C. Poussot-Vassal
Prix de la recherche scientifique ONERA

C. Poussot-Vassal

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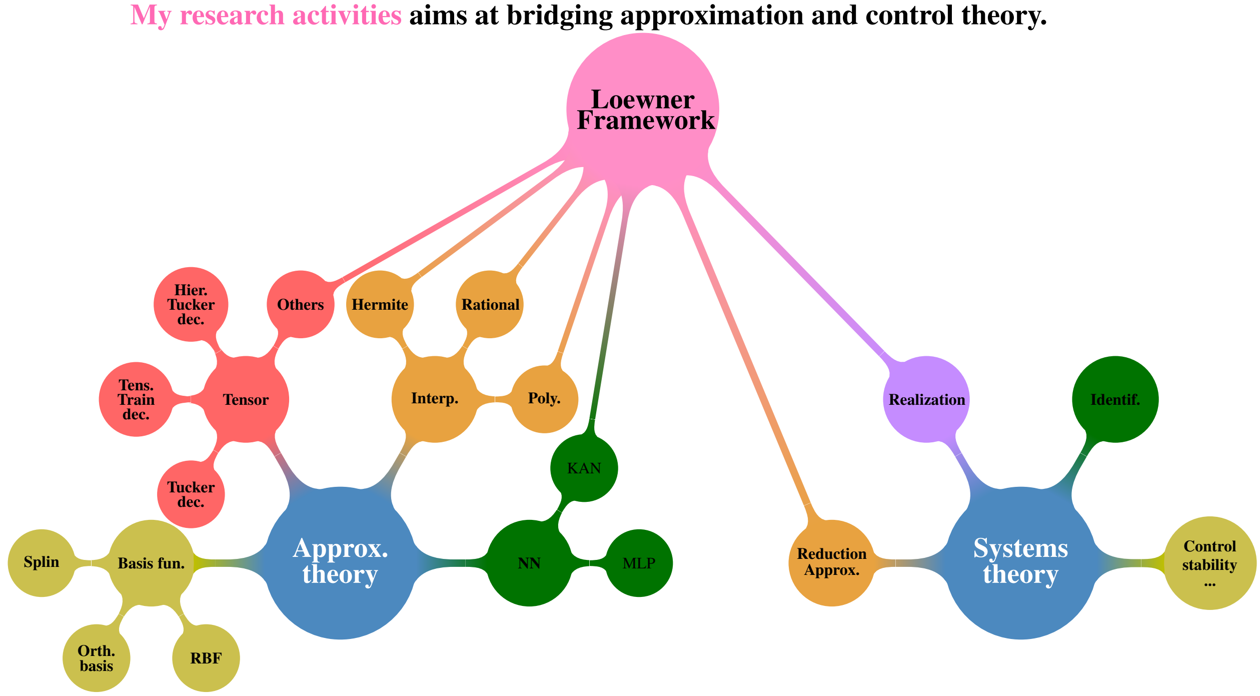
Contents

My research activities aims at bridging approximation and control theory.



Charles Poussot-Vassal (12/08/1982, Male, French, 2 childrens)

Researcher Director in dynamical systems and computational methods

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https://cpoussot.github.io/ & https://github.com/cpoussot

Current activity

since 2020 — CO-FUNDER AND PRESIDENT OF **MOR DIGITAL SYSTEMS** (TOULOUSE, FRANCE).
- ▷ *MDSPACK and MOR Toolbox, available at **http://mordigitalsystems.fr/**.*
- ▷ *Software solutions for dynamical model approximation, identification and processing.*

since May 2009 — RESEARCHER (RESEARCH DIRECTOR), **ONERA-DTIS** (TOULOUSE, FRANCE).
- ▷ *Topics: dynamical model approximation and control theory, linear algebra, applied mathematics.*
- ▷ *Main projects funding: UE, DGAC, National, Onera.*
- ▷ *Referred publications: 28/75/1/8 (journals / conferences / book / chapters).*
- ▷ *Academic coll.: MPI, Rice Univ., DLR, Pol. di Milano, CERFACS, ISAE.*
- ▷ *Industrial coll.: Airbus, Dassault-Aviation, EDF.*
- ▷ *Supervision: 1 post-doc, 6 Ph.D. (5 defended), 17 M.Sc. defended.*
- ▷ *Teaching: lecture and labs in control theory & applied math. at UPS, INSA Toulouse and ISAE.*

Former professional experiences

2009 (6 months) — RESEARCHER (ASSISTANT), **POLITECNICO DI MILANO** (MILAN, ITALY).
- ▷ *Modeling and control of semi-active suspension systems (book publication, Elsevier).*

2005-2008 (3 years) — RESEARCHER (PH.D.), **GIPSA-LAB/CNRS** CONTROL DPT. (GRENOBLE, FRANCE).
- ▷ *Study and control of the automotive vehicles dynamics (suspensions, brake, steering wheel, tires).*

before 2005 — RESEARCH ENGINEER TRAINEE.
- ▷ *(**INRIA**, Montbonnot, France) Friction compensation on a bipedal robot.*
- ▷ *(**ALCATEL Space**, Valence, France) Modeling and control of a brushless motor for braking systems.*
- ▷ *(**SOITEC**, Crolles, France) Installing and planning for clean-room devices.*

Skills

Languages	**Italian**: bilingual (International Baccalaurate); **English**: frequently used in the professional context (TOEIC: 800, ERASMUS exchange); **Spanish**: basic.
Engineering	Dynamical systems approximation and control theory, linear algebra, numerical simulation, digital implementation, signal processing, filtering.
Management	Research projects, European projects proposal and tracking, planning, budget.
Computer sciences	Matlab-Simulink, Scilab, LaTeX, Office suite.

Education & Degrees

HDR (2019) — **TOULOUSE INP** INSTITUT POLYTECHNIQUE DE TOULOUSE (TOULOUSE, FRANCE).
- ▷ *French habilitation in model approximation, systems theory and applied mathematics.*
- ▷ *Subject: Large-scale dynamical model approximation and its applications.*

Ph.D. (2005-2008) — **GRENOBLE INP** INSTITUT POLYTECHNIQUE DE GRENOBLE (GRENOBLE, FRANCE).
- ▷ *Ph.D. in systems and control theory.*
- ▷ *Subject: Multivariable robust linear parameter varying control of vehicles (Ministry grant).*

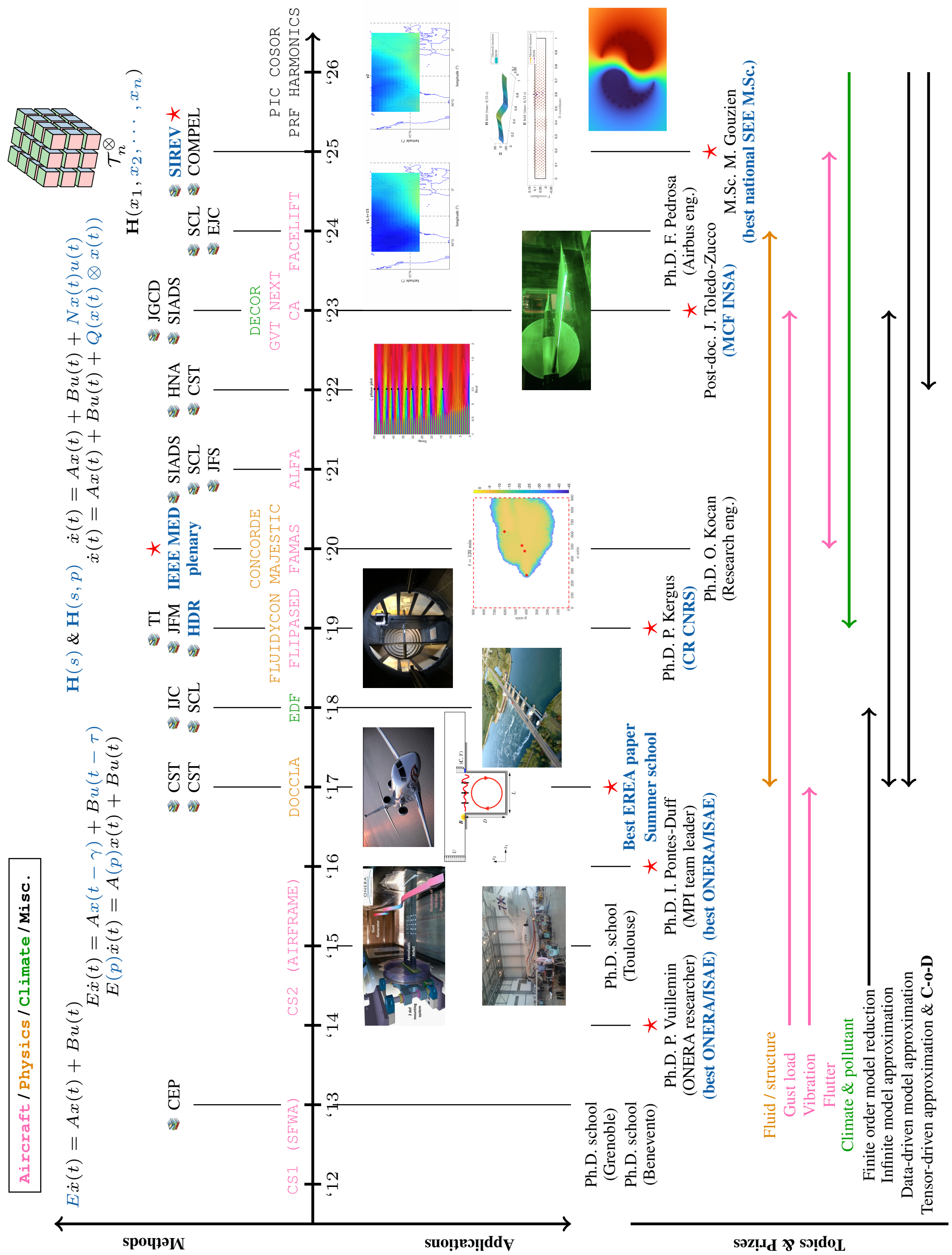
M.Sc. (2005) — **LTH** LUND INSTITUTE OF TECHNOLOGY (LUND, SWEDEN).
- ▷ ***M.Sc. (with honors)** in control theory, embedded systems, numerical analysis.*

Engineer (2000-2005) — **INPG-ESISAR** INSTITUT POLYTECHNIQUE DE GRENOBLE (VALENCE, FRANCE).
- ▷ ***Engineer (with honors)** in control theory, electronics and embedded systems.*

Extra activities & scientist

Community	Reviewer for app. math. & control journals (IFAC, IEEE CSS, Elsevier, SIAM, Springer...).
Sports	Skiing (competition level), Basketball, Cycling.
Others	First aid qualification, Driving licence.

ONERA activity & timeline overview: The below timeline shows the last 15 years of ONERA activities. Horizontal timeline lists the projects (names and types). The top part gathers methodological activities, *i.e.* topics of research (spotting journal papers, plenaries, and monograph). The middle part illustrates important applications (including industrial, wind tunnel and numerical results). Below part gather the prices, principal collaborators and covered topics. The ⋆ symbol marks highly notable (i) prizes (ii) publications, (iii) school organizations or (iv) collaborators career continuation.

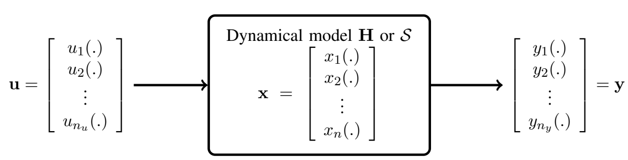


2 Research activities overview and ONERA outcomes

Forewords. Accurate and highly complex parametric (multivariate) models are centrals for every engineering activities involving simulation, forecasting, uncertainties propagation, optimization in a broad sense, etc. Indeed they are essential in any multi query (model-based) optimization process. However, there complexity limits the accuracy, scalability and applicability of every approaches. **Constructing representative simplified multivariate surrogate models** is essential to solve real-life problems. My research aims at providing both theoretical and practical outcomes to this problem. It belongs to the field of **approximation theory**, and more specifically to the **data-driven (multivariate) rational approximation** one. These problems are highly complex as they equally address numerical, computational and theoretical challenges. They are of highly strategical interest at the international level since they aim at leveraging computational burden and seek for reducing time & costs to (accurate) result, with application in every domains. This research led to contributions in two fields, linking **data and models**: (**$\mathbf{A_1}$**) dynamical system identification, construction & realization, reduction and approximation; (**$\mathbf{A_2}$**) tensor compression and multivariate rational approximation. My contributions yield to (i) new model- and data-driven dynamical model reduction and approximation algorithm (sections 3.2, 3.3 and 3.5) and to (ii) a fundamental scalable tensor-driven multivariate rational model approximation method, taming the curse of dimensionality (section 3.1). These contributions already found recognitions within the academic (articles, prices, plenary, tutorials) and the industrial (real applications, startup development) worlds, and impact engineers & researchers workflows (section 3.4).

($\mathbf{A_1}$) Dynamical model- & data-based (single variable) reduction & approximation. A dynamical system $\mathbf{\Sigma}$ is a physical process that can be described by evolution equations linking (i) inputs $\mathbf{u}$ to outputs $\mathbf{y}$ (external form $\mathbf{H}$) or (ii) inputs $\mathbf{u}$ to internal variables $\mathbf{x}$, to outputs $\mathbf{y}$ (internal form $\mathcal{S}$). If either $\mathbf{H}$ or $\mathcal{S}$ is available, approximation methods refer to as **model-driven**. Alternatively, if only a discrete input-output pair is available either in time- $\{\mathbf{u}(t_i), \mathbf{y}(t_i)\}_{i=1}^N$ or frequency-domain $\{\mathbf{u}(f_i), \mathbf{y}(f_i)\}_{i=1}^N$, we refer to **data-driven** methods.

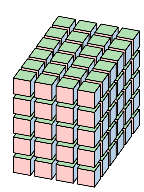
(**Internal time-domain model**) $\mathcal{S} \sim \mathbf{u} \rightarrow \mathbf{x} \rightarrow \mathbf{y}$
(**External frequency-domain model**) $\mathbf{H} \sim \mathbf{u} \rightarrow \mathbf{y}$ (Sections 3.3 and 3.5)



(**Time-domain data**) $\{\mathbf{u}(t_i), \mathbf{y}(t_i)\}_{i=1}^N$
(**Frequency-domain data**) $\{\mathbf{u}(f_i), \mathbf{y}(f_i)\}_{i=1}^N$ (Sections 3.2 and 3.4)

($\mathbf{A_2}$) Tensor-based multivariate approximation. An extension of $\mathbf{A_1}$ considers any unknown n-variable function $\mathbf{H}(x_1, x_2, \cdots, x_n)$, representing a process, an experimental setup or any software. By evaluating $\mathbf{H}$ over a finite discretization grid along each variable, each with finite dimension $\{N_1, N_2, \ldots, N_n\} \in \mathbb{N}$, we obtain a **tensor data** grid ($\mathcal{T}_n^{\otimes} \in \mathbb{C}^{N_1 \times N_2 \times \cdots \times N_n}$). In this setup, we refer to **tensor or data-driven multivariate** approximation and compression methods.

$$\left.\begin{array}{rcl} \mathbf{x}_1 & = & [\ x_1(1) \quad x_1(2) \quad \cdots \quad x_1(N_1)\ ] \\ & \vdots & \\ \mathbf{x}_n & = & [\ x_n(1) \quad x_n(2) \quad \cdots \quad x_n(N_n)\ ] \end{array}\right\} \xrightarrow{\mathbf{\Sigma}} \mathcal{T}_n^{\otimes}$$



(Section 3.1)

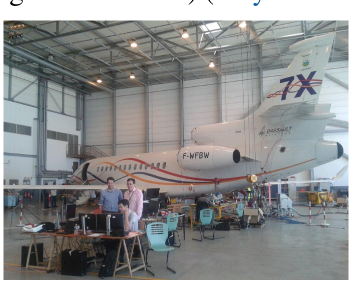
Surrogate model structures. Based on the above ($\mathbf{A_1}$) and ($\mathbf{A_2}$) paradigms, my research seeks for **(multivariate) simplified surrogate (static or dynamical) models** of different structure: **L-DAE**, **B-DAE**, **Q-DAE** or **pL-DAE** (respectively linear, bilinear, quadratic or parametric linear differential algebraic equations) or **Barycentric** rational and multivariate function.

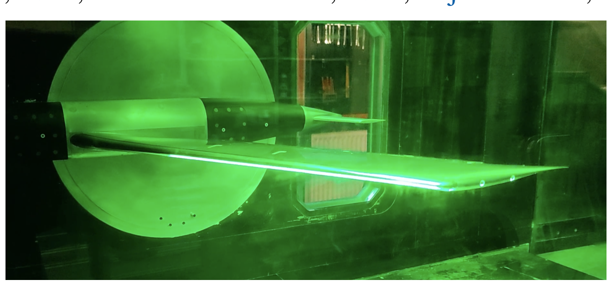
$$
\begin{array}{rrcll}
\text{L-DAE}: & \mathbf{E}\dot{\mathbf{x}}(t) & = & \mathbf{A}\mathbf{x}(t)+\mathbf{B}\mathbf{u}(t) & \mathbf{y}(t)=\mathbf{C}\mathbf{x}(t)\\
\text{B-DAE}: & \mathbf{E}\dot{\mathbf{x}}(t) & = & \mathbf{A}\mathbf{x}(t)+\mathbf{B}\mathbf{u}(t)+\mathbf{N}\mathbf{u}(t)\mathbf{x}(t) & \mathbf{y}(t)=\mathbf{C}\mathbf{x}(t)\\
\text{Q-DAE}: & \mathbf{E}\dot{\mathbf{x}}(t) & = & \mathbf{A}\mathbf{x}(t)+\mathbf{B}\mathbf{u}(t)+\mathbf{Q}(\mathbf{x}(t)\otimes\mathbf{x}(t)) & \mathbf{y}(t)=\mathbf{C}\mathbf{x}(t)\\
\text{pL-DAE}: & \mathbf{E}(\mathbf{p})\dot{\mathbf{x}}(t) & = & \mathbf{A}(\mathbf{p})\mathbf{x}(t)+\mathbf{B}(\mathbf{p})\mathbf{u}(t) & \mathbf{y}(t)=\mathbf{C}(\mathbf{p})\mathbf{x}(t)\\
\text{Barycentric}: & \mathbf{G}(x_1,\cdots,x_n) & = & \dfrac{\sum_{j_1=1}^{k_1}\cdots\sum_{j_n=1}^{k_n}\frac{c_{j_1,\cdots,j_n}\mathbf{w}_{j_1,\cdots,j_n}}{(x_1-\lambda_1(j_1))\cdots(x_n-\lambda_n(j_n))}}{\sum_{j_1=1}^{k_1}\cdots\sum_{j_n=1}^{k_n}\frac{c_{j_1,\cdots,j_n}}{(x_1-\lambda_1(j_1))\cdots(x_n-\lambda_n(j_n))}} & .
\end{array}
$$

As all above forms is fully adapted to most engineer and researcher toolkit, the surrogate can be used in place to the original model (or as a model of the data) for any task. The methods I develop also allow recovering the intrinsic properties of the system which has generated the data (*e.g.* complexity, stability, passivity, physical content, etc.). In this quest the tool is the **rational interpolation** achieved by mean of the **Loewner matrix** (Mayo and Antoulas, 2007; Antoulas et al., 2020, 2025).

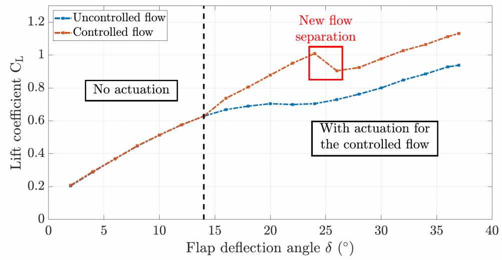
ONERA's outcomes and skills overview. As simplified models play a pivotal role in many domains (simulation, analysis, control synthesis, etc.), this research led to numerous outcomes for ONERA. This includes its use in **industrially-driven projects** (European Clean Sky 1 & 2, Flipased, Facelift, Clean Aviation / DGAC Majestic, ALFA, DECOR, GVT-Next, etc.), but also **prospective** ones (Ph.D. thesis, PRF FluiDyCon & HARMONICS and AID). In addition, **advanced presentations** in scientific groups, teaching in engineering school (ISAE, INSA, ENAC) and continuous training (Ecole de l'X, summer schools) were held. It contributed in opening ONERA DTIS to internal exchanges with DAAA, DOTA, DMAE, and in building national (*e.g.* ISAE, LAAS, INRIA) and international (*e.g.* Rice University, MPI Magdeburg, DLR) collaborations and researcher exchanges. It led to the creation of a cutting edge technological startup: **MOR Digital Systems**. Fundamental skills in **data-driven tensor approximation, simplified modeling and realization theory** are now mastered at ONERA, at a recognized international level. These skills already solved (i) complex real-life industrial problems proposed by **Dassault-Aviation**, **Airbus**, **EDF**, etc. and (ii) different research-oriented benchmarks involving **fluids**, **wave**, **structure** equations, etc. See below a snapshot of some of them.

Industrial aircraft applications (Clean Sky 1 & 2, Majestic). Within these major projects, an important collaboration with Dassault-Aviation and Airbus has been consolidated. I did provide solutions on different aircraft topics, all involving data-driven approximation at its core: gust load modeling and control, vibration modeling and control, and flutter modeling, detection and control. Notable results concern (i) the participation to the Falcon 7X ground vibration tests and vibration control flight tests at Istres (left-hand frame), and (ii) the validation of modeling and control methods for of gust load in transonic conditions over a 2D and 3D wing, at ONERA Meudon wind tunnel facility (right-hand frame) (Meyer et al., 2017; Poussot-Vassal et al., 2021; Vojkovic et al., 2023).

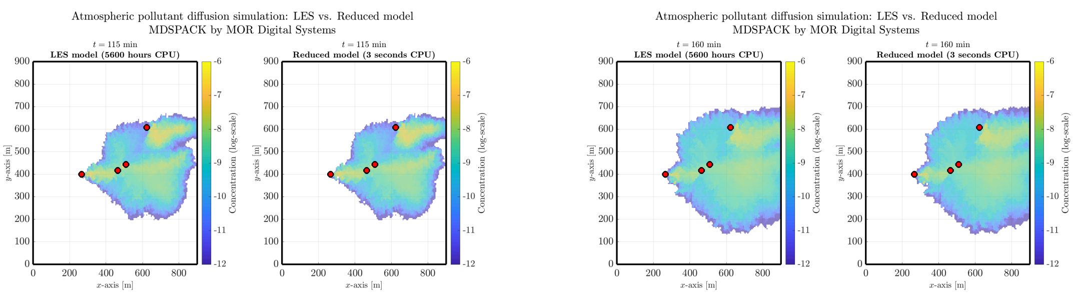




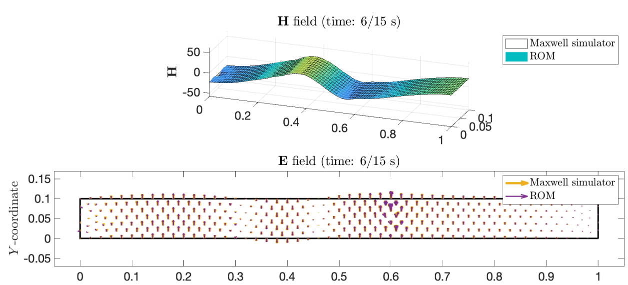
Fluid structure applications (FluiDyCon). Application at ONERA Lille wind tunnel facility of two flow separation strategies involving interpolatory approximation methods (a model-driven nonlinear positive and a data-driven linear one). Below frame shows the wind tunnel facility with the 2D wing and how much the separation is pushed away thanks to the control action (Arnoult et al., 2024).



Pollutant approximation (DECOR). Application of the data-driven methods to construct a simple **Q-DAE** model from a pollutant dispersion data set obtained with the high-fidelity **Meso-NH** software (implementing LES). Two time instants top views of pollutant plume. Left-hand frames: full simulator result obtained in **5,600 hours**; right-hand frames, simplified model results obtained in **3 seconds**.



Waveguide approximation (AID). Construction of a simplified passive dynamical model of a wave guide setup using data collected from a Maxwell's equation driven simulator. The reduced model recovers (i) the input/output behavior, (ii) the passive structure and properties, and (iii) enables the full state (approximate) reconstruction. The figure shows a snapshot of a wave guide magnetic ($\mathbf{H}$, top) and electric ($\mathbf{E}$, bottom) fields obtained by the expert simulator, in **10 minutes**, and the reduced model **obtained in 1 second** (Gouzien et al., 2024, ⋆ best SEE M.Sc. prize).



Disseminations, teaching & collaborations. I have been involved in six Ph.D. thesis (one on-going) and one post-doc. Among the five finished, one is now researcher at ONERA, one is team leader at MPI Magdeburg, one is CR at CNRS, one is consultant in aerospace and the last is structural engineer at Airbus. Post-doc now is MCF at INSA Toulouse. I also teach control theory and data-driven modeling at INSA, and applied mathematics at ISAE. I built long lasting collaborations with the Max Planck Institute (Magdeburg, Germany), the University of Rice (Texas, USA), the DLR (Göttingen, Germany), the Politecnico di Milano (Milan, Italy). Each led to multiple journal and conference articles, as well as researcher exchanges (three researchers visit ONERA for weeks).

3 Five major and representative publications

Most of my publications are related to studies on (very large-scale) data-driven (dynamical) model approximation, compression and reduced order model construction. It also includes closed-loop control design and dynamical systems performance analysis results. Applications cover numerous of topics, going from civilian aeronautical, fluid, aeroelastic and meteorological systems. On Google Scholar[1], on January 15th 2026, my **h-index was of 25**, my **i10-index of 65** and **3404 citations** are collected. Five relevant publications are listed and briefly detailed (sorted from earlier to older)[2] [3].

3.1 Tensor multivariate rational approximation & KST

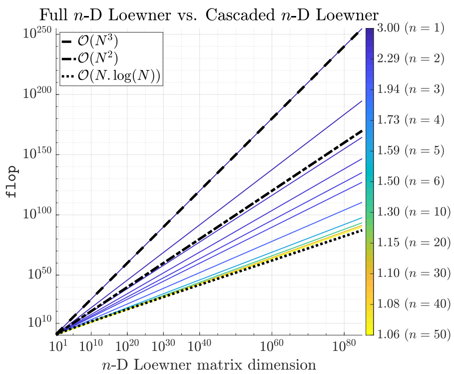
SIAM Review (Research Spotlight) (collaboration with Rice University & Max Planck Institute)
Antoulas et al. (2025), https://doi.org/10.1137/24M1656657
⋆ **first ONERA author in this journal.**

This article presents the **multivariate Loewner Framework (mLF)**. One important contribution in this work is to address the problem of dimensionality, occurring essentially when the number of variables and tensor size increase, thanks to a **variable decoupling**. We present connections between the mLF for rational interpolation of multivariate functions and the **Kolmogorov Superposition Theorem (KST) restricted to rational functions**, resulting in the formulation and numerical resolution of the KST for this special function class (Pólya and Szegö, 1925). As a byproduct, **taming the curse of dimensionality** in computational complexity, storage and numerical accuracy, is achieved (Bellman, 1966). In addition, this framework overcomes the limitation of the real domain allowing all variables to be complex. In details, the following essential contributions are established:

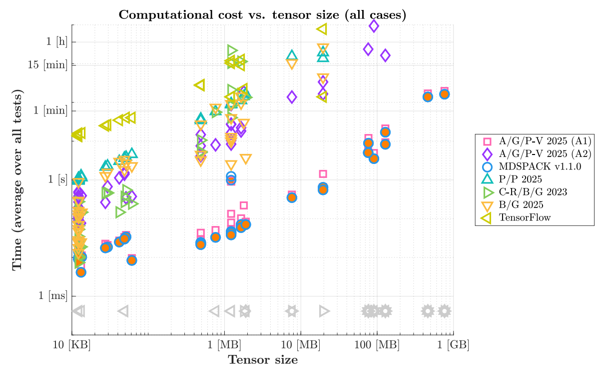
1. That n-variable rational functions in the **Barycentric** form $\mathbf{G}(x_1, \cdots, x_n)$ with realization **pL-DAE** (if $x_1 := s$ and $\mathbf{p} := [x_2, \cdots, x_n]$ are parameters) can be constructed to interpolate and/or approximate any tensorized n-D data $\mathcal{T}_n^{\otimes}$ or n-variable function $\mathbf{H}(x_1, \cdots, x_n)$;
2. That these n-variable rational functions can be obtained thanks to a sequence of small-scale single-variable interpolation (performed with Loewner matrices), therefore drastically taming the curse of dimensionality (both in memory and computational effort, leading to better accuracy);
3. That such sequence results in variable decoupling, providing a numerically robust solution to the KST, restricted to rational functions;
4. That the Loewner framework bridges "Approximation theory" (both functions and tensors) with "Systems theory", and provides connections with Kolmogorov Arnold Networks (KAN). See also figure on the first page of the document.

Figure 1a shows the worst case `flop` for varying number of variables n, highlighting the complexity huge drop thanks to the decoupling. Figures 1b and 1c compare the model computation time and approximation error of the **mLF**[4] and its implementation in MOR Digital Systems (2025, MDSPACK) with Poluektov and Polar (2025, KAN model), Balicki and Gugercin (2025, Rational model), Balicki and Gugercin (2025, Rational model) and Abadi et al. (2015, MLP model by Tensor Flow), for a collection of 50 examples.

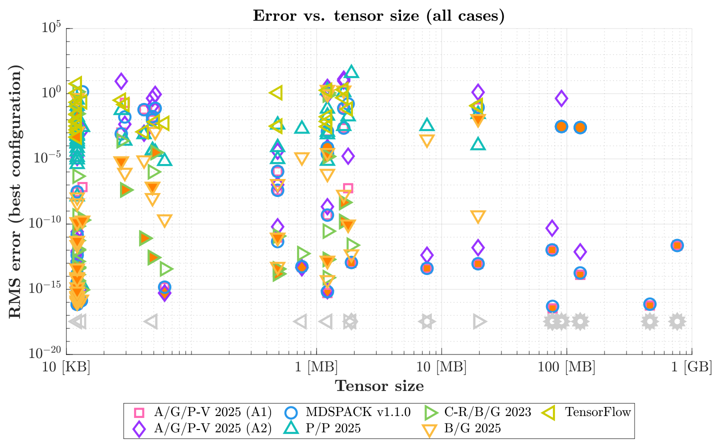
[1] https://scholar.google.fr/citations?user=7xZMn-AAAAAJ&hl=fr (Scholar)
[2] https://cpoussot.github.io/publications.html (full publication list).
[3] https://cpoussot.github.io/research.html (animations and visuals).
[4] https://github.com/cpoussot/mLF (research GitHub)



(a) `flop` complexity plot for the cascaded scheme for varying complexity orders n vs. some standard references (log-log scale).



(b) Model construction time vs. tensor size for varying methods, applied to 50 examples (log-log scale). Filled symbols mark the best method while grey symbols show not converged ones.



(c) Model normalized absolute error vs. tensor size for varying methods, applied to 50 examples (log-log scale). Filled symbols mark the best method while grey symbols show not converged ones.

Figure 1: Illustrations of Antoulas et al. (2025) result.

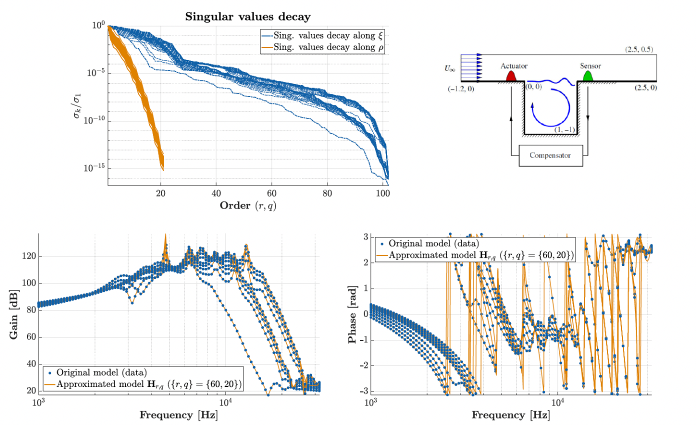
Figure 1a presents the theoretical impressive scalability of the approach. Then, Figure 1b assess the previous remark by showing that the proposed mLF is way faster than its competitors. At the same time, Figure 1c shows that, again, accuracy is preserved, for tensor with low complexity up to very large ones (up to 1GB tested). One important feature is that only the proposed mLF solution is capable to accurately approximate very large-scale tensors, where other methods fail.

This fundamental article, linking the KST with the Loewner rationale, stands as a very **strong theoretical result** which will undoubtedly pave the way for multiple theoretical developments ranging from approximation, computational, neural and control fields. It notably opens the range for, up to now, unreachable applications, limited by the computational load of standard computers. This **cutting-edge discovery** may alleviate many computational issue and both save time and energy.

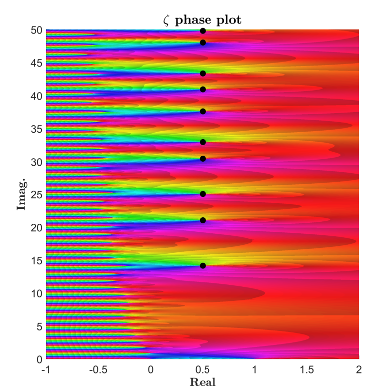
3.2 Review on dynamical model approximation

Handbook on Numerical Analysis (collaboration with Max Planck Institute & Rice University)
Gosea et al. (2022), https://doi.org/10.1016/bs.hna.2021.12.015

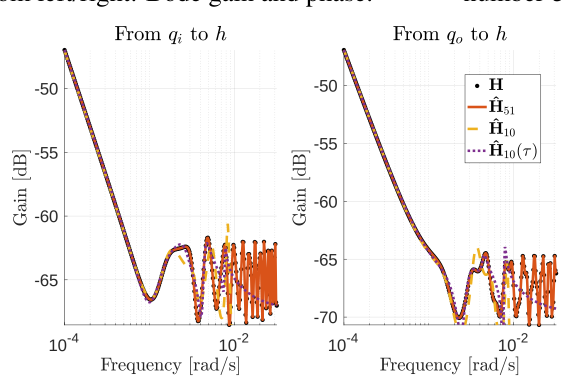
We discuss the modeling and model reduction features of Loewner framework. This data-driven approach, applicable to large-scale systems, originally developed for applications to linear time-invariant systems is extended and presented with high mathematical level. More in detail, we show that LF can be extended to a number of additional more complex scenarios, including **linear parametric** or **non-linear** dynamical systems. We also provide with **time-domain extensions**. Then, the application of the Loewner framework is illustrated by a collection of practical test cases. Firstly, for data-driven complexity reduction of the underlying model, and secondly, for dealing with control applications of complex systems (in particular, with feedback controller design). Figure 2a illustrates how it is possible to recover a parametric function of a collection of (differente Reynolds) very large-scale linear fluid setup (650,000 variables). Figures 2b and 2c show the rational approximation of the irrational **Riemann ζ** and **EDF** St Venant functions.



(a) Open cavity Reynolds dependent fluid model approximation. Top right: geometry. Top left: normalized singular value drop along the variables. Bottom left/right: Bode gain and phase.



(b) Riemann ζ function phase plot. Rational approximation recovers the number & values of non-trivial zeros.



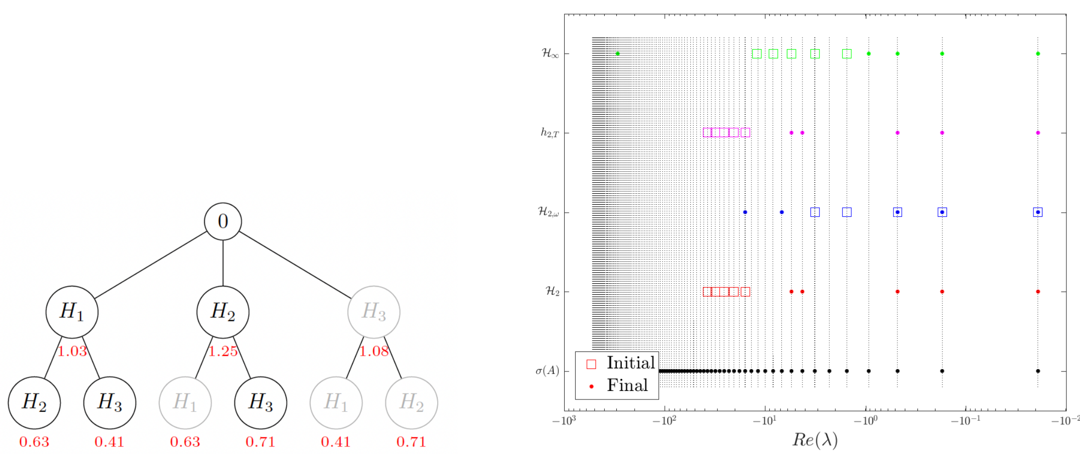
(c) EDF open channel Bode gain from up (q_i) and downstream (q_o), to the river height (h). Rational (with delay) $\hat{\mathbf{H}}$ ($\hat{\mathbf{H}}_\tau$) approximations of the irrational model $\mathbf{H}$.

Figure 2: Illustrations of Gosea et al. (2022) result.

3.3 Optimal modal truncation method

Systems & Control Letters (collaboration with NASA)
Vuillemin et al. (2021), https://doi.org/10.1016/j.sysconle.2021.105011

We **revisit - the old fashioned - modal truncation method** from an optimization point of view. In particular, the concept of dominant poles is formulated with respect to different system norms as the solution of the associated optimal modal truncation problem. Each norm is either related to a frequency- or time-domain objective. The considered problem is reformulated as an equivalent **convex integer or mixed-integer program**. Numerical examples highlight the concept and optimization approach. Figure 3a illustrates the combinatory nature of the optimization problem on a very simple configuration. Then, Figure 3b shows which modes are preserved according to the norm objective function. This suggests different modal selection according to the frequency/time of range of interest. One central element of this method is its acceptance and preference by many industrial partners. Indeed, the preservation of the modal content is often required by structure and aero-engineers in order to preserve the physical knowledge. This approach **responds to a real demand** from industrial collaborators and the different norms are appropriate to different practical demands.



(a) Illustration of the tree of possible combinations for the second order $\mathcal{H}_2$-optimal approximation.

(b) Poles of the initial model and its 5-th order counterparts obtained with optimal modal truncation in $\mathcal{H}_2$, $\mathcal{H}_{2,\omega}$, $h_{2,T}$ and $\mathcal{H}_\infty$-norms with $\omega = 20$ rad/s and $T = 10$s. Note that all poles are real and have been separated along the y axis for readability. Initial and final poles are indicated by squares and dots, respectively.

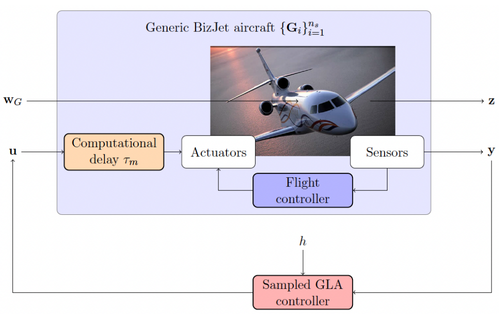
Figure 3: Illustrations of Vuillemin et al. (2021) results.

This contribution enriches the spectrum of possibilities for this well-known method. It provides a larger toolkit for engineers.

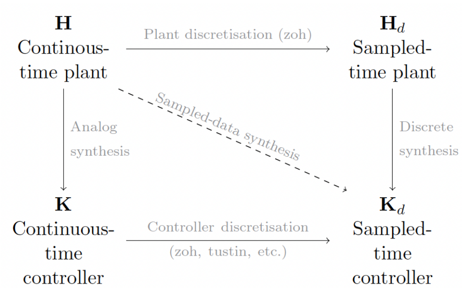
3.4 Gust load alleviation control applied on a Dassault-Aviation use-case

SIAM Journal on Applied Dynamical Systems (collaboration with Dassault-Aviation)
Poussot-Vassal et al. (2021), `https://doi.org/10.1137/20M1384014`

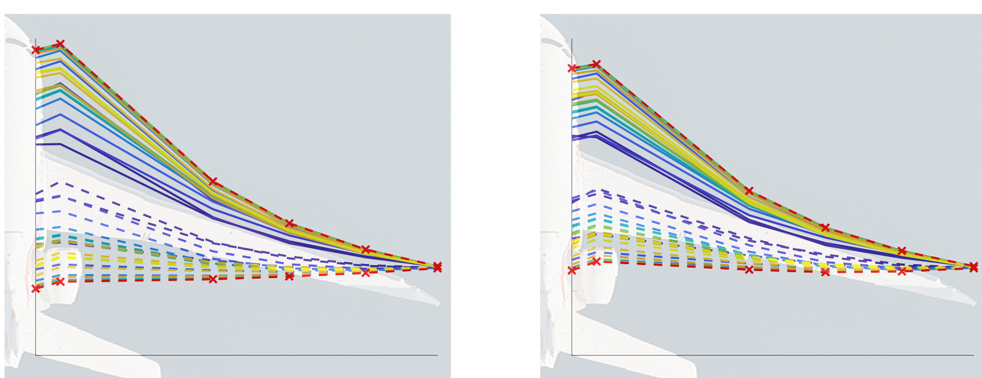
We deployed the interpolatory methods to solve an end-to-end industrial control problem proposed by **Dassault-Aviation**. This problem involves a collection of hundreds of complex large-scale irrational multi-delayed linear dynamical models (Figure 4a). In more details, the contribution shows how rational function interpolation is a pivotal tool (i) for constructing **frequency-limited reduced-order dynamical models** with controlled accuracy/complexity, appropriate for model-based control design and (ii) for **discretizing controllers** with an improved accuracy than standard Euler methods, in view of on-board control implementation (Figure 4b). This is illustrated along the paper through the design of an active feedback Gust Load Alleviation (GLA) function, applied on a generic business jet aircraft example. The closed-loop validation and performance evaluation are assessed through the use of a dedicated industrial simulator and considering certification objectives. Based on the proposed rationale, a robust control GLA law has been designed, leading to 8% of maximal load attenuation over the entire wing span (Figure 4c). Although application is centered on aircraft applications, the method is not restrictive and can be applied to any linear dynamical system.



(a) Active closed-loop GLA control scheme with the generic complex (large-scale, delayed irrational) business jet model.



(b) Different continuous to discrete-time path.



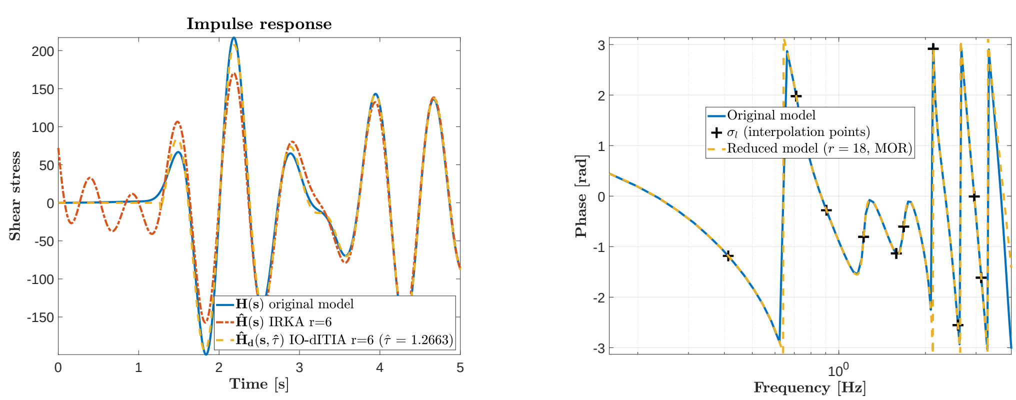
(c) Gust load envelope along the wing span (computed over thousand of gust shapes). Left-hand side: without GLA function. Right-hand side: with GLA function, leading to 10% of maximal load attenuation over the entire wing span.

Figure 4: Illustrations of Poussot-Vassal et al. (2021) results.

3.5 $\mathcal{H}_2$-optimal model reduction with input-output delays

Systems & Control Letters
Pontes Duff et al. (2018), `https://doi.org/10.1016/j.sysconle.2018.05.003`

The classic linear time invariant $\mathcal{H}_2$-optimal approximation is extended to multi-input multi-output reduced functions **including input/output delays**. This problem is of particular interest when the full complex order model represents a transport phenomenon, which is common in many applications (*e.g.* fluids, population displacements, etc.). The contribution proposed in this paper is twofold: firstly, based on the pole/residue decomposition, an $\mathcal{H}_2$-inner product formula in the presence of input/output delays is derived. Secondly, grounded on this inner form, the underlying $\mathcal{H}_2$ optimality conditions of the approximation problem are obtained. The result stands as an extension of the tangential interpolatory conditions for non-delayed models. It is also demonstrated that for fixed delay values, this problem can be recast as a rational function approximation one. An **iterative non linear optimization algorithm**, celebrated as Input Output delay Iterative Tangential Interpolation Algorithm (IO-dITIA), is sketched out and numerical results assess the theoretical contribution. This result extends the well known IRKA algorithm, being the gold standard model reduction algorithm. Figure 5a shows the time-domain impulse response of a linearized flow phenomena over an open-cavity structure given as a **L-DAE** with 650,000 internal variables, and its approximation with an input delayed reduced order **L-DAE** model of dimension 6 (complexity compression $\approx 10^5$). Figure 5b focusses on the Bode phase plot of this example showing how well the reduced model wit input delay catches the original large-scale model.



(a) Impulse response of the large-scale open cavity model, compared to two approximation: the gold standard IRKA and the proposed extension IO-dITIA.

(b) Bode phase plot comparison of the original model and its approximation with IO-dITIA. Crosses are the so-called interpolation points found by the IO-dIRKA.

Figure 5: Illustrations of Pontes Duff et al. (2018) results.

4 Perspectives

After this research activities and main contributions exposition (with heterogenous applications and problematics), reader may measures how versatile multivariate rational function reduced modeling and approximation is, and its potential at large. Clearly, the **(multivariate) data-driven rational model approximation landmark** is appealing for both theoretical and industrial applications. In what follows, some directions are sketched for the near and long-term future:

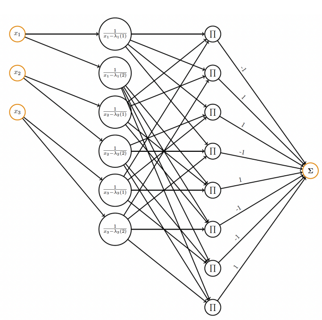
- **1(a)** Explore the linear **parametric and multivariate forms**. The recent results in tensor approximation ($\mathbf{A_2}$, Antoulas et al. (2025) and section 3.1) are very promising as they demonstrate a breakthrough in simplifying the computational complexity for addressing very complex real life problems. They already show superiority with respect to multiple competitors (using neural nets or rational forms). This theoretical and numerical development is an important priority and future studies should address computation issues, multiple input-output settings, etc. Connections with KAN is also of important interest (see below left frame). It is already on-going in collaboration with MPI Magdeburg and Rice University. The outcomes are very large within industry (not only the aircraft one) and for (large-scale) societal challenges.

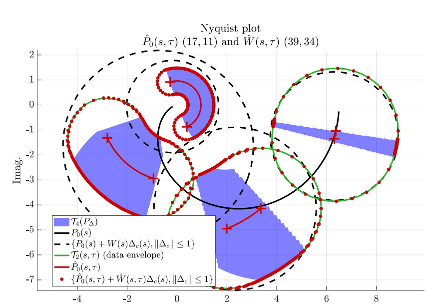
- **1(b)** Explore the **uncertain modeling**. One direct link with the previous item is the connection of the multivariate forms with the uncertain ones. One step is to consider some variables as parameters and others as uncertainties. Connecting both would benefit to robust control, modeling and uncertainty propagations communities. The below right frame shows the Nyquist plot of a parametrized uncertain toy model, revisiting and extending Zhou and Doyle (1997) results.

- **1(c)** Explore the linear **passive and port-Hamiltoninan forms**. One important property of systems concerns its energy storage, *e.g.* its dissipative properties. For many reasons, one may seek for identified passive models. This activity is already on-going in collaboration with the ISAE, with applications to the Maxwell and heat equations. In connection to the two first points, multivariate passive (and stable) models are also challenging targets.

- **2** Explore **data-driven stability and performance analysis**. Being able to analyze (dynamical) systems properties directly from data is central for model-free control or for fast evaluation and optimization. Indeed, this is may be a valuable tool for practitioners and an alternative to the tedious and time consuming actual tool.

- **3** **Real-life challenges...** In addition to the above methodological aspects related to the data-driven framework, in the context of **climate change**, different applications are essential to dig in. Climate forecasting and pollutants dispersion modeling and estimation are some of them. Indeed, simulation and optimization are some of the actual levers to better take care of the remaining resources and to propose tools to decision makers in order to organize the social life. On-going projects collaborations with the CERFACS and Météo France serve this objective.





References

Abadi, M., Agarwal, A., Barham, P., Brevdo, E., Chen, Z., Citro, C., Corrado, G. S., Davis, A., Dean, J., Devin, M., Ghemawat, S., Goodfellow, I., Harp, A., Irving, G., Isard, M., Jia, Y., Jozefowicz, R., Kaiser, L., Kudlur, M., Levenberg, J., Mané, D., Monga, R., Moore, S., Murray, D., Olah, C., Schuster, M., Shlens, J., Steiner, B., Sutskever, I., Talwar, K., Tucker, P., Vanhoucke, V., Vasudevan, V., Viégas, F., Vinyals, O., Warden, P., Wattenberg, M., Wicke, M., Yu, Y., and Zheng, X. (2015). TensorFlow: Large-scale machine learning on heterogeneous systems. Software available from https://www.tensorflow.org/.

Antoulas, A. C., Beattie, C. A., and Gugercin, S. (2020). *Interpolatory methods for model reduction*. SIAM Computational Science and Engineering, Philadelphia. https://doi.org/10.1137/1.9781611976083.

Antoulas, A. C., Gosea, I. V., and Poussot-Vassal, C. (2025). The Loewner framework for parametric systems: Taming the curse of dimensionality. *SIAM Review*, 67(4):737–770. https://doi.org/10.1137/24M1656657.

Arnoult, T., Acher, G., Nowinski, V., Vuillemin, P., Briat, C., Pernod, P., Ghouila-Houri, C., Talbi, A., Garnier, E., and Poussot-Vassal, C. (2024). Experimental closed-loop flow separation control: data- and phenomenological-driven approaches. *European Journal of Control*, 79:101082. https://doi.org/10.1016/j.ejcon.2024.101082.

Balicki, L. and Gugercin, S. (2025). Multivariate Rational Approximation via Low-Rank Tensors and the p-AAA Algorithm. https://arxiv.org/abs/2502.03204.

Bellman, R. (1966). Dynamic programming. *Science*, 153(3731):34–37. American Association for the Advancement of Science.

Gosea, I. V., Poussot-Vassal, C., and Antoulas, A. C. (2022). Data-driven modeling and control of large-scale dynamical systems in the Loewner framework. *Handbook of Numerical Analysis*, 23(Numerical Control: Part A):499–530. https://doi.org/10.1016/bs.hna.2021.12.015.

Gouzien, M., Poussot-Vassal, C., Haine, G., and Matignon, D. (2024). Port-Hamiltonian reduced order modelling of the 2D Maxwell equations. *Journal for Computation and Mathematics in Electrical and Electronic Engineering*, pages on–line. https://doi.org/10.1108/COMPEL-10-2024-0421.

Mayo, A. J. and Antoulas, A. C. (2007). A framework for the solution of the generalized realization problem. *Linear Algebra and its Applications*, 425(2-3):634–662. https://doi.org/10.1016/j.laa.2007.03.008.

Meyer, C., Broux, G., Prodigue, J., Cantinaud, O., and Poussot-Vassal, C. (2017). Demonstration of innovative vibration control on a Falcon Business Jet. In *Proceedings of the International Forum on Aeroelasticity and Structural Dynamics*, Como, Italy.

MOR Digital Systems (2025). MDSPACK (v1.1.0). Main page (https://mordigitalsystems.fr) & Documentation (https://mordigitalsystems.fr/static/mdspack_html/MDSpack-guide.html).

Poluektov, M. and Polar, A. (2025). Construction of the Kolmogorov-Arnold representation using the Newton-Kaczmarz method. https://arxiv.org/abs/2305.08194.

Pólya, G. and Szegö, G. (1925). *Aufgaben und Lehrsätze aus der Analysis I*. Die Grundlehren der Mathematischen Wissenschaften in Einzeldarstellungen mit besonderer Berücksichtigung der Anwendungsgebiete, Band XIX, Springer Verlag. https://link.springer.com/book/10.1007/978-3-662-38381-0.

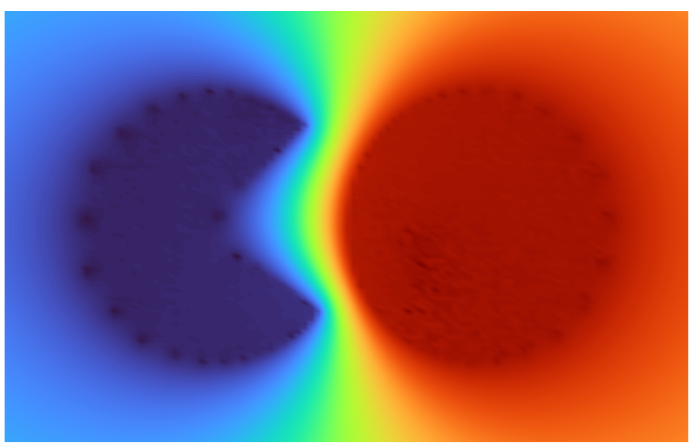
Pontes Duff, I., Poussot-Vassal, C., and Seren, C. (2018). Optimal $\mathcal{H}_2$ model approximation based on multiple input/output delays systems. *Systems & Control Letters*, 117:60–67. https://doi.org/10.1016/j.sysconle.2018.05.003.

Poussot-Vassal, C., Vuillemin, P., Cantinaud, O., and Sève, F. (2021). Interpolatory Methods for Generic BizJet Gust Load Alleviation Function. *SIAM Journal on Applied Dynamical Systems*, 20(4):2391–2411. https://doi.org/10.1137/20M1384014.

Vojkovic, T., Quero, D., Poussot-Vassal, C., and Vuillemin, P. (2023). Low-order parametric state-space modeling of MIMO systems in the Loewner framework. *SIAM Journal on Applied Dynamical Systems*, 22(4):3130–3164. https://doi.org/10.1137/22M1509898.

Vuillemin, P., Maillard, A., and Poussot-Vassal, C. (2021). Optimal modal truncation. *Systems & Control Letters*, 156:105011. https://doi.org/10.1016/j.sysconle.2021.105011.

Zhou, K. and Doyle, J. C. (1997). *Essentials Of Robust Control*. Prentice Hall.



Artistic view illustrating the Loewner based rational approximation applied to the Zolotarev 3rd and 4th problems with a Pac Man topology (submitted on January 2026, https://arxiv.org/abs/2511.04404).