

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

... a bridge between realization, approximation and identification

C. Poussot-Vassal

September 26, 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 (& +1f)**

Lecture Open perspectives (Andrea Brugnoli)

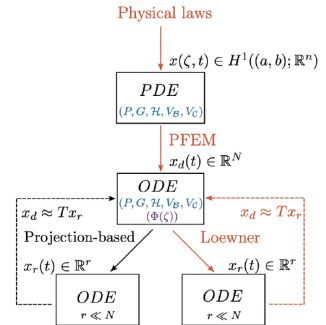


Figure by J.P. Toledo-Zucco



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.

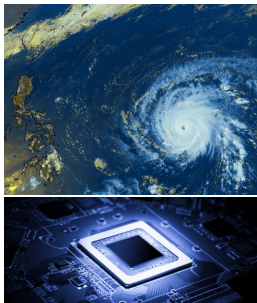


A.C. Antoulas, "*A new result on passivity preserving model reduction*", Systems & Control Letters, vol. 54, 2005.



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

Dynamical models are central tools in engineering...



Digitalisation and computer-based modeling for

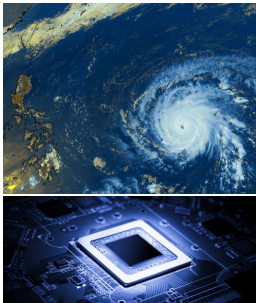
- ▶ simulation, optimisation, understanding
- ▶ control, estimation, analysis...

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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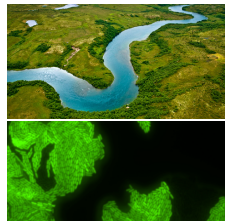
Develop robust and efficient tools to construct simplified dynamical models

... and in systems and control engineering

- ▶ **for verification and validation**
(μ , $\mathcal{H}_\infty$ -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
- ▶ limit model class



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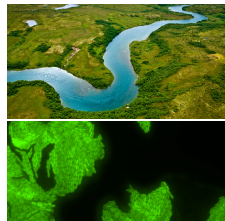
- ▶ important sim. time
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Model simplification

Simplified models

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

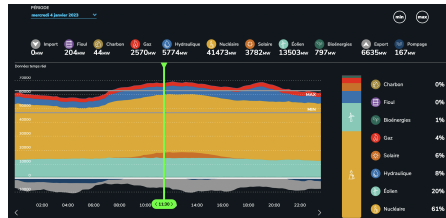


Forewords

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

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

Time-domain

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

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...



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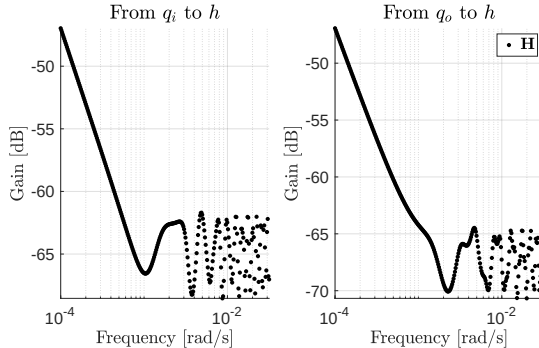
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- Model
(integral and delay action)
- $E\dot{\mathbf{x}} = \mathbf{A}\mathbf{x} + \mathbf{B}\mathbf{u}$
 $\mathbf{H}_{51}$
(full interpolant, **unstable**)
- $\hat{E}\dot{\hat{\mathbf{x}}} = \hat{\mathbf{A}}\hat{\mathbf{x}} + \hat{\mathbf{B}}\mathbf{u}$
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(reduced, **stable, integrator**)
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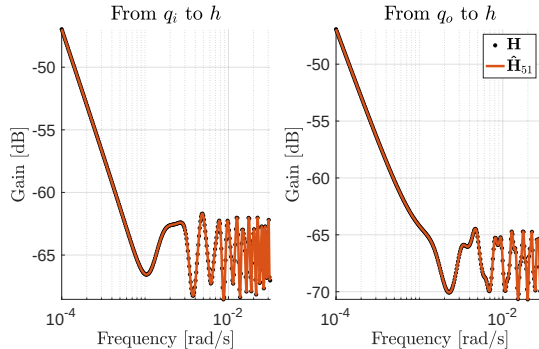
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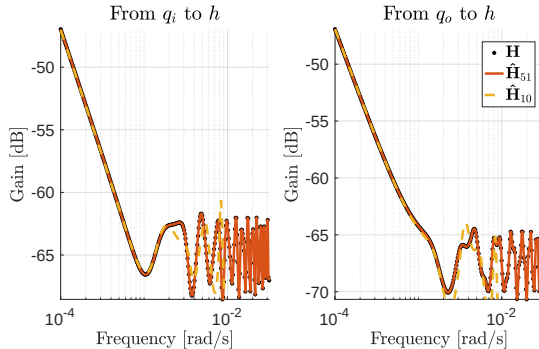
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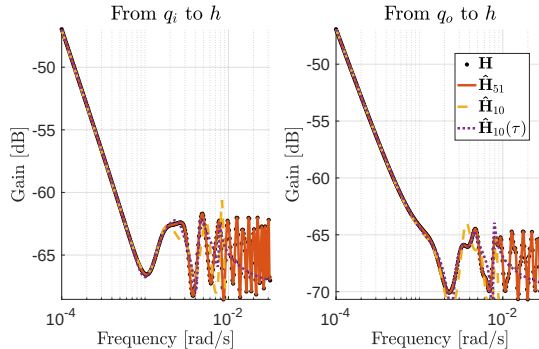
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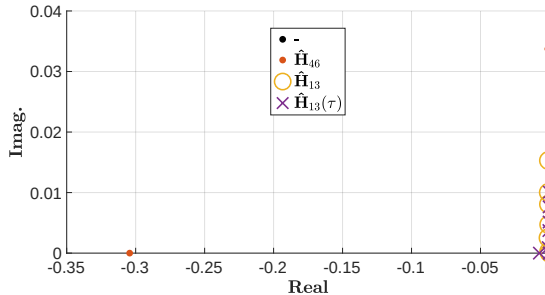
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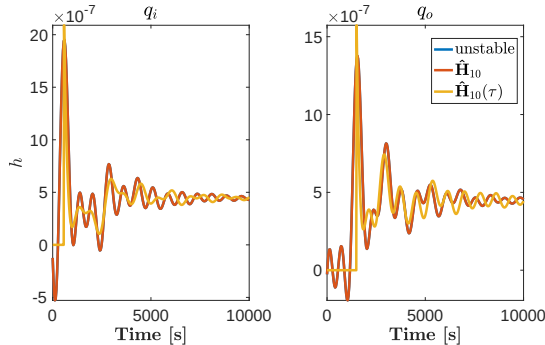
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Use-case: Maxwell (data & model-driven)

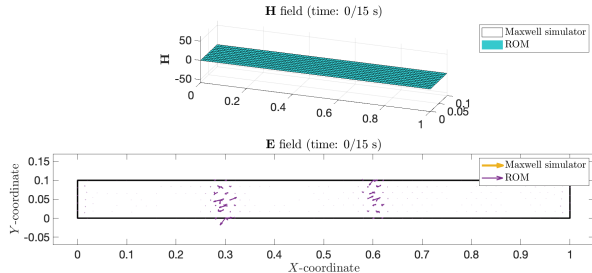
ANTENNA RESEARCH

Antenna models

- ▶ to optimize parameters
- ▶ for polar computation

Blend physics from

- ▶ Maxwell equations
- ▶ Kirchhoff equations



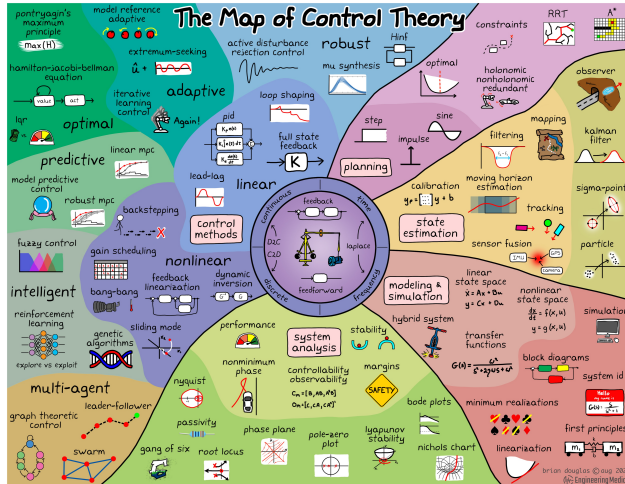
- ▶ Replace costly simulations by accurate simple model
- ▶ Preserve structure and properties (port-Hamiltonian)
- ▶ Allows for geometry optimization



M. Gouzien, C. P-V., 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.

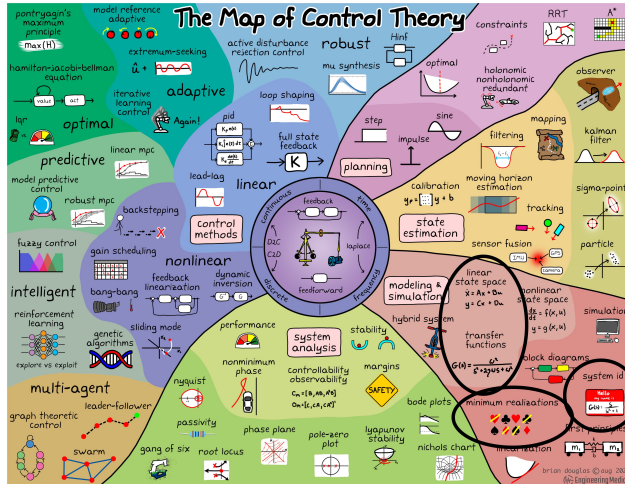
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The map of control theory (by Brian Douglas - <https://engineeringmedia.com/>)



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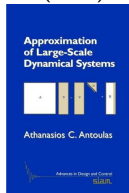
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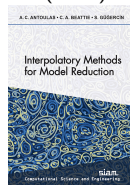
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- ▶ B-LTI, Q-LTI [Antoulas/Benner/Gosea/Karachalios/Pontes/Willcox/P-V./...]
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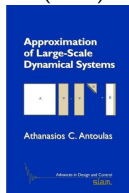
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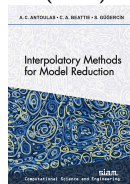
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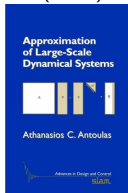
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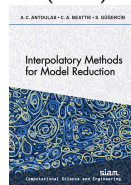
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Part 1 (reminder)

- ▶ 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

Forewords

Linear dynamical systems

Loewner

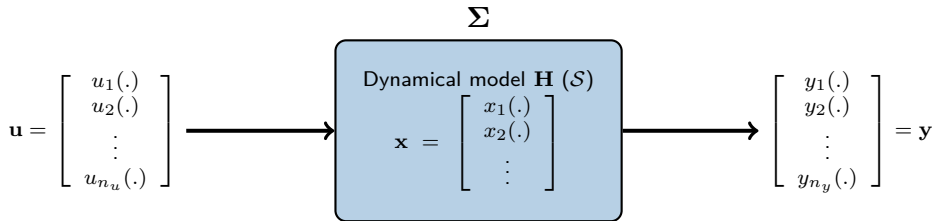
Loewner extensions (passive & pH)

Conclusions

Linear dynamical systems

Simplifications

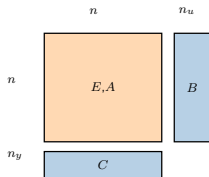
A dynamical model H (or $\mathcal{S}$) is a function mapping input u to output y signals of a system Σ



Let us stick (mainly) to linear systems only

Linear dynamical systems

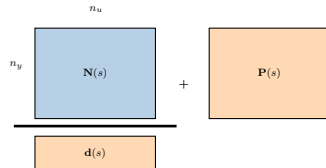
Realization and transfer functions



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

Realizations

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



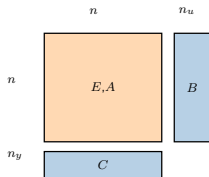
$$\begin{aligned} \mathbf{H}(s) &= C(sE - A)^{-1}B \\ &= \mathbf{N}(s)/\mathbf{d}(s) + \mathbf{P}(s) \end{aligned}$$

Transfer functions

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

Linear dynamical systems

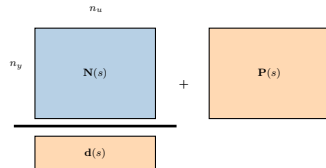
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Linear dynamical systems

Model, data and structures

Structures

L-ODE

L-ODE / DAE-1

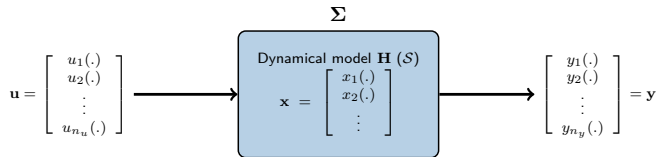
L-DAE

L-DDE

L-PDE

Model

(Time-domain) $\mathcal{S} \sim \mathbf{u} \rightarrow \mathbf{x} \rightarrow \mathbf{y}$
(Frequency-domain) $\mathbf{H} \sim \mathbf{u} \rightarrow \mathbf{y}$



Linear dynamical systems

Linear finite dimensional models

Structures

L-ODE

L-ODE / DAE-1

L-DAE

L-DDE

L-PDE

Transfer function

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

ODE realization $\mathcal{S}$

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

Singularities λ and zeros z

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

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 $(A, E)^a$

$$\lambda_{\mathcal{S}_2} = \Lambda \left(\left[\begin{array}{c|c} -1 & 1 \\ \hline 1 & 0 \end{array} \right], \left[\begin{array}{c|c} 1 & 0 \\ \hline 0 & 0 \end{array} \right] \right) = \{-1, \infty\}$$

$${}^a B^\top = \begin{bmatrix} 2 & -2 \end{bmatrix} \text{ and } C = \begin{bmatrix} 1 & 1 \end{bmatrix}$$

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

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

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

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

Singularities of matrix pencil (A, E)

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

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

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

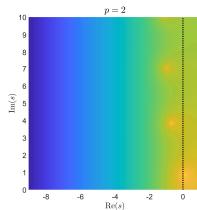
$$\mathbf{H}(s) = \frac{1}{s + e^{-ps}}$$

L-DDE realization $\mathcal{S}$

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

Singularities (periodic)

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



Linear dynamical systems

Linear infinite dimensional models

Structures

L-ODE

L-ODE / DAE-1

L-DAE

L-DDE

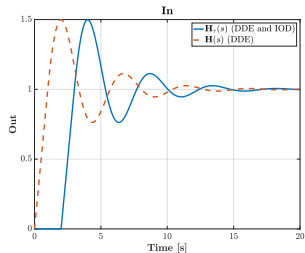
L-PDE

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

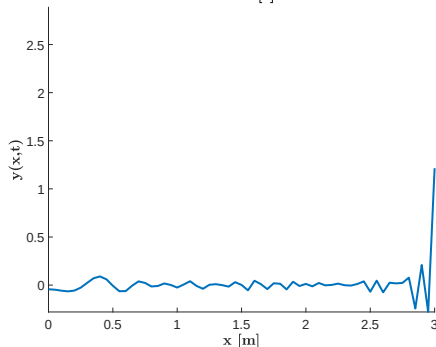
L-DDE

L-PDE

Transfer function (boundary controlled transport)

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

$t = 0$ [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

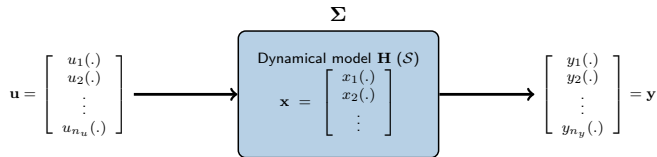
L-DAE

L-DDE

L-PDE

Model

(Time-domain) $\mathcal{S} \sim \mathbf{u} \rightarrow \mathbf{x} \rightarrow \mathbf{y}$
(Frequency-domain) $\mathbf{H} \sim \mathbf{u} \rightarrow \mathbf{y}$



Linear dynamical systems

Why all this? What is common?

Structures

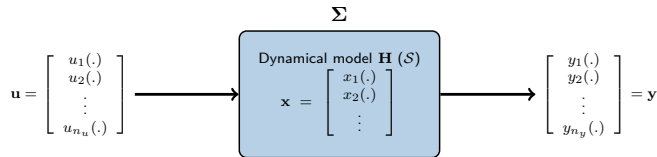
L-ODE
L-ODE / DAE-1
L-DAE
L-DDE
L-PDE

Data

Time-domain
Frequency-domain

Model

(Time-domain) $\mathcal{S} \sim \mathbf{u} \rightarrow \mathbf{x} \rightarrow \mathbf{y}$
(Frequency-domain) $\mathbf{H} \sim \mathbf{u} \rightarrow \mathbf{y}$



(Time-domain) $\{t_i, \mathbf{G}(t_i)\}_{i=1}^N$
(Frequency-domain) $\{z_i, \mathbf{G}(z_i)\}_{i=1}^N$

Data

Forewords

Linear dynamical systems

Loewner

Loewner extensions (passive & pH)

Conclusions

SISO interpolation problem

Given the right and left data (λ_j and μ_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.

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



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.

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 μ_i and λ_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.

Loewner

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

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

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 α_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 α_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.

Loewner

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

The free parameters α_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

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

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

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

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

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

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

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

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

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

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

Loewner

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

$$\mathbb{L} = \begin{bmatrix} \frac{\frac{2}{3}-1}{2-1} & \frac{\frac{2}{3}-\frac{1}{2}}{2-3} \\ \frac{\frac{2}{5}-1}{4-1} & \frac{\frac{2}{5}-\frac{1}{2}}{4-3} \end{bmatrix} = \begin{bmatrix} -\frac{1}{3} & -\frac{1}{6} \\ -\frac{1}{5} & -\frac{1}{10} \end{bmatrix}$$

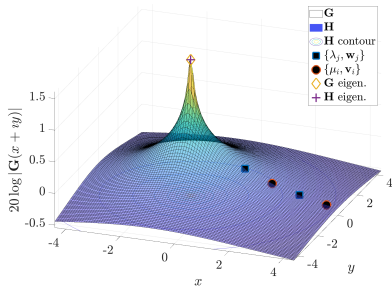
Loewner

Loewner barycentric examples (simple case, CAS=1)

Rational function satisfies

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

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



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

Evaluated at

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

Leads to

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

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

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

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

Loewner

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

Rational function satisfies

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

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

Evaluated at

$$\lambda_1 = \imath, \lambda_2 = 2\imath, \lambda_3 = -2 + \imath$$

$$\mu_1 = -\imath, \mu_2 = 2, \mu_3 = 0.5 - \imath$$

Leads to

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

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

Loewner

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

Rational function satisfies

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

Realization $n = 3$

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

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

Resulting in

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

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

Evaluated at

$$\lambda_1 = \imath, \lambda_2 = 2\imath, \lambda_3 = -2 + \imath \\ \mu_1 = -\imath, \mu_2 = 2, \mu_3 = 0.5 - \imath$$

Leads to

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

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

Loewner

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

Rational function satisfies

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

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

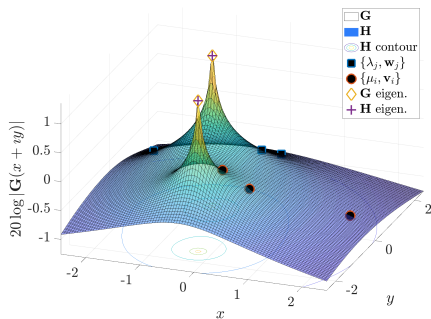
Evaluated at

$$\lambda_1 = i, \lambda_2 = 2i, \lambda_3 = -2 + i$$

$$\mu_1 = -i, \mu_2 = 2, \mu_3 = 0.5 - i$$

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

Code break (<https://github.com/cpoussot/lf>)

```
% 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

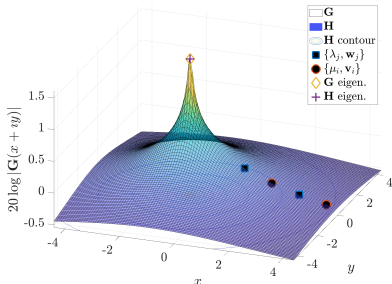
% Loewner
LL = lf.loewnerMatrix(la,mu,W,V);
c = null(sym(LL));
% Realization
C = c.'*W(:).';
B = zeros(k,1); B(end) = 1;
PHI = [s-la(1)*ones(k-1,1) diag(la(2:end))-s*eye(k-1); c.'];
Hr = simplify(C*(PHI\B));
```

Loewner

Code break (<https://github.com/cpoussot/lf>)

```
% Model (CAS=1)
S = ss(tf(2,[1 1])); S.E = 1;
[A,B,C,D,E] = dssdata(S);
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Hr = simplify(C*(PHI\B));
```



SISO interpolation problem

Given the right and left data (λ_j and μ_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.

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



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 (λ_j and μ_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.

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



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:

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

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

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

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

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

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

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

The **Loewner matrix** in this case is

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

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

The **shifted Loewner matrix** is:

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

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

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,

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

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

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

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

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

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

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

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

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

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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

$$\begin{aligned} W^\top E V \hat{\mathbf{x}}(t) &= W^\top A V \hat{\mathbf{x}}(t) + W^\top B \mathbf{u}(t) \\ \hat{\mathbf{y}}(t) &= C V \hat{\mathbf{x}}(t) + D \mathbf{u}(t) \end{aligned}$$

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

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

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)

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

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

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



Therefore,

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

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.



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

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



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

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

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

► 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 (ν) 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

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



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

$$\lambda_1 = 1, \lambda_2 = 2 \\ \mu_1 = -1, \mu_2 = -2$$

Leads to

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

Loewner

Loewner examples (simple case, CAS=4)

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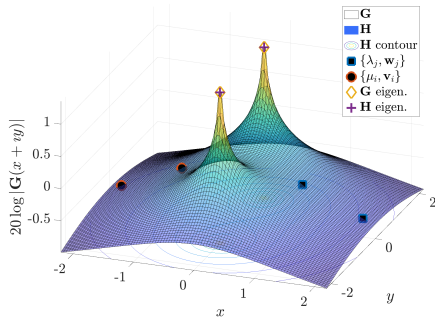
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$$\mathbf{w}_1 = \frac{1}{2}, \mathbf{w}_2 = \frac{1}{5}$$

$$\mathbf{v}_1 = \frac{1}{2}, \mathbf{v}_2 = \frac{1}{5}$$

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

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



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 (ν) 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

$$\lambda_1 = 1, \lambda_2 = 2 \\ \mu_1 = -1, \mu_2 = -2$$

Leads to

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

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

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

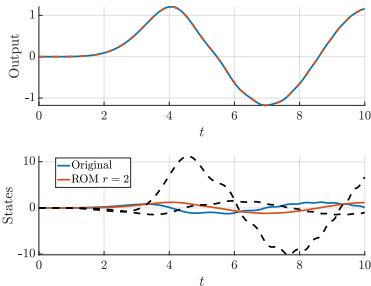
Loewner

Loewner examples (simple case, CAS=4)

Rational function satisfies

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

Output and internal variables



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

Evaluated at

$$\lambda_1 = 1, \lambda_2 = 2 \\ \mu_1 = -1, \mu_2 = -2$$

Leads to

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

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

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

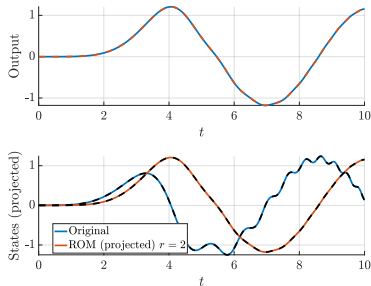
Loewner

Loewner examples (simple case, CAS=4)

Rational function satisfies

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

Output and internal **projected** variables



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

Evaluated at

$$\lambda_1 = 1, \lambda_2 = 2$$

$$\mu_1 = -1, \mu_2 = -2$$

Leads to

$$\mathbf{w}_1 = \frac{1}{2}, \mathbf{w}_2 = \frac{1}{5}$$

$$\mathbf{v}_1 = \frac{1}{2}, \mathbf{v}_2 = \frac{1}{5}$$

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

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

Loewner

Loewner examples (rectangular case, CAS=5)

Rational function satisfies

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

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

Evaluated at

$$\lambda_1 = 1, \lambda_2 = 2, \lambda_2 = 3$$

$$\mu_1 = -1, \mu_2 = -2$$

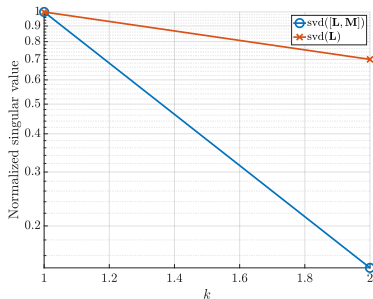
Loewner

Loewner examples (rectangular case, CAS=5)

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

$$\lambda_1 = 1, \lambda_2 = 2, \lambda_3 = 3$$

$$\mu_1 = -1, \mu_2 = -2$$

Leads to

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

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

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

Loewner

Loewner examples (rectangular case, CAS=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 (ν) orders

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

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

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

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

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

Evaluated at

$$\lambda_1 = 1, \lambda_2 = 2, \lambda_3 = 3$$

$$\mu_1 = -1, \mu_2 = -2$$

Leads to

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

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

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

Loewner

Loewner examples (lot of data case, CAS=6)

Rational function satisfies

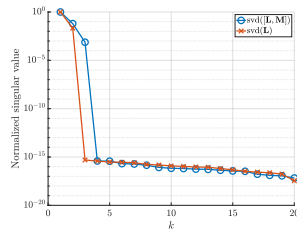
$$\mathbf{H}(\lambda_j) = \mathbf{w}_j \text{ and } \mathbf{H}(\mu_i) = \mathbf{v}_i$$

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

Evaluated at

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

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



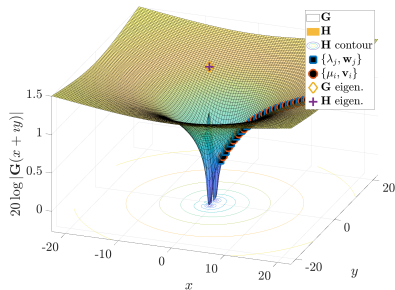
Loewner

Loewner examples (lot of data case, CAS=6)

Rational function satisfies

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

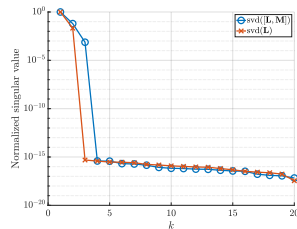
Realization $n = 20$: $\mathbf{H}(s) = \mathbf{W}(-s\mathbb{L} + \mathbf{M})^{-1}\mathbf{V}$



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

Evaluated at

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



Loewner

Loewner examples (lot of data case, CAS=6)

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 (ν) orders

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

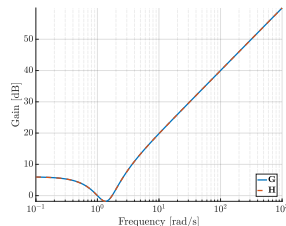
$$\text{rank}(\mathbb{L}) = \nu = 2$$

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

Evaluated at

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

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



Loewner

Loewner examples (lot of data case, CAS=6)

Rational function satisfies

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

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

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

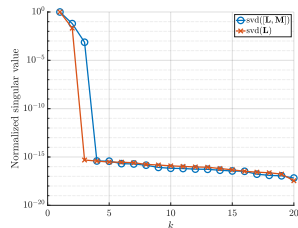
$$\begin{aligned} \mathbf{H}(s) &= \mathbf{W} \mathbf{X} (-s \mathbf{Y}^\top \mathbb{L} \mathbf{X} + \mathbf{Y}^\top \mathbb{M} \mathbf{X})^{-1} \mathbf{Y}^\top \mathbf{V} \\ &= \frac{s^2 + s + 2}{s + 1} \end{aligned}$$

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

Evaluated at

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

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



Loewner

Loewner 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

$$\lambda_1 = i, \lambda_2 = 2i, \lambda_3 = -2 + i$$

$$\mu_1 = -i, \mu_2 = 2, \mu_3 = 0.5 - i$$

Leads to

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

Loewner

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

Rational function satisfies

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

Rank reveals the underlying rational (r) and McMillan (ν) 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

$$\lambda_1 = i, \lambda_2 = 2i, \lambda_3 = -2 + i$$

$$\mu_1 = -i, \mu_2 = 2, \mu_3 = 0.5 - i$$

Leads to

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

$$\hat{\mathbb{L}} = \begin{bmatrix} -0.207 + 0.9568i & -0.1276 - 0.0294i \\ -0.0438 - 0.0818i & 0.039 - 0.1089i \end{bmatrix}$$

$$\hat{\mathbb{M}} = \begin{bmatrix} 0.4738 - 0.0560i & 0.0089 - 0.3392i \\ 0.2253 - 0.1607i & -0.0342 + 0.1308i \end{bmatrix}$$

```
% 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

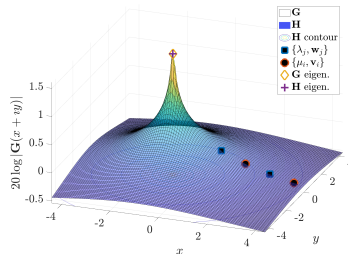
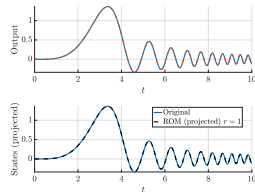
% Loewner
[hr,info] = lf.loewner_tng(la,mu,W,V,R,L);
```

Loewner

Code break (<https://github.com/cpoussot/lf>)

```
% 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

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Loewner extensions (passive & pH)

Passive & port-Hamiltonian

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Passivity

$$\dot{\mathbf{x}} = A\mathbf{x} + B\mathbf{u}$$

$$\mathbf{y} = C\mathbf{x} + D\mathbf{u}$$

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

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

pH

$$\dot{\mathbf{x}} = (J - R)Q\mathbf{x} + (G - P)\mathbf{u}$$

$$\mathbf{y} = (G + P)^{\top}Q\mathbf{x} + (N + S)\mathbf{u}$$

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

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

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

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

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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

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

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

Loewner extensions (passive & pH)

Passive & port-Hamiltonian

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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 $\Phi_{\mathbf{H}}(j\omega) > 0$ and **positive-real** if $\Phi_{\mathbf{H}}(j\omega) \geq 0$ for all $\omega \in \mathbb{R}$, $\Phi_{\mathbf{H}}(j\omega) = \mathbf{H}(j\omega)^H + \mathbf{H}(j\omega)$

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

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



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

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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. $W(X, S) \succ 0$) of the normalized pH system, $S : (A, B, C, D)$, it follows that 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

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

Loewner extensions (passive & pH)

Passive & port-Hamiltonian

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

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

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

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

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:

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

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

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

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

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

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

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 $\Sigma_{n\text{-pH}} := (I_n, T\hat{A}T^{-1}, T\hat{B}, \hat{C}T^{-1}, D)$,

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

one obtains the equivalent pH-form by solving

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



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

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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 $\hat{\Sigma}_{\text{n-pH}} := (I_n, T\hat{A}T^{-1}, T\hat{B}, \hat{C}T^{-1}, D_s)$

► 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.



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 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 Chloesky decomposition $\mathbb{L} = T^\top T$
- Construct $\hat{\Sigma}_{\text{n-pH}} := (I_n, T\hat{A}T^{-1}, T\hat{B}, \hat{C}T^{-1}, D_s)$
- 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 passive.



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)

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.



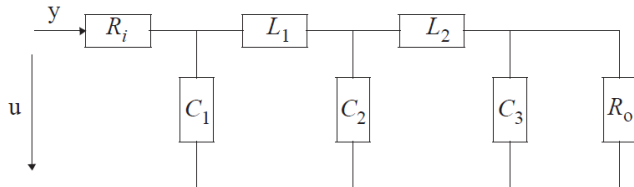
C.P-V., D. Matignon, G. Haine and P. Vuillemin, "*Data-driven port-Hamiltonian structured identification for non-strictly passive systems*", in Proceedings of European Control Conference (ECC), Bucharest, Romania, July 2023.

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
- ▶ $C_i = \frac{1}{10}$ F
- ▶ $L_i = \frac{1}{10}$ H
- ▶ $R_i = \frac{1}{2}\Omega$
- ▶ $R_o = 5\Omega$

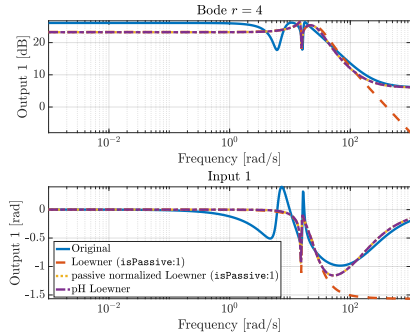
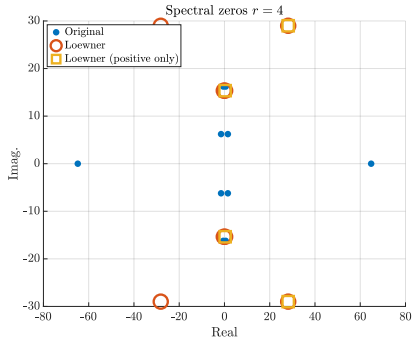


$$A = \begin{bmatrix} -20 & -10 & 0 & 0 & 0 \\ 10 & 0 & -10 & 0 & 0 \\ 0 & 10 & 0 & -10 & 0 \\ 0 & 0 & 10 & 0 & -10 \\ 0 & 0 & 0 & 10 & -2 \end{bmatrix}, B = \begin{bmatrix} 20 \\ 0 \\ 0 \\ 0 \\ 0 \end{bmatrix}$$
$$C = \begin{bmatrix} 20 & 0 & 0 & 0 & 0 \end{bmatrix}, D = 2$$

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

Loewner extensions (passive & pH)

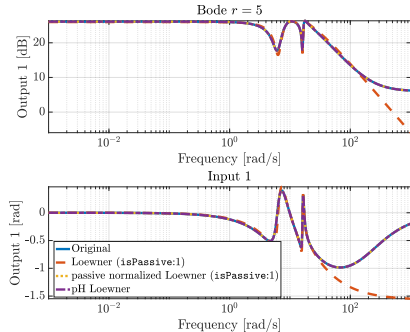
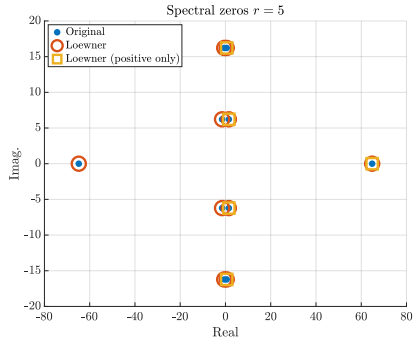
RLC ladder network (by A.C. Antoulas, CAS='siso_passive_aca')



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

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

where

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

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

Loewner extensions (passive & pH)

RLC ladder network (by A.C. Antoulas, CAS='siso_passive_aca')

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

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

► $\mathcal{V} = -\mathcal{V}^\top,$

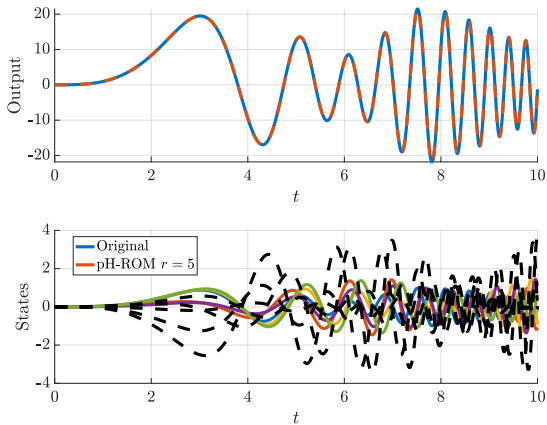
$$\mathcal{V} = \begin{pmatrix} 0 & 54.7 & 39.1 & -15.0 & -66.2 & 49.6 \\ -54.7 & 0 & 16.3 & -0.0922 & -0.782 & 4.79 \\ -39.1 & -16.3 & 0 & -0.0412 & -0.45 & 5.15 \\ 15.0 & 0.0922 & 0.0412 & 0 & 6.32 & -0.922 \\ 66.2 & 0.782 & 0.45 & -6.32 & 0 & -6.23 \\ -49.6 & -4.79 & -5.15 & 0.922 & 6.23 & 0 \end{pmatrix}$$

► $Q = Q^\top \succeq 0$

$$\Lambda(Q) = 1$$

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

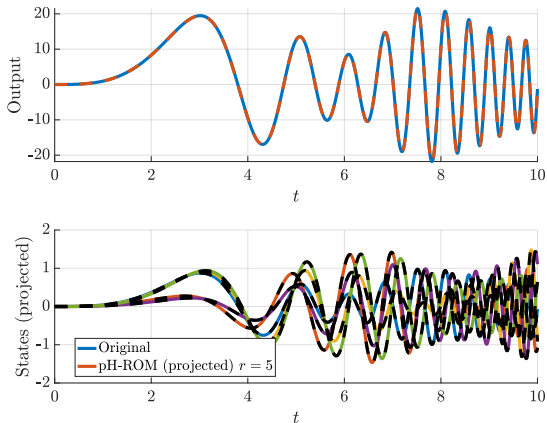
$$\mathbf{x}(t) \approx V \hat{\mathbf{x}}(t)$$

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')



Time-domain lifting

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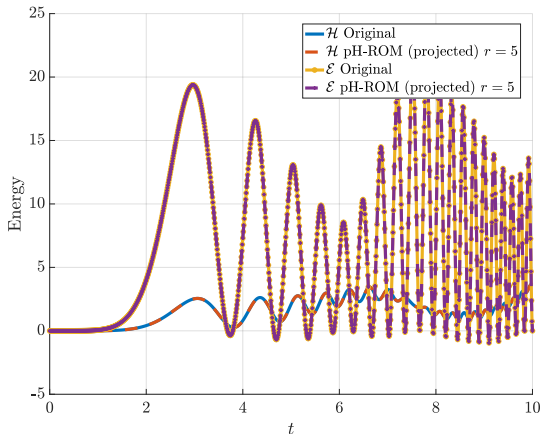
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Loewner extensions (passive & pH)

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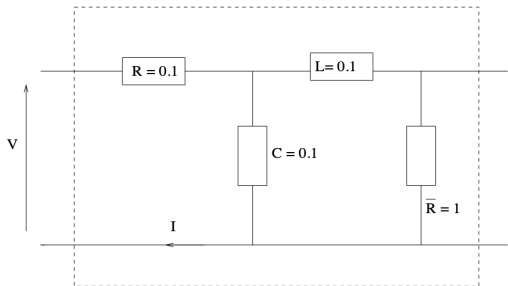
Loewner extensions (passive & pH)

RLC ladder network (by S. Gugercin, CAS='siso_passive_gugercin')

Variables & parameters

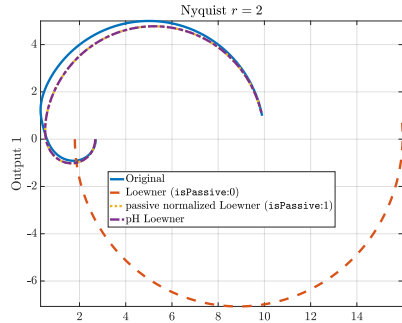
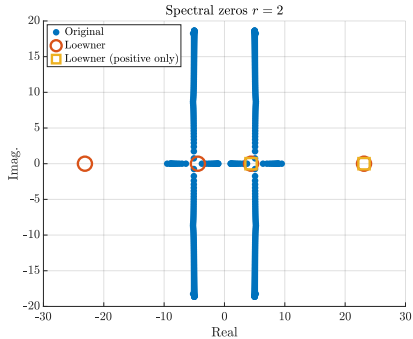
Circuit of 100 sections interconnected in cascade; each section is as shown in Figure. The input is the voltage V and the output is the current I , of the first section.

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



Loewner extensions (passive & pH)

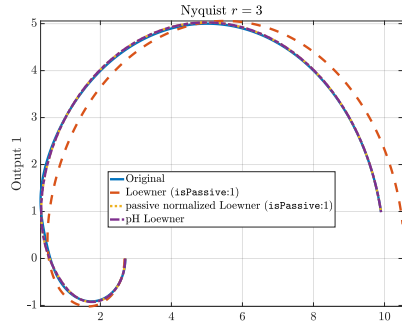
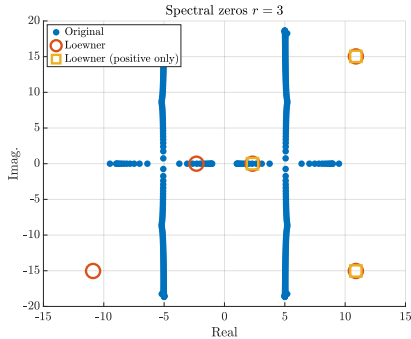
RLC ladder network (by S. Gugercin, CAS='siso_passive_gugercin')



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

Loewner extensions (passive & pH)

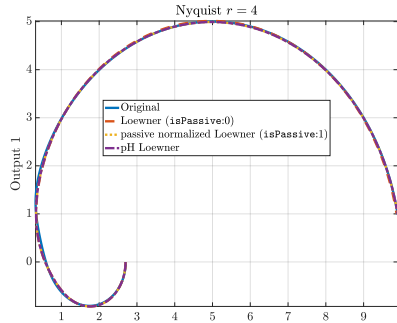
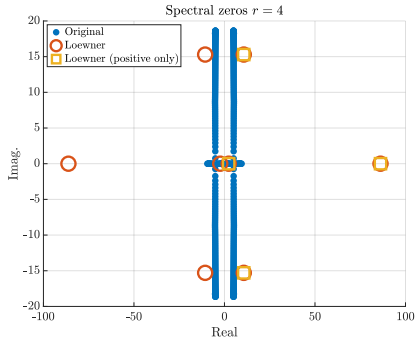
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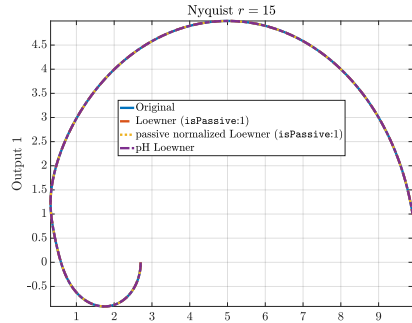
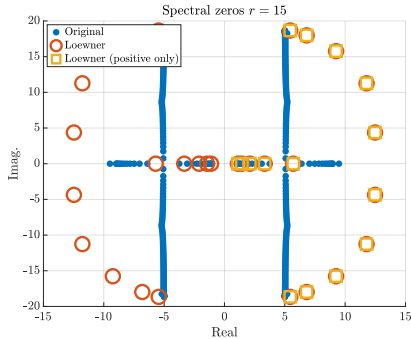
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Loewner extensions (passive & pH)

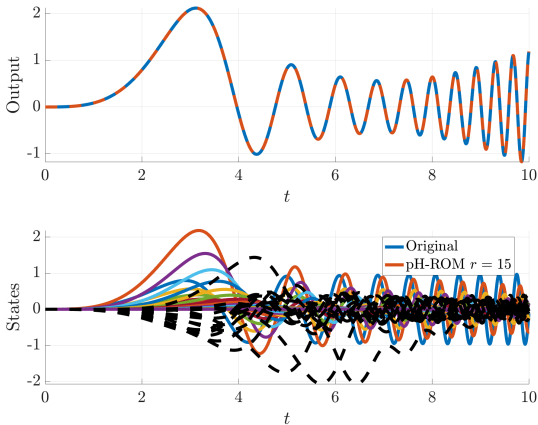
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Loewner extensions (passive & pH)

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Time-domain lifting

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Loewner extensions (passive & pH)

RLC ladder network (by S. Gugercin, CAS='siso_passive_gugercin')

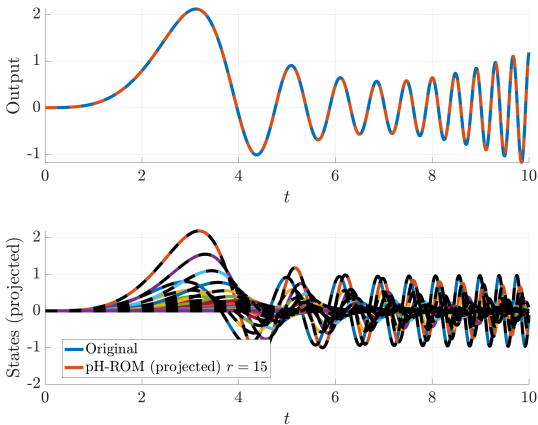
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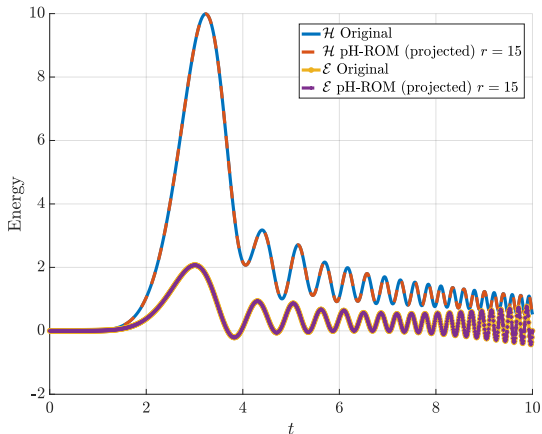
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RLC ladder network (by S. Gugercin, CAS='siso_passive_gugercin')



Time-domain lifting

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

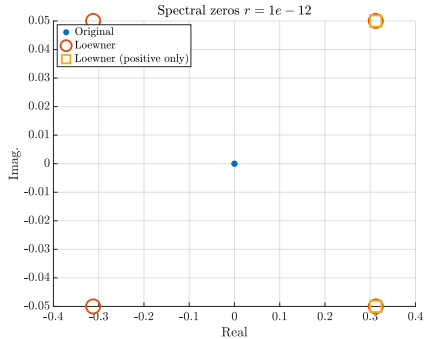
$$\mathbf{x}(t) \approx V\hat{\mathbf{x}}(t).$$

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)

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:

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

pH form ("first choice")

Finally, the pHs realisation with this choice is:

$$\frac{d}{dt} \begin{pmatrix} x(t) \\ \dot{x}(t) \end{pmatrix} = \left(\begin{bmatrix} 0 & \frac{1}{m} \\ -\frac{1}{m} & 0 \end{bmatrix} - \begin{bmatrix} 0 & 0 \\ 0 & \frac{b}{m^2} \end{bmatrix} \right) \begin{pmatrix} kx(t) \\ m\dot{x}(t) \end{pmatrix} + \begin{bmatrix} 0 \\ \frac{1}{m} \end{bmatrix} F(t).$$

In this case, the control F , as it is divided by m , is nothing but an acceleration, and the output is

$$y(t) = \begin{bmatrix} 0 & \frac{1}{m} \end{bmatrix} \begin{pmatrix} kx(t) \\ m\dot{x}(t) \end{pmatrix} = m\dot{x}(t) \text{ is the linear momentum.}$$

- Spectral zeros very close to axis
- Numerical issues circumvented by **shifting**
- To validate...

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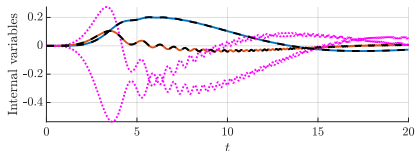
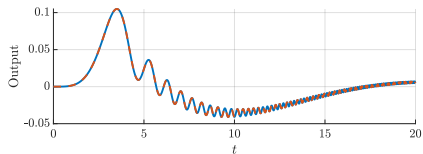
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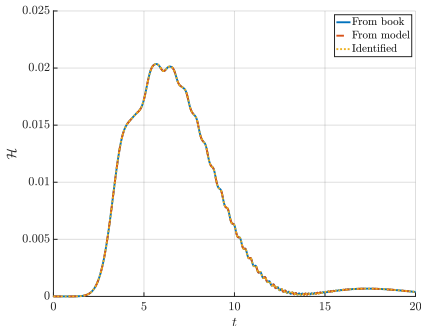
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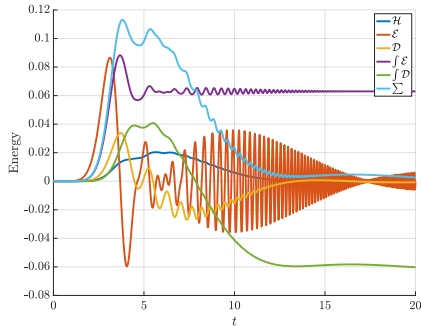
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Loewner extensions (passive & pH)

Infinite dimensional MIMO case (by A. Brugnoli reshaped by D. Matignon)

Presentation

a

Loewner extensions (passive & pH)

Infinite dimensional MIMO case (by A. Brugnoli reshaped by D. Matignon)

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



... still so much to do

- ▶ Technical references, slides and code at

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

... a bridge between realization, approximation and identification

C. Poussot-Vassal

September 26, 2025

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



Conclusions

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Loewner

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Conclusions

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Conclusions

The map of mathematics (by Dominic Walliman)

