

# Loewner Framework for data-driven reduced order modeling (with pH-structure preserving)

... a bridge between realization, approximation and identification

C. Poussot-Vassal

September 22, 2025

coll. with P. Vuillemin, D. Matignon, G. Haine & M. Fournié



# Forewords

Advancement (energy driven approach...)

Lecture Motivations, pH energy philosophy (Denis Matignon)

Lecture pH in 1-D, infinite dimension (Andrea Brugnoli)

Lecture pH in  $n$ -D, infinite dimension (Denis Matignon)

Lecture PFEM for pH (Michel Fournié)

Lecture PFEM for pH with applications (Michel Fournié)

Lecture **Model reduction, approximation and passivity in the LF**

Lab Discretize a PDE with PFEM (& SCRIMP)

Lab **Simplify the PFEM using LF with passivity preservation (& +lf)**

Lecture Open perspectives (Andrea Brugnoli)

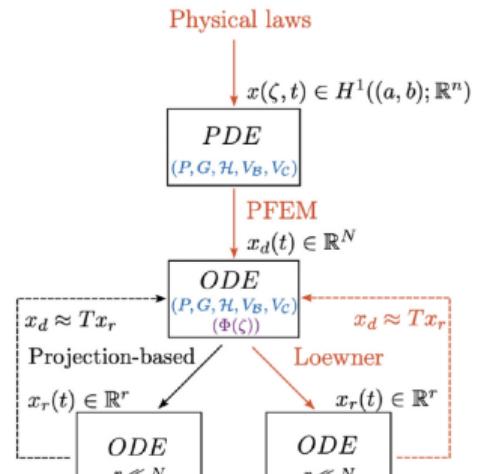


Figure by J.P. Toledo-Zucco

A.C. Antoulas, S. Lefteriu and A.C. Ionita, "[Chapter 8: A Tutorial Introduction to the Loewner Framework for Model Reduction](#)", Model Reduction and Approximation: Theory and Algorithms, 2016.

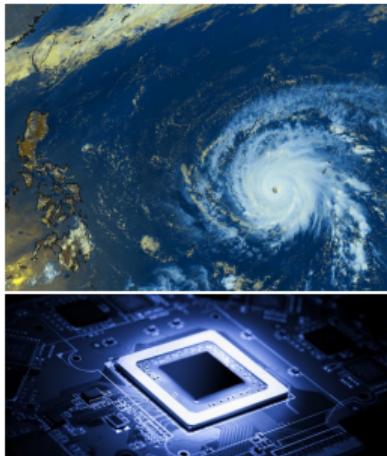
A.C. Antoulas, "[A new result on passivity preserving model reduction](#)", Systems & Control Letters, vol. 54, 2005.

P. Benner, P. Goyal and P. Van-Dooren, "[Identification of Port-Hamiltonian Systems from Frequency Response Data](#)", Systems & Control Letters, vol. 143, 2020.

# Forewords

Dynamical models, what for?

## Dynamical models are centrals tools in engineering...



Digitalisation and computer-based modeling for

- ▶ simulation, optimisation, understanding
- ▶ control, estimation, analysis...

However

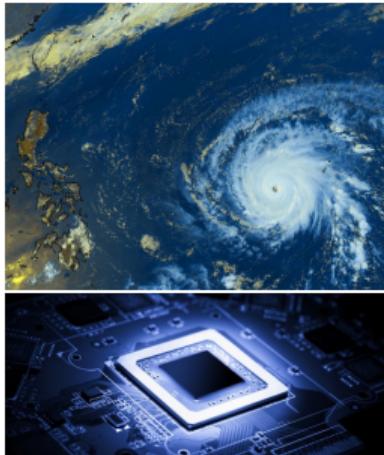
Finite machine precision, computational burden, memory management and actual solvers

- ▶ induces important time consumption
- ▶ generate inaccurate results
- ▶ limit the class of models to deal with
- ▶ limit the amount of data to treat

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- ▶ limit the class of models to deal with
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Develop robust and efficient tools to construct simplified dynamical models

# Forewords

Dynamical models, what for?

## ... and in systems and control engineering

- ▶ **for verification and validation**  
( $\mu$ ,  $\mathcal{H}_\infty$ -norm, pseudo-spectra, Monte Carlo)
- ▶ **for detection**  
(fault isolation, param. estim.)
- ▶ **for uncertainty propagation**  
(Multi Disc. Optim., robust optim.)
- ▶ **for feedback control synthesis**  
( $\mathcal{H}_\infty/\mathcal{H}_2$ -norm, MPC, adaptive)



## Complex models

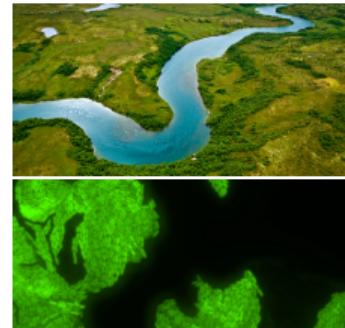
- ▶ important sim. time
- ▶ memory burden
- ▶ inaccurate results
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### Complex models

- ▶ important sim. time
- ▶ memory burden
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- ▶ limit model class



### Model simplification

### Simplified models

- ▶ reduced sim. time
- ▶ memory saving
- ▶ accurate results
- ▶ rational model

# Forewords

Use-case: EDF hydroelectric open-channel (model-driven)

## Hydraulic-driven electricity

- ▶ Dams & run-of-the-river ( $\approx 10\%$ )
- ▶ Run-of-the-river ( $\approx 5\%$ )
- ▶ Rely on [open-channel hydraulic systems](#)
- ▶ Need for analysis and control



January 4th, 2023

# Forewords

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## Time-domain

$$\begin{aligned}\frac{\partial S}{\partial t} + \frac{\partial Q}{\partial x} &= 0 \\ \frac{\partial Q}{\partial t} + \frac{\partial(Q^2/S)}{\partial x} + gS \frac{\partial H}{\partial x} &= gS(I - J),\end{aligned}$$

## Frequency-domain

$$\begin{aligned}h(s, x) &= G_i(s, x)q_i(s) - G_o(s, x)q_o(s) \\ G_i(s, x) &= \frac{\lambda_1(s)e^{\lambda_2(s)L + \lambda_1(s)x} - \lambda_2(s)e^{\lambda_1(s)L + \lambda_2(s)x}}{B_0s(e^{\lambda_1(s)L} - e^{\lambda_2(s)L})} \\ G_o(s, x) &= \frac{\lambda_1(s)e^{\lambda_1(s)x} - \lambda_2(s)e^{\lambda_2(s)x}}{B_0s(e^{\lambda_1(s)L} - e^{\lambda_2(s)L})}\end{aligned}$$

Both are  $x$ -position dependent, hard to simulate in practice...



V. Dalmas, G. Robert, C. P-V., I. Pontes Duff and C. Seren, *"From infinite dimensional modeling to parametric reduced order approximation: Application to open-channel flow for hydroelectricity"*, in Proceedings of the 15th European Control Conference (ECC'16), Aalborg, Denmark, July, 2016.

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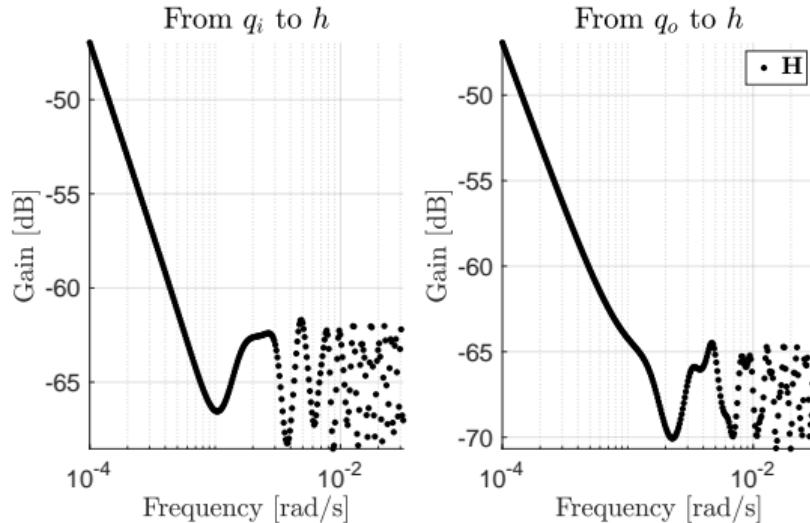
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- ▶ Model  
(integral and delay action)
- ▶  $\dot{E}\hat{x} = Ax + Bu$   
 $H_{51}$   
(full interpolant, unstable)
- ▶  $\dot{\hat{E}}\hat{x} = \hat{A}\hat{x} + \hat{B}u$   
 $\hat{H}_{10}$   
(reduced, stable, integrator)
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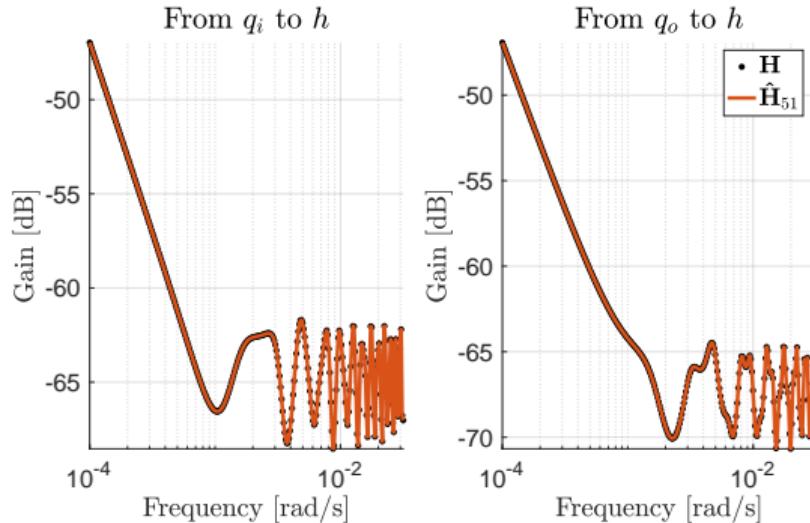
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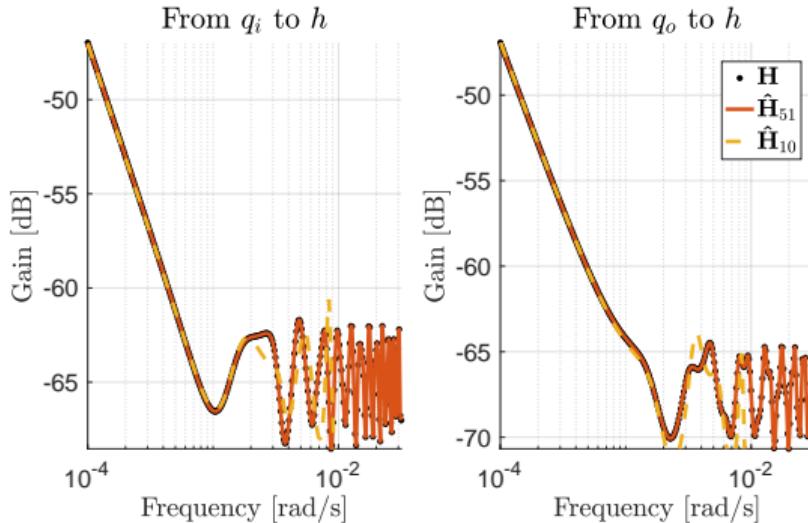
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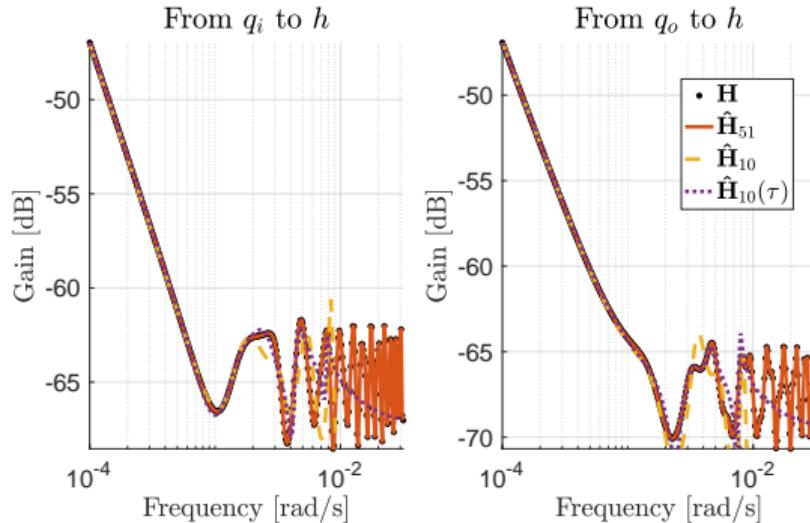
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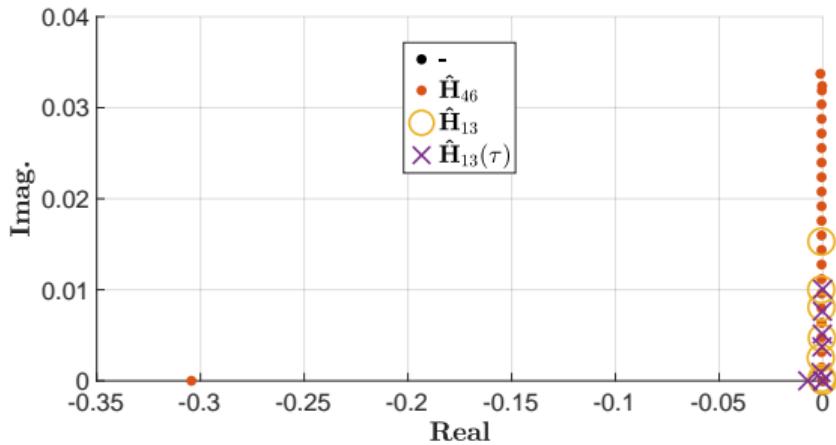
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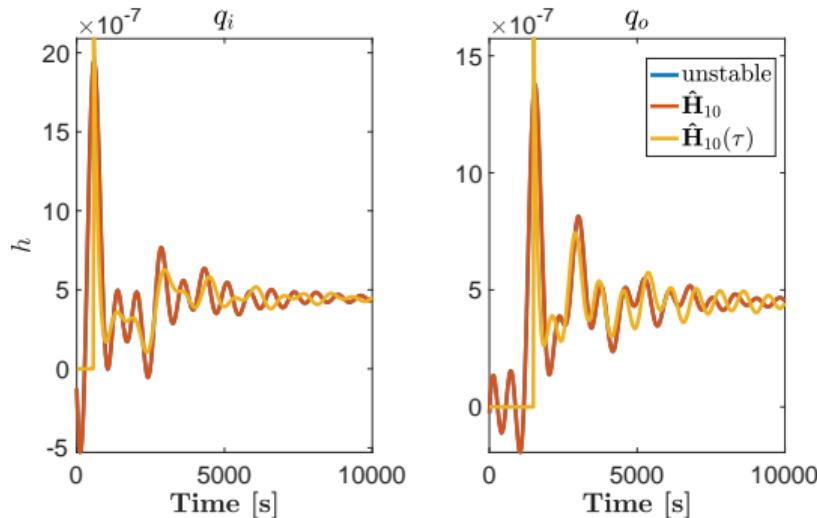
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## ANTENNA RESEARCH

### Antenna models

- ▶ to optimize parameters
- ▶ for polar computation

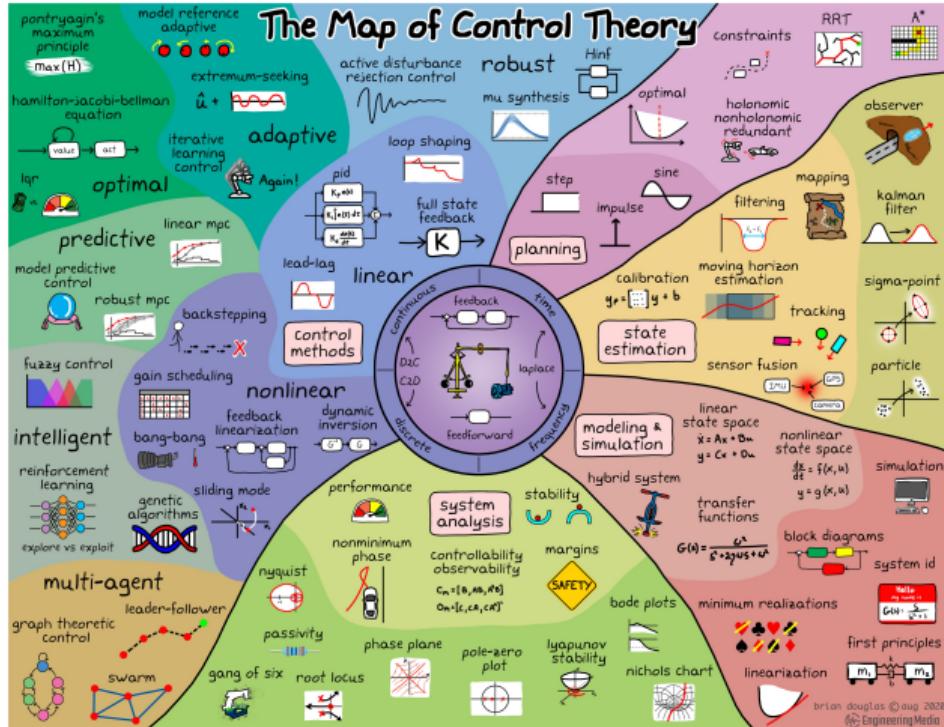
### Blend physics from

- ▶ Maxwell equations
- ▶ Kirchoff equations

- ▶ Replace costly simulations by accurate simple model
- ▶ Preserve structure and properties (port-Hamiltonian)
- ▶ Allows for geometry optimization

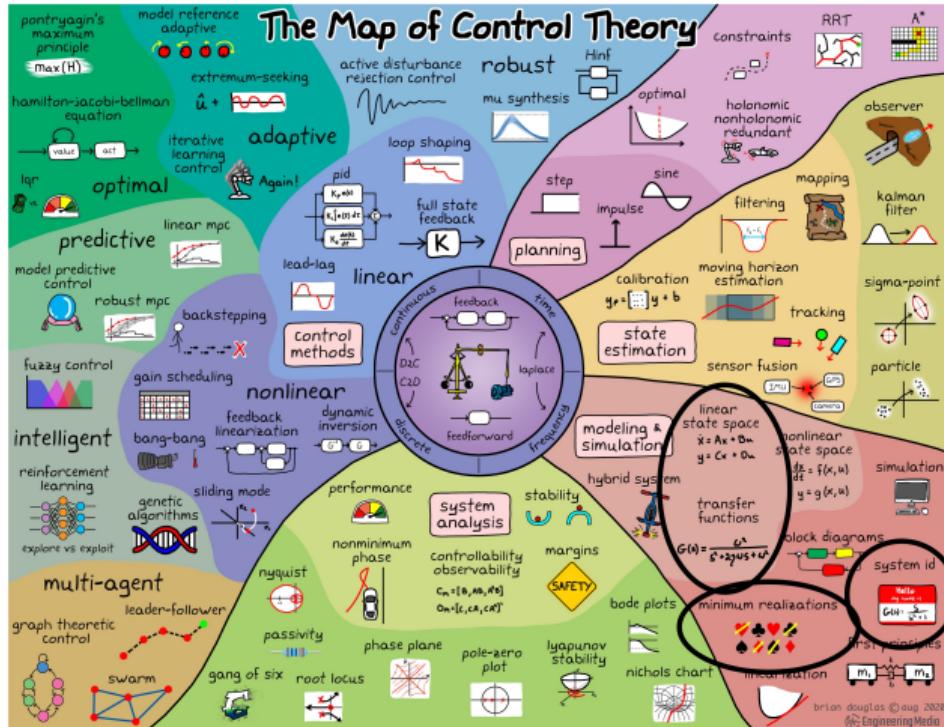
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The map of control theory (by Brian Douglas - <https://engineeringmedia.com/>)



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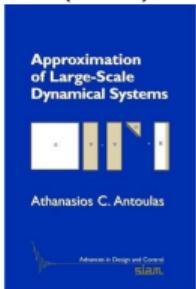
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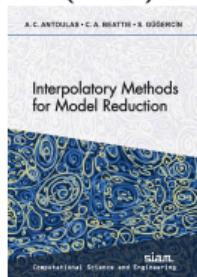
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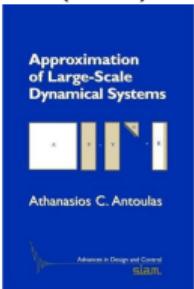


- ▶ Pencil & realization [Antoulas/Mayo/Trefethen/Embree/Ionita/...]
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  - ▶ B-LTI, Q-LTI [Antoulas/Benner/Gosea/Karachalios/Pontes/Willcox/P-V./...]
  - ▶ pHs [Van-Dooren/Beattie/Gugercin/Benner/Schwerdtner/Matignon/...]
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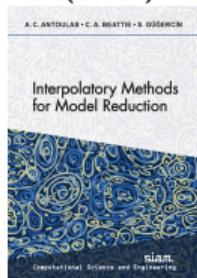
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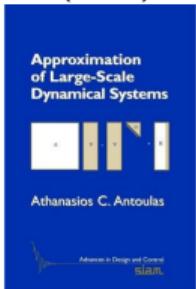
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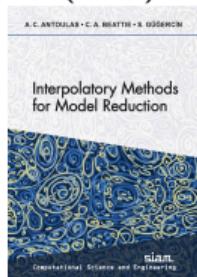
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## Part 1 (reminder)

- ▶ Linear dynamical systems
- ▶ Realization and transfer functions

## Part 2 (Loewner)

- ▶ Realization minimality
- ▶ Data-driven approximation
- ▶ Barycentric form

## Part 3 (Loewner extended)

- ▶ Linear passive model (& pH)
- ▶ Linear parametric model



*Karel Löwner (Czech)  
1893 - 1968  
Ph.D. advisor: G.A. Pick*

# Content

Forewords

**Linear dynamical systems**

Loewner

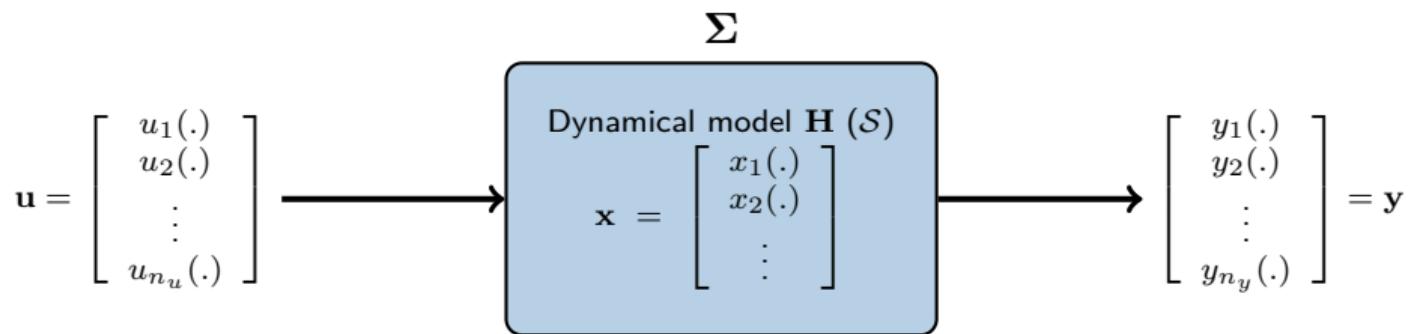
Loewner extensions (passive & pH)

Conclusions

# Linear dynamical systems

Simplifications

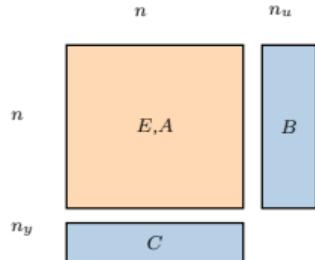
A dynamical model  $H$  (or  $\mathcal{S}$ ) is a function mapping input  $u$  to output  $y$  signals of a system  $\Sigma$



Let us stick (mainly) to linear systems only

# Linear dynamical systems

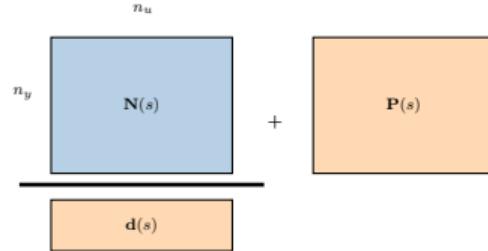
## Realization and transfer functions



$$\mathcal{S} : \begin{cases} E\dot{\mathbf{x}}(t) &= A\mathbf{x}(t) + Bu(t) \\ \mathbf{y}(t) &= C\mathbf{x}(t) \end{cases}$$

### Realizations

- $E, A, B, C$  are (real) matrices
- Internal knowledge  $\mathbf{u} \mapsto \mathbf{x} \mapsto \mathbf{y}$
- Realizations are infinite
- $\mathbf{u}(t) \in \mathbb{R}^{n_u}$   
 $\mathbf{y}(t) \in \mathbb{R}^{n_y}$   
 $\mathbf{x}(t) \in \mathbb{R}^n$



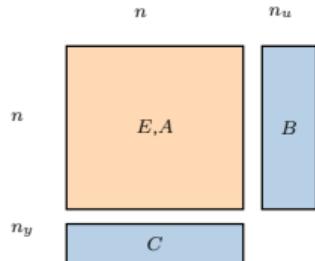
$$\begin{aligned} \mathbf{H}(s) &= C(sE - A)^{-1}B \\ &= \mathbf{N}(s)/\mathbf{d}(s) + \mathbf{P}(s) \end{aligned}$$

### Transfer functions

- $\mathbf{H}$  is a (complex) function
- External knowledge  $\mathbf{u} \mapsto \mathbf{y}$
- Transfer functions are unique
- $\mathbf{u}(s) \in \mathbb{C}^{n_u}$   
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# Linear dynamical systems

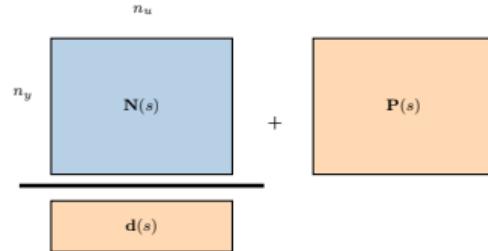
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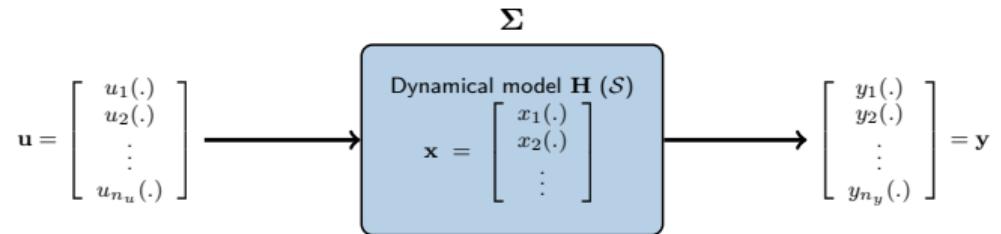
Model, data and structures

## Structures

- L-ODE
- L-ODE / DAE-1
- L-DAE
- L-DDE
- L-PDE

## Model

$$\begin{array}{ll} \text{(Time-domain)} & \mathcal{S} \sim \mathbf{u} \rightarrow \mathbf{x} \rightarrow \mathbf{y} \\ \text{(Frequency-domain)} & \mathbf{H} \sim \mathbf{u} \rightarrow \mathbf{y} \end{array}$$



# Linear dynamical systems

Linear finite dimensional models

## Structures

### L-ODE

L-ODE / DAE-1

L-DAE

L-DDE

L-PDE

## Transfer function

$$H(s) = \frac{2}{s+1}$$

## ODE realization $\mathcal{S}$

$$\begin{aligned}\dot{x} &= -x + 2u \\ y &= x\end{aligned}$$

## Singularities $\lambda$ and zeros $z$

$$\begin{aligned}\lambda_{\mathcal{S}} &= \text{eig}(A, E) \\ &= \Lambda(-1, 1) \\ &= \{-1\} \\ z_{\mathcal{S}} &= \text{eig}([A \ B; \ C \ D], \text{blkdiag}(E, \text{zeros}(ny, nu))) \\ &= \Lambda\left(\begin{bmatrix} A & B \\ C & D \end{bmatrix}\right) \\ &= \{\infty, \infty\}\end{aligned}$$

# Linear dynamical systems

Linear finite dimensional models

## Structures

L-ODE

L-ODE / DAE-1

L-DAE

L-DDE

L-PDE

## Transfer function

$$\mathbf{H}(s) = \frac{2}{s+1} + 2 = \frac{2s+4}{s+1}$$

## ODE realization $\mathcal{S}_1$

$$\begin{aligned}\dot{x} &= -x + 2u \\ y &= x + 2u\end{aligned}$$

## Singularities of matrix pencil $(A, E)$

$$\lambda_{\mathcal{S}_1} = \Lambda(-1, 1) = \{-1\}$$

# Linear dynamical systems

Linear finite dimensional models

## Structures

L-ODE

L-ODE / DAE-1

L-DAE

L-DDE

L-PDE

## Transfer function

$$\mathbf{H}(s) = \frac{2}{s+1} + 2 = \frac{2s+4}{s+1}$$

## DAE index-1 realization $\mathcal{S}_2$

$$\begin{aligned}\dot{x}_1 &= -x_1 + 2u \\ 0 &= -x_2 + 2u = x_2 - 2u \\ y &= x_1 + x_2\end{aligned}$$

Singularities of matrix pencil  $(A, E)^a$

$$\lambda_{\mathcal{S}_2} = \Lambda \left( \left[ \begin{array}{c|c} -1 & \\ \hline & 1 \end{array} \right], \left[ \begin{array}{c|c} 1 & \\ \hline & 1 \end{array} \right] \right) = \{-1, \infty\}$$

---

$$^a B^\top = \left[ \begin{array}{cc} 2 & -2 \end{array} \right] \text{ and } C = \left[ \begin{array}{cc} 1 & 1 \end{array} \right]$$

# Linear dynamical systems

Linear finite dimensional models

## Structures

L-ODE

L-ODE / DAE-1

L-DAE

L-DDE

L-PDE

## Transfer function

$$\mathbf{H}(s) = \frac{2}{s+1} + 2 = \frac{2s+4}{s+1}$$

DAE index-1 realization  $\mathcal{S}_2$  (canonical form)

$$\left( \left[ \begin{array}{c|c} A_1 = -1 & \\ \hline & I_{n_2} = 1 \end{array} \right], \left[ \begin{array}{c|c} I_{n_1} = 1 & \\ \hline & N = 0 \end{array} \right] \right)$$

Index is the  $k$ -nilpotent degree of  $N$

- ▶ Finite dynamic modes  
 $n_1 = 1$
- ▶ Infinite dynamic (impulsive) modes  
 $\text{rank}(E) - n_1 = \text{rank}(N) = 1 - 1 = 0$
- ▶ Non dynamic modes  
 $n - \text{rank}(E) = 2 - 1 = 1$

# Linear dynamical systems

Linear finite dimensional models

## Structures

L-ODE

L-ODE / DAE-1

**L-DAE**

L-DDE

L-PDE

## Transfer function

$$\mathbf{H}(s) = \frac{2}{s+1} + s = \frac{s^2 + s + 2}{s+1}$$

## DAE index-2 realization $\mathcal{S}$

$$\begin{aligned}\dot{x}_2 &= x_1 \\ \dot{x}_3 &= x_2 \\ x_2 &= -x_3 + u = x_3 - u \\ y &= x_1 + x_2 + 2x_3\end{aligned}$$

Singularities of matrix pencil  $(A, E)$

$$\lambda_{\mathcal{S}} = \{-1, \infty, \infty\}$$

- ▶ Finite dynamic modes  $n_1 = 1$
- ▶ Impulsive modes  $\text{rank}(E) - n_1 = 2 - 1 = 1$
- ▶ Non dynamic modes  $n - \text{rank}(E) = 3 - 2 = 1$

# Linear dynamical systems

Linear finite dimensional models

## Structures

L-ODE

L-ODE / DAE-1

**L-DAE**

L-DDE

L-PDE

## Transfer function

$$H(s) = \frac{2}{s+1} + s = \frac{s^2 + s + 2}{s+1}$$

## DAE index-2 realization $\mathcal{S}$

$$\begin{aligned}\dot{x}_2 &= x_1 \\ \dot{x}_3 &= x_2 \\ x_2 &= -x_3 + u = x_3 - u \\ y &= x_1 + x_2 + 2x_3\end{aligned}$$

## Singularities of matrix pencil $(A, E)$

$$\lambda_{\mathcal{S}} = \{-1, \infty, \infty\}$$

- ▶ Finite dynamic modes  $n_1 = 1$
- ▶ Impulsive modes  $\text{rank}(E) - n_1 = 2 - 1 = 1$
- ▶ Non dynamic modes  $n - \text{rank}(E) = 3 - 2 = 1$

# Linear dynamical systems

Linear finite dimensional models (about observability, controllability, minimality...)

## Structures

L-ODE

L-ODE / DAE-1

L-DAE

L-DDE

L-PDE

- ▶ Reachability matrix

$$\mathcal{R}_n(A, B) = \begin{bmatrix} B & AB & A^2B & \cdots & A^nB \end{bmatrix}$$

- ▶ Observability matrix

$$\mathcal{O}_n(A, C) = \begin{bmatrix} C^\top & A^\top C^\top & (A^\top)^2 C^\top & \cdots & (A^\top)^n C^\top \end{bmatrix}^\top$$

- ▶ Minimality: both controllable and observable.

- ▶ Connection with Markov parameters

$$H_0 = D, H_k = CA^{k-1}B \ (k > 1)$$

$$\mathcal{O}_n \mathcal{R}_n = \begin{bmatrix} H_1 & H_2 & \cdots & H_n \\ H_2 & H_3 & \cdots & H_{n+1} \\ \vdots & & \ddots & \vdots \\ H_n & H_{n+1} & \cdots & H_{2n-1} \end{bmatrix}$$

# Linear dynamical systems

Linear infinite dimensional models

## Structures

L-ODE

L-ODE / DAE-1

L-DAE

**L-DDE**

L-PDE

## Transfer function

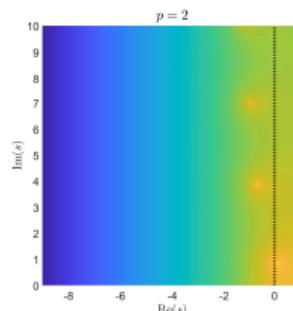
$$\mathbf{H}(s) = \frac{1}{s + e^{-ps}}$$

## L-DDE realization $\mathcal{S}$

$$\begin{aligned}\dot{x} &= -x(t-p) + u \\ y &= x\end{aligned}$$

## Singularities (periodic)

$$\lambda_{\mathcal{S}} = \{\omega \text{ s.t. } s + \cos(s) - i \sin(s) = 0\}$$



# Linear dynamical systems

Linear infinite dimensional models

## Structures

L-ODE

L-ODE / DAE-1

L-DAE

**L-DDE**

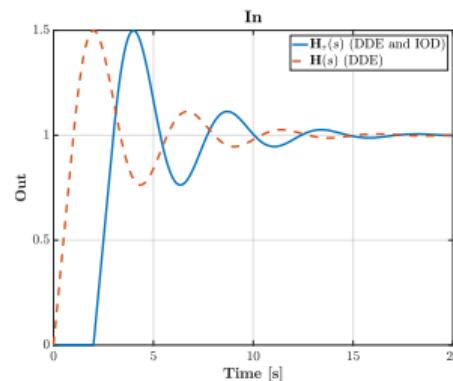
L-PDE

## Transfer function

$$\mathbf{H}_\tau(s) = \frac{1}{s + e^{-ps}} e^{-2s}$$

## L-DDE realization $\mathcal{S}$

$$\begin{aligned}\dot{x} &= -x(t-p) + u(t-2) \\ y &= x\end{aligned}$$



# Linear dynamical systems

Linear infinite dimensional models

## Structures

L-ODE

L-ODE / DAE-1

L-DAE

L-DDE

**L-PDE**

Transfer function (boundary controlled transport)

$$\mathbf{H}(s) = \frac{\omega_0^2}{s^2 + m\omega_0 s + \omega_0^2} \frac{\sqrt{\pi}}{\sqrt{s}} e^{-x^2 s}$$

# Linear dynamical systems

Linear infinite dimensional models

## Structures

L-ODE

L-ODE / DAE-1

L-DAE

L-DDE

**L-PDE**

Transfer function (boundary controlled transport)

$$\mathbf{H}(s) = \frac{\omega_0^2}{s^2 + m\omega_0 s + \omega_0^2} \frac{\sqrt{\pi}}{\sqrt{s}} e^{-x^2 s}$$

**L-PDE** "realization"  $\mathcal{S}$

$$\begin{aligned}\frac{\partial \tilde{y}(x, t)}{\partial x} + 2x \frac{\partial \tilde{y}(x, t)}{\partial t} &= 0 \\ \tilde{y}(x, 0) &= 0 \\ \tilde{y}(0, t) &= \frac{1}{\sqrt{t}} \star \tilde{u}_f(0, t)\end{aligned}$$

$$\frac{\omega_0^2}{s^2 + m\omega_0 s + \omega_0^2} u(0, s) = u_f(0, s)$$

Singularities

$$\lambda_{\mathcal{S}} = \{0, \lambda_1, \overline{\lambda_1}\}$$

# Linear dynamical systems

Why all this? What is common?

## Structures

- L-ODE
- L-ODE / DAE-1
- L-DAE
- L-DDE
- L-PDE

## Model

- ▶  $(A, B, C)$  and  $\mathbf{H}(s)$
- ▶  $(A, B, C, D)$  and  $\mathbf{H}(s)$
- ▶  $(E, A, B, C)$  and  $\mathbf{H}(s)$
- ▶  $(A_i \dots, B, C, \tau_i)$  and  $\mathbf{H}(s)$
- ▶  $\mathbf{H}(s)$

# Linear dynamical systems

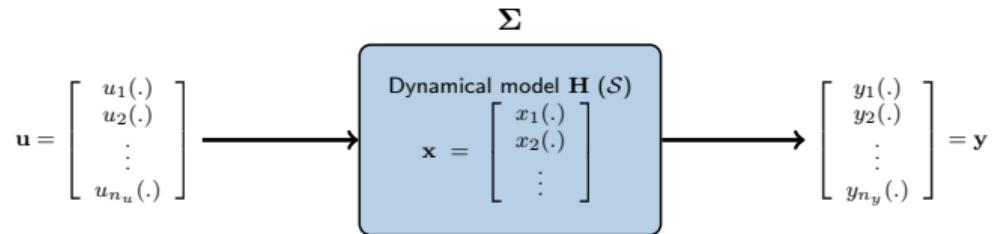
Why all this? What is common?

## Structures

- L-ODE
- L-ODE / DAE-1
- L-DAE
- L-DDE
- L-PDE

## Model

$$\begin{array}{ll} \text{(Time-domain)} & \mathcal{S} \sim \mathbf{u} \rightarrow \mathbf{x} \rightarrow \mathbf{y} \\ \text{(Frequency-domain)} & \mathbf{H} \sim \mathbf{u} \rightarrow \mathbf{y} \end{array}$$



# Linear dynamical systems

Why all this? What is common?

## Structures

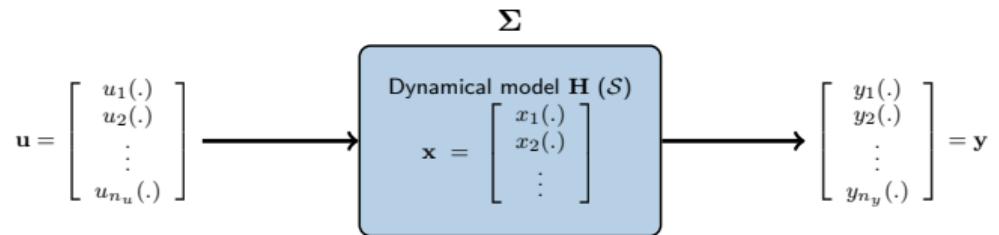
- L-ODE
- L-ODE / DAE-1
- L-DAE
- L-DDE
- L-PDE

## Data

- Time-domain
- Frequency-domain

## Model

$$\begin{array}{ll} \text{(Time-domain)} & \mathcal{S} \sim \mathbf{u} \rightarrow \mathbf{x} \rightarrow \mathbf{y} \\ \text{(Frequency-domain)} & \mathbf{H} \sim \mathbf{u} \rightarrow \mathbf{y} \end{array}$$



$$\begin{array}{ll} \text{(Time-domain)} & \{t_i, \mathbf{G}(t_i)\}_{i=1}^N \\ \text{(Frequency-domain)} & \{z_i, \mathbf{G}(z_i)\}_{i=1}^{\bar{N}} \end{array}$$

## Data

# Content

Forewords

Linear dynamical systems

**Loewner**

Loewner extensions (passive & pH)

Conclusions

## SISO interpolation problem

Given the right and left data ( $\lambda_j$  and  $\mu_i$  are distinct):

$$\begin{aligned}\{\lambda_j, \mathbf{w}_j\} \quad j = 1, \dots, k \\ \{\mu_i, \mathbf{v}_i^\top\} \quad i = 1, \dots, q\end{aligned}$$

we seek  $\mathcal{S} : (E, A, B, C)$ , whose transfer function is  $\mathbf{H}(s) = C(sE - A)^{-1}B$  s.t.

$$\begin{aligned}\mathbf{H}(\lambda_j) &= \mathbf{w}_j \quad j = 1, \dots, k \\ \mathbf{H}(\mu_i) &= \mathbf{v}_i^\top \quad i = 1, \dots, q\end{aligned}$$

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 A.J. Mayo and A.C. Antoulas, "*A framework for the solution of the generalized realization problem*", Linear Algebra and its Applications, vol. 425(2-3), 2007.

 I.V. Gosea, C. P-V. and A.C. Antoulas, "*Data-driven modeling and control of large-scale dynamical systems in the Loewner framework*", Handbook in Numerical Analysis, vol. 23, January 2022.

## Loewner Matrix

Given a **row / left** array of pairs of complex numbers  $\{\mu_i, \mathbf{v}_i\}$ ,  $i = 1, \dots, q$ , and a **column / right** array of pairs of complex numbers  $\{\lambda_j, \mathbf{w}_j\}$ ,  $j = 1, \dots, k$  with  $\mu_i$  and  $\lambda_j$  distinct, the associated Loewner matrix is:

$$\mathbb{L} = \begin{bmatrix} \frac{\mathbf{v}_1^\top - \mathbf{w}_1}{\mu_1 - \lambda_1} & \cdots & \frac{\mathbf{v}_1^\top - \mathbf{w}_k}{\mu_1 - \lambda_k} \\ \vdots & \ddots & \vdots \\ \frac{\mathbf{v}_q^\top - \mathbf{w}_1}{\mu_q - \lambda_1} & \cdots & \frac{\mathbf{v}_q^\top - \mathbf{w}_k}{\mu_q - \lambda_k} \end{bmatrix} \in \mathbb{C}^{q \times k}.$$

If there is an underlying function  $\mathbf{H}$  then

$$\mathbf{w}_j = \mathbf{H}(\lambda_j) \text{ and } \mathbf{v}_i = \mathbf{H}(\mu_i).$$

We will present the Loewner framework in connection with

- (i) rational interpolation and consequently in connection with
- (ii) reduced-order modeling of linear dynamical systems given frequency domain data.

The Loewner matrix rank encodes the minimal complexity of the solutions of the interpolation problem.

$$P := \{(x_i, y_i) : i = 1, \dots, N, x_i \neq x_j, i \neq j\}$$

The idea behind the present approach to rational interpolation is to use a formula for rational interpolants which is similar to the one defining the Lagrange polynomial. First we partition the array  $P$  in two disjoint subarrays:

$$\begin{aligned} P_c &:= \{(\lambda_j, \mathbf{w}_j) \mid j = 1, \dots, k\} \\ P_r &:= \{(\mu_i, \mathbf{v}_i) \mid i = 1, \dots, q\} \end{aligned}$$

e.g.  $N = k + q$

$$\begin{aligned} \lambda_j &= x_j & \mathbf{w}_j &= y_j & j &= 1, \dots, k \\ \mu_i &= x_{k+i} & \mathbf{v}_i &= y_{k+i} & i &= 1, \dots, q \end{aligned}$$

Using array  $P_c$ , for constants  $\alpha_j$  and  $\mathbf{w}_j$ , consider  $\mathbf{H}(s)$  given by

$$\sum_{j=1}^k \alpha_j \frac{\mathbf{H}(s) - \mathbf{w}_j}{s - \lambda_j} = 0, \quad \alpha_j \neq 0$$

For constants  $\alpha_j$  and  $\mathbf{w}_j$ , consider  $\mathbf{H}(s)$  given by

$$\sum_{j=1}^k \alpha_j \frac{\mathbf{H}(s) - \mathbf{w}_j}{s - \lambda_j} = 0, \quad \alpha_j \neq 0$$

solving for  $\mathbf{H}$ , we get

$$\mathbf{H}(s) = \frac{\sum_{j=1}^k \frac{\alpha_j \mathbf{w}_j}{s - \lambda_j}}{\sum_{j=1}^k \frac{\alpha_j}{s - \lambda_j}}$$

It follows that

$$\mathbf{H}(\lambda_j) = \mathbf{w}_j$$

ensures  $P_c$  constraints by construction. This is the barycentric (rational) Lagrange interpolation formula.

The free parameters  $\alpha_j$  can be determined so that the additional constraints contained in array  $P_r$  are satisfied:

$$\mathbf{H}(\mu_i) = \mathbf{v}_i$$

Then it follows  $\mathbb{L}\mathbf{c} = 0$ , where

$$\mathbb{L} = \begin{bmatrix} \frac{\mathbf{v}_1^T - \mathbf{w}_1}{\mu_1 - \lambda_1} & \cdots & \frac{\mathbf{v}_1^T - \mathbf{w}_k}{\mu_1 - \lambda_k} \\ \vdots & \ddots & \vdots \\ \frac{\mathbf{v}_q^T - \mathbf{w}_1}{\mu_q - \lambda_1} & \cdots & \frac{\mathbf{v}_q^T - \mathbf{w}_k}{\mu_q - \lambda_k} \end{bmatrix} \in \mathbb{C}^{q \times k} \text{ and } \mathbf{c} = \begin{bmatrix} \alpha_1 \\ \alpha_2 \\ \vdots \\ \alpha_k \end{bmatrix} \in \mathbb{C}^k.$$

## Lemma

Given the rational function  $\mathbf{H}$  and an array of points  $P$ , where  $y_j = \mathbf{H}(x_j)$  and  $x_j$  is not a pole of  $\mathbf{H}$ , let  $\mathbb{L}$  be a  $q \times k$  Loewner matrix, for some partitioning  $P_c, P_r$  of  $P$ . Then

$$q, k \geq \deg(\mathbf{H}) \Rightarrow \operatorname{rank} \mathbb{L} = \deg(\mathbf{H})$$

# Loewner

Scalar rational interpolation and the Loewner matrix (a rational Lagrange-type formula)

$$\begin{cases} P_c &:= \{(\lambda_j; \mathbf{w}_j), j = 1, \dots, k\} \\ P_r &:= \{(\mu_i; \mathbf{v}_i), i = 1, \dots, q\} \end{cases}$$

## Loewner matrix

$$\mathbb{L} \in \mathbb{C}^{q \times k}$$

$$(\mathbb{L})_{i,j} = \frac{\mathbf{v}_i - \mathbf{w}_j}{\mu_i - \lambda_j}$$

$$M\mathbb{L} - \mathbb{L}\Lambda = V - W$$

## Lagrangian form

$$\mathbf{g}(s) = \frac{\sum_{j=1}^k \frac{\alpha_j \mathbf{w}_j}{s - \lambda_j}}{\sum_{j=1}^k \frac{\alpha_j}{s - \lambda_j}}$$

## Null space

$$\text{span}(\mathbf{c}) = \mathcal{N}(\mathbb{L})$$

$$\mathbf{c} = \begin{bmatrix} \alpha_1 \\ \alpha_2 \\ \vdots \\ \alpha_k \end{bmatrix} \in \mathbb{C}^k$$

Data generated from  $\mathbf{H}(s) = (s^2 + 4)/(s + 1)$  of complexity (2), with  $k = 3, q = 4$

$$\left. \begin{array}{lcl} \lambda_j & = & [1, 3, 5] \\ \mu_i & = & [2, 4, 6, 8] \end{array} \right\} \xrightarrow{\mathbf{H}} \left\{ \begin{array}{lcl} \mathbf{w}_j & = & [5/2, 13/4, 29/6] \\ \mathbf{v}_i & = & [8/3, 4, 40/7, 68/9] \end{array} \right.$$

## Loewner matrix

$$\mathbb{L} = \begin{bmatrix} \frac{1}{6} & \frac{7}{12} & \frac{13}{18} \\ \frac{1}{2} & \frac{3}{4} & \frac{5}{6} \\ \frac{9}{14} & \frac{23}{28} & \frac{37}{42} \\ \frac{13}{18} & \frac{31}{36} & \frac{49}{54} \end{bmatrix} \in \mathbb{C}^{4 \times 3}$$

## Lagrangian form

$$\mathbf{g}(s) = \frac{\frac{5}{6(s-1)} - \frac{13}{3(s-3)} + \frac{29}{6(s-5)}}{\frac{1}{3(s-1)} - \frac{4}{3(s-3)} + \frac{1}{s-5}} = \mathbf{H}(s)$$

## Null space

$$\text{span}(\mathbf{c}) = \mathcal{N}(\mathbb{L})$$

$$\mathbf{c} = \begin{bmatrix} \frac{1}{3} \\ -\frac{4}{3} \\ 1 \end{bmatrix}$$

Consider system  $\mathbf{H}$  in barycentric form

$$\mathbf{H}(s) = \frac{\sum_i^n \beta_i \mathbf{q}_i(s)}{\sum_i^n \alpha_i \mathbf{q}_i(s)}, \text{ where } \mathbf{q}_i(s) = \prod_{i'=1, i' \neq i}^n (s - \lambda_{i'})$$

Constructing the Loewner matrix with  $\{\lambda_1, \dots, \lambda_k\}, \{\mathbf{w}_1, \dots, \mathbf{w}_k\}$  and solving

$$\mathbf{L}\mathbf{c} = 0$$

leads to  $\mathbf{H}$  in Lagrangian basis

$$\mathbf{H}(s) = \underbrace{\mathbf{c}^\top \mathbf{w}}_C \underbrace{\left[ \begin{array}{c} \mathbf{L}_{s,\lambda,k} \\ \mathbf{c}^\top \end{array} \right]}_{\Phi(s)^{-1}}^{-1} \underbrace{\begin{bmatrix} 0 \\ 1 \end{bmatrix}}_B$$

$$\mathbf{L}_{s,\lambda,n} = \begin{bmatrix} s - \lambda_1 & \lambda_2 - s & & \\ s - \lambda_1 & & \lambda_3 - s & \\ \vdots & & \ddots & \end{bmatrix} \in \mathbb{R}^{n \times (n+1)} \text{ and } \Phi(s) \in \mathbb{C}^{(n+1) \times (n+1)}$$

Consider system  $\mathbf{H}$  in barycentric form

$$\mathbf{H}(s) = \frac{\sum_i^n \beta_i \mathbf{q}_i(s)}{\sum_i^n \alpha_i \mathbf{q}_i(s)}, \text{ where } \mathbf{q}_i(s) = \prod_{i'=1, i' \neq i}^n (s - \lambda_{i'})$$

Constructing the Loewner matrix with  $\{\lambda_1, \dots, \lambda_k\}, \{\mathbf{w}_1, \dots, \mathbf{w}_k\}$  and solving

$$\mathbf{L}\mathbf{c} = 0$$

leads to  $\mathbf{H}$  in Lagrangian basis

$$\mathbf{H}(s) = \underbrace{\mathbf{c}^\top \mathbf{w}}_C \underbrace{\left[ \begin{array}{c} \mathbf{L}_{s,\lambda,k} \\ \mathbf{c}^\top \end{array} \right]}_{\Phi(s)^{-1}}^{-1} \underbrace{\left[ \begin{array}{c} 0 \\ 1 \end{array} \right]}_B$$

$$\mathbf{L}_{s,\lambda,n} = \begin{bmatrix} s - \lambda_1 & \lambda_2 - s & & \\ s - \lambda_1 & & \lambda_3 - s & \\ \vdots & & \ddots & \end{bmatrix} \in \mathbb{R}^{n \times (n+1)} \text{ and } \Phi(s) \in \mathbb{C}^{(n+1) \times (n+1)}$$

# Loewner

Loewner barycentric examples (simple case, CAS=1)

Rational function satisfies

$$\mathbf{H}(\lambda_j) = \mathbf{w}_j \text{ and } \mathbf{H}(\mu_i) = \mathbf{v}_i$$

$$\mathbf{G}(s) = \frac{2}{s+1}$$

Evaluated at

$$\lambda_1 = 1, \lambda_2 = 3 \text{ and } \mu_1 = 2, \mu_2 = 4$$

Leads to

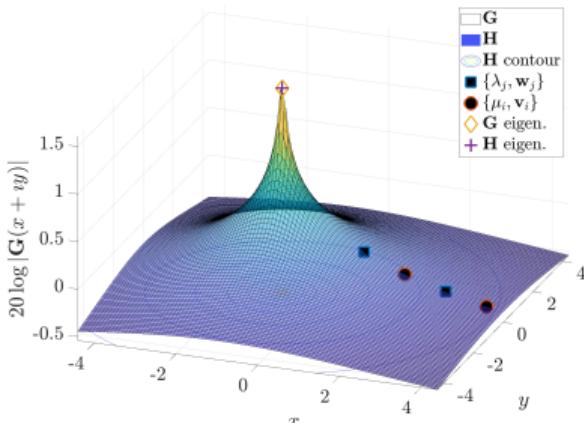
$$\mathbf{w}_1 = 1, \mathbf{w}_2 = \frac{1}{2} \text{ and } \mathbf{v}_1 = \frac{2}{3}, \mathbf{v}_2 = \frac{2}{5}$$

$$\mathbb{L} = \left[ \begin{array}{cc} \frac{\frac{2}{3}-1}{\frac{2}{3}-1} & \frac{\frac{2}{3}-\frac{1}{2}}{\frac{2}{3}-3} \\ \frac{\frac{2}{3}-1}{\frac{2}{5}-1} & \frac{\frac{2}{5}-\frac{1}{2}}{\frac{2}{5}-3} \end{array} \right] = \left[ \begin{array}{cc} -\frac{1}{3} & -\frac{1}{6} \\ -\frac{1}{5} & -\frac{1}{10} \end{array} \right]$$

Rational function satisfies

$$\mathbf{H}(\lambda_j) = \mathbf{w}_j \text{ and } \mathbf{H}(\mu_i) = \mathbf{v}_i$$

Realization  $n = 2$ ,  $\mathbf{H}(s) = C\Phi(s)^{-1}B = \mathbf{G}(s)$



$$\mathbf{G}(s) = \frac{2}{s+1}$$

Evaluated at

$$\lambda_1 = 1, \lambda_2 = 3 \text{ and } \mu_1 = 2, \mu_2 = 4$$

Leads to

$$\mathbf{w}_1 = 1, \mathbf{w}_2 = \frac{1}{2} \text{ and } \mathbf{v}_1 = \frac{2}{3}, \mathbf{v}_2 = \frac{2}{5}$$

$$\ker(\mathbb{L}) = \begin{bmatrix} -1 \\ 2 \end{bmatrix} = \mathbf{c}$$

$$C = \mathbf{c}^\top \mathbf{w} = \begin{bmatrix} -1 & 1 \end{bmatrix}, B = \begin{bmatrix} 0 \\ 1 \end{bmatrix}$$

$$\Phi(s) = \begin{bmatrix} \mathbf{L}_{s,\lambda,1} \\ \mathbf{c}^\top \end{bmatrix} = \begin{bmatrix} s-1 & 3-s \\ -1 & 2 \end{bmatrix}$$

Rational function satisfies

$$\mathbf{H}(\lambda_j) = \mathbf{w}_j \text{ and } \mathbf{H}(\mu_i) = \mathbf{v}_i$$

$$\mathbf{G}(s) = \frac{1}{s^2 + (1 + i)s + (1 + i)}$$

Evaluated at

$$\begin{aligned}\lambda_1 &= i, \lambda_2 = 2i, \lambda_3 = -2 + i \\ \mu_1 &= -i, \mu_2 = 2, \mu_3 = 0.5 - i\end{aligned}$$

Leads to

$$\mathbf{w}_1, \mathbf{w}_2, \mathbf{w}_3 \text{ and } \mathbf{v}_1, \mathbf{v}_2, \mathbf{v}_3$$

$$\mathbb{L} = \begin{bmatrix} -\frac{1}{5} + \frac{3}{5}i & -\frac{1}{34} + \frac{13}{34}i & \frac{5}{17} + \frac{3}{17}i \\ \frac{17}{290} + \frac{59}{290}i & \frac{57}{986} + \frac{75}{986}i & \frac{31}{986} - \frac{63}{986}i \\ -\frac{46}{265} + \frac{108}{265}i & -\frac{37}{901} + \frac{209}{901}i & \frac{118}{901} + \frac{64}{901}i \end{bmatrix}$$

Rational function satisfies

$$\mathbf{H}(\lambda_j) = \mathbf{w}_j \text{ and } \mathbf{H}(\mu_i) = \mathbf{v}_i$$

Realization  $n = 3$

$$C = [c_1 \mathbf{w}_1 \quad c_2 \mathbf{w}_2 \quad c_3 \mathbf{w}_3], \quad B = \begin{bmatrix} 0 \\ 0 \\ 1 \end{bmatrix}$$

$$\Phi(s) = \begin{bmatrix} s - i & 2i - s & -2 + i - s \\ s - i & c_2 & c_3 \\ c_1 & & \end{bmatrix}$$

Resulting in

$$\frac{-i}{-s^2i + s(1-i) + (1-i)} = \mathbf{G}(s)$$

$$\mathbf{G}(s) = \frac{1}{s^2 + (1+i)s + (1+i)}$$

Evaluated at

$$\begin{aligned} \lambda_1 &= i, \lambda_2 = 2i, \lambda_3 = -2 + i \\ \mu_1 &= -i, \mu_2 = 2, \mu_3 = 0.5 - i \end{aligned}$$

Leads to

$$\mathbf{w}_1, \mathbf{w}_2, \mathbf{w}_3 \text{ and } \mathbf{v}_1, \mathbf{v}_2, \mathbf{v}_3$$

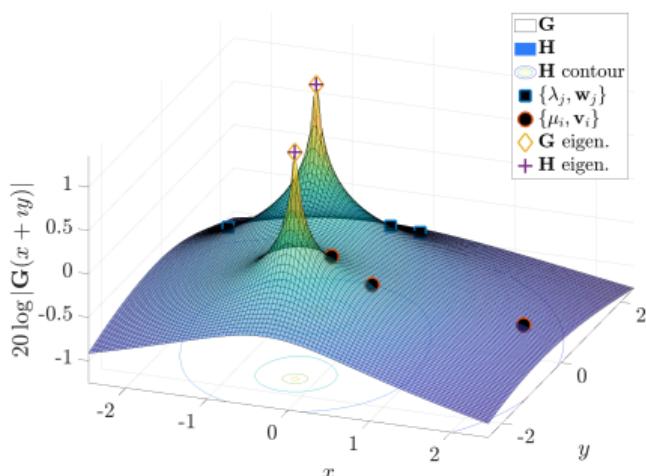
$$\ker(\mathbb{L}) = \begin{bmatrix} 13/17 - 16i/17 \\ -2 + 2i \\ 1 \end{bmatrix} = \begin{bmatrix} c_1 \\ c_2 \\ c_3 \end{bmatrix}$$

# Loewner

Loewner barycentric examples (complex dynamical tippe top case, CAS=3)

Rational function satisfies

$$\mathbf{H}(\lambda_j) = \mathbf{w}_j \text{ and } \mathbf{H}(\mu_i) = \mathbf{v}_i$$



$$\mathbf{G}(s) = \frac{1}{s^2 + (1+i)s + (1+i)}$$

Evaluated at

$$\begin{aligned}\lambda_1 &= i, \lambda_2 = 2i, \lambda_3 = -2 + i \\ \mu_1 &= -i, \mu_2 = 2, \mu_3 = 0.5 - i\end{aligned}$$

Leads to

$$\mathbf{w}_1, \mathbf{w}_2, \mathbf{w}_3 \text{ and } \mathbf{v}_1, \mathbf{v}_2, \mathbf{v}_3$$

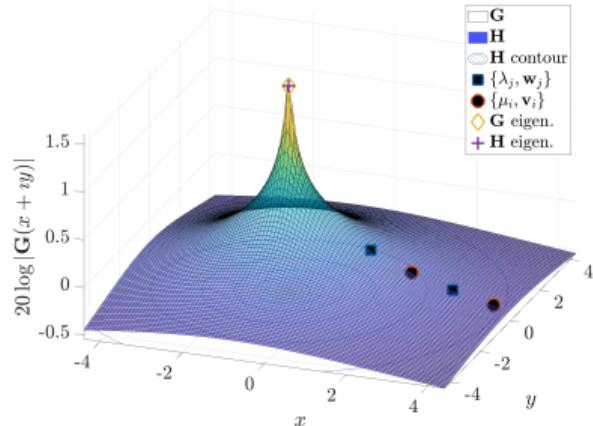
$$\ker(\mathbb{L}) = \begin{bmatrix} 13/17 - 16i/17 \\ -2 + 2i \\ 1 \end{bmatrix} = \begin{bmatrix} c_1 \\ c_2 \\ c_3 \end{bmatrix}$$

```
% Model (CAS=1)
S = ss(tf(2,[1 1])); S.E = 1;
[A,B,C,D,E] = dssdata(S);
G = @(s) C*((s*E-A)\B)+D;
% IP , responses
la = [1 3]; k = length(la);
mu = [2 4]; q = length(mu);
for ii = 1:k; W(1,1,ii) = G(la(ii)); end
for ii = 1:q; V(1,1,ii) = G(mu(ii)); end

% Loewner
LL = lf.loewnerMatrix(la,mu,W,V);
c = null(sym(LL));
% Realization
C = c.*W(:).';
B = zeros(k,1); B(end) = 1;
PHI = [s-la(1)*ones(k-1,1) diag(la(2:end))-s*eye(k-1); c.'];
Hr = simplify(C*(PHI\B));
```

```
% Model (CAS=1)
S = ss(tf(2,[1 1])); S.E = 1;
[A,B,C,D,E] = dssdata(S);
G = @(s) C*((s*E-A)\B)+D;
% IP , responses
la = [1 3]; k = length(la);
mu = [2 4]; q = length(mu);
for ii = 1:k; W(1,1,ii) = G(la(ii)); end
for ii = 1:q; V(1,1,ii) = G(mu(ii)); end

% Loewner
LL = lf.loewnerMatrix(la,mu,W,V);
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PHI = [s-la(1)*ones(k-1,1) diag(la(2:end))-s*eye(k-1); c.'];
Hr = simplify(C*(PHI\B));
```



## SISO interpolation problem

Given the right and left data ( $\lambda_j$  and  $\mu_i$  are distinct):

$$\begin{aligned}\{\lambda_j, \mathbf{w}_j\} \quad j = 1, \dots, k \\ \{\mu_i, \mathbf{v}_i^\top\} \quad i = 1, \dots, q\end{aligned}$$

we seek  $\mathcal{S} : (E, A, B, C)$ , whose transfer function is  $\mathbf{H}(s) = C(sE - A)^{-1}B$  s.t.

$$\begin{aligned}\mathbf{H}(\lambda_j) &= \mathbf{w}_j \quad j = 1, \dots, k \\ \mathbf{H}(\mu_i) &= \mathbf{v}_i^\top \quad i = 1, \dots, q\end{aligned}$$

---

 A.J. Mayo and A.C. Antoulas, "A framework for the solution of the generalized realization problem", Linear Algebra and its Applications, vol. 425(2-3), 2007.

 I.V. Gosea, C. P-V. and A.C. Antoulas, "Data-driven modeling and control of large-scale dynamical systems in the Loewner framework", Handbook in Numerical Analysis, vol. 23, January 2022.

## MIMO tangential interpolation problem

Given the right and left data ( $\lambda_j$  and  $\mu_i$  are distinct):

$$\begin{aligned} \{\lambda_j, \mathbf{r}_j, \mathbf{w}_j\} \quad j = 1, \dots, k \\ \{\mu_i, \mathbf{l}_i^\top, \mathbf{v}_i^\top\} \quad i = 1, \dots, q \end{aligned}$$

we seek  $\mathcal{S} : (E, A, B, C)$ , whose transfer function is  $\mathbf{H}(s) = C(sE - A)^{-1}B$  s.t.

$$\begin{aligned} \mathbf{H}(\lambda_j)\mathbf{r}_j &= \mathbf{w}_j \quad j = 1, \dots, k \\ \mathbf{l}_i^\top \mathbf{H}(\mu_i) &= \mathbf{v}_i^\top \quad i = 1, \dots, q \end{aligned}$$

 A.J. Mayo and A.C. Antoulas, "*A framework for the solution of the generalized realization problem*", Linear Algebra and its Applications, vol. 425(2-3), 2007.

 I.V. Gosea, C. P-V. and A.C. Antoulas, "*Data-driven modeling and control of large-scale dynamical systems in the Loewner framework*", Handbook in Numerical Analysis, vol. 23, January 2022.

The **right data** can be expressed as:

$$\begin{aligned}\mathbf{\Lambda} &= \mathbf{diag} [\lambda_1, \dots, \lambda_k] \in \mathbb{C}^{k \times k}, \\ \mathbf{R} &= \begin{bmatrix} \mathbf{r}_1 & \mathbf{r}_2 & \dots & \mathbf{r}_k \end{bmatrix} \in \mathbb{C}^{n_u \times k} \\ \mathbf{W} &= \begin{bmatrix} \mathbf{w}_1 & \mathbf{w}_2 & \dots & \mathbf{w}_k \end{bmatrix} \in \mathbb{C}^{n_y \times k}\end{aligned}$$

and the **left data** can be expressed as:

$$\begin{aligned}\mathbf{M} &= \mathbf{diag} [\mu_1, \dots, \mu_q] \in \mathbb{C}^{q \times q} \\ \mathbf{L}^\top &= \begin{bmatrix} \mathbf{l}_1 & \mathbf{l}_2 & \dots & \mathbf{l}_q \end{bmatrix} \in \mathbb{C}^{n_y \times q} \\ \mathbf{V}^\top &= \begin{bmatrix} \mathbf{v}_1 & \mathbf{v}_2 & \dots & \mathbf{v}_q \end{bmatrix} \in \mathbb{C}^{n_u \times q}\end{aligned}$$

The Loewner matrix in this case is

$$\mathbb{L} = \begin{bmatrix} \frac{\mathbf{v}_1^\top \mathbf{r}_1 - \mathbf{l}_1^\top \mathbf{w}_1}{\mu_1 - \lambda_1} & \dots & \frac{\mathbf{v}_1^\top \mathbf{r}_k - \mathbf{l}_1^\top \mathbf{w}_k}{\mu_1 - \lambda_k} \\ \vdots & \ddots & \vdots \\ \frac{\mathbf{v}_q^\top \mathbf{r}_1 - \mathbf{l}_q^\top \mathbf{w}_1}{\mu_q - \lambda_1} & \dots & \frac{\mathbf{v}_q^\top \mathbf{r}_k - \mathbf{l}_q^\top \mathbf{w}_k}{\mu_q - \lambda_k} \end{bmatrix} \in \mathbb{C}^{q \times k}$$

With this notation  $\mathbb{L}$  satisfy the Sylvester equation :  $\mathbf{ML} - \mathbb{L}\mathbf{\Lambda} = \mathbf{VR} - \mathbf{LW}$ .

The **right data** can be expressed as:

$$\begin{aligned}\mathbf{\Lambda} &= \mathbf{diag} [\lambda_1, \dots, \lambda_k] \in \mathbb{C}^{k \times k}, \\ \mathbf{R} &= \begin{bmatrix} \mathbf{r}_1 & \mathbf{r}_2 & \dots & \mathbf{r}_k \end{bmatrix} \in \mathbb{C}^{n_u \times k} \\ \mathbf{W} &= \begin{bmatrix} \mathbf{w}_1 & \mathbf{w}_2 & \dots & \mathbf{w}_k \end{bmatrix} \in \mathbb{C}^{n_y \times k}\end{aligned}$$

and the **left data** can be expressed as:

$$\begin{aligned}\mathbf{M} &= \mathbf{diag} [\mu_1, \dots, \mu_q] \in \mathbb{C}^{q \times q} \\ \mathbf{L}^\top &= \begin{bmatrix} \mathbf{l}_1 & \mathbf{l}_2 & \dots & \mathbf{l}_q \end{bmatrix} \in \mathbb{C}^{n_y \times q} \\ \mathbf{V}^\top &= \begin{bmatrix} \mathbf{v}_1 & \mathbf{v}_2 & \dots & \mathbf{v}_q \end{bmatrix} \in \mathbb{C}^{n_u \times q}\end{aligned}$$

The **Loewner matrix** in this case is

$$\mathbb{L} = \begin{bmatrix} \frac{\mathbf{v}_1^\top \mathbf{r}_1 - \mathbf{l}_1^\top \mathbf{w}_1}{\mu_1 - \lambda_1} & \dots & \frac{\mathbf{v}_1^\top \mathbf{r}_k - \mathbf{l}_1^\top \mathbf{w}_k}{\mu_1 - \lambda_k} \\ \vdots & \ddots & \vdots \\ \frac{\mathbf{v}_q^\top \mathbf{r}_1 - \mathbf{l}_q^\top \mathbf{w}_1}{\mu_q - \lambda_1} & \dots & \frac{\mathbf{v}_q^\top \mathbf{r}_k - \mathbf{l}_q^\top \mathbf{w}_k}{\mu_q - \lambda_k} \end{bmatrix} \in \mathbb{C}^{q \times k}$$

With this notation  $\mathbb{L}$  satisfy the **Sylvester equation** :  $\mathbf{M}\mathbb{L} - \mathbb{L}\mathbf{\Lambda} = \mathbf{V}\mathbf{R} - \mathbf{L}\mathbf{W}$ .

The Loewner matrix is:

$$\mathbb{L} = \begin{bmatrix} \frac{\mathbf{v}_1^\top \mathbf{r}_1 - \mathbf{l}_1^\top \mathbf{w}_1}{\mu_1 - \lambda_1} & \dots & \frac{\mathbf{v}_1^\top \mathbf{r}_k - \mathbf{l}_1^\top \mathbf{w}_k}{\mu_1 - \lambda_k} \\ \vdots & \ddots & \vdots \\ \frac{\mathbf{v}_q^\top \mathbf{r}_1 - \mathbf{l}_q^\top \mathbf{w}_1}{\mu_q - \lambda_1} & \dots & \frac{\mathbf{v}_q^\top \mathbf{r}_k - \mathbf{l}_q^\top \mathbf{w}_k}{\mu_q - \lambda_k} \end{bmatrix} \in \mathbb{C}^{q \times k}$$

$$\mathbf{M}\mathbb{L} - \mathbb{L}\boldsymbol{\Lambda} = \mathbf{V}\mathbf{R} - \mathbf{L}\mathbf{W}$$

The shifted Loewner matrix is:

$$\mathbb{M} = \begin{bmatrix} \frac{\mu_1 \mathbf{v}_1^\top \mathbf{r}_1 - \mathbf{l}_1^\top \mathbf{w}_1 \lambda_1}{\mu_1 - \lambda_1} & \dots & \frac{\mu_1 \mathbf{v}_1^\top \mathbf{r}_k - \mathbf{l}_1^\top \mathbf{w}_k \lambda_k}{\mu_1 - \lambda_k} \\ \vdots & \ddots & \vdots \\ \frac{\mu_q \mathbf{v}_q^\top \mathbf{r}_1 - \mathbf{l}_q^\top \mathbf{w}_1 \lambda_1}{\mu_q - \lambda_1} & \dots & \frac{\mu_q \mathbf{v}_q^\top \mathbf{r}_k - \mathbf{l}_q^\top \mathbf{w}_k \lambda_k}{\mu_q - \lambda_k} \end{bmatrix} \in \mathbb{C}^{q \times k}$$

$$\mathbf{M}\mathbb{M} - \mathbb{M}\boldsymbol{\Lambda} = \mathbf{M}\mathbf{V}\mathbf{R} - \mathbf{L}\mathbf{W}\boldsymbol{\Lambda}$$

If data are sampled from  $\mathbf{G}(s) = C(sE - A)^{-1}B$ , let us define :

$$\mathcal{O}_q = \begin{bmatrix} \mathbf{l}_1^\top C(\mu_1 E - A)^{-1} \\ \vdots \\ \mathbf{l}_q^\top C(\mu_q E - A)^{-1} \end{bmatrix} \in \mathbb{C}^{q \times n}, \quad \mathcal{R}_k = \left[ (\lambda_1 E - A)^{-1} B \mathbf{r}_1, \dots, (\lambda_k E - A)^{-1} B \mathbf{r}_k \right] \in \mathbb{C}^{n \times k}$$

be the **generalized tangential observability** and **controllability matrices**. Then,

$$\begin{aligned} [\mathbb{L}]_{ij} &= \frac{\mathbf{v}_i^\top \mathbf{r}_j - \mathbf{l}_i^\top \mathbf{w}_j}{\mu_i - \lambda_j} \\ &= -\mathbf{l}_i^\top C(\mu_j E - A)^{-1} E(\lambda_i E - A)^{-1} B \mathbf{r}_j \\ &= -[\mathcal{O}_q]_i E [\mathcal{R}_k]_j \end{aligned}$$

$$\begin{aligned} [\mathbb{M}]_{ij} &= \frac{\mu_i \mathbf{v}_i^\top \mathbf{r}_j - \mathbf{l}_i^\top \mathbf{w}_j \lambda_j}{\mu_i - \lambda_j} \\ &= -\mathbf{l}_i^\top C(\mu_j E - A)^{-1} A(\lambda_i E - A)^{-1} B \mathbf{r}_j \\ &= -[\mathcal{O}_q]_i A [\mathcal{R}_k]_j \end{aligned}$$

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Assume that  $k = q$ , then  $\mathbf{H}(s) = C(sE - A)^{-1}B$  with

$$E = -\mathbb{L}, \quad A = -\mathbb{M}, \quad , \quad B = \mathbf{V}, \quad C = \mathbf{W},$$

is a **minimal descriptor realization** interpolating the data.

Suppose that we have more data than necessary. The problem has a solution if

$$\text{rank}[\xi\mathbb{L} - \mathbb{M}] = \text{rank}[\mathbb{L}, \mathbb{M}] = \text{rank} \begin{bmatrix} \mathbb{L} \\ \mathbb{M} \end{bmatrix} = r, \quad \xi \in \{\lambda_i\} \cup \{\mu_j\}$$

$$[\mathbb{L}, \mathbb{M}] = \mathbf{Y}\Sigma_L \tilde{X}^\top, \quad \begin{bmatrix} \mathbb{L} \\ \mathbb{M} \end{bmatrix} = \tilde{Y}\Sigma_r \mathbf{X}^H, \quad \mathbf{Y}, \mathbf{X} \in \mathbb{C}^{N \times n}.$$

A realization  $(E, A, B, C)$  of an (approximate) interpolant is given by:

$$E = -\mathbf{Y}^H \mathbb{L} \mathbf{X}, \quad A = -\mathbf{Y}^H \mathbb{M} \mathbf{X}, \quad B = -\mathbf{Y}^H \mathbf{V}, \quad C = \mathbf{W} \mathbf{X}$$

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$$E = -\mathbb{L}, \quad A = -\mathbb{M}, \quad , \quad B = \mathbf{V}, \quad C = \mathbf{W},$$

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$$[\mathbb{L}, \mathbb{M}] = \mathbf{Y}\Sigma_l \tilde{X}^\top, \quad \begin{bmatrix} \mathbb{L} \\ \mathbb{M} \end{bmatrix} = \tilde{Y}\Sigma_r \mathbf{X}^H, \quad \mathbf{Y}, \mathbf{X} \in \mathbb{C}^{N \times n}.$$

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$$E = -\mathbf{Y}^H \mathbb{L} \mathbf{X}, \quad A = -\mathbf{Y}^H \mathbb{M} \mathbf{X}, \quad B = -\mathbf{Y}^H \mathbf{V}, \quad C = \mathbf{W} \mathbf{X}$$

Being known the full state realization  $\mathcal{S}$

$$\begin{aligned} E\dot{\mathbf{x}}(t) &= A\mathbf{x}(t) + B\mathbf{u}(t) \\ \mathbf{y}(t) &= C\mathbf{x}(t) + D\mathbf{u}(t) \end{aligned}$$

The Petrov-Galerkin reduced order model  $\hat{\mathcal{S}}$  is obtained with projectors  $W, V \in \mathbb{C}^{n \times r}$  as

$$\begin{aligned} W^\top EV\dot{\hat{\mathbf{x}}}(t) &= W^\top AV\hat{\mathbf{x}}(t) + W^\top B\mathbf{u}(t) \\ \hat{\mathbf{y}}(t) &= CV\hat{\mathbf{x}}(t) + D\mathbf{u}(t) \end{aligned}$$

The above equations assume  $W = \text{span}(\mathcal{W})$ ,  $V = \text{span}(\mathcal{V})$  selected such that they meet the approximation objective:

$$\mathbf{x}(t) \approx V\hat{\mathbf{x}}(t), \quad , \quad \hat{\mathbf{x}}_0 = W^\top \mathbf{x}_0$$

Choosing two different bases  $V'$  and  $W'$  that respectively span the same subspaces  $\mathcal{V}$  and  $\mathcal{W}$  result in the same reconstructed solution  $\mathbf{x}(t)$ . Thus, subspaces are relevant, not basis.

Now recall,

$$\mathcal{O}E\mathcal{R} = \mathbb{L} \quad \text{and} \quad \mathcal{O}A\mathcal{R} = \mathbb{M},$$

where the generalized reachability and observability matrices are (complex conjugation trick for realness)

$$\mathcal{R} = \begin{bmatrix} \mathbf{r}_1^\top B^\top (\lambda_1 E - A)^{-\top} \\ \bar{\mathbf{r}}_1^\top B^\top (\bar{\lambda}_1 E - A)^{-\top} \\ \vdots \\ \mathbf{r}_{k/2}^\top B^\top (\lambda_{k/2} E - A)^{-\top} \\ \bar{\mathbf{r}}_{k/2}^\top B^\top (\bar{\lambda}_{k/2} E - A)^{-\top} \end{bmatrix}^\top \quad \text{and} \quad \mathcal{O} = \begin{bmatrix} \mathbf{l}_1 C(\mu_1 E - A)^{-1} \\ \bar{\mathbf{l}}_1 C(\bar{\mu}_1 E - A)^{-1} \\ \vdots \\ \mathbf{l}_{q/2} C(\mu_{q/2} E - A)^{-1} \\ \bar{\mathbf{l}}_{q/2} C(\bar{\mu}_{q/2} E - A)^{-1} \end{bmatrix}.$$

$$(Y^\top J^H \mathcal{O})^\top E(\mathcal{R}JX) = \mathbb{L}, \quad \text{and} \quad (Y^\top J^H \mathcal{O})^\top A(\mathcal{R}JX) = \mathbb{M},$$

$$J_0 = \frac{1}{\sqrt{2}} \begin{bmatrix} 1 & i \\ 1 & -i \end{bmatrix} \quad \text{and} \quad J = I_{k/2} \otimes (J_0 \otimes I_m),$$

Therefore,

$$\underbrace{(Y^\top J^H \mathcal{O})^\top}_{W^\top} E \underbrace{(\mathcal{R}JX)}_V = \mathbb{L}, \quad \text{and} \quad \underbrace{((Y^\top J^H \mathcal{O})^\top A}_{W^\top} \underbrace{(\mathcal{R}JX)}_V = \mathbb{M},$$

Therefore,

$$W = Y^\top J^H \mathcal{O} \quad \text{and} \quad V = \mathcal{R}JX.$$

and

$$\mathbf{x}(t) \approx V \hat{\mathbf{x}}_r(t) \quad \text{where} \quad V = \mathcal{R}JX.$$

can be recovered (approximated) solely from ROM simulation.



M. Gouzien, C. Poussot-Vassal, G. Haine and D. Matignon, "A Port-Hamiltonian reduced order modelling of the 2D Maxwell equations", journal for Computation and Mathematics in Electrical and Electronic Engineering, 2025.

Given  $\{\lambda_j, \mathbf{r}_j, \mathbf{w}_j\}$  and  $\{\mu_i, \mathbf{l}_i, \mathbf{v}_i\}$ , seek  $\mathbf{H}$  s.t.

$$\mathbf{H}(\lambda_j) \mathbf{r}_j = \mathbf{w}_j \text{ and } \mathbf{l}_i \mathbf{H}(\mu_i) = \mathbf{v}_i$$

$$j = 1, \dots, k; i = 1, \dots, q.$$

Rational interpolation

$$\mathbf{H}(s) = \mathbf{W}(-s\mathbb{L} + \mathbb{M})^{-1}\mathbf{V}$$



A.C. Antoulas, S. Lefteriu and A.C. Ionita, "[Chapter 8: A Tutorial Introduction to the Loewner Framework for Model Reduction](#)", Model Reduction and Approximation: Theory and Algorithms, 2016.

Given  $\{\lambda_j, \mathbf{r}_j, \mathbf{w}_j\}$  and  $\{\mu_i, \mathbf{l}_i, \mathbf{v}_i\}$ , seek  $\mathbf{H}$  s.t.

$$\mathbf{H}(\lambda_j)\mathbf{r}_j = \mathbf{w}_j \text{ and } \mathbf{l}_i \mathbf{H}(\mu_i) = \mathbf{v}_i$$

$j = 1, \dots, k; i = 1, \dots, q.$

Rational interpolation  
 $\mathbf{H}(s) = \mathbf{W}(-s\mathbb{L} + \mathbb{M})^{-1}\mathbf{V}$

- ▶ underlying rational ( $r$ ) order

$$\begin{aligned} r &= \text{rank}(\xi\mathbb{L} - \mathbb{M}) \\ &= \text{rank}([\mathbb{L}, \mathbb{M}]) \\ &= \text{rank}([\mathbb{L}^H, \mathbb{M}^H]^H) \end{aligned}$$

- ▶ and McMillan ( $\nu$ ) order

$$\nu = \text{rank}(\mathbb{L})$$

- ▶  $\mathbb{L}$  and  $\mathbb{M}$  are input-output independents.
- ▶ Minimal realization
- ▶ If  $\mathcal{S}$  is known, then internal state  $\mathbf{x} \in \mathbb{R}^n$  is recovered by

$$\mathbf{x}(t) \approx V\hat{\mathbf{x}}_r(t) \quad \text{where} \quad V = \mathcal{R}JX.$$

Rational function satisfies

$$\mathbf{H}(\lambda_j) = \mathbf{w}_j \text{ and } \mathbf{H}(\mu_i) = \mathbf{v}_i$$

$$\mathbf{G}(s) = \frac{1}{s^2 + 1}$$

Evaluated at

$$\begin{aligned}\lambda_1 &= 1, \lambda_2 = 2 \\ \mu_1 &= -1, \mu_2 = -2\end{aligned}$$

Leads to

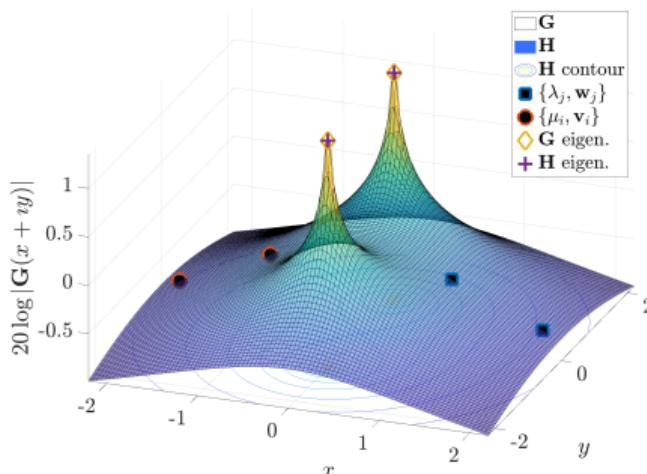
$$\begin{aligned}\mathbf{w}_1 &= \frac{1}{2}, \mathbf{w}_2 = \frac{1}{5} \\ \mathbf{v}_1 &= \frac{1}{2}, \mathbf{v}_2 = \frac{1}{5}.\end{aligned}$$

# Loewner

Loewner examples (simple case, CAS=4)

Rational function satisfies

$$\mathbf{H}(\lambda_j) = \mathbf{w}_j \text{ and } \mathbf{H}(\mu_i) = \mathbf{v}_i$$



$$\mathbf{G}(s) = \frac{1}{s^2 + 1}$$

Evaluated at

$$\begin{aligned}\lambda_1 &= 1, \lambda_2 = 2 \\ \mu_1 &= -1, \mu_2 = -2\end{aligned}$$

Leads to

$$\begin{aligned}\mathbf{w}_1 &= \frac{1}{2}, \mathbf{w}_2 = \frac{1}{5} \\ \mathbf{v}_1 &= \frac{1}{2}, \mathbf{v}_2 = \frac{1}{5}.\end{aligned}$$

$$\mathbf{W} = \begin{bmatrix} \frac{1}{2} & \frac{1}{5} \end{bmatrix}, \quad \mathbf{V} = \begin{bmatrix} \frac{1}{2} \\ \frac{1}{5} \end{bmatrix}$$

$$\mathbf{L} = \begin{bmatrix} 0 & -\frac{1}{10} \\ \frac{1}{10} & 0 \end{bmatrix}, \quad \mathbf{M} = \begin{bmatrix} \frac{1}{2} & \frac{3}{10} \\ \frac{3}{10} & \frac{1}{5} \end{bmatrix}$$

# Loewner

Loewner examples (simple case, CAS=4)

Rational function satisfies

$$\mathbf{H}(\lambda_j) = \mathbf{w}_j \text{ and } \mathbf{H}(\mu_i) = \mathbf{v}_i$$

Rank reveals the underlying rational ( $r$ ) and McMillan ( $\nu$ ) orders

$$\text{rank}(\xi\mathbb{L} - \mathbb{M}) = r$$

$$\text{rank}(\mathbb{L}) = \nu$$

$r = 2$  and  $\nu = 2$ ,  $(\mathbb{M}, \mathbb{L})$  pencil regular

$$\mathbf{H}(s) = \mathbf{W}(-s\mathbb{L} + \mathbb{M})^{-1}\mathbf{V} = \mathbf{G}(s)$$

$$\mathbf{G}(s) = \frac{1}{s^2 + 1}$$

Evaluated at

$$\begin{aligned}\lambda_1 &= 1, \lambda_2 = 2 \\ \mu_1 &= -1, \mu_2 = -2\end{aligned}$$

Leads to

$$\begin{aligned}\mathbf{w}_1 &= \frac{1}{2}, \mathbf{w}_2 = \frac{1}{5} \\ \mathbf{v}_1 &= \frac{1}{2}, \mathbf{v}_2 = \frac{1}{5}.\end{aligned}$$

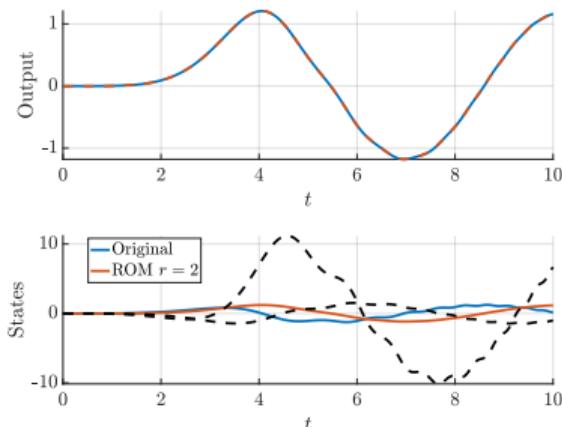
$$\mathbf{W} = \begin{bmatrix} \frac{1}{2} & \frac{1}{5} \end{bmatrix}, \mathbf{V} = \begin{bmatrix} \frac{1}{2} \\ \frac{1}{5} \end{bmatrix}$$

$$\mathbb{L} = \begin{bmatrix} 0 & -\frac{1}{10} \\ \frac{1}{10} & 0 \end{bmatrix}, \mathbb{M} = \begin{bmatrix} \frac{1}{2} & \frac{3}{10} \\ \frac{3}{10} & \frac{1}{5} \end{bmatrix}$$

Rational function satisfies

$$\mathbf{H}(\lambda_j) = \mathbf{w}_j \text{ and } \mathbf{H}(\mu_i) = \mathbf{v}_i$$

Output and internal variables



$$\mathbf{G}(s) = \frac{1}{s^2 + 1}$$

Evaluated at

$$\begin{aligned}\lambda_1 &= 1, \lambda_2 = 2 \\ \mu_1 &= -1, \mu_2 = -2\end{aligned}$$

Leads to

$$\begin{aligned}\mathbf{w}_1 &= \frac{1}{2}, \mathbf{w}_2 = \frac{1}{5} \\ \mathbf{v}_1 &= \frac{1}{2}, \mathbf{v}_2 = \frac{1}{5}.\end{aligned}$$

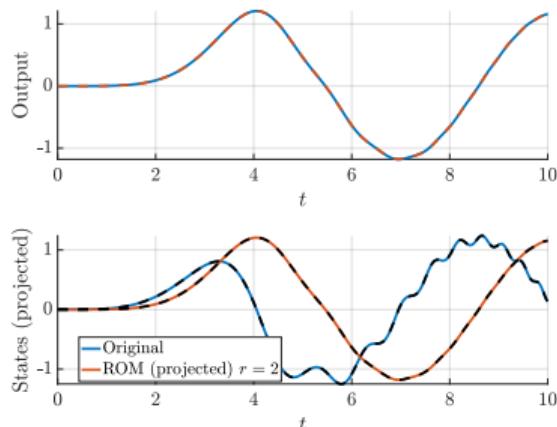
$$\mathbf{W} = \begin{bmatrix} \frac{1}{2} & \frac{1}{5} \end{bmatrix}, \mathbf{V} = \begin{bmatrix} \frac{1}{2} \\ \frac{1}{5} \end{bmatrix}$$

$$\mathbf{L} = \begin{bmatrix} 0 & -\frac{1}{10} \\ \frac{1}{10} & 0 \end{bmatrix}, \mathbf{M} = \begin{bmatrix} \frac{1}{2} & \frac{3}{10} \\ \frac{3}{10} & \frac{1}{5} \end{bmatrix}$$

Rational function satisfies

$$\mathbf{H}(\lambda_j) = \mathbf{w}_j \text{ and } \mathbf{H}(\mu_i) = \mathbf{v}_i$$

Output and internal **projected** variables



$$\mathbf{G}(s) = \frac{1}{s^2 + 1}$$

Evaluated at

$$\begin{aligned}\lambda_1 &= 1, \lambda_2 = 2 \\ \mu_1 &= -1, \mu_2 = -2\end{aligned}$$

Leads to

$$\begin{aligned}\mathbf{w}_1 &= \frac{1}{2}, \mathbf{w}_2 = \frac{1}{5} \\ \mathbf{v}_1 &= \frac{1}{2}, \mathbf{v}_2 = \frac{1}{5}.\end{aligned}$$

$$\mathbf{W} = \begin{bmatrix} \frac{1}{2} & \frac{1}{5} \end{bmatrix}, \quad \mathbf{V} = \begin{bmatrix} \frac{1}{2} \\ \frac{1}{5} \end{bmatrix}$$

$$\mathbf{L} = \begin{bmatrix} 0 & -\frac{1}{10} \\ \frac{1}{10} & 0 \end{bmatrix}, \quad \mathbf{M} = \begin{bmatrix} \frac{1}{2} & \frac{3}{10} \\ \frac{3}{10} & \frac{1}{5} \end{bmatrix}$$

Rational function satisfies

$$\mathbf{H}(\lambda_j) = \mathbf{w}_j \text{ and } \mathbf{H}(\mu_i) = \mathbf{v}_i$$

$$\mathbf{G}(s) = \frac{1}{s^2 + 1}$$

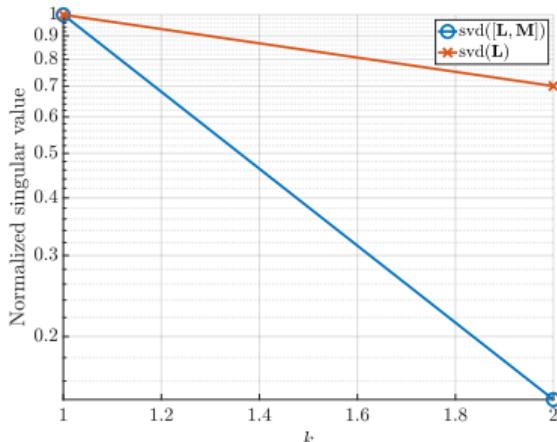
Evaluated at

$$\begin{aligned}\lambda_1 &= 1, \lambda_2 = 2, \lambda_3 = 3 \\ \mu_1 &= -1, \mu_2 = -2\end{aligned}$$

Rational function satisfies

$$\mathbf{H}(\lambda_j) = \mathbf{w}_j \text{ and } \mathbf{H}(\mu_i) = \mathbf{v}_i$$

Realization rect.:  $\mathbf{H}(s) = \mathbf{W}(-s\mathbb{L} + \mathbb{M})^\dagger \mathbf{V}$



$$\mathbf{G}(s) = \frac{1}{s^2 + 1}$$

Evaluated at

$$\begin{aligned}\lambda_1 &= 1, \lambda_2 = 2, \lambda_3 = 3 \\ \mu_1 &= -1, \mu_2 = -2\end{aligned}$$

Leads to

$$\mathbf{W} = \begin{bmatrix} \frac{1}{2} & \frac{1}{5} & \frac{1}{10} \end{bmatrix}, \quad \mathbf{V} = \begin{bmatrix} \frac{1}{2} \\ \frac{1}{5} \end{bmatrix}$$

$$\mathbb{L} = \begin{bmatrix} 0 & -\frac{1}{10} & -\frac{1}{10} \\ \frac{1}{10} & 0 & -\frac{1}{50} \end{bmatrix}$$

$$\mathbb{M} = \begin{bmatrix} \frac{1}{2} & \frac{3}{10} & \frac{1}{5} \\ \frac{3}{10} & \frac{1}{5} & \frac{7}{50} \end{bmatrix}$$

Rational function satisfies

$$\mathbf{H}(\lambda_j) = \mathbf{w}_j \text{ and } \mathbf{H}(\mu_i) = \mathbf{v}_i$$

Rank reveals the underlying rational ( $r$ ) and McMillan ( $\nu$ ) orders

$$\text{rank}(\xi \mathbb{L} - \mathbb{M}) = r$$

$$\text{rank}(\mathbb{L}) = \nu$$

$r = 2$  and  $\nu = 2$

$$\begin{aligned}\mathbf{H}(s) &= \mathbf{W}(-s\mathbb{L} + \mathbb{M})^\dagger \mathbf{V} \\ &= \frac{1}{s^2 - 4.650e - 16s + 1}\end{aligned}$$

$$\mathbf{G}(s) = \frac{1}{s^2 + 1}$$

Evaluated at

$$\begin{aligned}\lambda_1 &= 1, \lambda_2 = 2, \lambda_3 = 3 \\ \mu_1 &= -1, \mu_2 = -2\end{aligned}$$

Leads to

$$\mathbf{W} = \begin{bmatrix} \frac{1}{2} & \frac{1}{5} & \frac{1}{10} \end{bmatrix}, \quad \mathbf{V} = \begin{bmatrix} \frac{1}{2} \\ \frac{1}{5} \end{bmatrix}$$

$$\mathbb{L} = \begin{bmatrix} 0 & -\frac{1}{10} & -\frac{1}{10} \\ \frac{1}{10} & 0 & -\frac{1}{50} \end{bmatrix}$$

$$\mathbb{M} = \begin{bmatrix} \frac{1}{2} & \frac{3}{10} & \frac{1}{5} \\ \frac{3}{10} & \frac{1}{5} & \frac{7}{50} \end{bmatrix}$$

Rational function satisfies

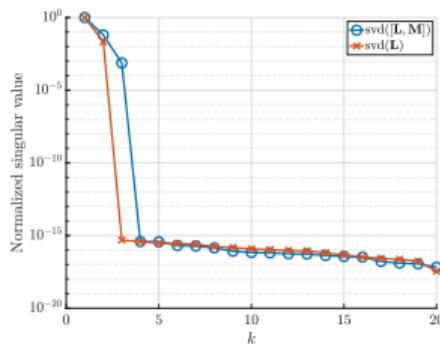
$$\mathbf{H}(\lambda_j) = \mathbf{w}_j \text{ and } \mathbf{H}(\mu_i) = \mathbf{v}_i$$

$$\mathbf{G}(s) = \frac{s^2 + s + 2}{s + 1}$$

Evaluated at

$$\lambda_{1\dots 20} = [1, 2, \dots, 20]$$

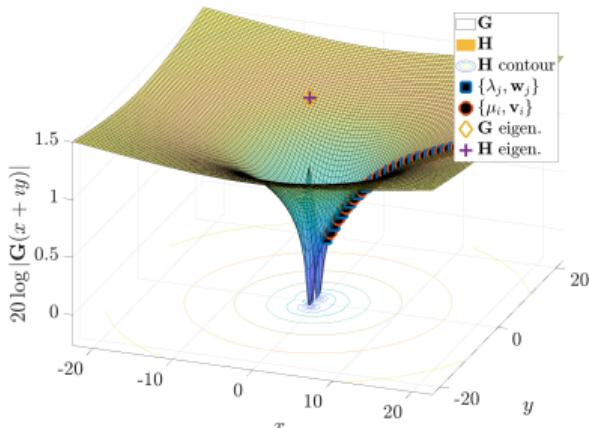
$$\mu_{1\dots 20} = [1.5, 2.5, \dots, 20.5]$$



Rational function satisfies

$$\mathbf{H}(\lambda_j) = \mathbf{w}_j \text{ and } \mathbf{H}(\mu_i) = \mathbf{v}_i$$

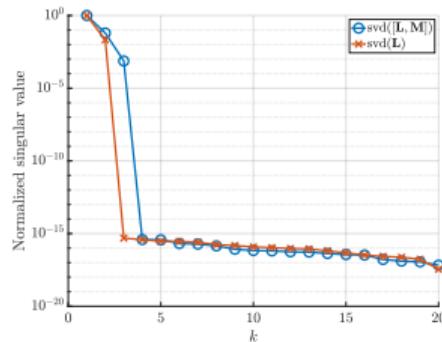
Realization  $n = 20$ :  $\mathbf{H}(s) = \mathbf{W}(-s\mathbb{L} + \mathbb{M})^{-1}\mathbf{V}$



$$\mathbf{G}(s) = \frac{s^2 + s + 2}{s + 1}$$

Evaluated at

$$\begin{aligned}\lambda_{1\dots 20} &= [1, 2, \dots, 20] \\ \mu_{1\dots 20} &= [1.5, 2.5, \dots, 20.5]\end{aligned}$$



Rational function satisfies

$$\mathbf{H}(\lambda_j) = \mathbf{w}_j \text{ and } \mathbf{H}(\mu_i) = \mathbf{v}_i$$

Rank reveals the underlying rational ( $r$ ) and McMillan ( $\nu$ ) orders

$$\text{rank}(\xi\mathbb{L} - \mathbb{M}) = r = 3$$

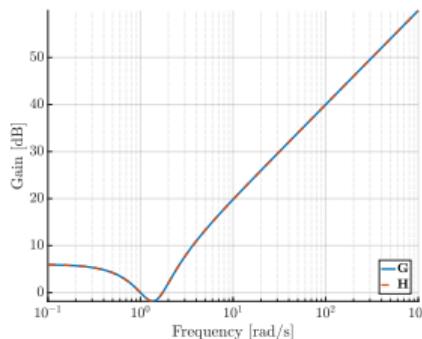
$$\text{rank}(\mathbb{L}) = \nu = 2$$

$$\mathbf{G}(s) = \frac{s^2 + s + 2}{s + 1}$$

Evaluated at

$$\lambda_{1\dots 20} = [1, 2, \dots, 20]$$

$$\mu_{1\dots 20} = [1.5, 2.5, \dots, 20.5]$$



Rational function satisfies

$$\mathbf{H}(\lambda_j) = \mathbf{w}_j \text{ and } \mathbf{H}(\mu_i) = \mathbf{v}_i$$

Rank reveals the underlying rational ( $r$ ) and McMillan ( $\nu$ ) orders

$$\text{rank}(\xi\mathbb{L} - \mathbb{M}) = r = 3$$

$$\text{rank}(\mathbb{L}) = \nu = 2$$

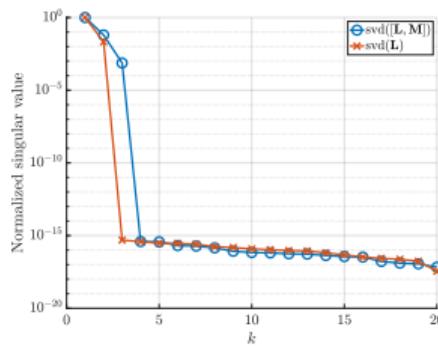
$$\begin{aligned}\mathbf{H}(s) &= \mathbf{W} \mathbf{X} (-s \mathbf{Y}^T \mathbb{L} \mathbf{X} + \mathbf{Y}^T \mathbb{M} \mathbf{X})^{-1} \mathbf{Y}^T \mathbf{V} \\ &= \frac{s^2 + s + 2}{s + 1}\end{aligned}$$

$$\mathbf{G}(s) = \frac{s^2 + s + 2}{s + 1}$$

Evaluated at

$$\lambda_{1\dots 20} = [1, 2, \dots, 20]$$

$$\mu_{1\dots 20} = [1.5, 2.5, \dots, 20.5]$$



Rational function satisfies

$$\mathbf{H}(\lambda_j) = \mathbf{w}_j \text{ and } \mathbf{H}(\mu_i) = \mathbf{v}_i$$

$$\mathbf{G}(s) = \frac{1}{s^2 + (1 + i)s + (1 + i)}$$

Evaluated at

$$\begin{aligned}\lambda_1 &= i, \lambda_2 = 2i, \lambda_3 = -2 + i \\ \mu_1 &= -i, \mu_2 = 2, \mu_3 = 0.5 - i\end{aligned}$$

Leads to

$$\mathbf{w}_1, \mathbf{w}_2, \mathbf{w}_3 \text{ and } \mathbf{v}_1, \mathbf{v}_2, \mathbf{v}_3$$

Rational function satisfies

$$\mathbf{H}(\lambda_j) = \mathbf{w}_j \text{ and } \mathbf{H}(\mu_i) = \mathbf{v}_i$$

Rank reveals the underlying rational ( $r$ ) and McMillan ( $\nu$ ) orders

$$\text{rank}(\xi \mathbb{L} - \mathbb{M}) = r$$

$$\text{rank}(\mathbb{L}) = \nu$$

$$\mathbf{H}(s) = \frac{(1 + 2.22e - 16i)}{s^2 + (1 + i)s + (1 + i)}$$

$$\mathbf{G}(s) = \frac{1}{s^2 + (1 + i)s + (1 + i)}$$

Evaluated at

$$\begin{aligned}\lambda_1 &= i, \lambda_2 = 2i, \lambda_3 = -2 + i \\ \mu_1 &= -i, \mu_2 = 2, \mu_3 = 0.5 - i\end{aligned}$$

Leads to

$$\mathbf{w}_1, \mathbf{w}_2, \mathbf{w}_3 \text{ and } \mathbf{v}_1, \mathbf{v}_2, \mathbf{v}_3$$

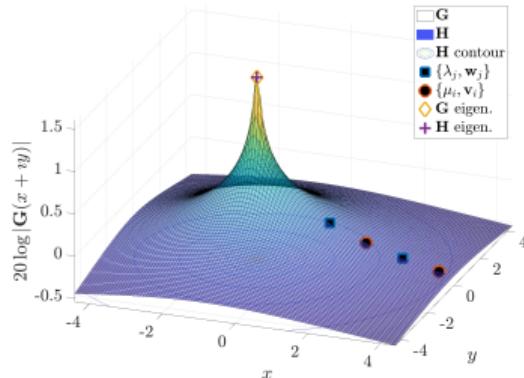
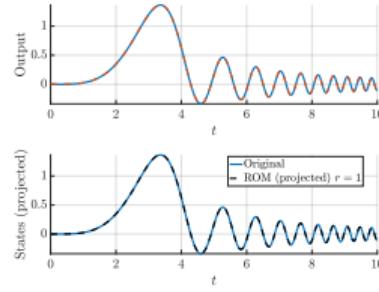
$$\begin{aligned}\hat{\mathbb{L}} &= \begin{bmatrix} -0.207 + 0.9568i & -0.1276 - 0.0294i \\ -0.0438 - 0.0818i & 0.039 - 0.1089i \end{bmatrix} \\ \hat{\mathbb{M}} &= \begin{bmatrix} 0.4738 - 0.0560i & 0.0089 - 0.3392i \\ 0.2253 - 0.1607i & -0.0342 + 0.1308i \end{bmatrix}\end{aligned}$$

```
% Model (CAS = 1)
S = ss(tf(2,[1 1])); S.E = 1;
[A,B,C,D,E] = dssdata(S);
G = @(s) C*((s*E-A)\B)+D;
% IP , responses , tangent
la = [1 3];
mu = [2 4];
k = length(la);
q = length(mu);
R = ones(1,k);
L = ones(q,1);
for ii = 1:k; W(1,1,ii) = G(la(ii)); end
for ii = 1:q; V(1,1,ii) = G(mu(ii)); end

% Loewner
[hr,info] = lf.loewner_tng(la,mu,W,V,R,L);
```

```
% Model (CAS = 1)
S = ss(tf(2,[1 1])); S.E = 1;
[A,B,C,D,E] = dssdata(S);
G = @(s) C*((s*E-A)\B)+D;
% IP , responses , tangent
la = [1 3];
mu = [2 4];
k = length(la);
q = length(mu);
R = ones(1,k);
L = ones(q,1);
for ii = 1:k; W(1,1,ii) = G(la(ii)); end
for ii = 1:q; V(1,1,ii) = G(mu(ii)); end

% Loewner
[hr,info] = lf.loewner_tng(la,mu,W,V,R,L);
```



# Content

Forewords

Linear dynamical systems

Loewner

**Loewner extensions (passive & pH)**

Conclusions

# Loewner extensions (passive & pH)

More structures and properties

## Structures

L-ODE  
L-ODE / DAE-1  
L-DAE  
L-DDE  
L-PDE

L-pH  
pL-DAE  
B-DAE  
Q-DAE

## Model

- ▶  $(A, B, C)$  and  $\mathbf{H}(s)$
  - ▶  $(A, B, C, D)$  and  $\mathbf{H}(s)$
  - ▶  $(E, A, B, C)$  and  $\mathbf{H}(s)$
  - ▶  $(A_i \dots, B, C, \tau_i)$  and  $\mathbf{H}(s)$
  - ▶  $\mathbf{H}(s)$
- 
- ▶  $(Q, J, R, G, P, N, S)$  and  $\mathbf{H}(s)$
  - ▶  $(E_j, A_j, B_j, C_j)$  and  $\mathbf{H}(s, p_j)$
  - ▶  $(A, B, C, N)$  and  $\mathbf{H}(s_1, s_2, \dots, s_k)$
  - ▶  $(A, B, C, Q)$  and  $\mathbf{H}(s_1, s_2, \dots, s_k)$

# Loewner extensions (passive & pH)

More structures and properties

## Structures

L-ODE  
L-ODE / DAE-1  
L-DAE  
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## Model

- ▶  $(A, B, C)$  and  $\mathbf{H}(s)$
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  - ▶  $\mathbf{H}(s)$
- 
- ▶  $(Q, J, R, G, P, N, S)$  and  $\mathbf{H}(s)$
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  - ▶  $(A, B, C, Q)$  and  $\mathbf{H}(s_1, s_2, \dots, s_k)$

# Loewner extensions (passive & pH)

Passive & port-Hamiltonian

## Structures

L-ODE  
L-ODE / DAE-1  
L-DAE  
L-DDE  
L-PDE

## L-pH

pL-DAE  
B-DAE  
Q-DAE

## Passivity

$$\begin{aligned}\dot{\mathbf{x}} &= A\mathbf{x} + B\mathbf{u} \\ \mathbf{y} &= C\mathbf{x} + D\mathbf{u}\end{aligned}$$

$$\Phi_{\mathbf{H}}(s) = \mathbf{H}(s) + \mathbf{H}^{\top}(-s)$$

satisfy  $\Phi_{\mathbf{H}}(\imath\omega) > 0$ ,  $\text{Re}(\lambda_S) < 0$  and  $D \succ 0$ .

## pH

$$\begin{aligned}\dot{\mathbf{x}} &= (J - R)Q\mathbf{x} + (G - P)\mathbf{u} \\ \mathbf{y} &= (G + P)^{\top}Q\mathbf{x} + (N + S)\mathbf{u}\end{aligned}$$

$$\mathcal{V} = \begin{bmatrix} -J & -G \\ G^{\top} & N \end{bmatrix} \text{ and } \mathcal{W} = \begin{bmatrix} R & P \\ P^{\top} & S \end{bmatrix}$$

satisfy  $\mathcal{V} = -\mathcal{V}^{\top}$ ,  $\mathcal{W} = \mathcal{W}^{\top} \succeq 0$  and  $Q = Q^{\top} \succeq 0$

# Loewner extensions (passive & pH)

Passive & port-Hamiltonian

## Structures

L-ODE  
L-ODE / DAE-1  
L-DAE  
L-DDE  
L-PDE

## L-pH

pL-DAE  
B-DAE  
Q-DAE

## Passivity

$$\begin{aligned}\dot{\mathbf{x}} &= A\mathbf{x} + B\mathbf{u} \\ \mathbf{y} &= C\mathbf{x} + D\mathbf{u}\end{aligned}$$

$$\Phi_{\mathbf{H}}(s) = \mathbf{H}(s) + \mathbf{H}^{\top}(-s)$$

satisfy  $\Phi_{\mathbf{H}}(\omega) > 0$ ,  $\text{Re}(\lambda_S) < 0$  and  $D \succ 0$ .

## pH

$$\begin{aligned}\dot{\mathbf{x}} &= (J - R)Q\mathbf{x} + (G - P)\mathbf{u} \\ \mathbf{y} &= (G + P)^{\top}Q\mathbf{x} + (N + S)\mathbf{u}\end{aligned}$$

$$\mathcal{V} = \begin{bmatrix} -J & -G \\ G^{\top} & N \end{bmatrix} \text{ and } \mathcal{W} = \begin{bmatrix} R & P \\ P^{\top} & S \end{bmatrix}$$

satisfy  $\mathcal{V} = -\mathcal{V}^{\top}$ ,  $\mathcal{W} = \mathcal{W}^{\top} \succeq 0$  and  $Q = Q^{\top} \succeq 0$

# Loewner extensions (passive & pH)

Passive & port-Hamiltonian

## Structures

L-ODE  
L-ODE / DAE-1  
L-DAE  
L-DDE  
L-PDE

**L-pH**  
pL-DAE  
B-DAE  
Q-DAE

## Transfer function

$$\mathbf{H}(s) = \frac{2s + 4}{s + 1}$$

## ODE realization $\mathcal{S}_1$

$$\begin{aligned}\dot{x} &= -x + 2u \\ y &= x + 2u\end{aligned}$$

## Passivity

- ▶  $\text{Re}(\Lambda(A)) = -1 < 0$
- ▶  $D = 2 \succ 0$
- ▶  $\Phi_{\mathbf{H}}(\imath\omega) = \mathbf{H}(\imath\omega) + \mathbf{H}(-\imath\omega)^{\top} > 0$

$$\begin{aligned}\Phi_{\mathbf{H}}(s) &= \frac{4(s^2 - 2)}{s^2 - 1} \\ \Phi_{\mathbf{H}}(\imath\omega) &= \frac{4(\omega^2 + 2)}{\omega^2 + 1}\end{aligned}$$

# Loewner extensions (passive & pH)

Passive & port-Hamiltonian

## Structures

L-ODE  
L-ODE / DAE-1  
L-DAE  
L-DDE  
L-PDE

**L-pH**  
pL-DAE  
B-DAE  
Q-DAE

## Transfer function

$$\mathbf{H}(s) = \frac{2s + 4}{s + 1}$$

## ODE realization $\mathcal{S}_1$

$$\begin{aligned}\dot{x} &= -x + 2u \\ y &= x + 2u\end{aligned}$$

## L-pH realization $\mathcal{S}_2$

$$\begin{aligned}\dot{\mathbf{x}} &= (J - R)Q\mathbf{x} + (G - P)\mathbf{u} = (0 - 1)1\mathbf{x} + (-2 - \sqrt{2})\mathbf{u} \\ \mathbf{y} &= (G + P)^\top Q\mathbf{x} + (N + S)\mathbf{u} = (-2 + \sqrt{2})\mathbf{x} + (0 + 2)\mathbf{u}\end{aligned}$$

where  $\mathcal{V} = -\mathcal{V}^\top$ ,  $\mathcal{W} = \mathcal{W}^\top \succeq 0$  and  $Q = Q^\top \succeq 0$

$$\mathcal{V} = \begin{bmatrix} 0 & 2 \\ -2 & 0 \end{bmatrix} \text{ and } \mathcal{W} = \begin{bmatrix} 1 & \sqrt{2} \\ \sqrt{2} & 2 \end{bmatrix}$$

# Loewner extensions (passive & pH)

Passive & port-Hamiltonian

The transfer function  $\mathbf{H}(s)$  is

- ▶ strictly passive if it is **strictly positive-real** and **asymptotically stable**.
- ▶ (non strictly) passive if it is **positive-real** and **stable**.

The rational transfer function  $\mathbf{H}(s)$  is **strictly positive-real** if  $\Phi_{\mathbf{H}}(\imath\omega) > 0$  and **positive-real** if  $\Phi_{\mathbf{H}}(\imath\omega) \geq 0$  for all  $\omega \in \mathbb{R}$ ,  $\Phi_{\mathbf{H}}(\imath\omega) = \mathbf{H}(\imath\omega)^H + \mathbf{H}(\imath\omega)$

Real  $X \succ 0$  is a **(strict)** passivity certificate for realization  $\mathcal{S} : (A, B, C, D)$  iff.

$$W(X, \mathcal{S}) = \begin{bmatrix} -A^T X - XA & C^T - XB \\ (\star)^T & D + D^T \end{bmatrix} \succeq (\succ) 0$$

---

 P. Benner, P. Goyal and P. Van-Dooren, "Identification of Port-Hamiltonian Systems from Frequency Response Data", Systems & Control Letters, vol. 143, 2020.

# Loewner extensions (passive & pH)

Passive & port-Hamiltonian

## LTI pH model

LTI pH system model of a proper transfer function  $\mathbf{H}$ , has the state-space form

$$\begin{aligned}\dot{\mathbf{x}} &= (J - R)Q\mathbf{x} + (G - P)\mathbf{u} \\ \mathbf{y} &= (G + P)^\top Q\mathbf{x} + (N + S)\mathbf{u}\end{aligned}$$

where

$$\mathcal{V} = \begin{bmatrix} -J & -G \\ G^\top & N \end{bmatrix} \text{ and } \mathcal{W} = \begin{bmatrix} R & P \\ P^\top & S \end{bmatrix}$$

satisfy  $\mathcal{V} = -\mathcal{V}^\top$ ,  $\mathcal{W} = \mathcal{W}^\top \succeq 0$  and  $Q = Q^\top \succeq 0$

## LTI strictly passive & LTI pH equivalence

If  $Q$ ,  $\mathcal{W}$  are invertible,  $\mathbf{X} = Q$  is a strict passivity certificate (i.e.  $W(\mathbf{X}, \mathcal{S}) \succ 0$ ) of the normalized pH system,  $\mathcal{S} : (A, B, C, D)$ , it follows that  $\mathcal{S}$ , can always be transformed in the pH realization.

# Loewner extensions (passive & pH)

Passive & port-Hamiltonian

## LTI pH model

LTI pH system model of a proper transfer function  $\mathbf{H}$ , has the state-space form

$$\begin{aligned}\dot{\mathbf{x}} &= (J - R)Q\mathbf{x} + (G - P)\mathbf{u} \\ \mathbf{y} &= (G + P)^\top Q\mathbf{x} + (N + S)\mathbf{u}\end{aligned}$$

where

$$\mathcal{V} = \begin{bmatrix} -J & -G \\ G^\top & N \end{bmatrix} \text{ and } \mathcal{W} = \begin{bmatrix} R & P \\ P^\top & S \end{bmatrix}$$

satisfy  $\mathcal{V} = -\mathcal{V}^\top$ ,  $\mathcal{W} = \mathcal{W}^\top \succeq 0$  and  $Q = Q^\top \succeq 0$

## LTI strictly passive & LTI pH equivalence

If  $Q$ ,  $\mathcal{W}$  are invertible,  $X = Q$  is a strict passivity certificate (i.e.  $W(X, \mathcal{S}) \succ 0$ ) of the normalized pH system,  $\mathcal{S} : (A, B, C, D)$ , it follows that  $\mathcal{S}$ , can always be transformed in the pH realization.

# Loewner extensions (passive & pH)

Passive & port-Hamiltonian

The **right data** can be expressed as:

$$\begin{aligned}\mathbf{\Lambda} &= \mathbf{diag} [\lambda_1, \dots, \lambda_k] \in \mathbb{C}^{k \times k}, \\ \mathbf{R} &= \begin{bmatrix} \mathbf{r}_1 & \mathbf{r}_2 & \dots & \mathbf{r}_k \end{bmatrix} \in \mathbb{C}^{m \times k} \\ \mathbf{W} &= \begin{bmatrix} \mathbf{w}_1 & \mathbf{w}_2 & \dots & \mathbf{w}_k \end{bmatrix} \in \mathbb{C}^{m \times k}\end{aligned}$$

and the **left data** can be expressed as:

$$\begin{aligned}\mathbf{M} &= -\mathbf{\Lambda}^H = \mathbf{diag} [\mu_1, \dots, \mu_q] \in \mathbb{C}^{q \times q} \\ \mathbf{L}^\top &= \mathbf{R}^H = \begin{bmatrix} \mathbf{l}_1 & \mathbf{l}_2 & \dots & \mathbf{l}_q \end{bmatrix} \in \mathbb{C}^{m \times q} \\ \mathbf{V}^\top &= -\mathbf{W}^H = \begin{bmatrix} \mathbf{v}_1 & \mathbf{v}_2 & \dots & \mathbf{v}_q \end{bmatrix} \in \mathbb{C}^{m \times q}\end{aligned}$$

Spectral zeros are  $(\lambda_j, \mathbf{r}_j)$  from standard Loewner ( $n$  zeros in the open right half-plane)

$$\begin{bmatrix} 0 & A & B \\ A^\top & 0 & C^\top \\ B^\top & C & D + D^\top \end{bmatrix} \begin{bmatrix} p_j \\ q_j \\ \mathbf{r}_j \end{bmatrix} = \lambda_j \begin{bmatrix} 0 & E & 0 \\ E^\top & 0 & 0 \\ 0 & 0 & 0 \end{bmatrix} \begin{bmatrix} p_j \\ q_j \\ \mathbf{r}_j \end{bmatrix}$$



A.C. Antoulas, "A new result on passivity preserving model reduction", Systems & Control Letters, vol. 54, 2005.



P. Benner, P. Goyal and P. Van-Dooren, "Identification of Port-Hamiltonian Systems from Frequency Response Data", Systems & Control Letters, vol. 143, 2020.

# Loewner extensions (passive & pH)

Passive & port-Hamiltonian

The **right data** can be expressed as:

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# Loewner extensions (passive & pH)

Passive & port-Hamiltonian

Then  $\mathbf{H}(s) \in \mathbb{C}^{m \times m}$  of McMillan degree  $n$  and  $\mathcal{S}$  is a normalized pH form and satisfies

$$\mathbf{H}(\infty) = D, \quad \mathbf{H}(\lambda_j)\mathbf{r}_j = \mathbf{w}_j, \quad \mathbf{r}_j^H \mathbf{H}(-\overline{\lambda_j}) = -\mathbf{w}_j^H, \quad D + D^\top \succ 0 \text{ and } \mathbb{L} \succ 0$$

By construction, one obtains an Hermitian  $\mathbb{L} \in \mathbb{C}^{r \times r}$  and a skew symmetric  $\mathbb{M} \in \mathbb{C}^{r \times r}$  matrix. By setting,  $\mathbf{H}(\infty) = D$ , one recovers an  $m \times m$  real transfer function  $\hat{\mathbf{H}}$ . As  $\mathbb{L} \succ 0$ , one may apply the Cholesky decomposition  $\mathbb{L} = T^\top T$ . Then the *normalized pH model* is obtained as  $\Sigma_{\text{n-pH}} := (I_n, T\hat{A}T^{-1}, T\hat{B}, \hat{C}T^{-1}, D)$ ,

$$\mathbf{S} := \begin{bmatrix} -T\hat{A}T^{-1} & -T\hat{B} \\ \hat{C}T^{-1} & D \end{bmatrix},$$

one obtains the equivalent pH-form by solving

$$\begin{bmatrix} -J & -G \\ G^\top & N \end{bmatrix} := \frac{\mathbf{S} - \mathbf{S}^\top}{2} \quad \text{and} \quad \begin{bmatrix} R & P \\ P^\top & S \end{bmatrix} := \frac{\mathbf{S} + \mathbf{S}^\top}{2}.$$

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 P. Benner, P. Goyal and P. Van-Dooren, "Identification of Port-Hamiltonian Systems from Frequency Response Data", Systems & Control Letters, vol. 143, 2020.

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 P. Benner, P. Goyal and P. Van-Dooren, "Identification of Port-Hamiltonian Systems from Frequency Response Data", Systems & Control Letters, vol. 143, 2020.

# Loewner extensions (passive & pH)

Passive & port-Hamiltonian

Require  $\{\lambda_j^0, \mathbf{r}_j^0, \mathbf{w}_j^0\}$ ,  $\{\mu_i^0, \mathbf{l}_i^{0\top}, \mathbf{v}_i^{0\top}\}$ ,  $D$ , objective order  $r$ .

+ Shift data with  $D_s$  as  $\mathbf{w}_j \leftarrow \mathbf{w}_j^0 + D_s$  and  $\mathbf{v}_i \leftarrow \mathbf{v}_i^0 + D_s$

- ▶ Construct the  $r$ -th order Loewner interpolant  $\hat{\Sigma} := (-\mathbb{L}, -\mathbb{M}, \mathbf{V}, \mathbf{W}, 0_m)$
- ▶ Compute the equivalent formulation  $\hat{\Sigma} := (I_r, \hat{A}, \hat{B}, \hat{C}, D_s)$  with transfer  $\hat{\mathbf{H}}$
- + Compute projection  $\hat{\Sigma} \leftarrow P_\infty(\hat{\Sigma})$
- ▶ Compute spectral zeros and directions  $(\xi_j, \mathbf{x}_j)$  of  $\hat{\Sigma}$
- ▶ Set  $\lambda_j \leftarrow \xi_j$ ,  $\mathbf{r}_j \leftarrow \mathbf{x}_j$ ,  $\mathbf{w}_j = \hat{\mathbf{H}}(\lambda_j)\mathbf{r}_j$
- ▶ Construct  $\mathbb{L}$  and  $\mathbb{M}$
- ▶ Set  $\mathbb{M} \leftarrow \mathbb{M} - \mathbf{LDR}$ ,  $\mathbf{V} \leftarrow \mathbf{V} - \mathbf{LD}$  and  $\mathbf{W} \leftarrow \mathbf{W} - \mathbf{DR}$
- ▶ Compute Cholesky decomposition  $\mathbb{L} = T^\top T \Rightarrow$  Numerical issue if NSP
- ▶ Construct  $\hat{\Sigma}_{n\text{-pH}} := (I_n, T\hat{A}T^{-1}, T\hat{B}, \hat{C}T^{-1}, D_s)$
- ▶ Construct  $\hat{\Sigma}_{\text{pH}} := (M, Q, J, R, G, P, N, S)$
- + Set  $S \leftarrow S - D_s$

Ensure  $\hat{\Sigma}_{\text{pH}}$  ensuring interpolatory conditions and strictly passive.

# Loewner extensions (passive & pH)

Passive & port-Hamiltonian

Require  $\{\lambda_j^0, \mathbf{r}_j^0, \mathbf{w}_j^0\}$ ,  $\{\mu_i^0, \mathbf{l}_i^{0\top}, \mathbf{v}_i^{0\top}\}$ ,  $D$ , objective order  $r$  and shift  $D_s$ .

- + Shift data with  $D_s$  as  $\mathbf{w}_j \leftarrow \mathbf{w}_j^0 + D_s$  and  $\mathbf{v}_i \leftarrow \mathbf{v}_i^0 + D_s$
- ▶ Construct the  $r$ -th order Loewner interpolant  $\hat{\Sigma} := (-\mathbb{L}, -\mathbb{M}, \mathbf{V}, \mathbf{W}, 0_m)$
- ▶ Compute the equivalent formulation  $\hat{\Sigma} := (I_r, \hat{A}, \hat{B}, \hat{C}, D_s)$  with transfer  $\hat{\mathbf{H}}$
- + Compute projection  $\hat{\Sigma} \leftarrow P_\infty(\hat{\Sigma})$
- ▶ Compute spectral zeros and directions  $(\xi_j, \mathbf{x}_j)$  of  $\hat{\Sigma}$
- ▶ Set  $\lambda_j \leftarrow \xi_j$ ,  $\mathbf{r}_j \leftarrow \mathbf{x}_j$ ,  $\mathbf{w}_j = \hat{\mathbf{H}}(\lambda_j)\mathbf{r}_j$
- ▶ Construct  $\mathbb{L}$  and  $\mathbb{M}$
- ▶ Set  $\mathbb{M} \leftarrow \mathbb{M} - \mathbf{L}(D + D_s)\mathbf{R}$ ,  $\mathbf{V} \leftarrow \mathbf{V} - \mathbf{L}(D + D_s)$  and  $\mathbf{W} \leftarrow \mathbf{W} - (D + D_s)\mathbf{R}$
- ▶ Compute Cholesky decomposition  $\mathbb{L} = T^\top T$
- ▶ Construct  $\hat{\Sigma}_{n-pH} := (I_n, T\hat{A}T^{-1}, T\hat{B}, \hat{C}T^{-1}, D_s)$
- ▶ Construct  $\hat{\Sigma}_{pH} := (M, Q, J, R, G, P, N, S)$
- + Set  $S \leftarrow S - D_s$

Ensure  $\hat{\Sigma}_{pH}$  ensuring interpolatory conditions and passive.

# Loewner extensions (passive & pH)

Passive & port-Hamiltonian (comments)

## Deal with non strict passivity

This typically occurs when no direct feed-through term exist. As a consequence, the resulting spectral zeros exhibit zeros on the imaginary axis. The first and last bullets address this point.

## Deal with stability

Loewner rational model  $\hat{\mathbf{H}}$  may present unstable singularities. Therefore we suggest a *post stabilisation* onto  $\mathcal{RH}_\infty$  as

$$P_\infty(\hat{\mathbf{H}}) = \arg \inf_{\mathbf{G} \in \mathcal{RH}_\infty} \|\hat{\mathbf{H}} - \mathbf{G}\|_{\mathcal{L}_\infty}.$$

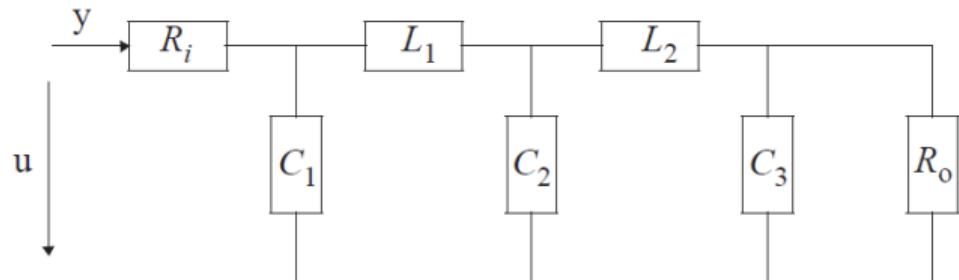
- 
-  T. Breiten and B. Unger, "Passivity preserving model reduction via spectral factorization", *Automatica*. vol. 142, pp. 110368, 2022.
  -  M. Kohler, "On the closest stable descriptor system in the respective spaces  $\mathcal{RH}_2$  and  $\mathcal{RH}_\infty$ ", *Linear Algebra and its Applications*, vol. 443, pp. 34–49, 2014.
  -  C.P-V., D. Matignon, G. Haine and P. Vuillemin, "Data-driven port-Hamiltonian structured identification for non-strictly passive systems", in Proceedings of European Control Conference (ECC), Bucharest, Romania, July 2023.

# Loewner extensions (passive & pH)

RLC ladder network (by A.C. Antoulas, CAS='siso\_passive\_aca')

## Variables & parameters

- ▶  $x_1$ : voltage across  $C_1$
- ▶  $x_2$ : current across  $L_1$
- ▶  $x_3$ : voltage across  $C_2$
- ▶  $x_4$ : current across  $L_2$
- ▶  $x_5$ : voltage across  $C_3$
- ▶  $u$ : voltage
- ▶  $y$ : current
- ▶  $n = 5$  internal variables
- ▶  $C_i = \frac{1}{10} \text{ F}$
- ▶  $L_i = \frac{1}{10} \text{ H}$
- ▶  $R_i = \frac{1}{2} \Omega$
- ▶  $R_o = 5\Omega$

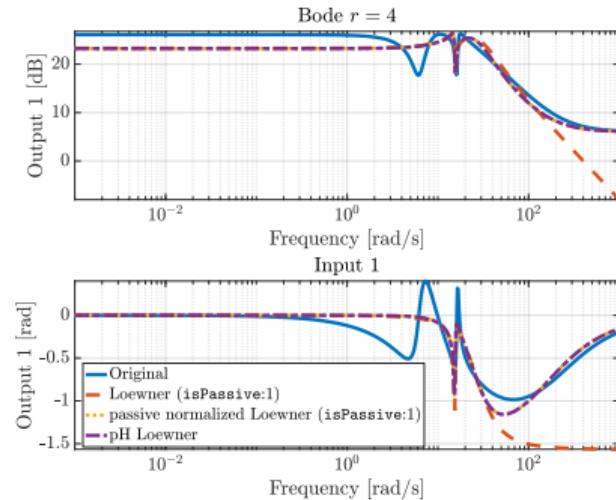
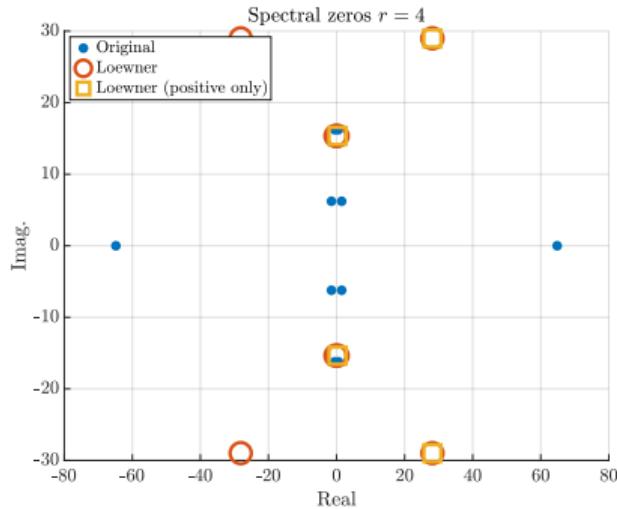


$$A = \begin{bmatrix} -20 & -10 & 0 & 0 & 0 \\ 10 & 0 & -10 & 0 & 0 \\ 0 & 10 & 0 & -10 & 0 \\ 0 & 0 & 10 & 0 & -10 \\ 0 & 0 & 0 & 10 & -2 \end{bmatrix}, B = \begin{bmatrix} 20 \\ 0 \\ 0 \\ 0 \\ 0 \end{bmatrix}$$
$$C = \begin{bmatrix} 20 & 0 & 0 & 0 & 0 \end{bmatrix}, D = 2$$

$$G(s) = \frac{2(s^5 + 222s^4 + 840s^3 + 66600s^2 + 118000s + 2220000)}{s^5 + 22s^4 + 440s^3 + 6600s^2 + 38000s + 220000}$$

# Loewner extensions (passive & pH)

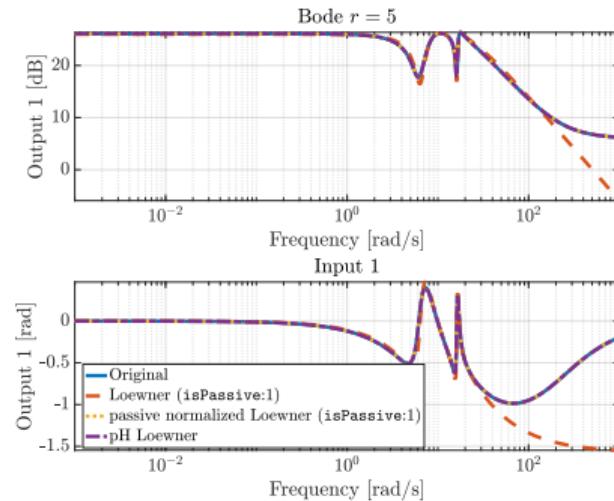
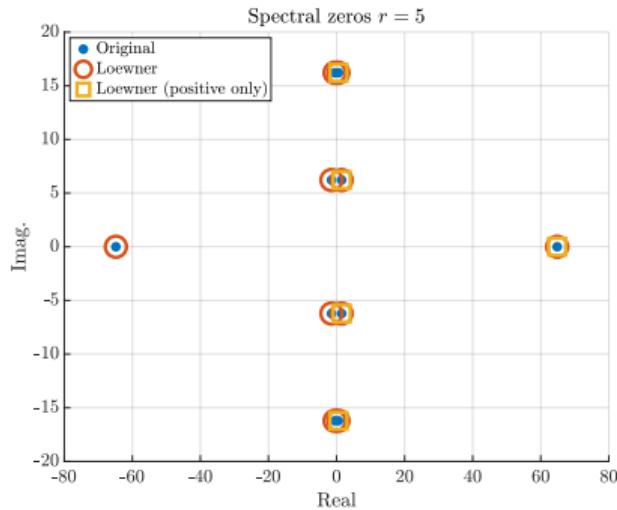
RLC ladder network (by A.C. Antoulas, CAS='siso\_passive\_aca')



Here **all models result stable and passive**; passive normalized allows pH reconstruction

# Loewner extensions (passive & pH)

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# Loewner extensions (passive & pH)

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Model

$$J = \begin{pmatrix} 0 & -54.7 & -39.1 & 15.0 & 66.2 \\ 54.7 & 0 & -16.3 & 0.0922 & 0.782 \\ 39.1 & 16.3 & 0 & 0.0412 & 0.45 \\ -15.0 & -0.0922 & -0.0412 & 0 & -6.32 \\ -66.2 & -0.782 & -0.45 & 6.32 & 0 \end{pmatrix} \quad G = \begin{pmatrix} -49.6 \\ -4.79 \\ -5.15 \\ 0.922 \\ 6.23 \end{pmatrix} \quad P = \begin{pmatrix} 45.0 \\ -5.27 \\ -5.65 \\ 1.21 \\ 8.16 \end{pmatrix}$$

$$R = \begin{pmatrix} 29.8 & 54.3 & 38.6 & -14.8 & -64.3 \\ 54.3 & -1.11 & -0.482 & 0.243 & 1.44 \\ 38.6 & -0.482 & -0.968 & 0.197 & 1.13 \\ -14.8 & 0.243 & 0.197 & -1.59 & -0.504 \\ -64.3 & 1.44 & 1.13 & -0.504 & -4.16 \end{pmatrix} \quad N = 0 \quad S = 2 \quad Q = I_5$$

# Loewner extensions (passive & pH)

RLC ladder network (by A.C. Antoulas, CAS='siso\_passive\_aca')

- $\mathcal{W} = \mathcal{W}^\top \succeq 0$

$$\mathcal{W} = \begin{pmatrix} 29.8 & 54.3 & 38.6 & -14.8 & -64.3 & 45.0 \\ 54.3 & -1.11 & -0.482 & 0.243 & 1.44 & -5.27 \\ 38.6 & -0.482 & -0.968 & 0.197 & 1.13 & -5.65 \\ -14.8 & 0.243 & 0.197 & -1.59 & -0.504 & 1.21 \\ -64.3 & 1.44 & 1.13 & -0.504 & -4.16 & 8.16 \\ 45.0 & -5.27 & -5.65 & 1.21 & 8.16 & 2.0 \end{pmatrix}$$

- $\mathcal{V} = -\mathcal{V}^\top,$

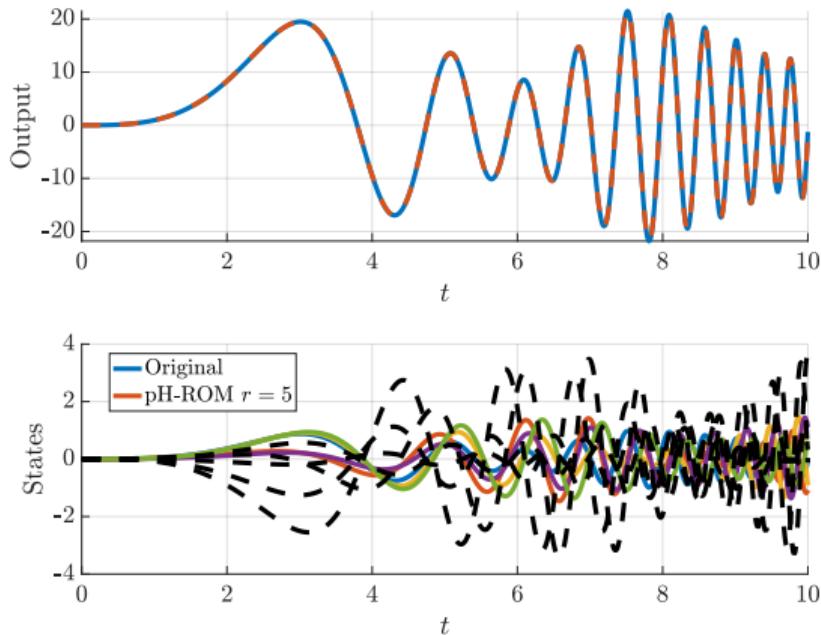
$$\mathcal{V} = \begin{pmatrix} 0 & 54.7 & 39.1 & -15.0 & -66.2 & 49.6 \\ -54.7 & 0 & 16.3 & -0.0922 & -0.782 & 4.79 \\ -39.1 & -16.3 & 0 & -0.0412 & -0.45 & 5.15 \\ 15.0 & 0.0922 & 0.0412 & 0 & 6.32 & -0.922 \\ 66.2 & 0.782 & 0.45 & -6.32 & 0 & -6.23 \\ -49.6 & -4.79 & -5.15 & 0.922 & 6.23 & 0 \end{pmatrix}$$

- $Q = Q^\top \succeq 0$

$$\Lambda(Q) = 1$$

# Loewner extensions (passive & pH)

RLC ladder network (by A.C. Antoulas, CAS='siso\_passive\_aca')



## Time-domain lifting

Simulate and store  $\hat{\mathbf{x}}(t)$ , then lift thanks to generalized reachable subspace

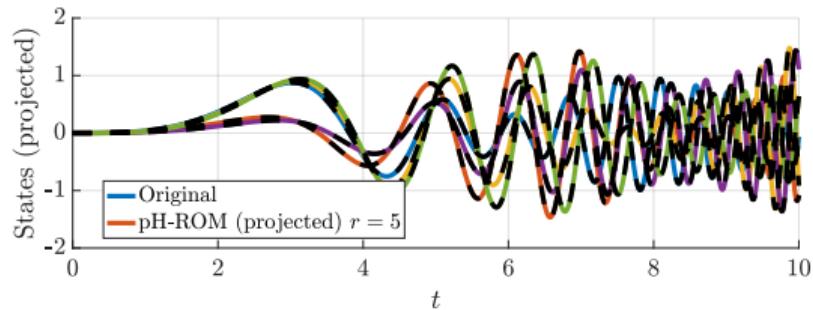
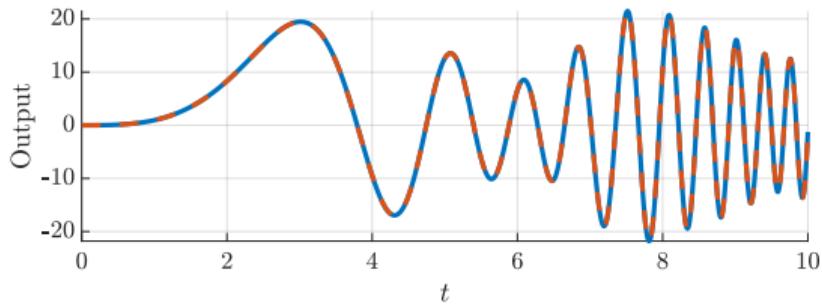
$$\mathbf{x}(t) \approx V\hat{\mathbf{x}}(t)$$

As the system is a normalized passive one, the Hamiltonian energy  $\mathcal{H}(t)$ , internal dissipated power  $\mathcal{D}(t)$  exchange power  $\mathcal{E}(t)$  are given by

$$\begin{aligned}\mathcal{H}(t) &= \hat{\mathbf{x}}(t)^\top \hat{\mathbf{x}}(t) \\ \mathcal{D}(t) &= \hat{\mathbf{x}}(t)^\top (J - R)\hat{\mathbf{x}}(t) \\ \mathcal{E}(t) &= \mathbf{u}(t)^\top \hat{\mathbf{y}}(t)\end{aligned}$$

# Loewner extensions (passive & pH)

RLC ladder network (by A.C. Antoulas, CAS='siso\_passive\_aca')



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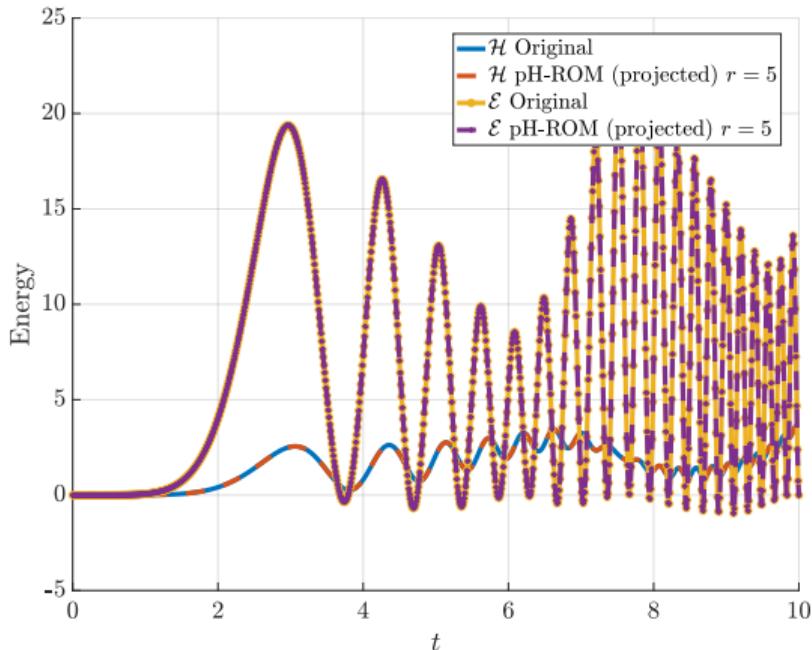
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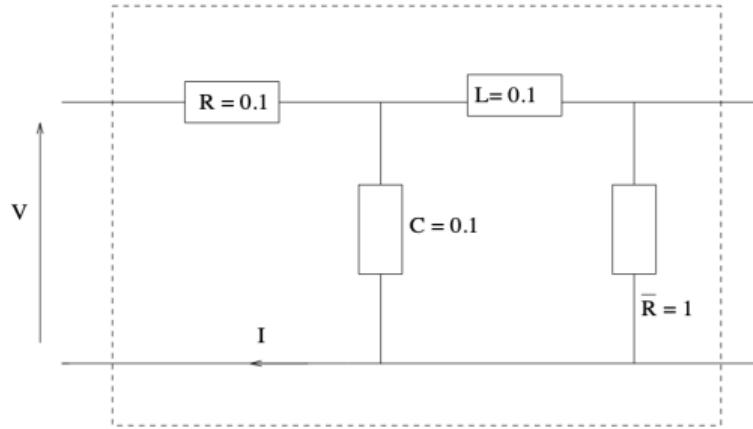
# Loewner extensions (passive & pH)

RLC ladder network (by S. Gugercin, CAS='siso\_passive\_gugercin')

## Variables & parameters

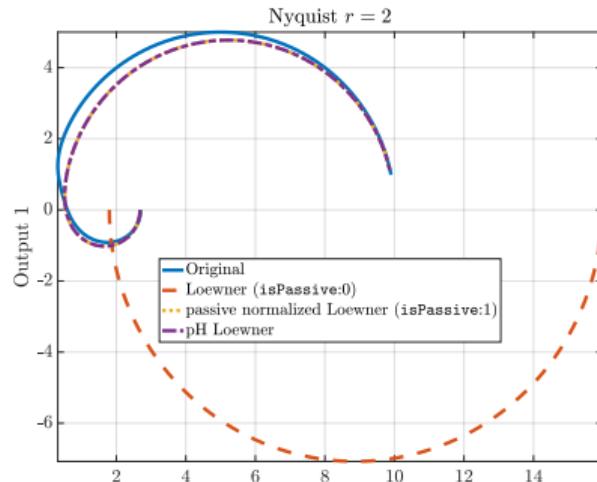
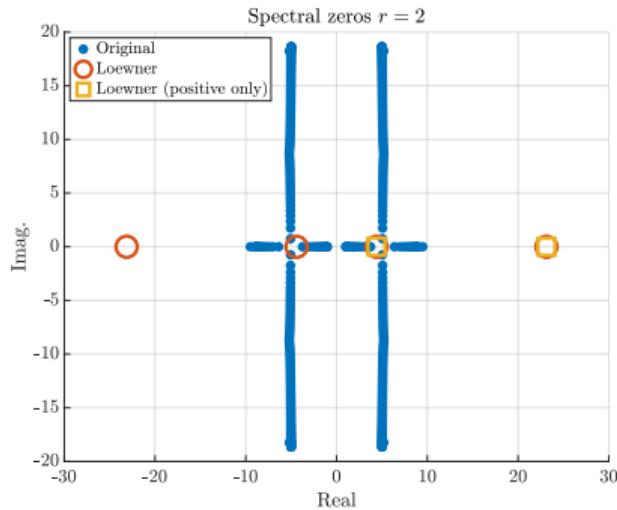
Circuit of 100 sections interconnected in cascade; each section is as shown in Figure. The input is the voltage  $V$  and the output is the current  $I$ , of the first section.

- ▶  $x_i$ : voltage along  $C_i$  and current along  $L_i$
- ▶  $u$ : voltage  $V$
- ▶  $y$ : current  $I$
- ▶  $n = 200$  internal variables
- ▶  $C_i = \frac{1}{10} \text{ F}$
- ▶  $L_i = \frac{1}{10} \text{ H}$
- ▶  $R_i = \frac{1}{10} \Omega$
- ▶  $\bar{R} = 1 \Omega$



# Loewner extensions (passive & pH)

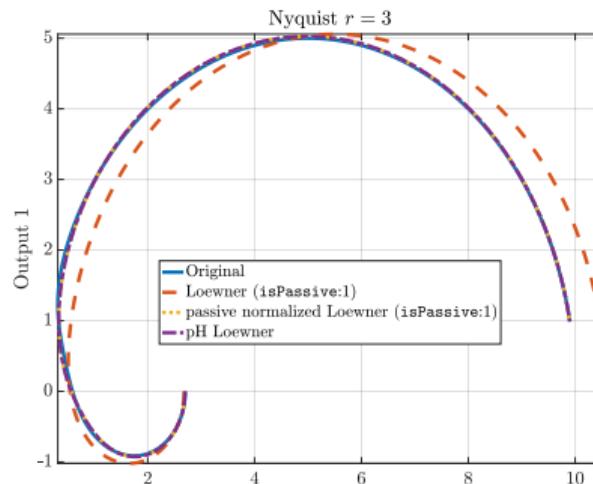
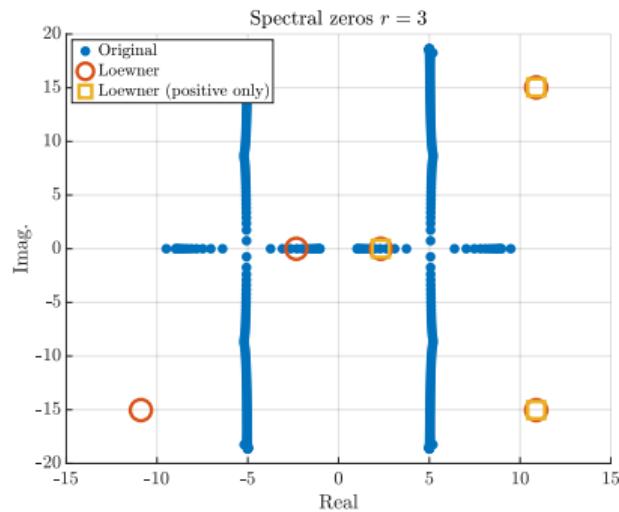
RLC ladder network (by S. Gugercin, CAS='siso\_passive\_gugercin')



Here **NOT all models result stable and passive**; passive normalized allows pH reconstruction

# Loewner extensions (passive & pH)

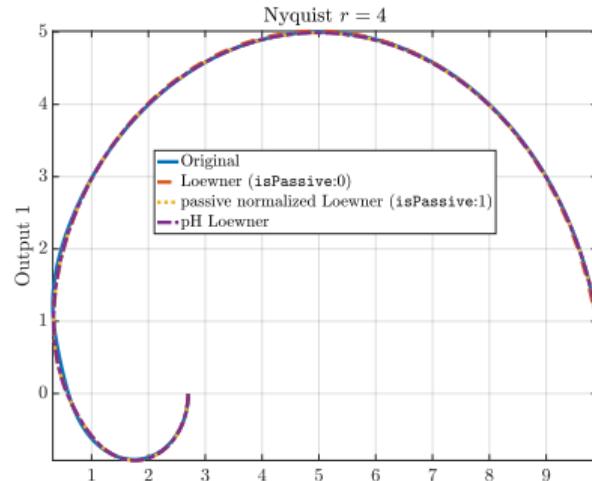
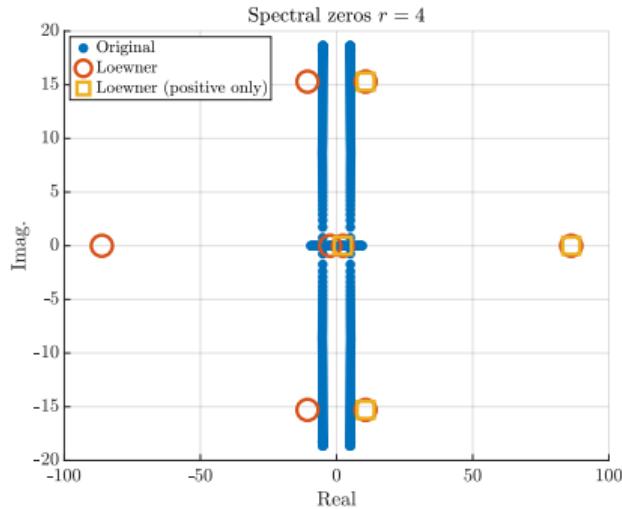
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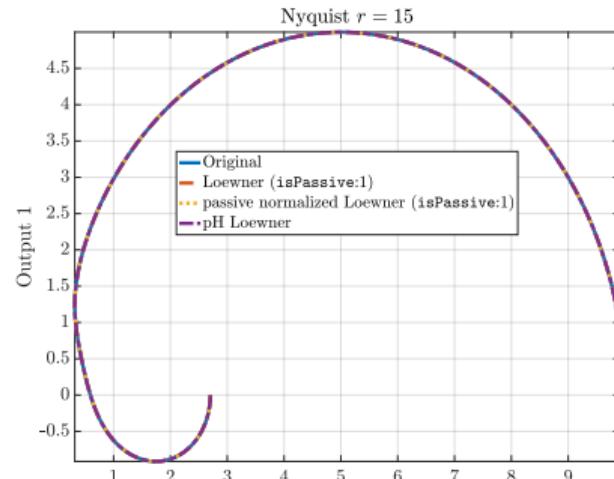
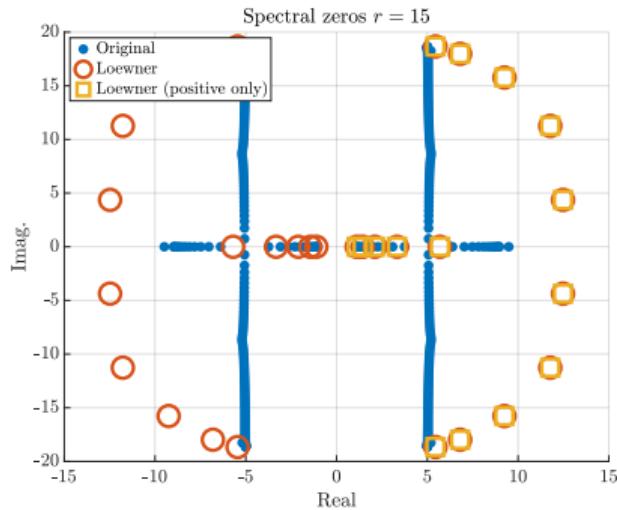
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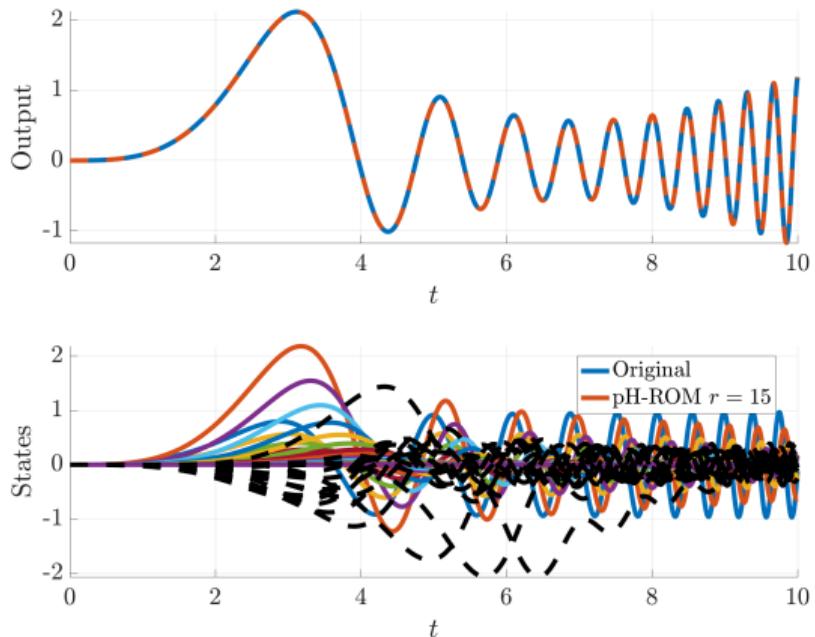
RLC ladder network (by S. Gugercin, CAS='siso\_passive\_gugercin')



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## Time-domain lifting

Simulate and store  $\hat{\mathbf{x}}(t)$ , then lift thanks to generalized reachable subspace

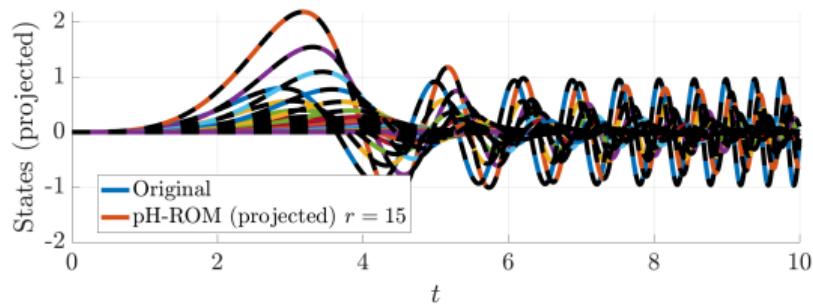
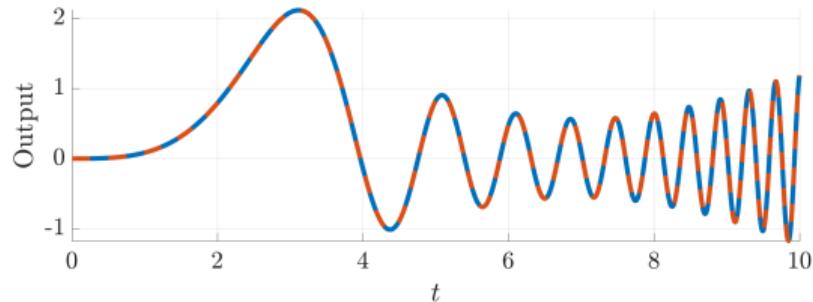
$$\mathbf{x}(t) \approx V\hat{\mathbf{x}}(t).$$

As the system is a normalized passive one, the Hamiltonian energy  $\mathcal{H}(t)$ , internal dissipated power  $\mathcal{D}(t)$  exchange power  $\mathcal{E}(t)$  are given by

$$\begin{aligned}\mathcal{H}(t) &= \hat{\mathbf{x}}(t)^\top \hat{\mathbf{x}}(t) \\ \mathcal{D}(t) &= \hat{\mathbf{x}}(t)^\top (J - R)\hat{\mathbf{x}}(t) \\ \mathcal{E}(t) &= \mathbf{u}(t)^\top \hat{\mathbf{y}}(t)\end{aligned}$$

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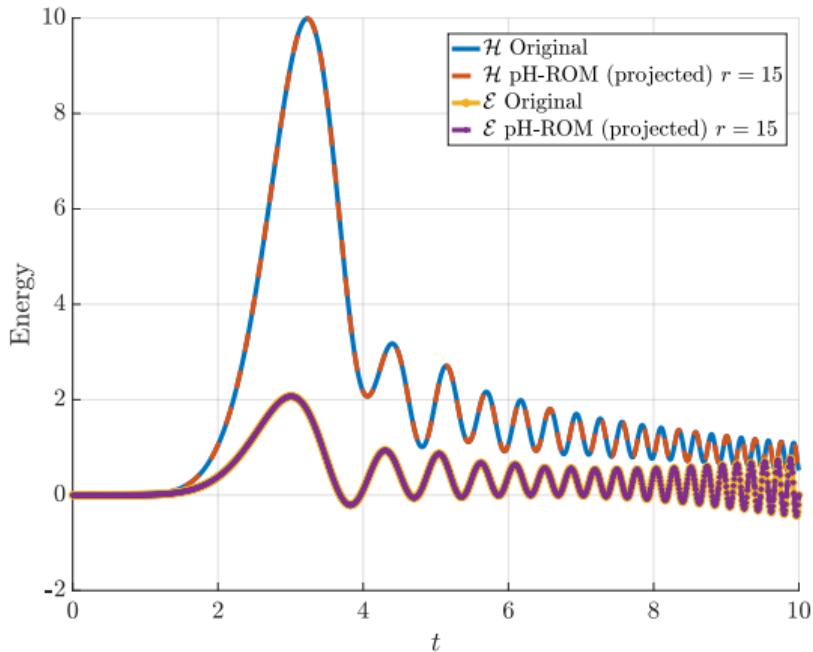
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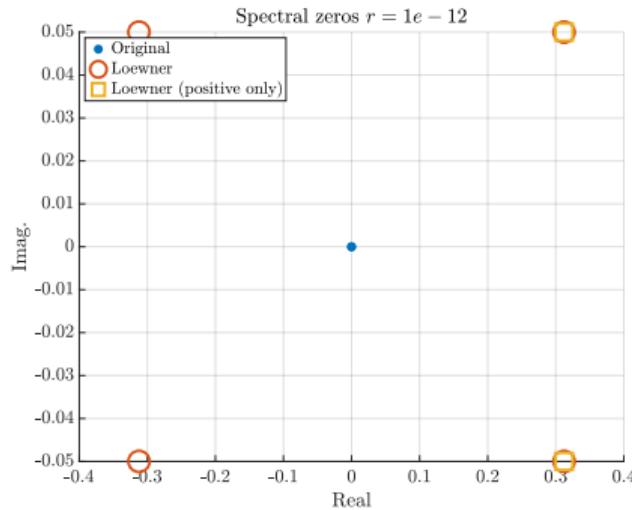
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# Loewner extensions (passive & pH)

Mass-spring-damper (by D. Matignon, see #1 class)



## State-space form

Mass-Spring-Damper

Let us come back to the model given in the motivation.

A usual way to rewrite it in first order form is to define a vector "position-velocity". This leads to:

$$\frac{d}{dt} \begin{pmatrix} x(t) \\ \dot{x}(t) \end{pmatrix} = \begin{bmatrix} 0 & 1 \\ -k/m & -b/m \end{bmatrix} \begin{pmatrix} x(t) \\ \dot{x}(t) \end{pmatrix} + \begin{bmatrix} 0 \\ 1/m \end{bmatrix} F(t),$$

## pH form ("first choice")

Finally, the pHs realisation with this choice is:

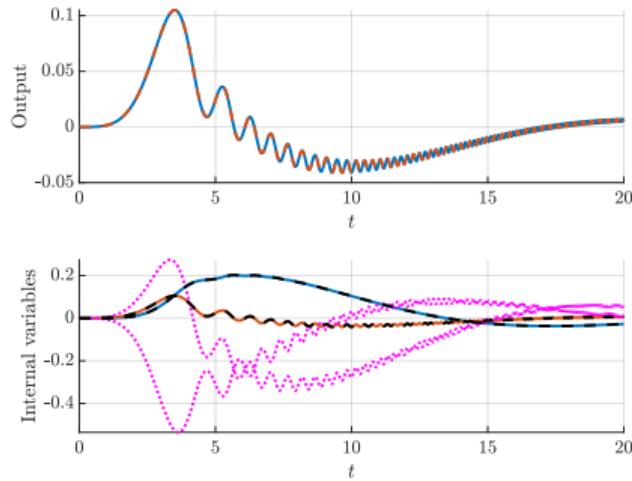
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In this case, the control  $F$ , as it is divided by  $m$ , is nothing but an acceleration, and the output is  $y(t) = \begin{bmatrix} 0 & 1/m \end{bmatrix} \begin{pmatrix} kx(t) \\ m\dot{x}(t) \end{pmatrix} = m\dot{x}(t)$  is the linear momentum.

- ▶ Spectral zeros very close to axis
- ▶ Numerical issues circumvented by **shifting**

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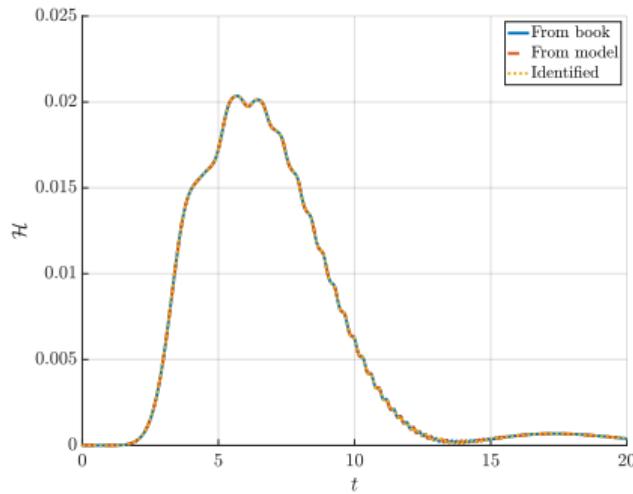
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# Content

Forewords

Linear dynamical systems

Loewner

Loewner extensions (passive & pH)

**Conclusions**

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Loewner... a versatile tool

- ▶ solves the LTI realization problem
- ▶ solves data-driven model reduction
- ▶ solves data-driven model approximation
- ▶ ... and pH
- ▶ ... and also, parametric, bilinear, quadratic...  
→ direct impact in engineers life



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**mor** Digital  
Systems

# Loewner Framework for data-driven reduced order modeling (with pH-structure preserving)

... a bridge between realization, approximation and identification

C. Poussot-Vassal

September 22, 2025

coll. with P. Vuillemin, D. Matignon, G. Haine & M. Fournié



# Conclusions

The map of mathematics (by Dominic Walliman)

