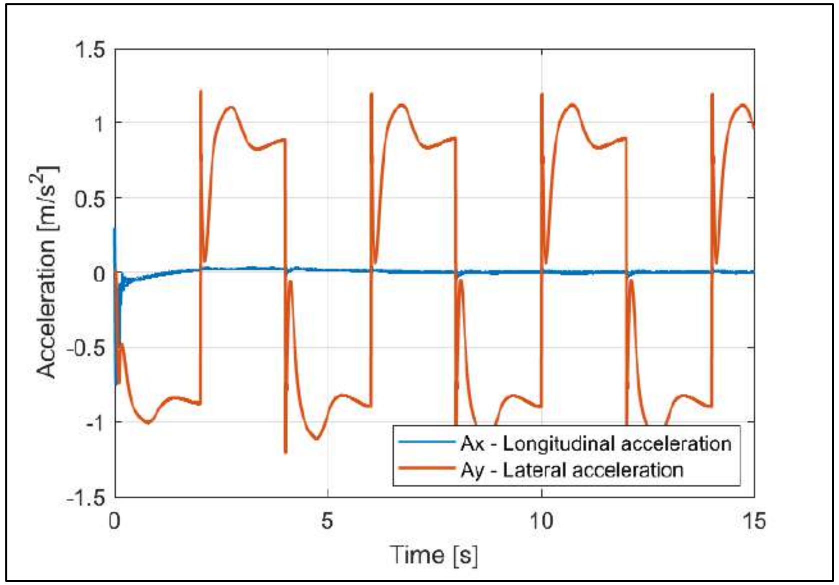
Semi-Active Stiffness Control

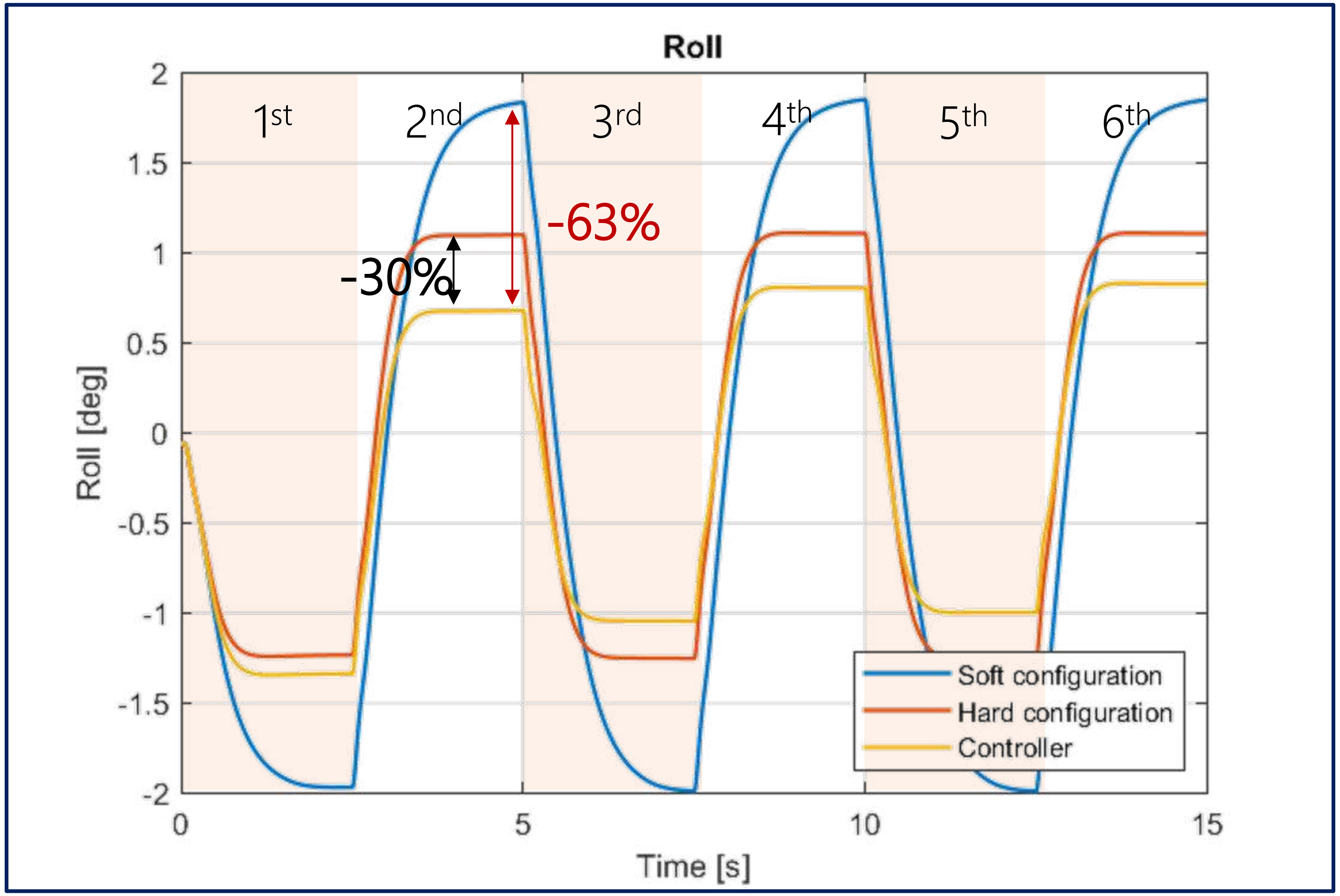
When maneuver inversion is detected a rapid **opening and closing sequence** is actuated in order to **change** the **working curve**, selecting the one that **minimize the stroke** for the second maneuver force.



Semi-Active Stiffness Control

All the maneuvers except for the first one benefits from the equilibrium change, achieving improvements of up to **63%**





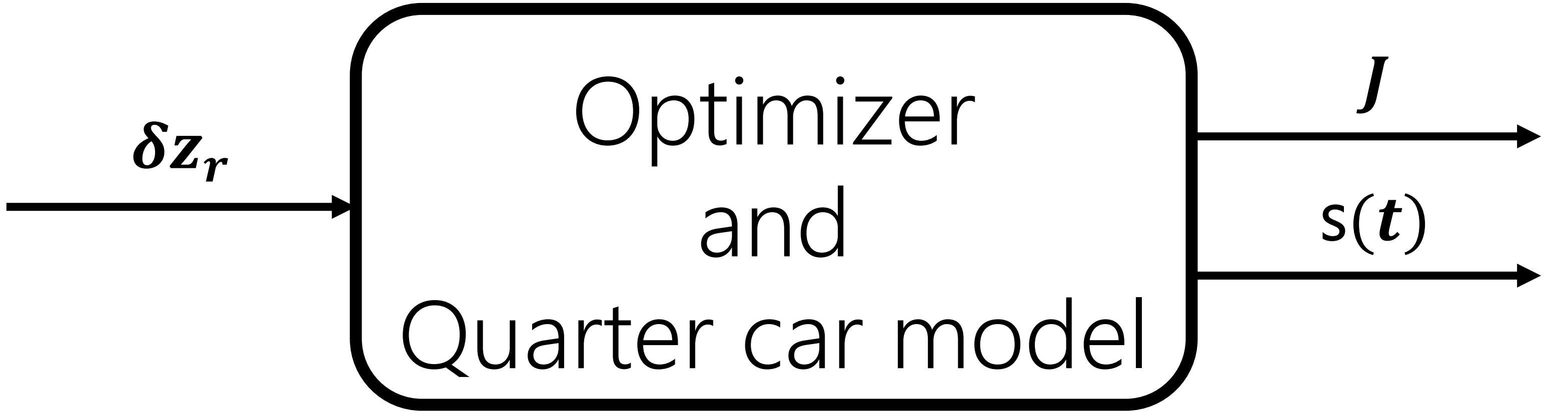
Steering to the **left** Steering to the **right**

Semi-Active Stiffness Control

Is genuine semi-active stiffness control beneficial?

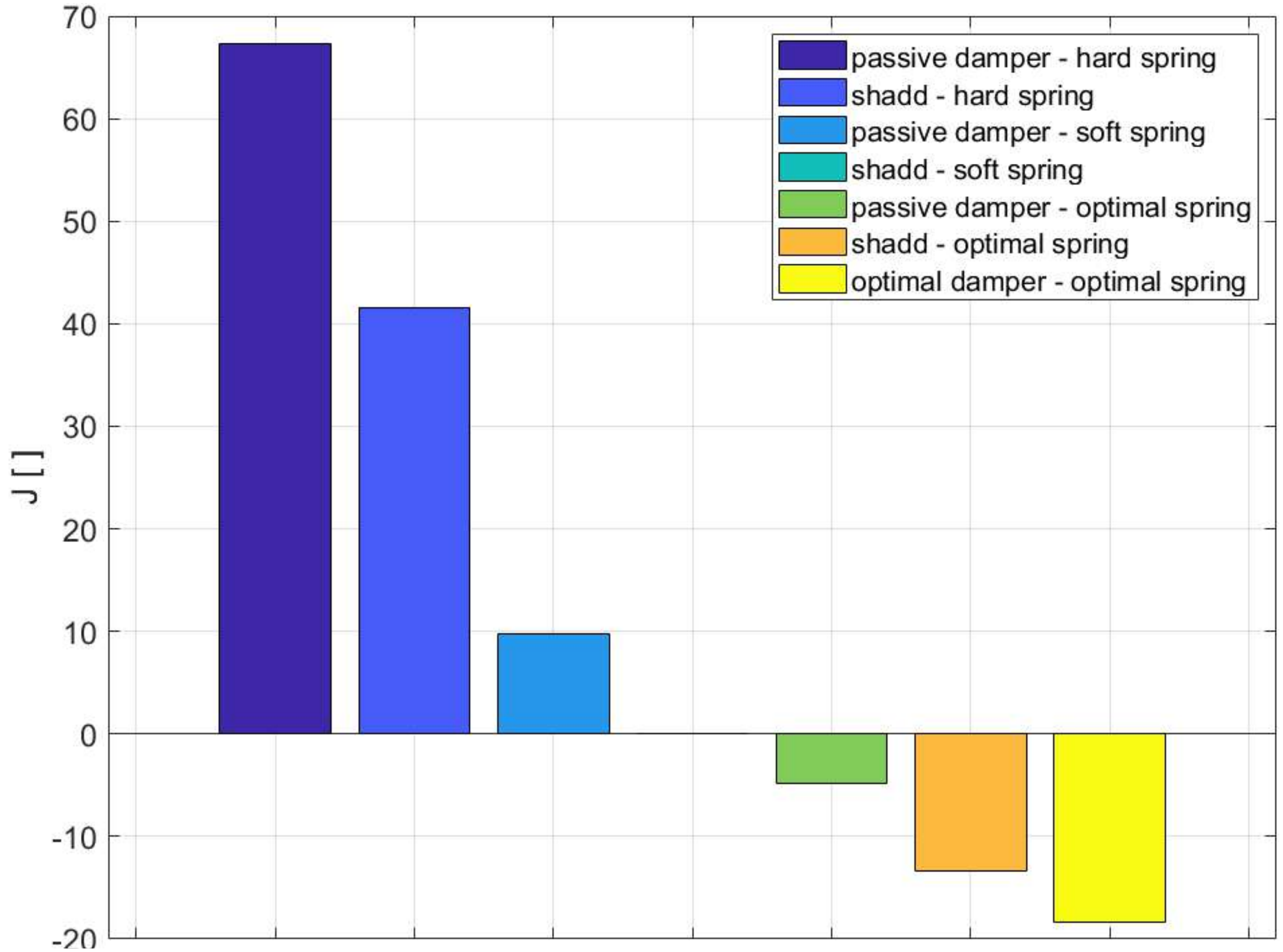
Semi-Active Stiffness Control

Is genuine semi-active stiffness control beneficial?



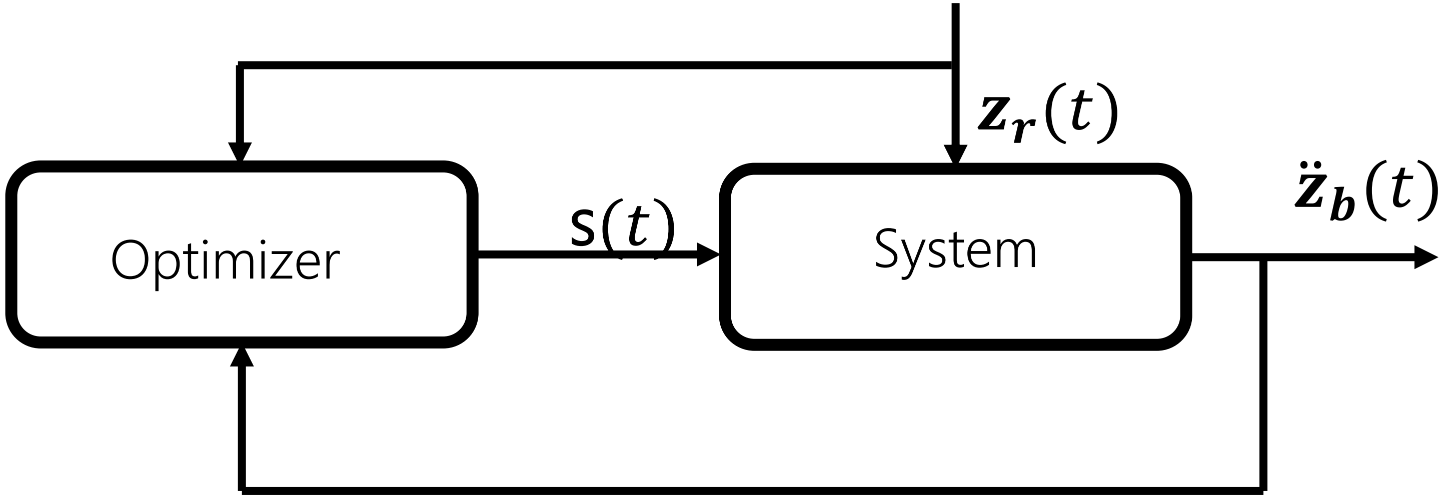
- *Offline optimization* : perfect road profile **preview**
- Find the sequence of openings/closings of the valve minimizing $J = \frac{\int_0^T \delta \ddot{z}_{b(t)}^2 \, dt}{\int_0^T \delta z_{r(t)}^2 \, dt}$

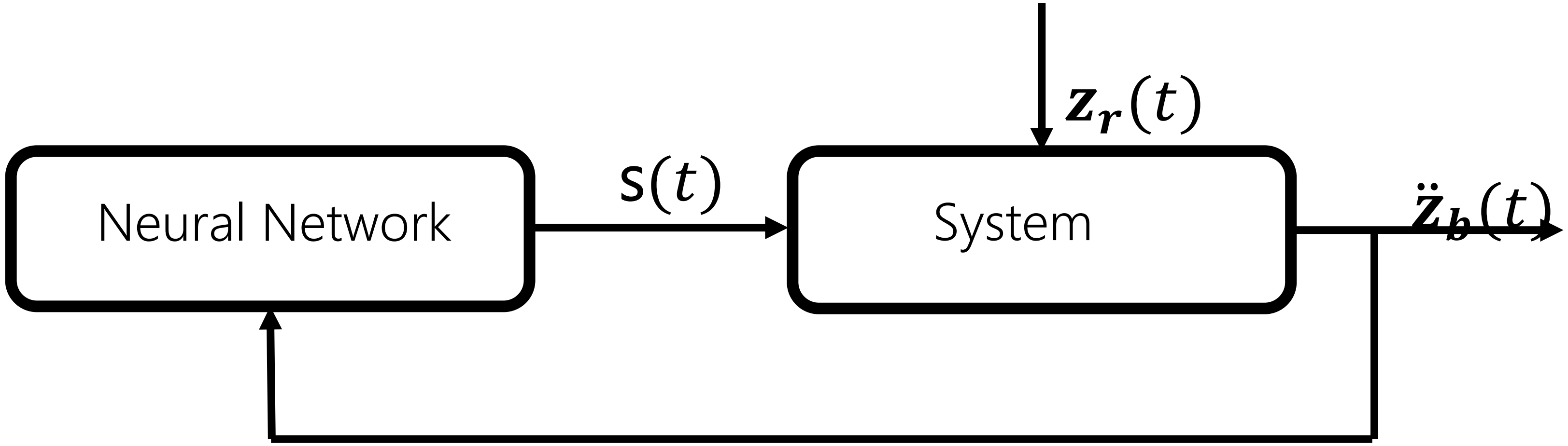
Semi-Active Stiffness Control



Semi-Active Stiffness Control

Causal Control – Neural Network Based





Collected features:

- Body position
- Body velocity
- Body acceleration
- Tire position
- Tire velocity
- Main chamber pressure
- Auxiliary chamber pressure
- Absolute value of the pressure difference
- Opening signal
- Closing signal
- Current Valve State

} Vehicle Body Features

Collected features:

- Body position
- Body velocity
- Body acceleration
- Tire position
- Tire velocity
- Main chamber pressure
- Auxiliary chamber pressure
- Absolute value of the pressure difference
- Opening signal
- Closing signal
- Current Valve State

} Vehicle Tire Features

Collected features:

- Body position
- Body velocity
- Body acceleration
- Tire position
- Tire velocity
- Main chamber pressure
- Auxiliary chamber pressure
- Absolute value of the pressure difference
- Opening signal
- Closing signal
- Current Valve State

} Multi-chamber Pressure Variables

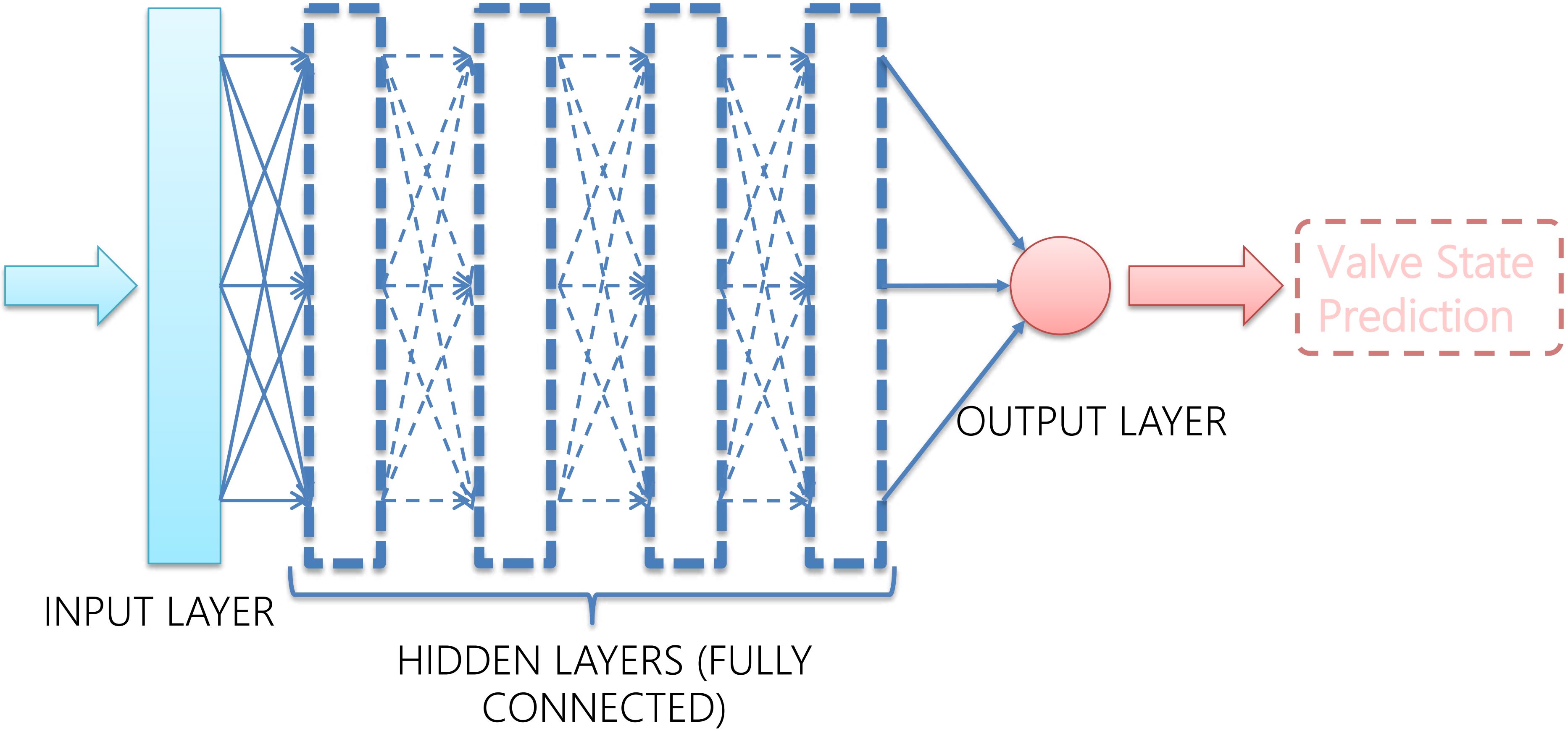
Collected features:

- Body position
- Body velocity
- Body acceleration
- Tire position
- Tire velocity
- Main chamber pressure
- Auxiliary chamber pressure
- Absolute value of the pressure difference
- Opening signal
- Closing signal
- Current Valve State

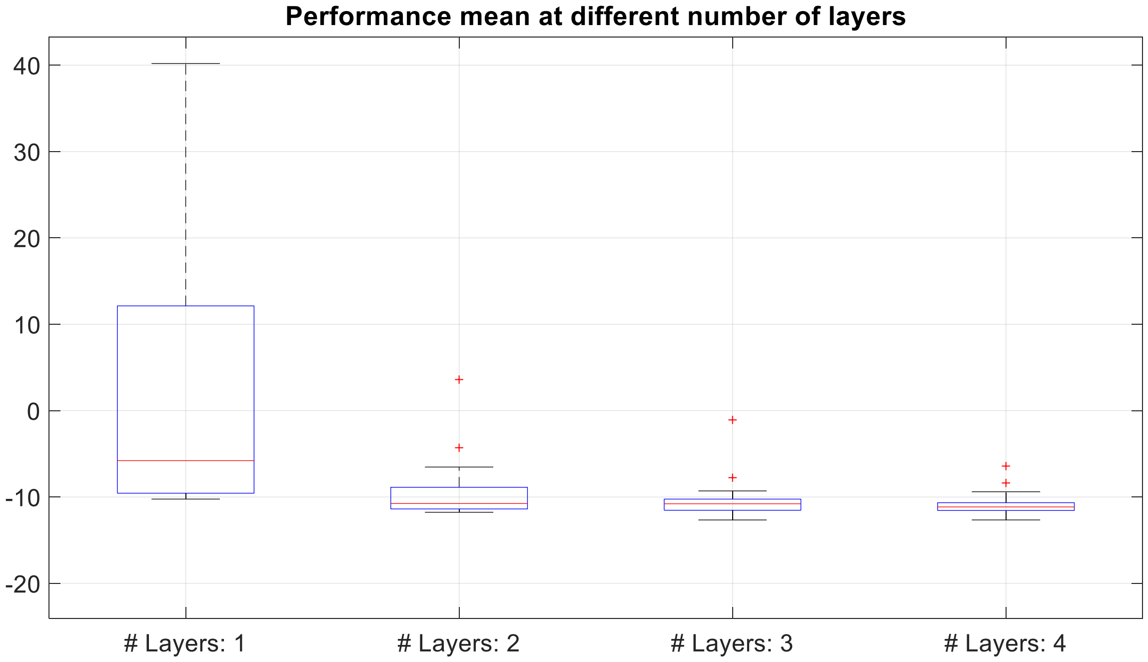
} Multi-chamber Valve Variables

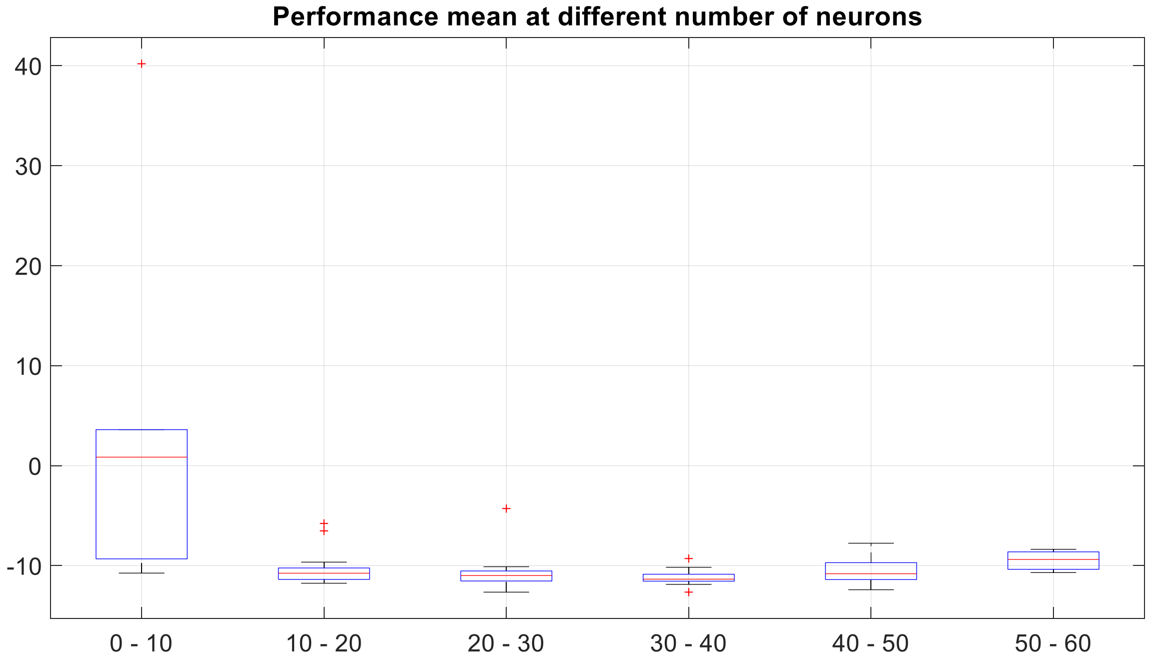
INPUT DATA DIVISION:

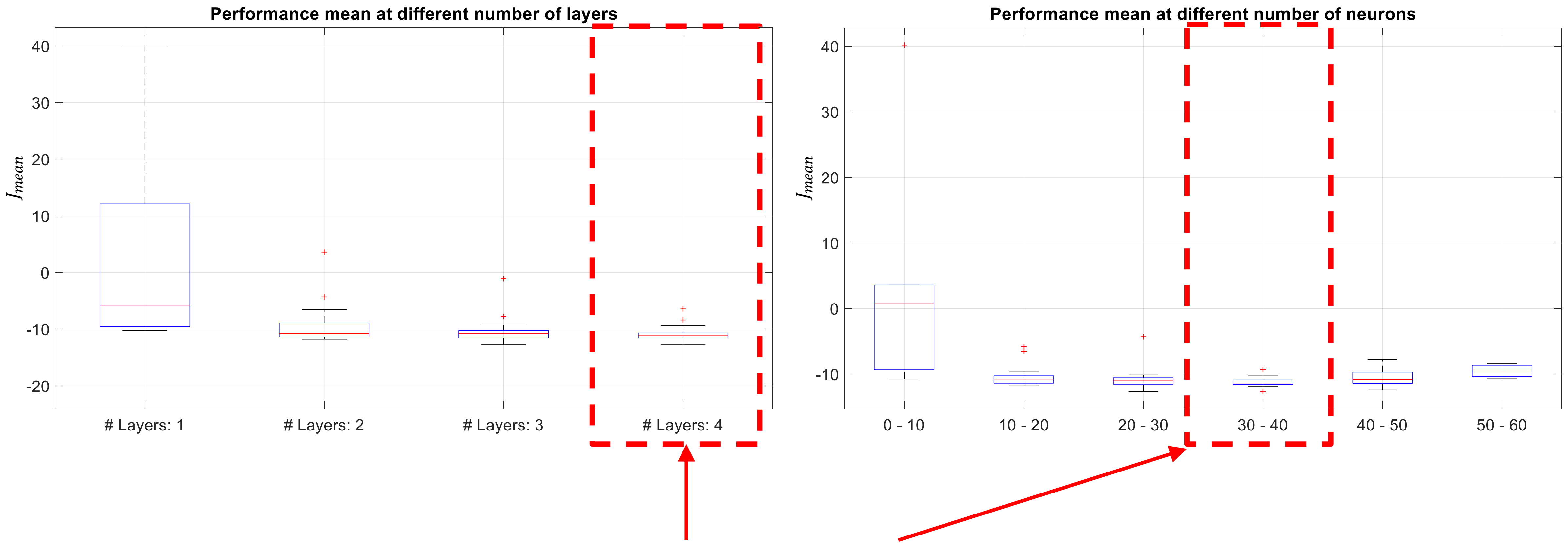
- 70% of the reduced dataset used as TRAINING SET.
- 15% used as VALIDATION SET
- 15% used as TEST SET



Causal Control – Neural Network Based



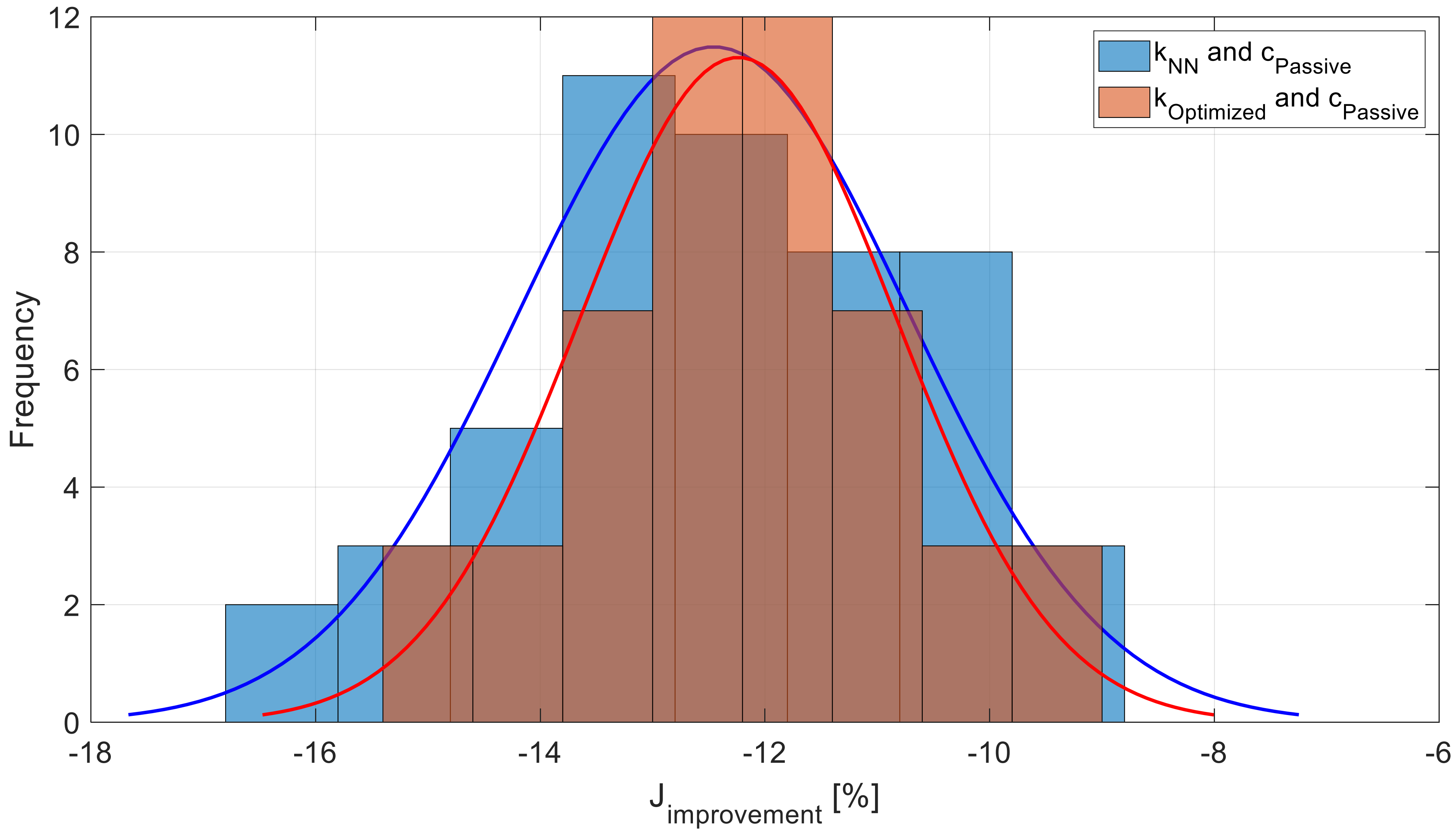




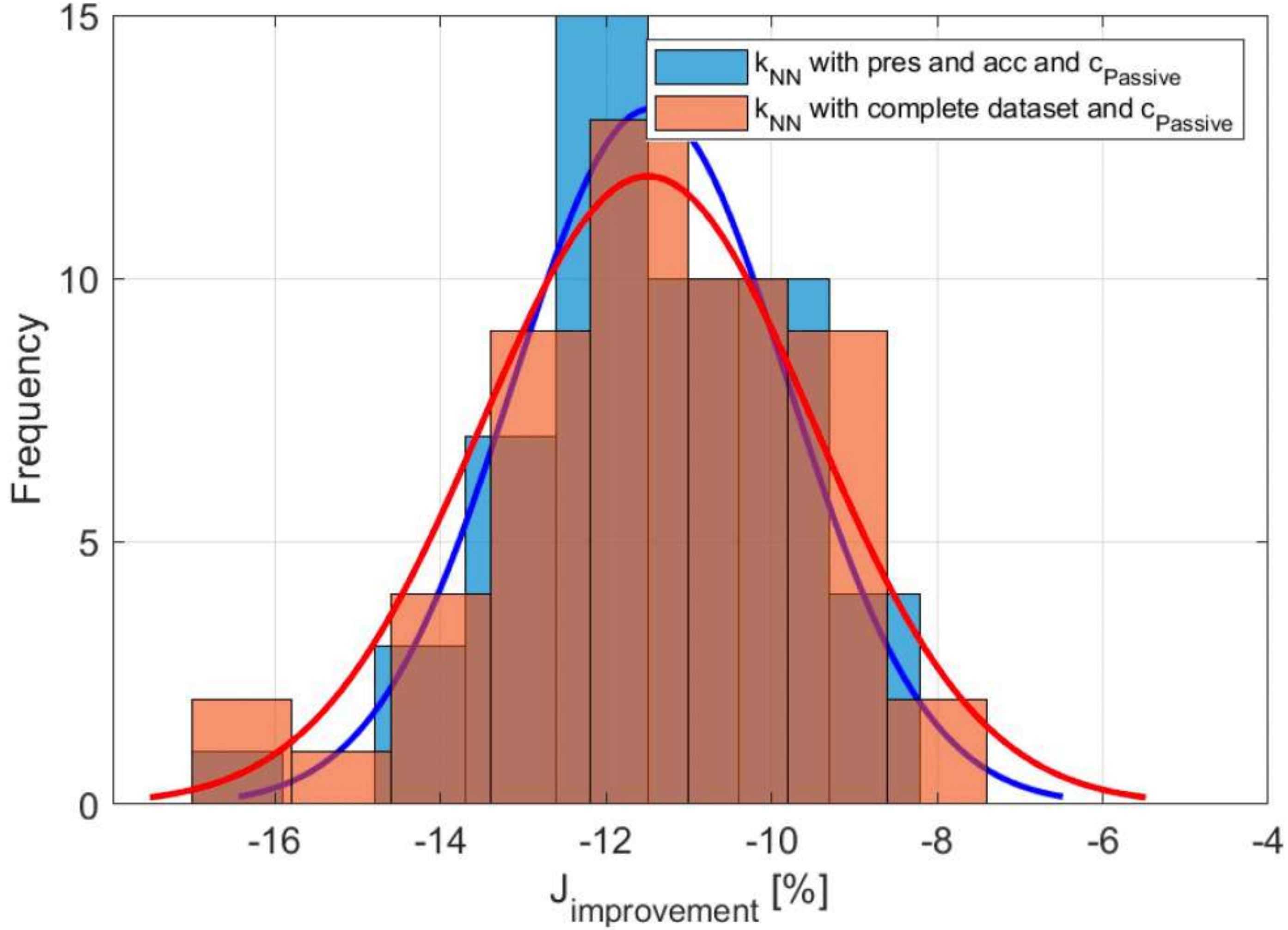
Best Structure Configuration

Semi-Active Stiffness Control

Causal Control – Neural Network Based



Feature Reduction Analysis

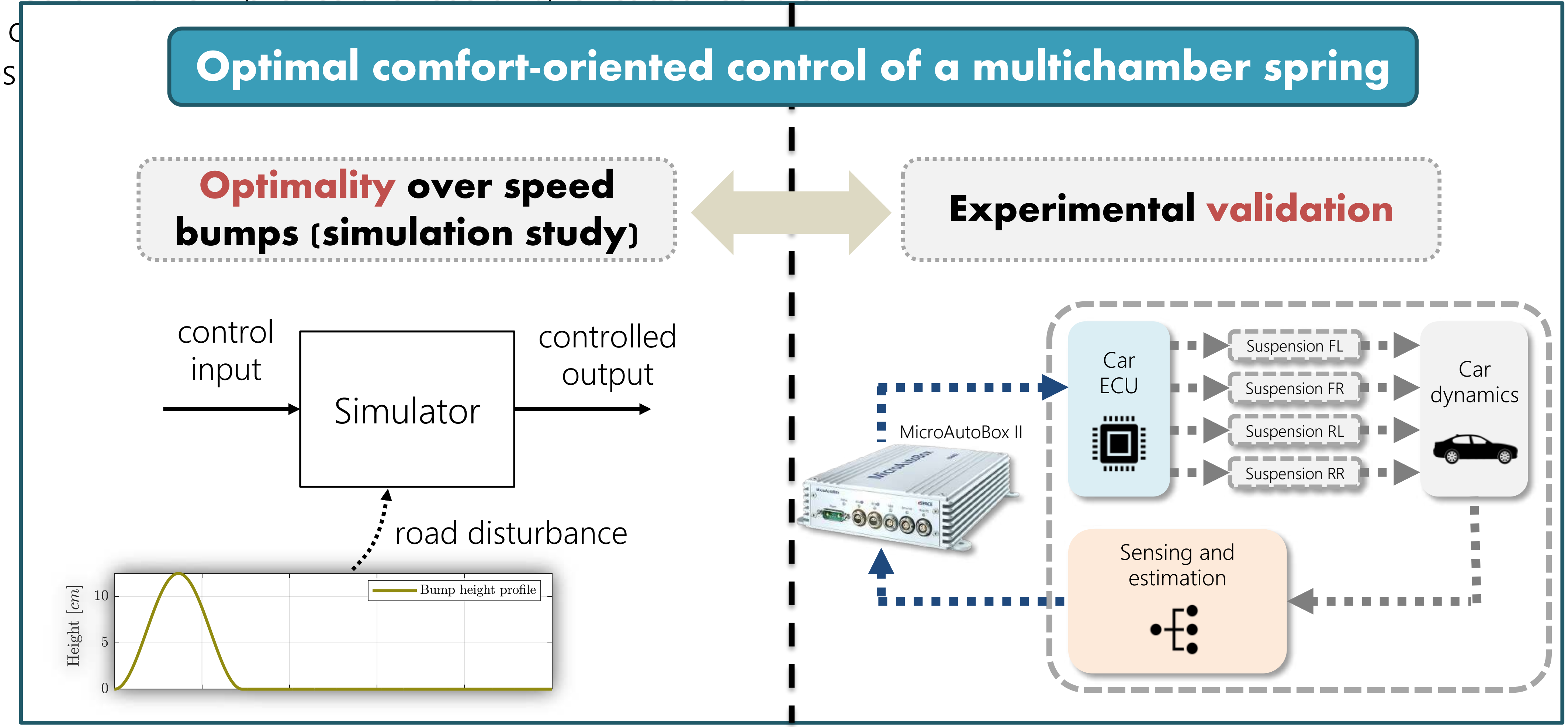


The neural network proves the feasibility of causal control.
Too complex for actual implementation
Does not provide an interpretation

The neural network proves the feasibility of causal control.

Too c

Does



Road preview

Comfort-oriented optimization

A Finite Horizon Optimal Control Problem is solved over an optimization horizon T_w in order to find a globally optimal input.

$$\min_{s_\tau,\tau=1,\dots,f_cT_w} \sqrt{\frac{1}{T_w}\int_{t_0}^{t_0+T_w} \ddot{z}_b(t)^2\, dt}$$ **Cost function**

subject to:

$$x(t+i+1) = f\big(x(t+i), u(t+i)\big)$$ **Discretized model equations**

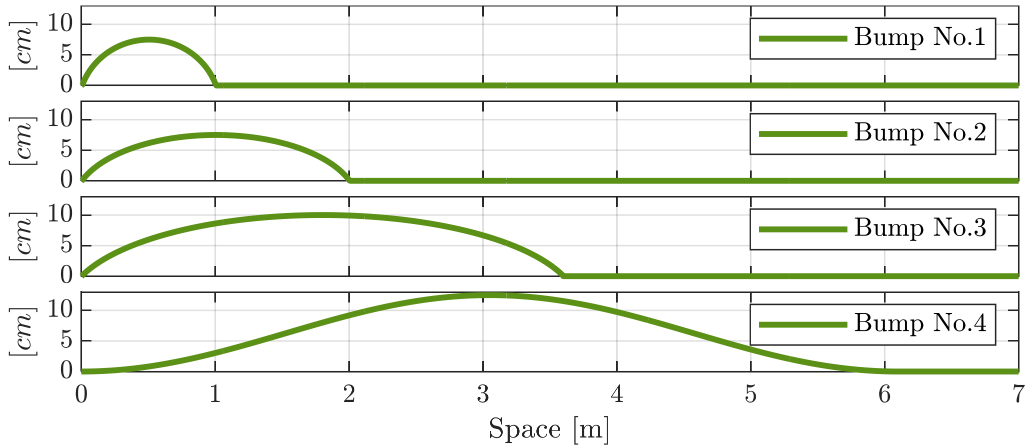
$$x(t_0) = \tilde{x}(t_0)$$ **Initial state**

$$s_\tau \in \{0,1\}, \forall\tau = 1, \dots, f_cT_w$$ **Input boundaries**

$$z_r(t) = \tilde{z}(t), t \in [t_0, t_0 + T_w)$$ **Road preview**

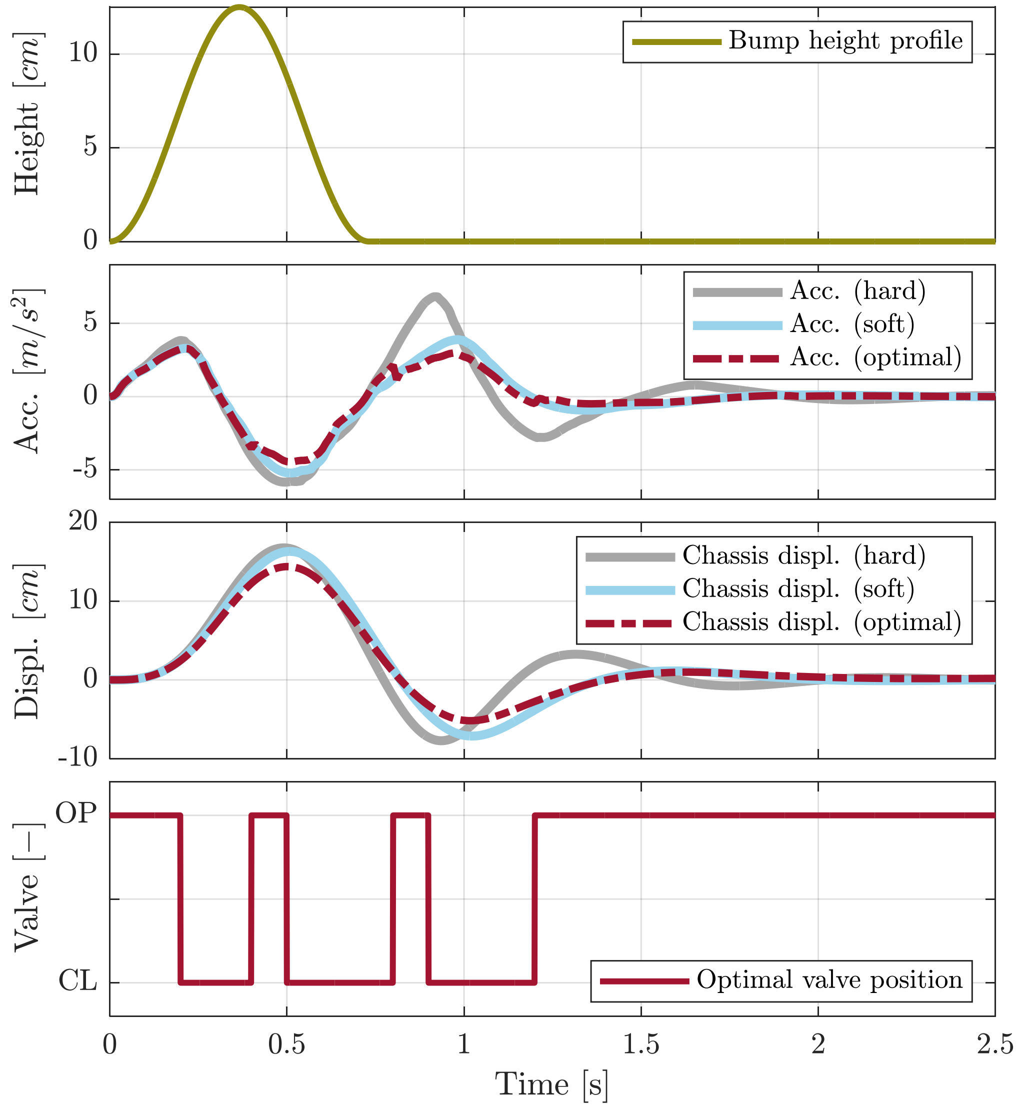
Assumption: road profile

Road preview is assumed. Four different bump types are considered.



Type	Height [cm]	Length [cm]
No. 1	7.5	100
No. 2	7.5	200
No. 3	10	360
No. 4	12.5	610

Optimization results



Optimal results

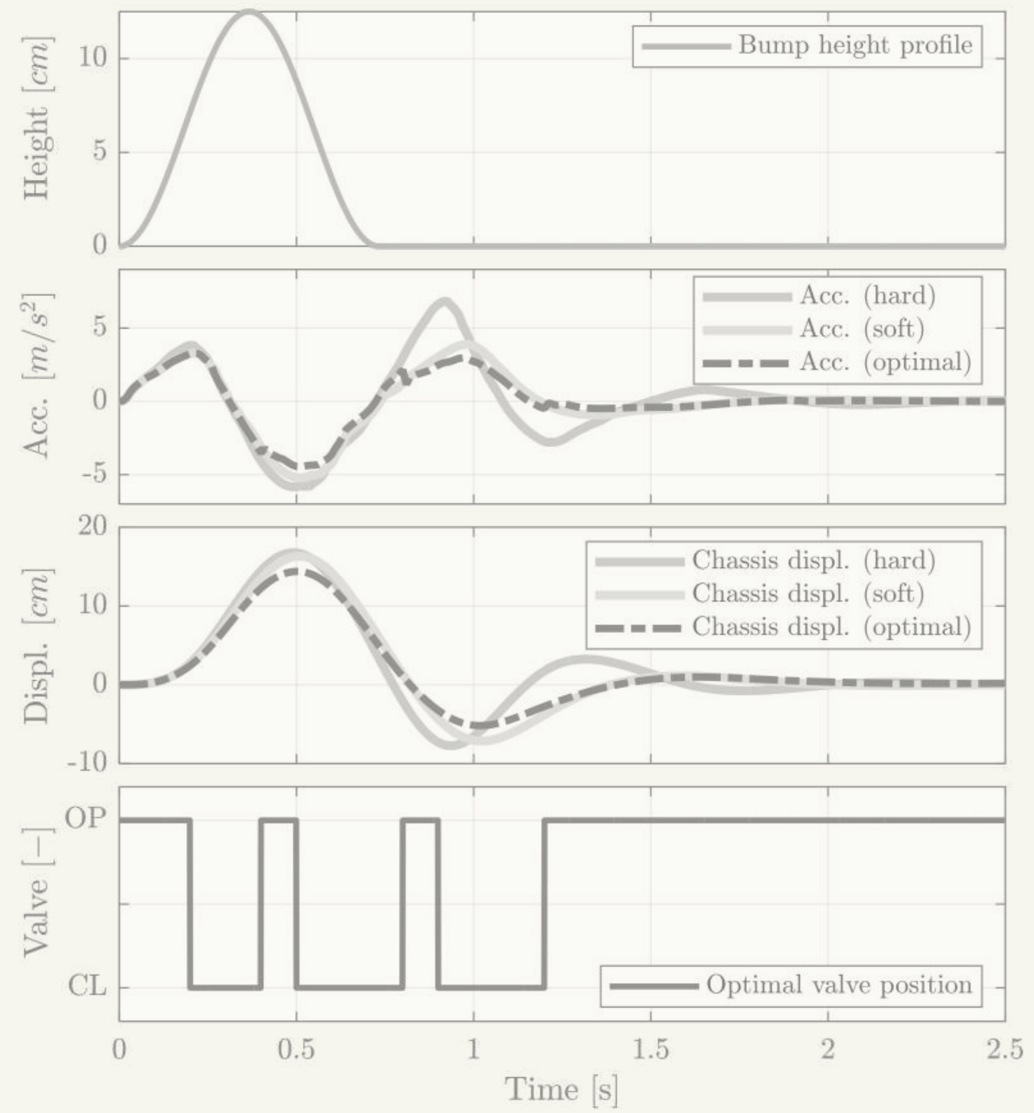
Vertical acceleration is reduced thanks to valve switching.

A bump is a single-event type of perturbation which particularly excites the **body resonance** ($\approx 1.2\ Hz$, most important chassis vertical movement).

Soft spring performs better than hard spring at the body resonance frequency and ensures a natural motion during settling.

The **controlled spring outperforms the passive configurations**, especially in the release phase of the bump, while keeping the motion natural.

Improvement indexes over bump types

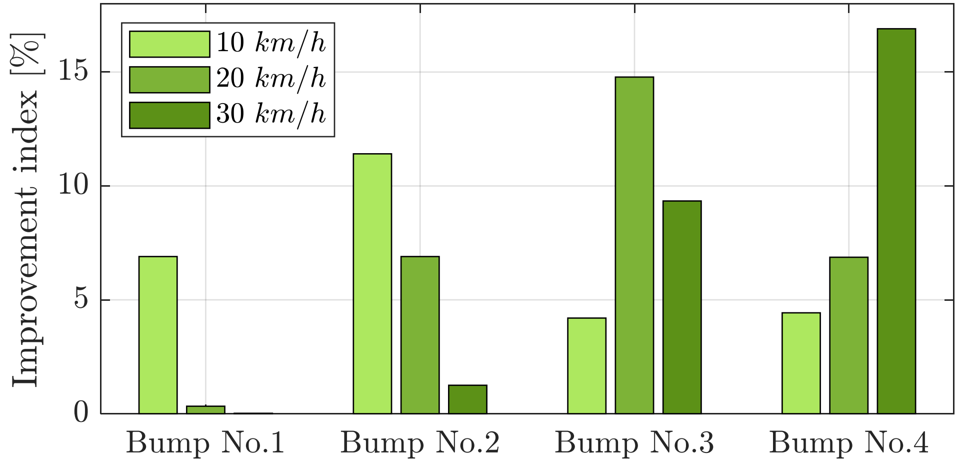


Take-home messages

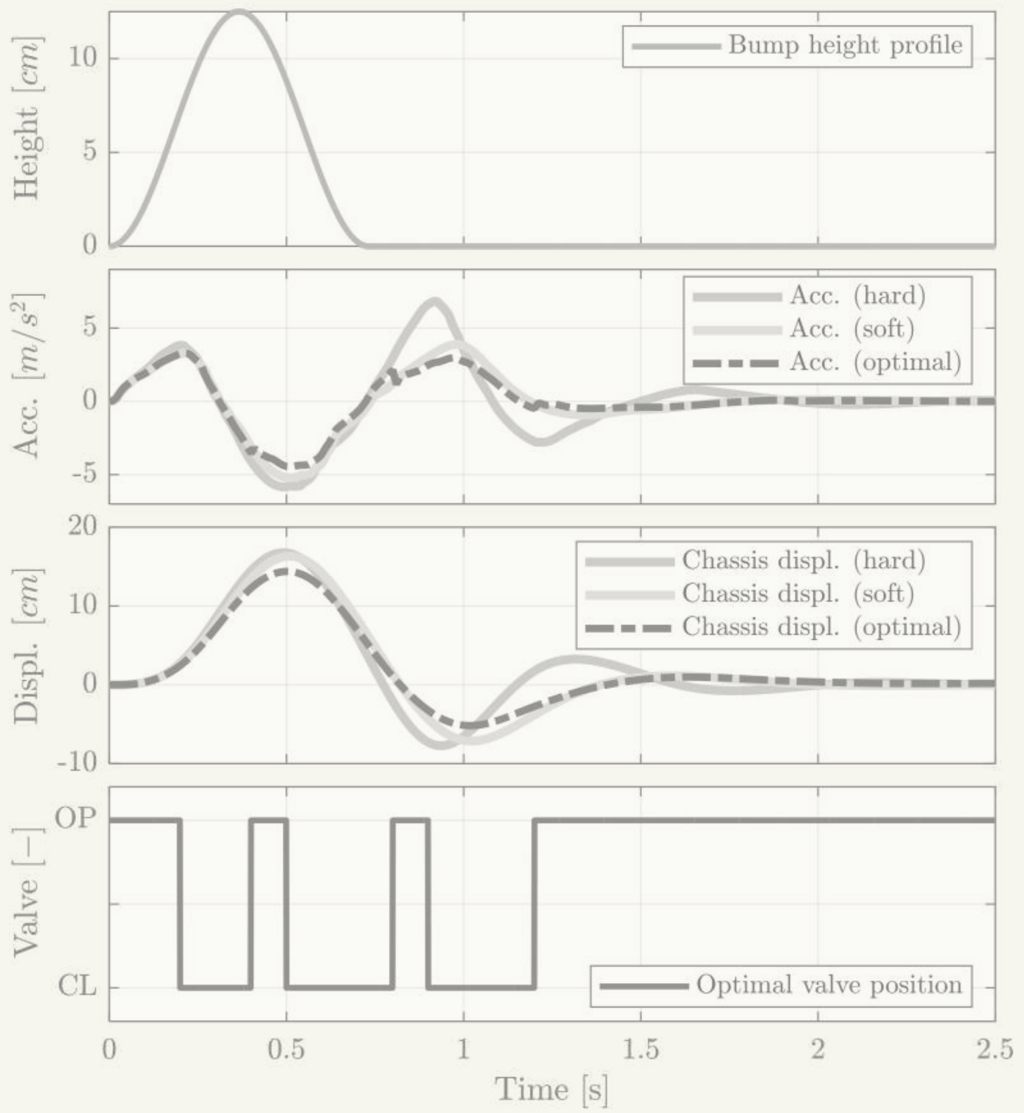
- Improvement indexes:

$$J_{impr} = \frac{J - J_{soft}}{J_{soft}} \times 100$$

Improvements are up to 17%, depending on the velocity. This result is consistent with the previous work.

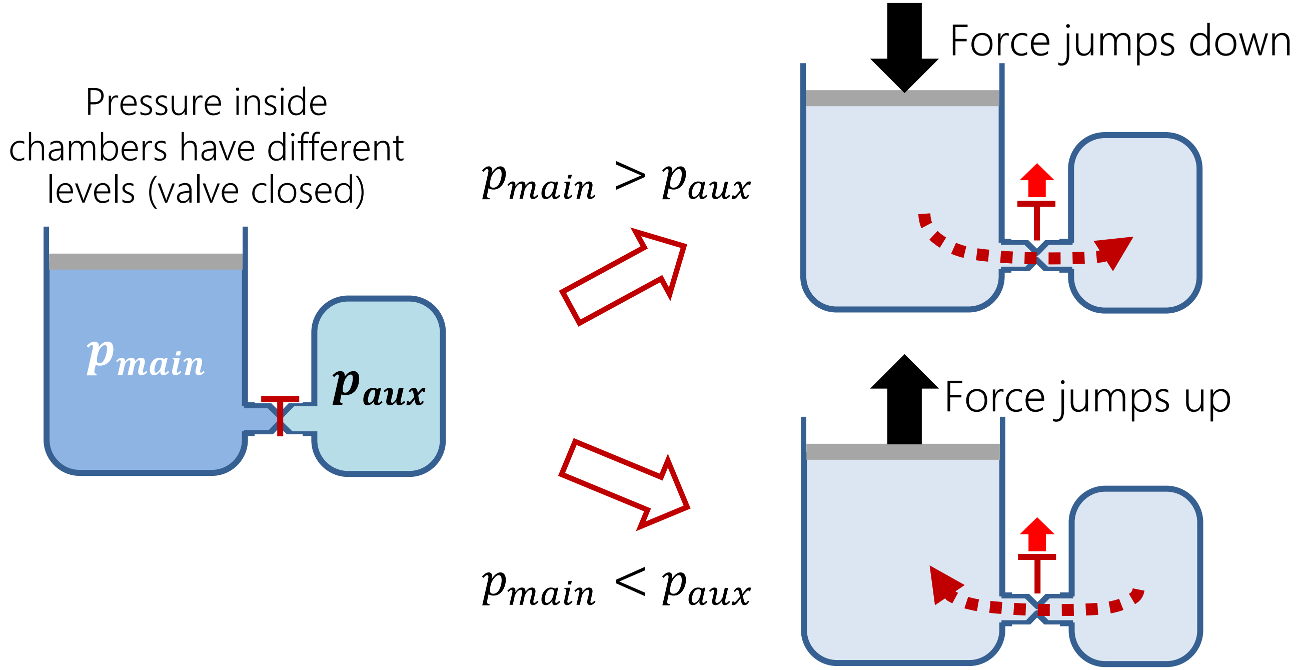


Energy release principle

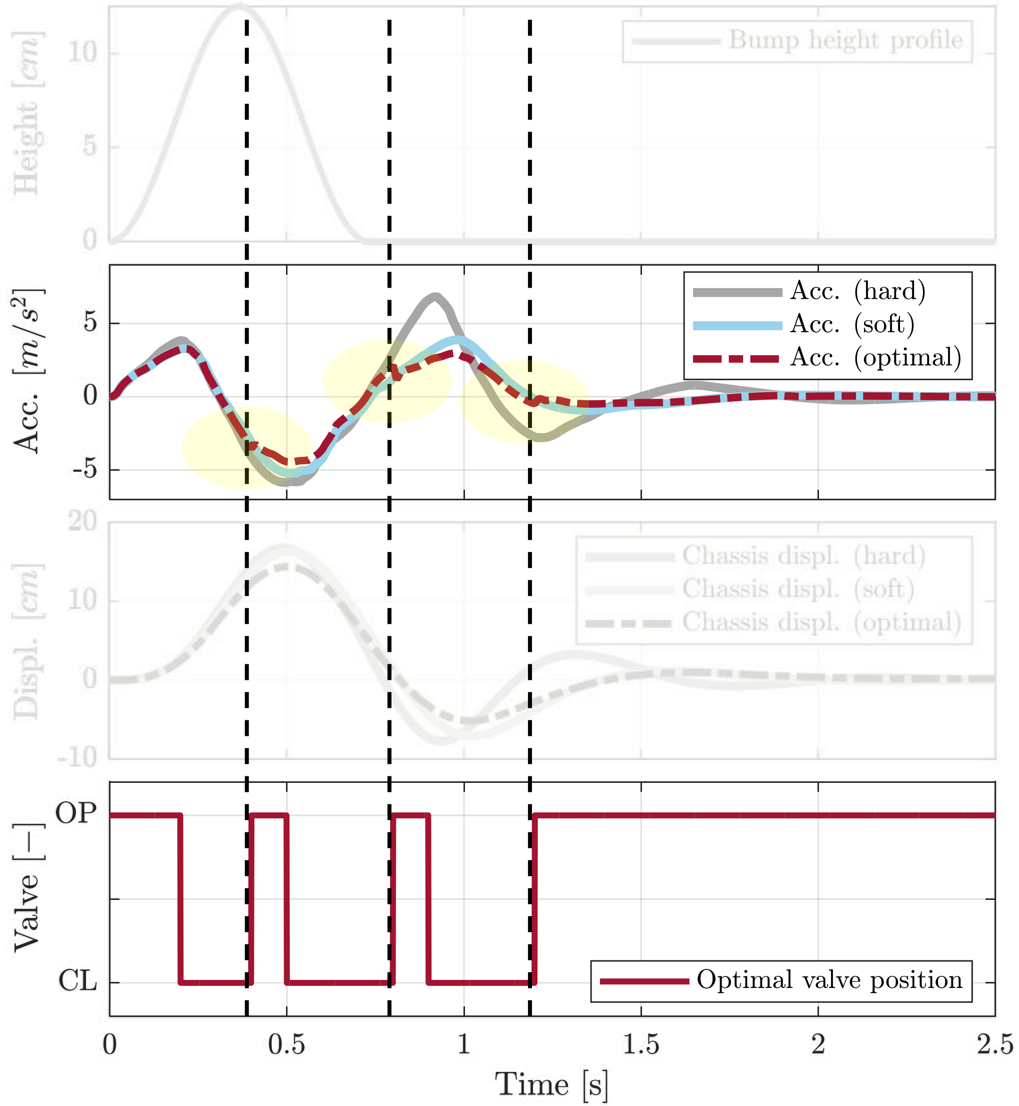


Take-home messages

- **(controlled) energy release principle**
  It is a physical way to insert active energy into the system, by storing and releasing pressurized air by valve switching.



Energy release principle



(controlled) energy release principle

The valve is **optimally closed** so to create unequally pressurized chambers (energy storage phase).

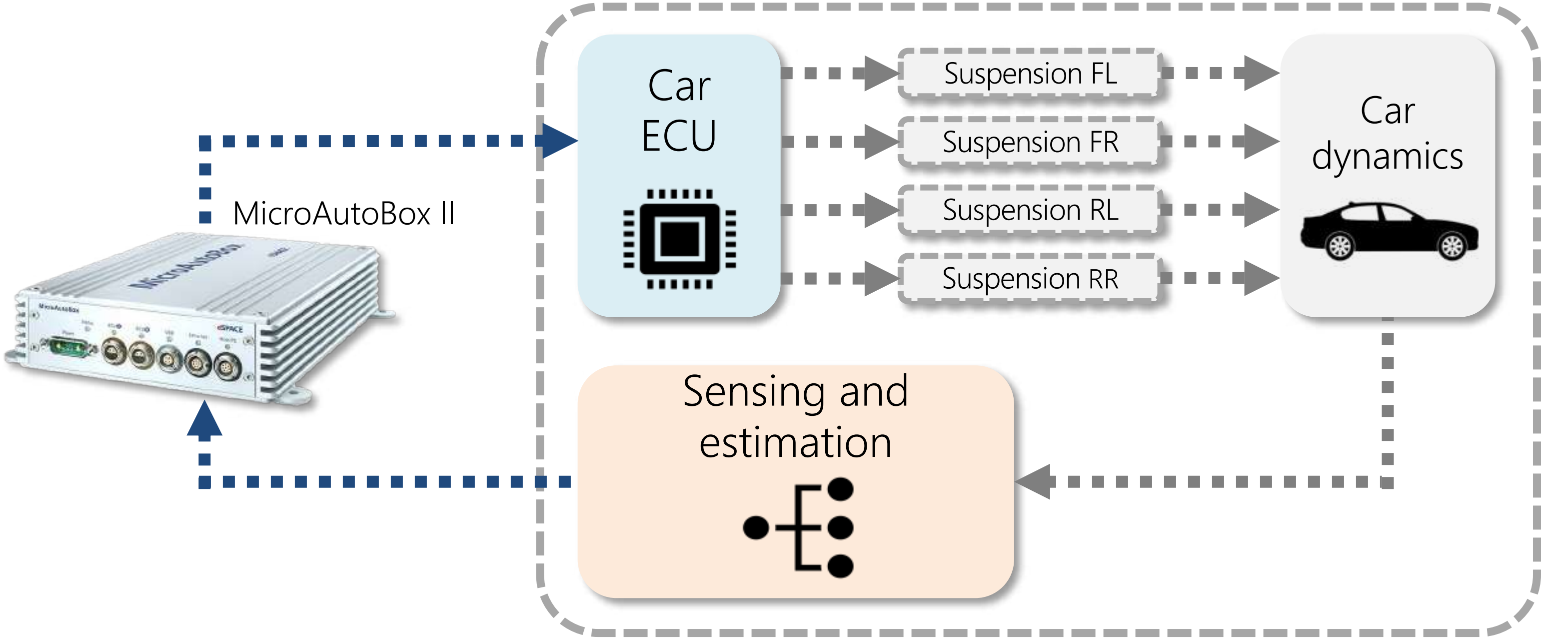
Air is released by opening at an instant where the kick force is beneficial for the vertical acceleration. **Optimal opening** happen in proximity of the maxima (and minima) of the vertical acceleration, so to cut the wave peaks.

Experimental setup

- Availability of 4 multichamber air springs.

The control strategy is computed by an external rapid prototyping ECU and is applied independently to the four suspensions.

- **Delay (estimated)** due to transmission and actuation: 30 ms
- **Control sampling time**: 100 ms



HYUNDAI

- Comfort indexes:
  - Single corner vertical accelerations (given by single-axis accelerometers)
  - Vehicle pitch rate (given by a central 6-DOF IMU)

Openloop strategy with activation threshold

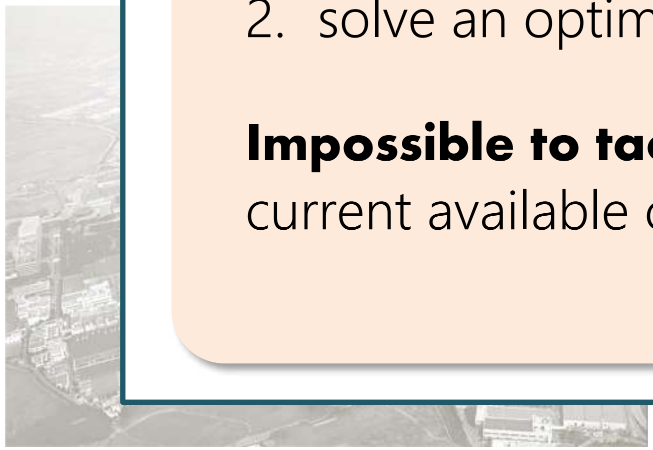
How to make optimal control «online»

Closed-loop global strategy

The ECU should **at each iteration**:

1. preview in advance the road profile;
2. solve an optimization problem.

Impossible to tackle in practice with current available computational power.



Openloop strategy with activation threshold

How to make optimal control «online»

Closed-loop global strategy

The ECU should **at each iteration**:

1. preview in advance the road profile;
2. solve an optimization problem.

Impossible to tackle in practice with current available computational power.

≈

Open-loop strategy with activation threshold

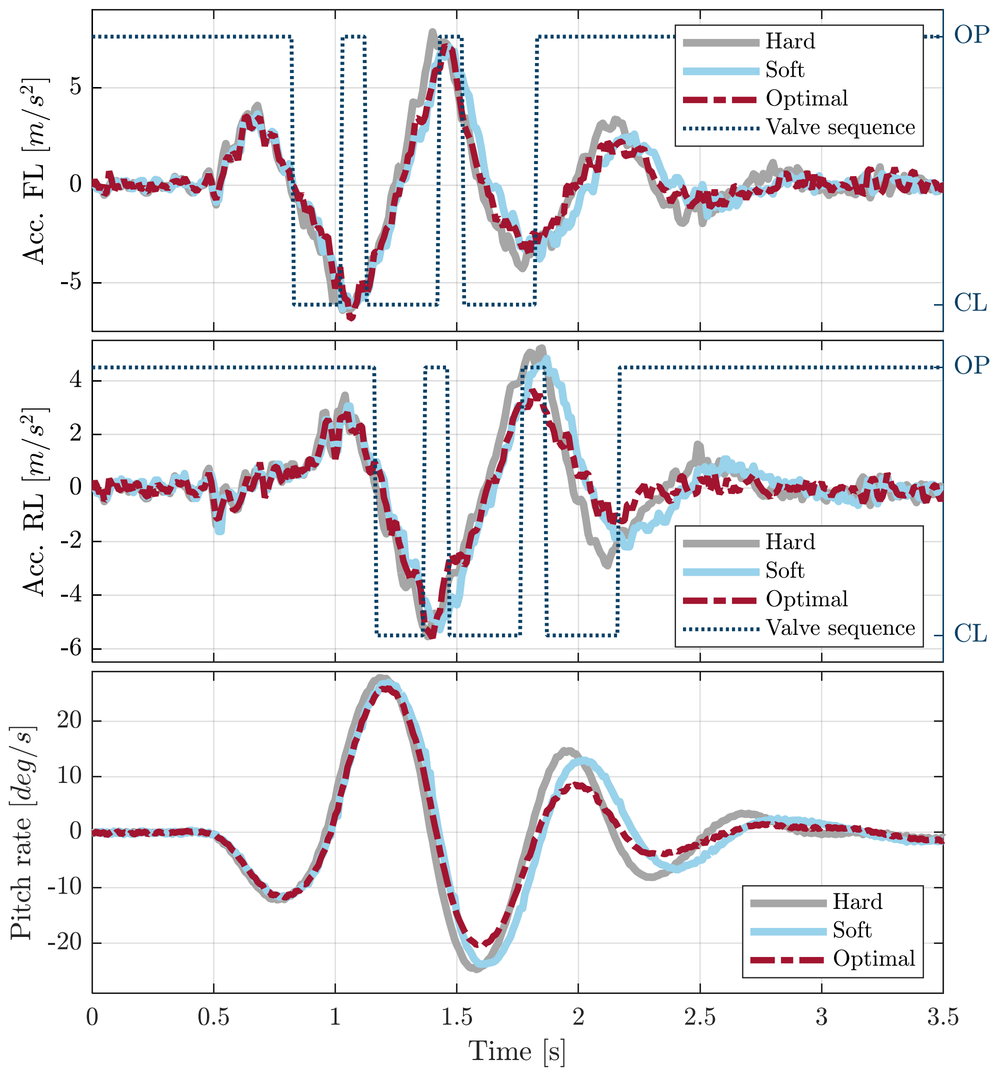
The ECU **at each iteration**:

1. Takes values of acceleration;
2. **Apply in open loop** the global optimal valve sequence (found offline using same system parameters) when a threshold in acceleration is exceeded.

Activation threshold ($2\ m/s^2$) is chosen robustly to noise and disturbances.

HYUNDAI

Experimental results



Experimental results

FL corner, RL corner and pitch rate as signals of interest.

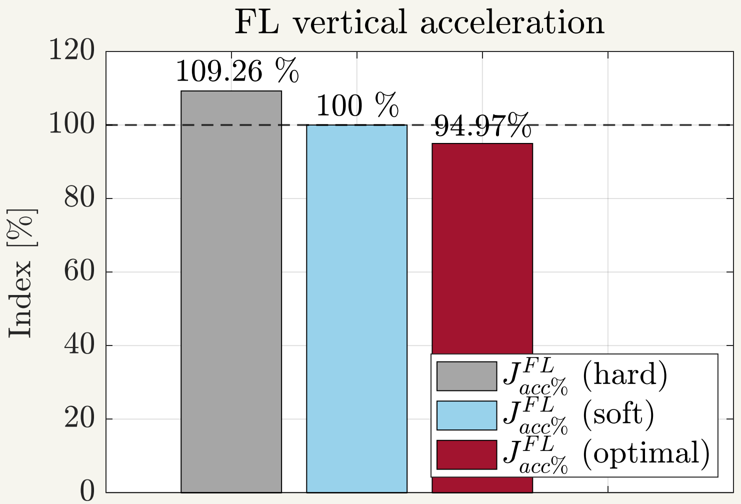
Dynamic valve switching **outperforms** the passive benchmark in all corners. Performance are higher in the bump release (in line with expectations).

Inequalities in the front/rear acceleration corners are given by a **different suspension sizing**. Also, performance can be enhanced by lowering delays.

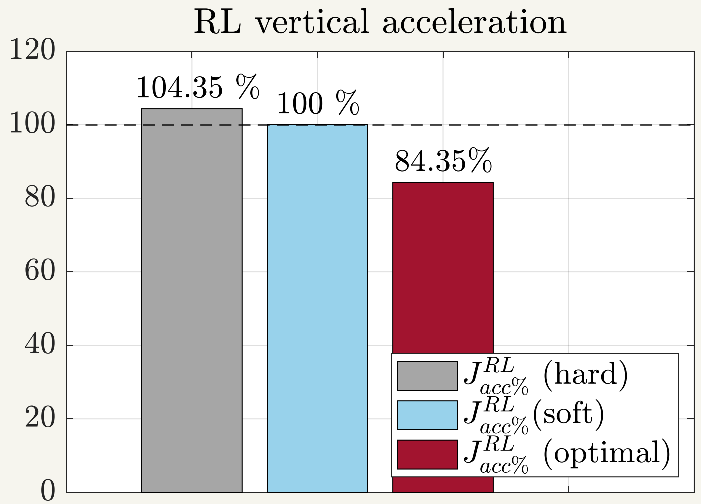
The **pitch rate is positively affected** by suspension control, even though only acceleration minimization is enforced in the control problem.

Experimentally measured performance indexes

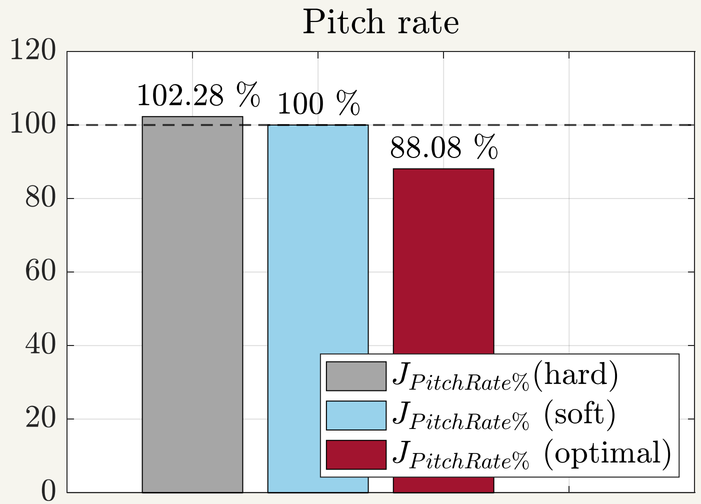
- Experimental indexes (normalized with respect to soft passive configuration)



5% improvement on front acceleration



16% improvement on rear acceleration

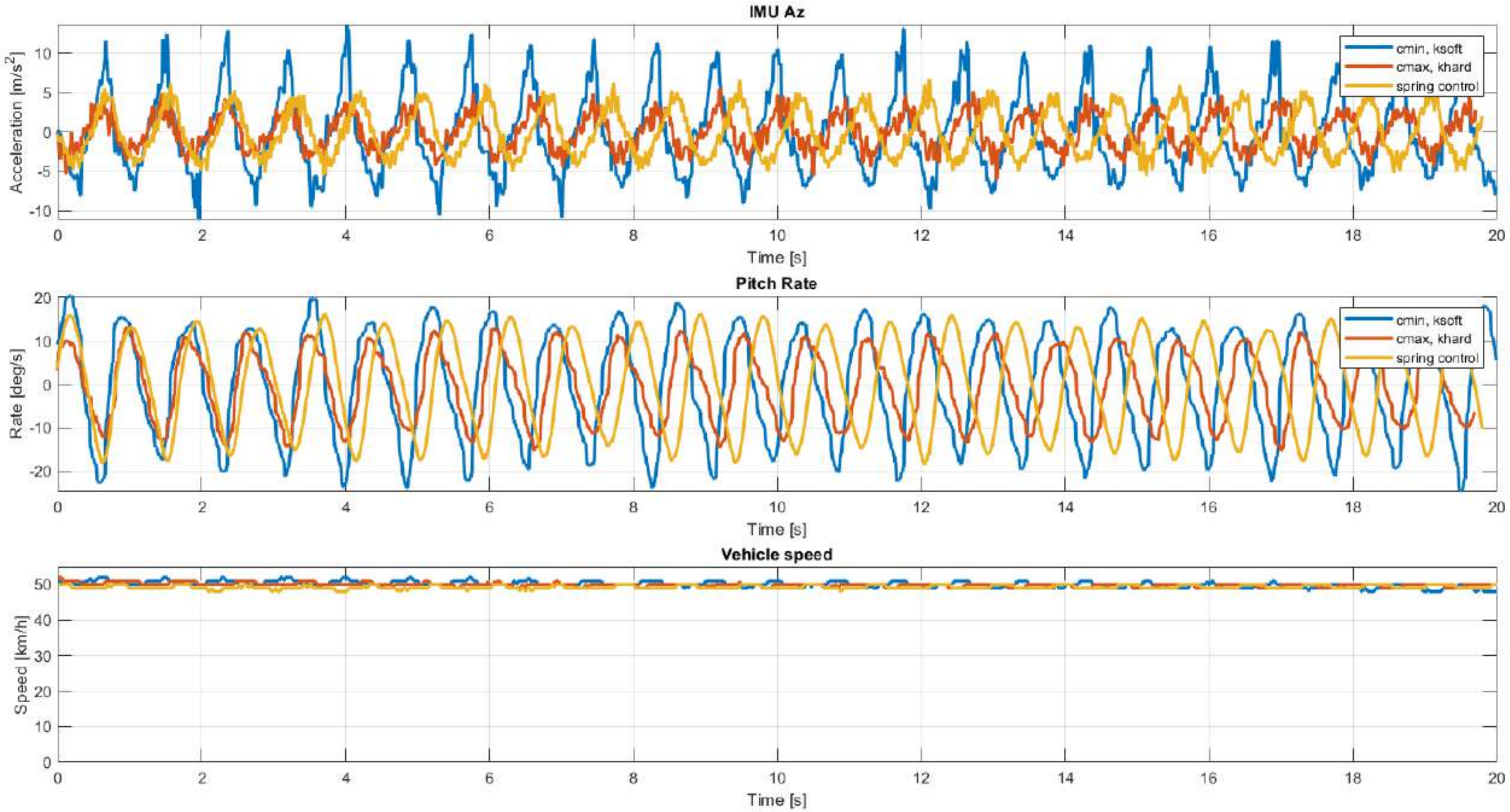


12% improvement on pitch rate

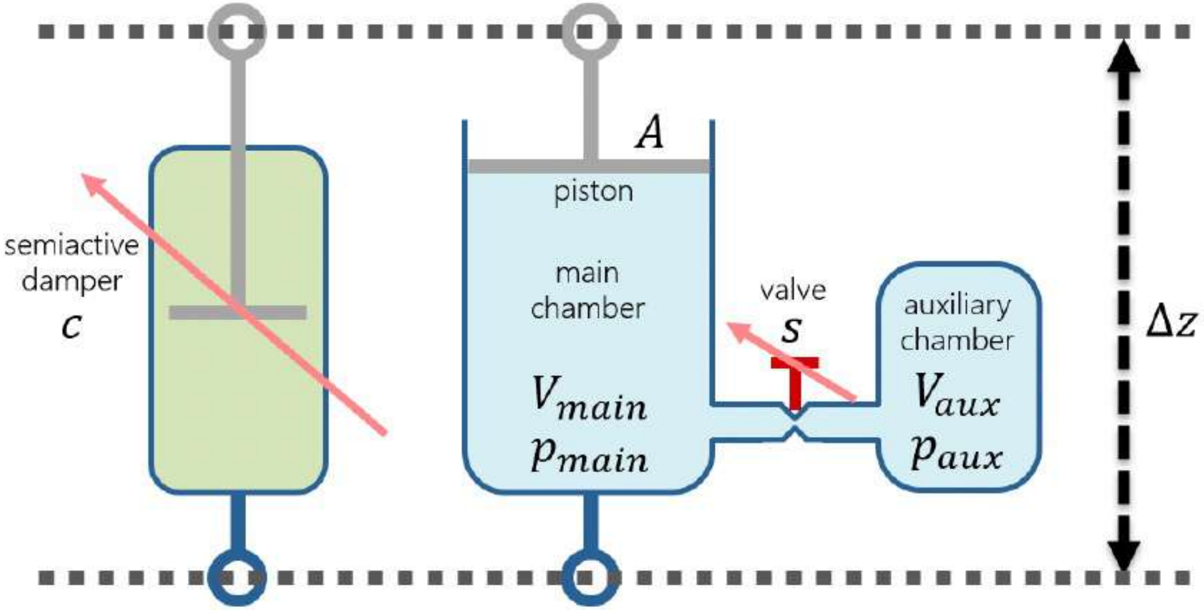
First experimental evidence of benefits induced by stiffness modulation

Experimentally measured performance indexes

The Energy release principle can be used to derive a SH-like causal control law for semi-active stiffness control.

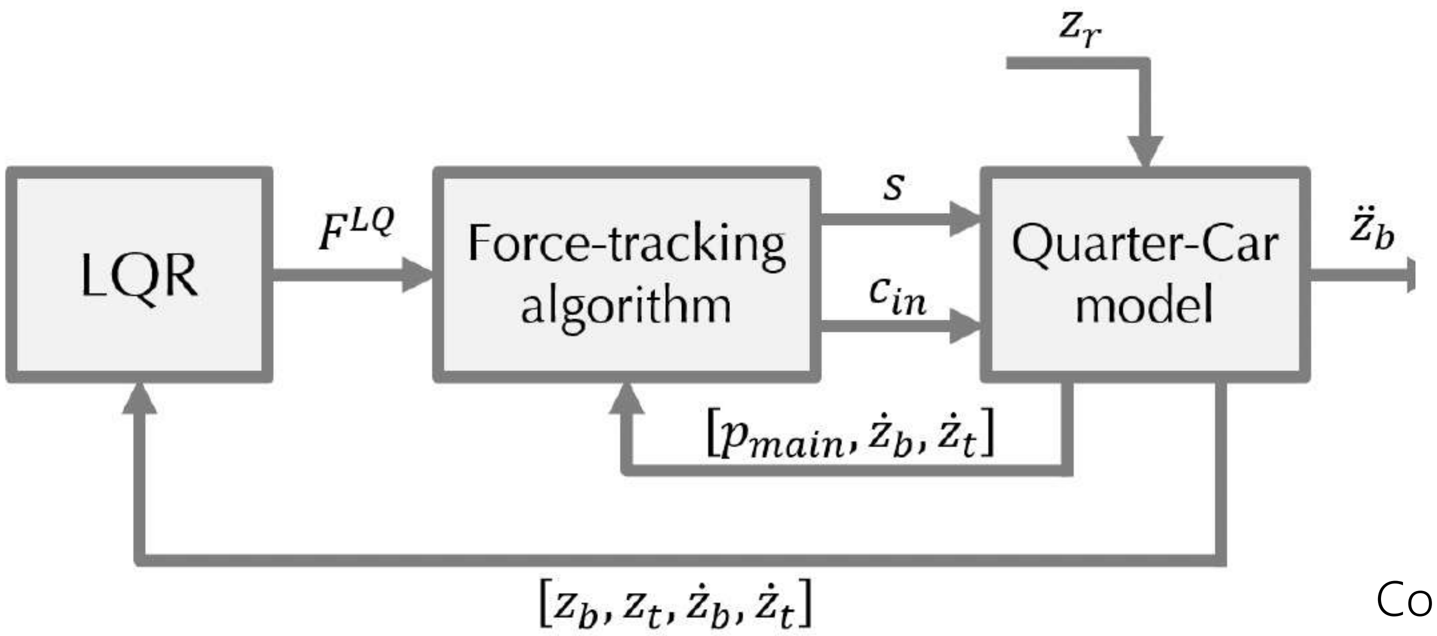


Coordinated Stiffness and Damping Control



$$F_{susp} = F_c + F_k$$

Coordinated Stiffness and Damping Contro with a hierarchical control system



$$\dot{\mathbf{x}} = \mathbf{A}\mathbf{x} + \mathbf{B}F^{LQ}$$
$$F^{LQ} = -\mathbf{K}\mathbf{x}$$

$$J^{LQ} = \lim_{T\to\infty} \frac{1}{T} \int_0^T \left[\ddot{z}_b^2 + \rho \Delta z^2\right] \mathrm{d}t$$

Comfort oriented control

Avoid end of stroke

Force tracking algorithm

The force tracking algorithm tries to minimize $e_F = F_{act} - F^{LQ}$

where $$F_{act} = -c\Delta\dot{z} + (p_{main} - p_{atm})A - Mg$$

Daisy chain algorithms:

Semi-Active

1) $$c_{in} = \mathrm{sat}_{[c_{min}, c_{max}]} \frac{(p_{main} - p_{atm})A - Mg - F^{LQ}}{\Delta\dot{z}}$$

Priority goes to the damper because of smoothness

2) The ideal chamber pressure is:

$$p^*_{main} = p_{atm} + \frac{1}{A}\left[c_{in}\Delta\dot{z} + Mg + F^{LQ}\right]$$

the main chamber pressure is not a directly controllable variable, a pressure tracking logic is needed

$$\dot{p}_{main} = \frac{-\,p_{main}\gamma A}{V_{main,0} + A\Delta z + s \cdot V_{aux}} \cdot \Delta\dot{z}$$

the valve position s does not change the sign of the pressure derivative, (that depends on the stroke speed only), but affects its absolute value, which increases with closed valve and decreases vice-versa.

Stiffness and Damping Control

When $(p_{main} - p^*_{main})\Delta\dot{z} > 0$

We have two options

$(p_{main} - p^*_{main}) > 0$ and $\Delta\dot{z} > 0$

P_{main} is greater than desired one

P_{main} will decrease

Speed up the increase → close the valve

Stiffness and Damping Control

When $(p_{main} - p^*_{main})\Delta\dot{z} > 0$

We have two options

$$(p_{main} - p^*_{main}) < 0 \quad \text{and} \quad \Delta\dot{z} < 0$$

P_{main} is smaller than desired one

P_{main} will increase

Speed up the increase → close the valve

Stiffness and Damping Control

while $t \le t_{end}$ **do**
  if $(p_{main} - p^*_{main})\Delta\dot{z} > 0$ **then**
    $s_t = 0$
  end if
  if $(p_{main} - p^*_{main})\Delta\dot{z} < 0$ OR $\Delta\dot{z} = 0$ **then**
    if $|p_{eq} - p^*_{main}| < |p_{main} - p^*_{main}|$ **then**
      $s_t = 1$
    else
      $s_t = s_{t-1}$
    end if
  end if
  if $p_{main} - p^*_{main} = 0$ **then**
    $s_t = s_{t-1}$
  end if
  $t \leftarrow t + 1$
end while

Equilibrium pressure.
Wait until you are close to the equibrium pressure to open the valve

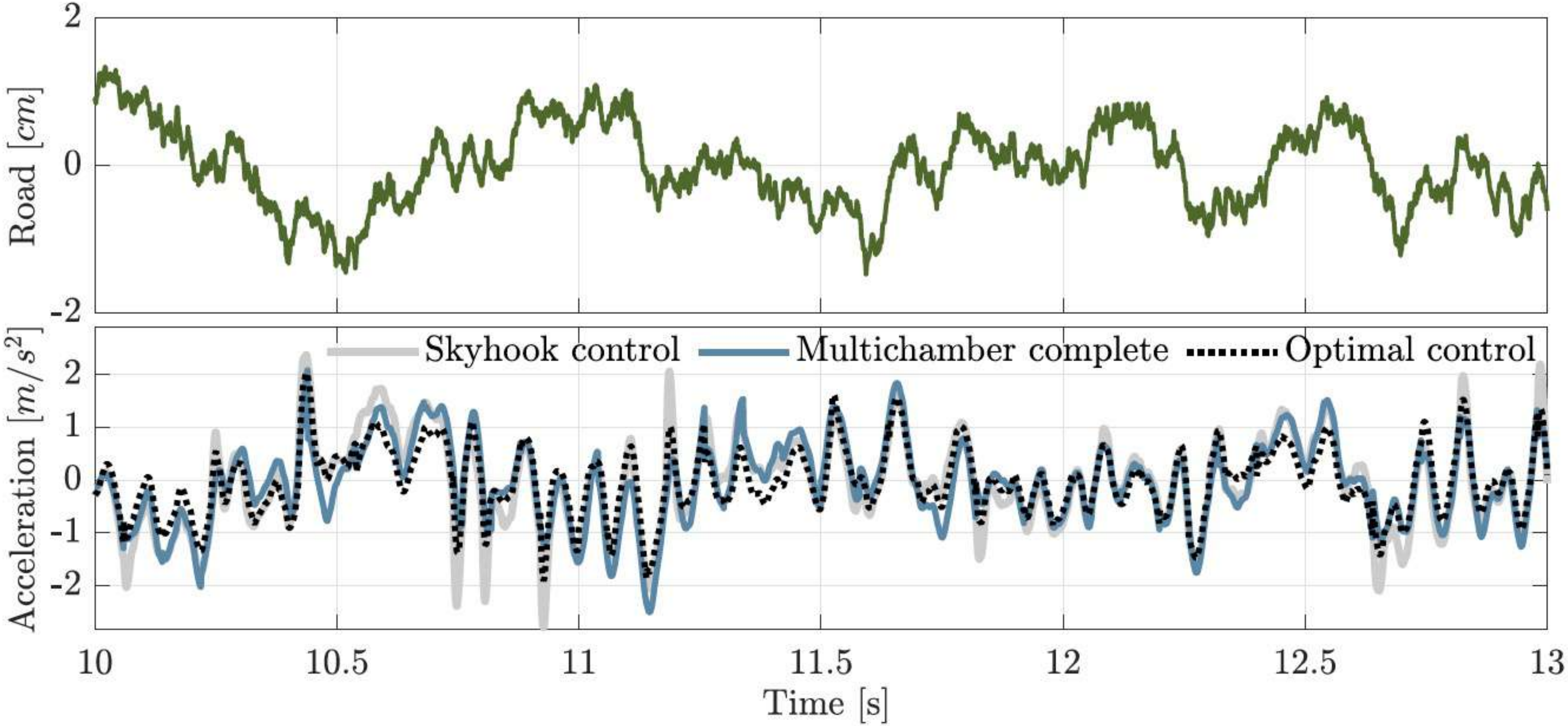
Stiffness and Damping Control

```
while t ≤ t_end do
    if (p_main − p*_main)Δż > 0 then
        s_t = 0
    end if
    if (p_main − p*_main)Δż < 0 OR Δż = 0 then
        if |p_eq − p*_main| < |p_main − p*_main| then
            s_t = 1
        else
            s_t = s_{t−1}
        end if
    end if
    if p_main − p*_main = 0 then
        s_t = s_{t−1}
    end if
    t ← t + 1
end while
```

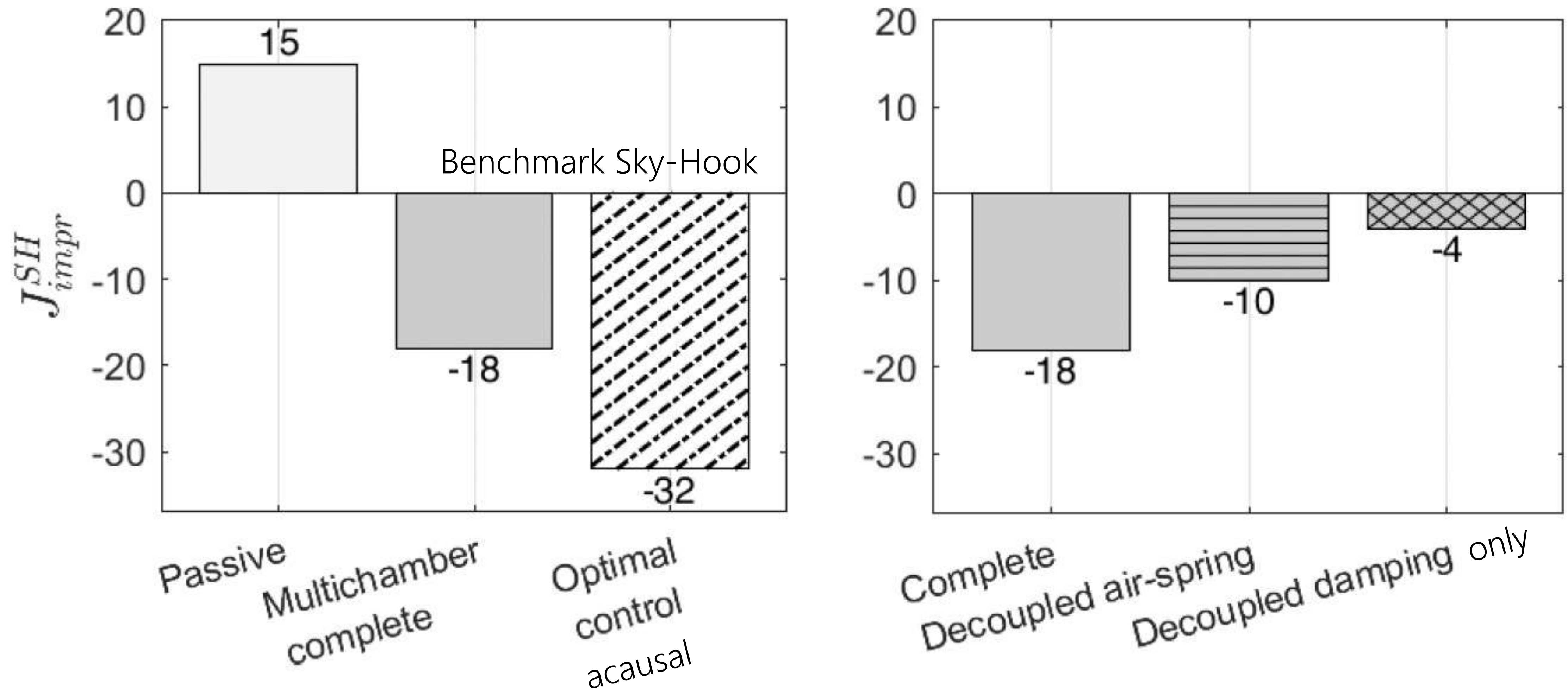
Equilibrium pressure.
Wait until you are close to the equibrium pressure to open the valve

It is a discrete time algorithm

Stiffness and Damping Control



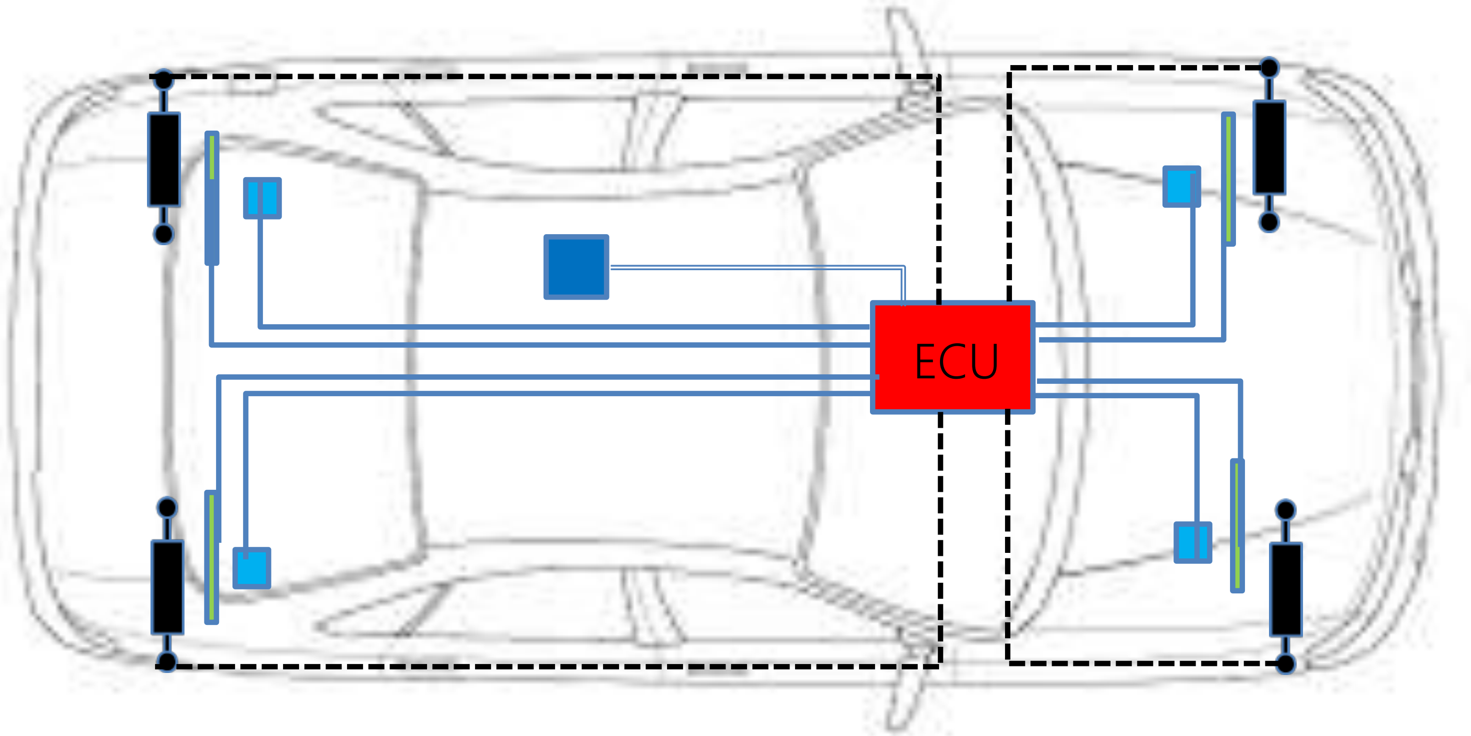
Stiffness and Damping Control

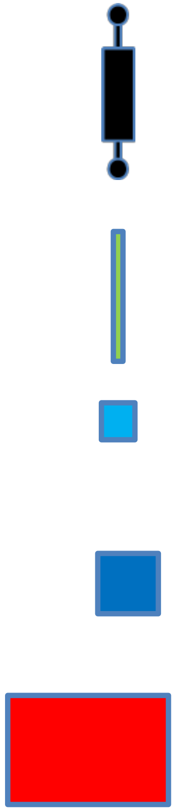


Outline

- Introduction
- Semi-Active Damping Control
    - Actuators
    - Models
    - Benchmark
    - Causal Control
- Semi-Active Stiffness Control
    - Actuators
    - Benchmark
    - Causal Control
- **Sensing Preliminaries**
- A look at the future
- Conclusions

Sensing Preliminaries

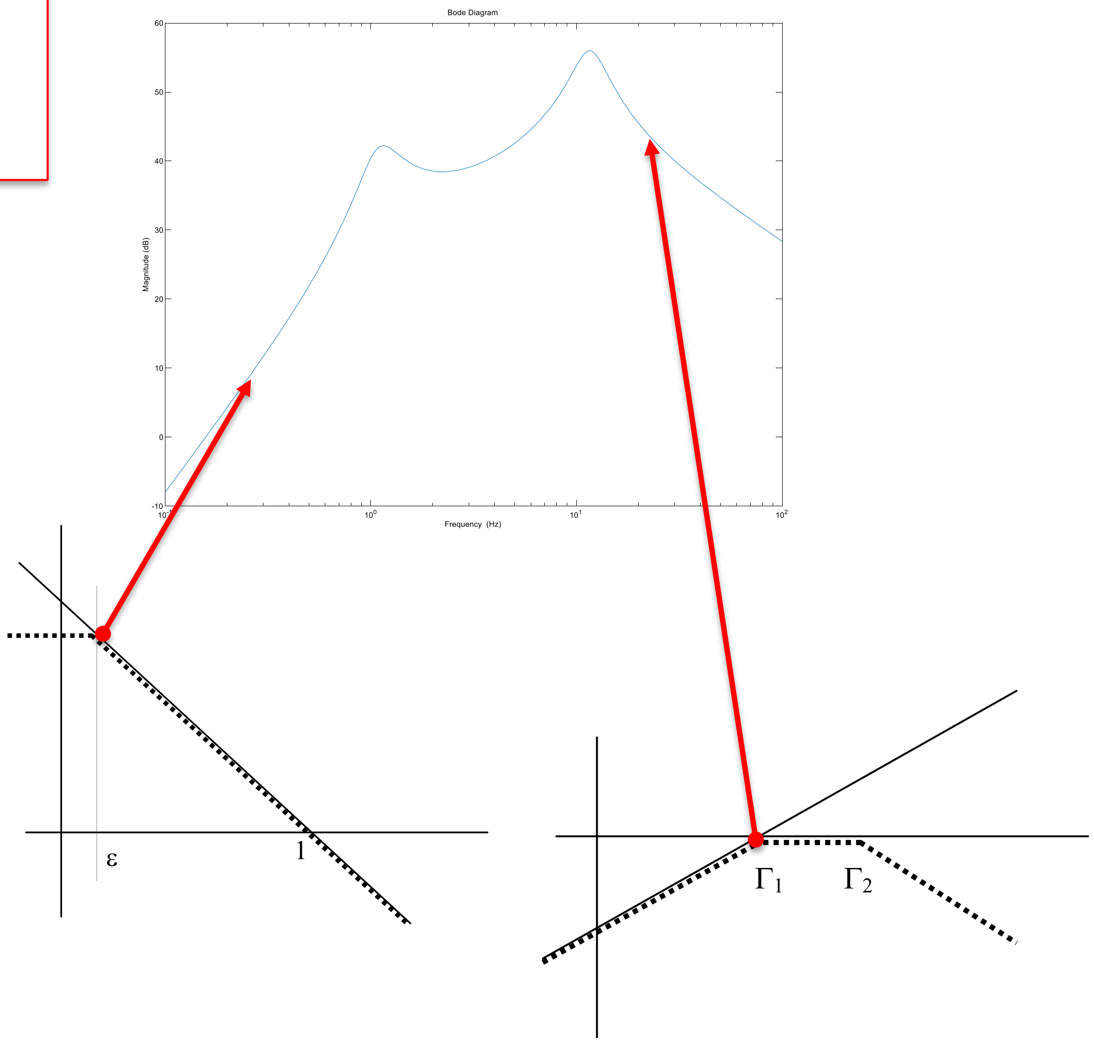




Sensing Preliminaries

Physical sensors (signal + noise):

- Body-accelerometer $\ddot{z} + d_a$
- Stroke sensor $(z - z_t) + d_e$



Body speed estimation

$$V(s) = A(s)\frac{1}{s} + D(s)\frac{1}{s}$$

⇩

$$V(s) = A(s)\frac{1}{s+\varepsilon} + D(s)\frac{1}{s+\varepsilon}$$

$$\varepsilon = 2\pi \cdot 0.1$$

(OK beyond 0.1Hz)

Stroke speed estimation

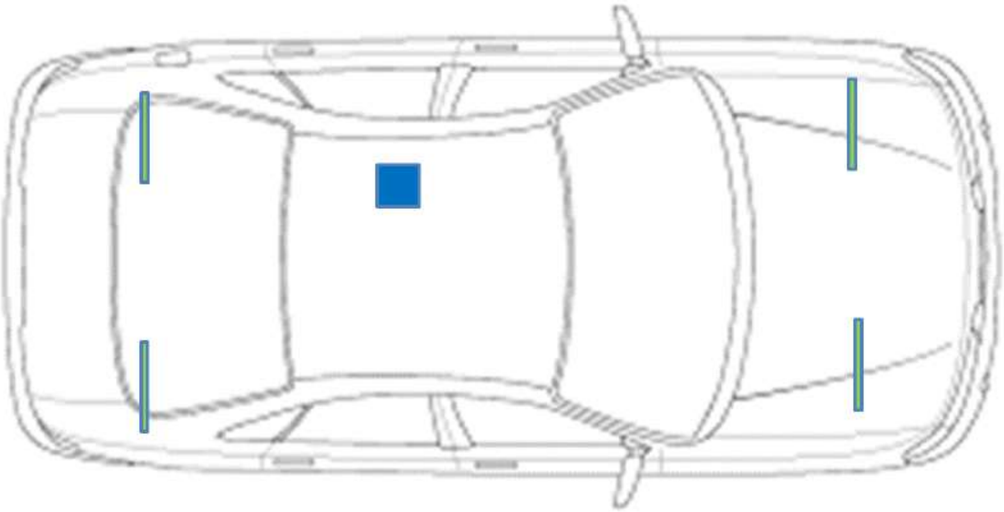
$$V(s) = sZ(s) + sD(s)$$

⇩

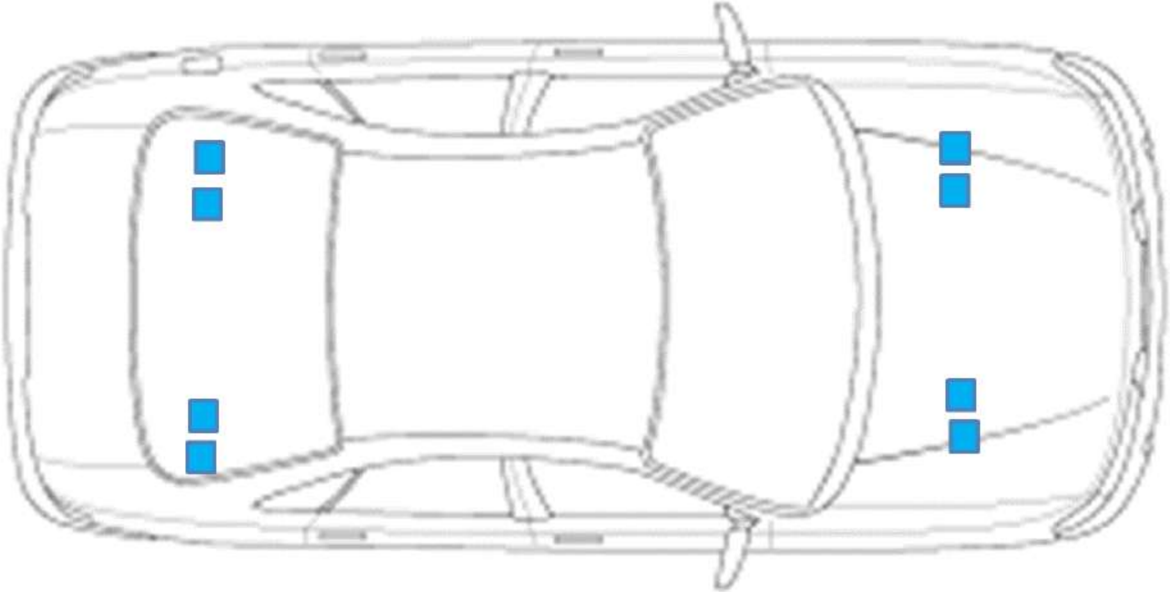
$$V(s) = \left(Z(s) + D(s)\right)s\frac{\Gamma_1}{s+\Gamma_1}\frac{\Gamma_2}{s+\Gamma_2}$$

$$\Gamma_1 = 2\pi \cdot 20,\ \Gamma_1 < \Gamma_2$$

(OK below 20Hz)

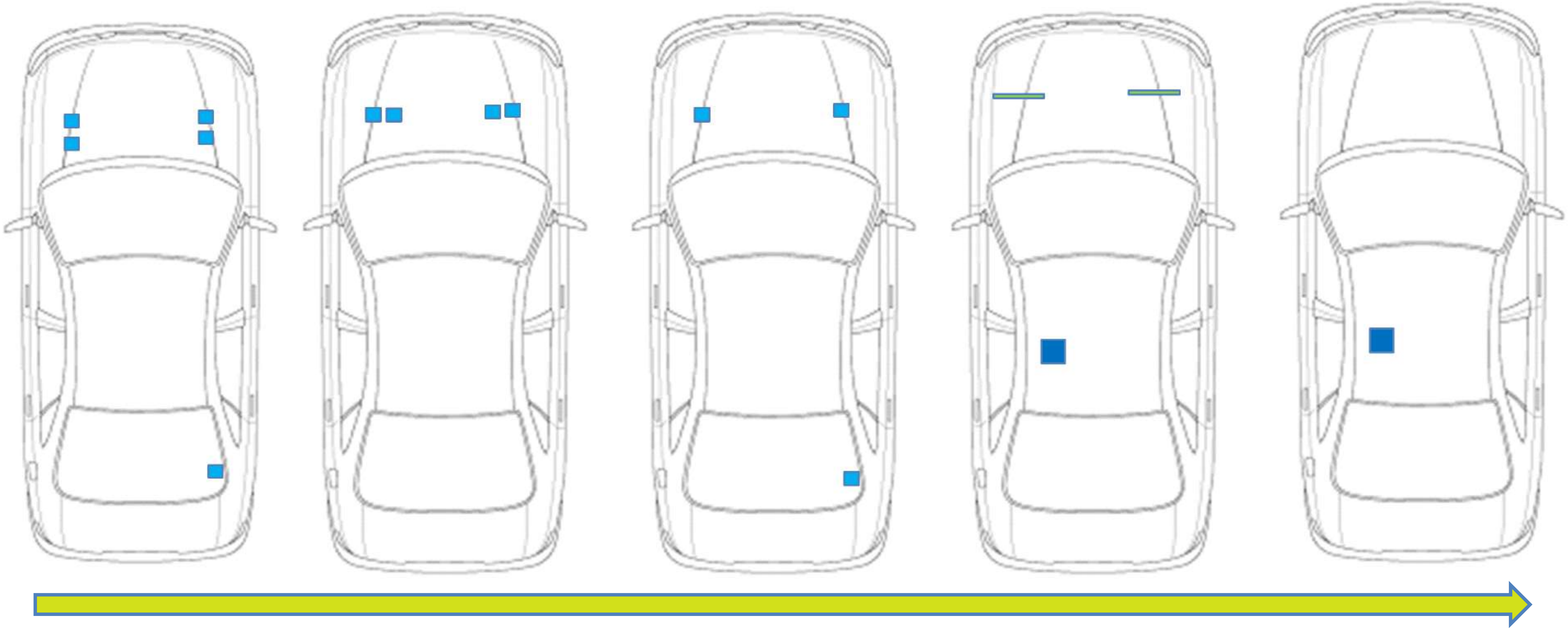


4 eleongation sensors only + IMU



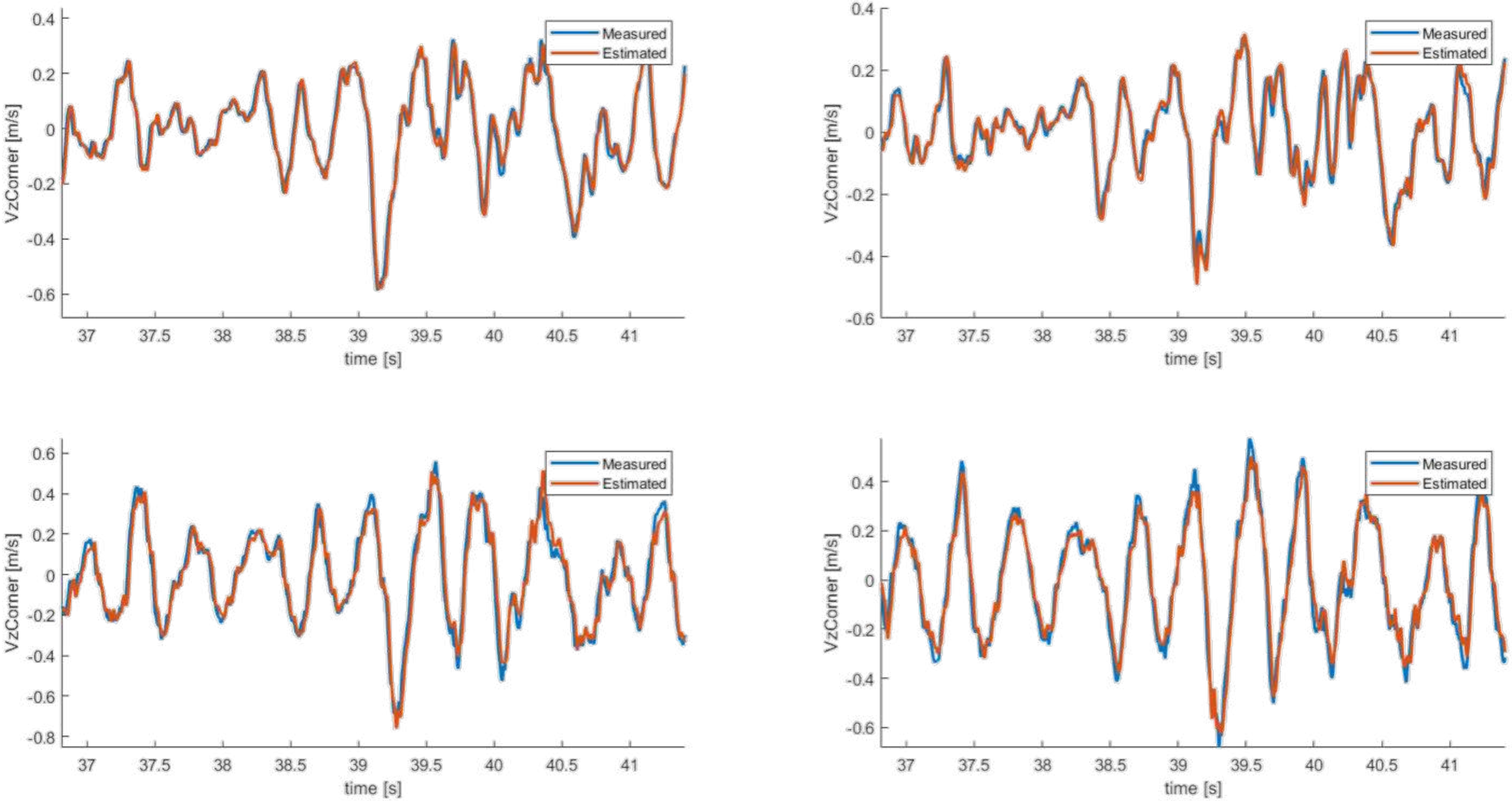
4 «twins» of accelerometers

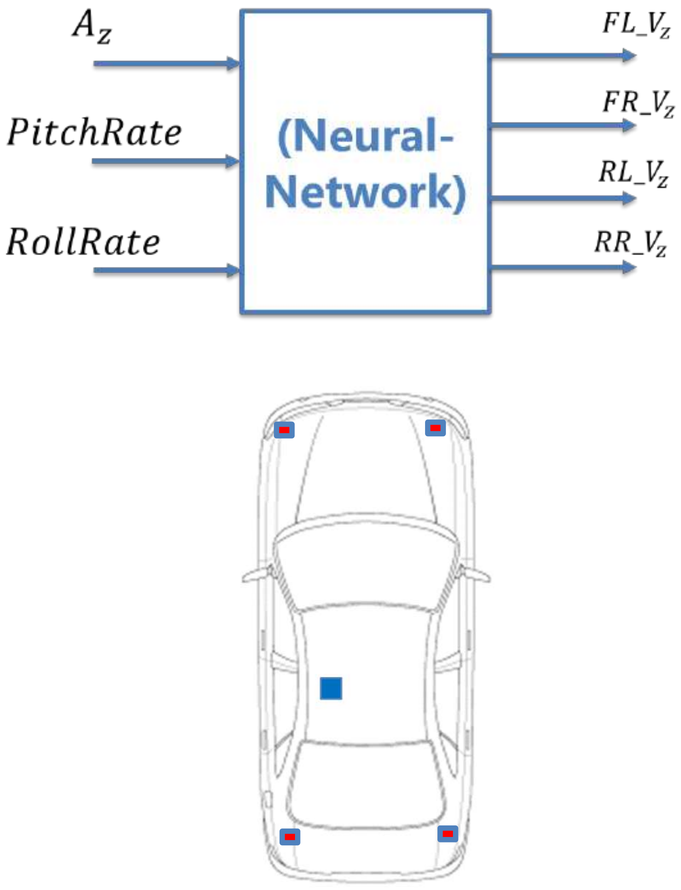
Sensing Preliminaries



Cost and HW-complexity reduction; SW-sensing complexity increase; performance reduction

Sensing Preliminaries





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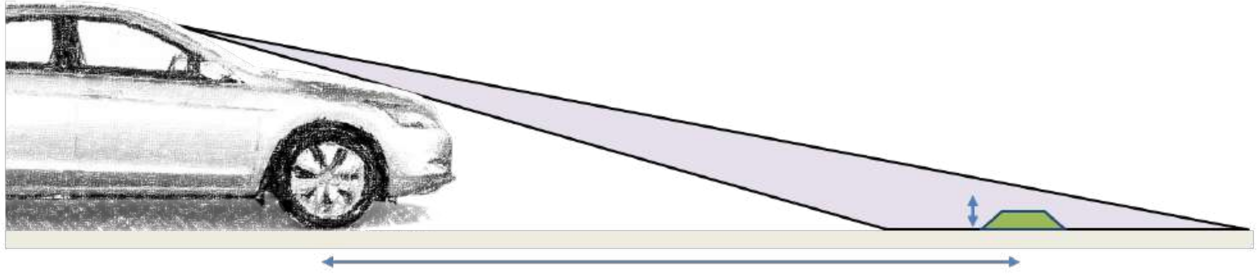
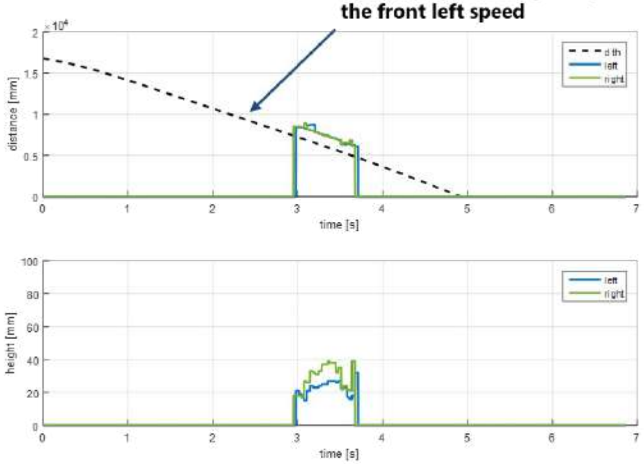
Future Development

Road Preview



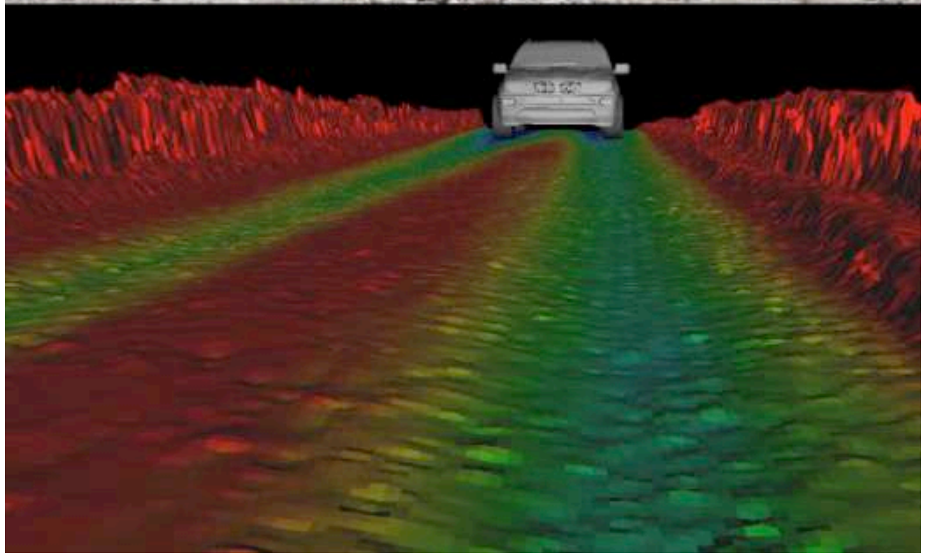
Theoretical distance from bump obtained integrating the front left speed

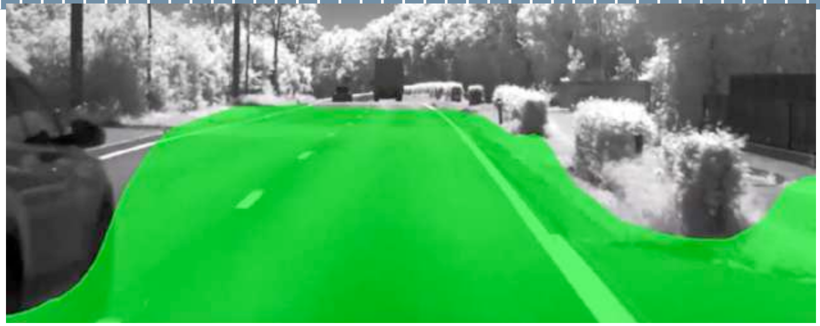


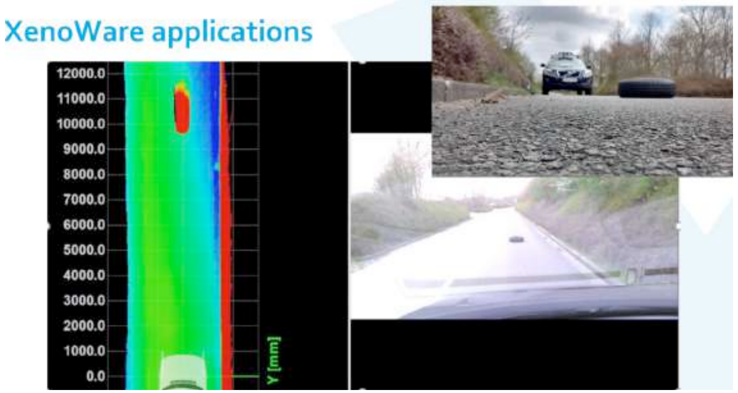
Low speed (< 15 km/h)

Future Development

Road Preview







Challenge: integrate navigation AND road-scanning LIDARS?

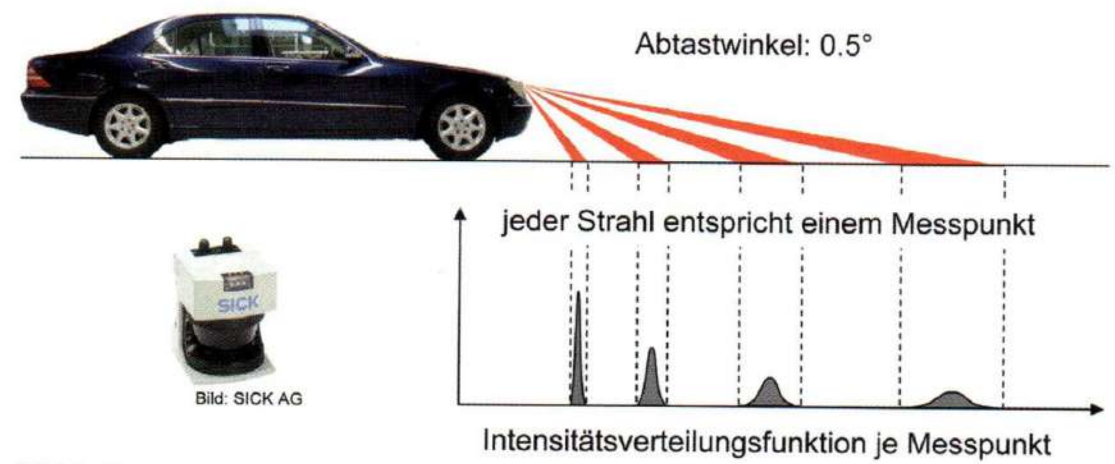
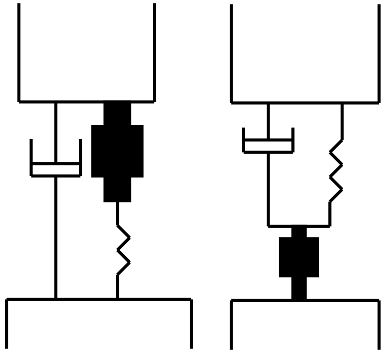


Bild 1: Die Lasersensoren tasten das Fahrbahnhöhenprofil ab, wobei jedem Spot eine individuelle Verteilungsfunktion zugeordnet wird

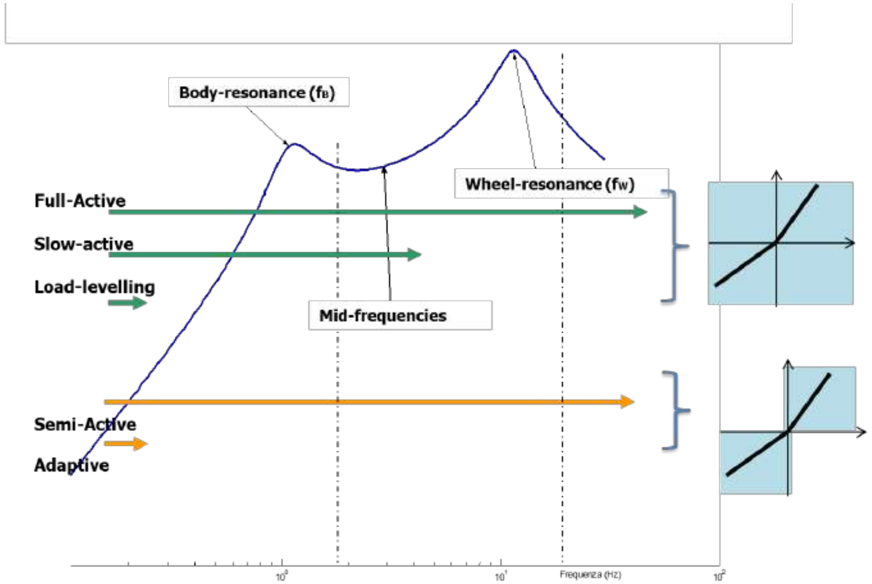
Future Development

Active Suspensions

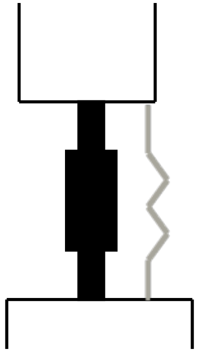


«Slow-active»

Body-bandwidth
(control cut-off around 3-5 Hz)



Actuator: can be electro-hydraulic or electro-mechanic



«Full-active»

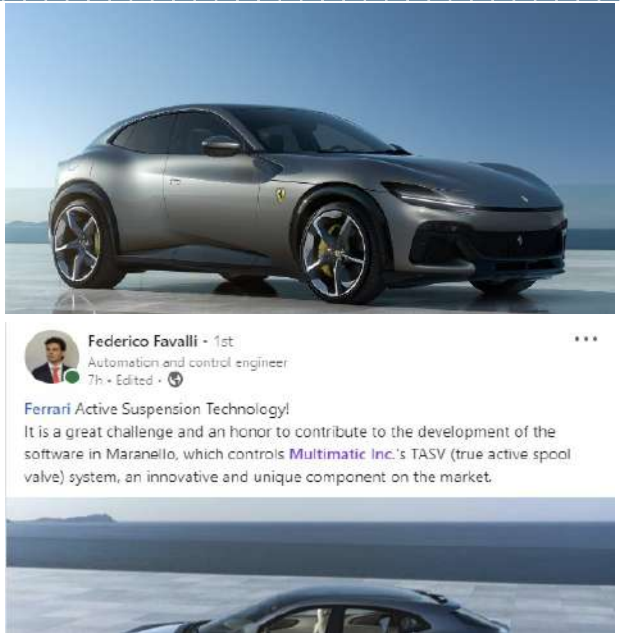
Full-bandwidth
(control cutoff around 20-30 Hz)

Future Development

Active Suspensions

Future Development

Active Suspensions



Just launched (13/9/22) Ferrari Purosangue
Completeley new full-active architecture (by multimatic)

4-quadrants e-motor + ballscrew
EH semi-activeamper (no oil-free)
Full-active (by Multimatic)

- **Easier than semi-active suspensions**
- System is **LINEAR**
- Classical linear control design tools (**optimal control, Hinf, etc…**) can be used
- **Multi-variables and multi-objective** control systems can be (easily) designed

Example: **LQR regulator** assuming the state vector is measurable (or estimated).

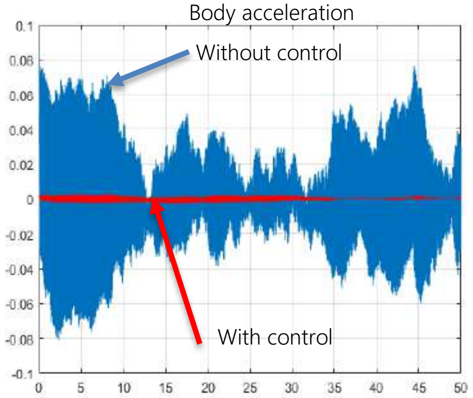
$$J = \lim_{T\to\infty} \frac{1}{T}\int_0^T [\ddot{z}^2 + \rho_1 (z - z_t)^2 + \rho_2 (z_t - z_r)^2]\, dt$$

Comfort objective

Elongation objective

Contact objective

With ρ_1 and ρ_2 very small (all emphasis on comfort)



$$J = \lim_{T\to\infty} \frac{1}{T}\int_0^T (x'Qx + u'Ru + 2x'Nu)\, dt$$

$$Q = \begin{vmatrix} \rho_1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & \rho_2 & 0 \\ 0 & 0 & 0 & 0 \end{vmatrix}, R = \gamma^2 =, N = \begin{vmatrix} 0 \\ 0 \\ 0 \\ 0 \end{vmatrix}$$

$$x = [z - z_t,\ \dot{z},\ z_t - z_r,\ \dot{z}_t]',\ u = F$$

$$F^{opt}(t) = -K^{opt} x(t)$$

$0 = A_n' P + P A_n + Q_n - P B R^{-1} B' P,\ P > 0,$ symmetric and unique solution

$$K^{opt} = R^{-1}(B'P + N')$$
$$A_n = A - BR^{-1}N'$$
$$Q_n = Q - NR^{-1}N'$$

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Conclusions

- Control Engineering Look at Suspension Control
- Objectives
- Control Oriented Models
- Technology
- Algorithms with an practical engineering perspective
- Tuning and Calibration

Essential Bibliography

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