C. Poussot-Vassal
Prix de la recherche scientifique **ONERA**

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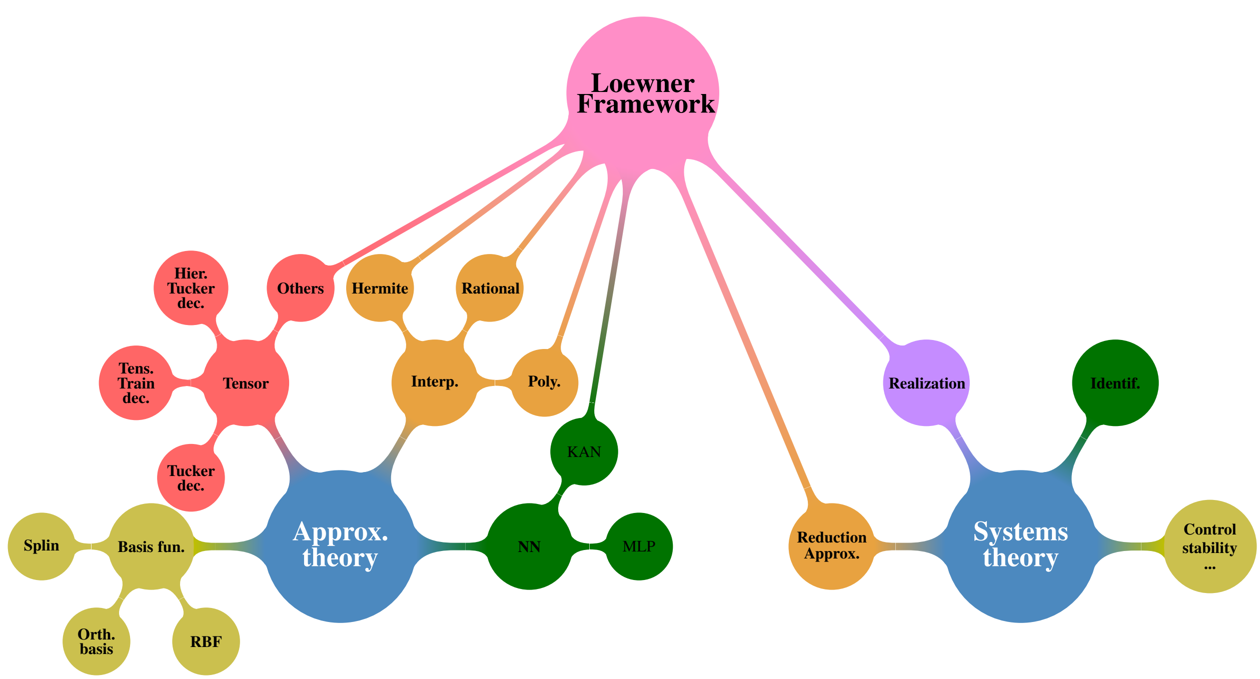
Contents



Loewner Framework 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).*

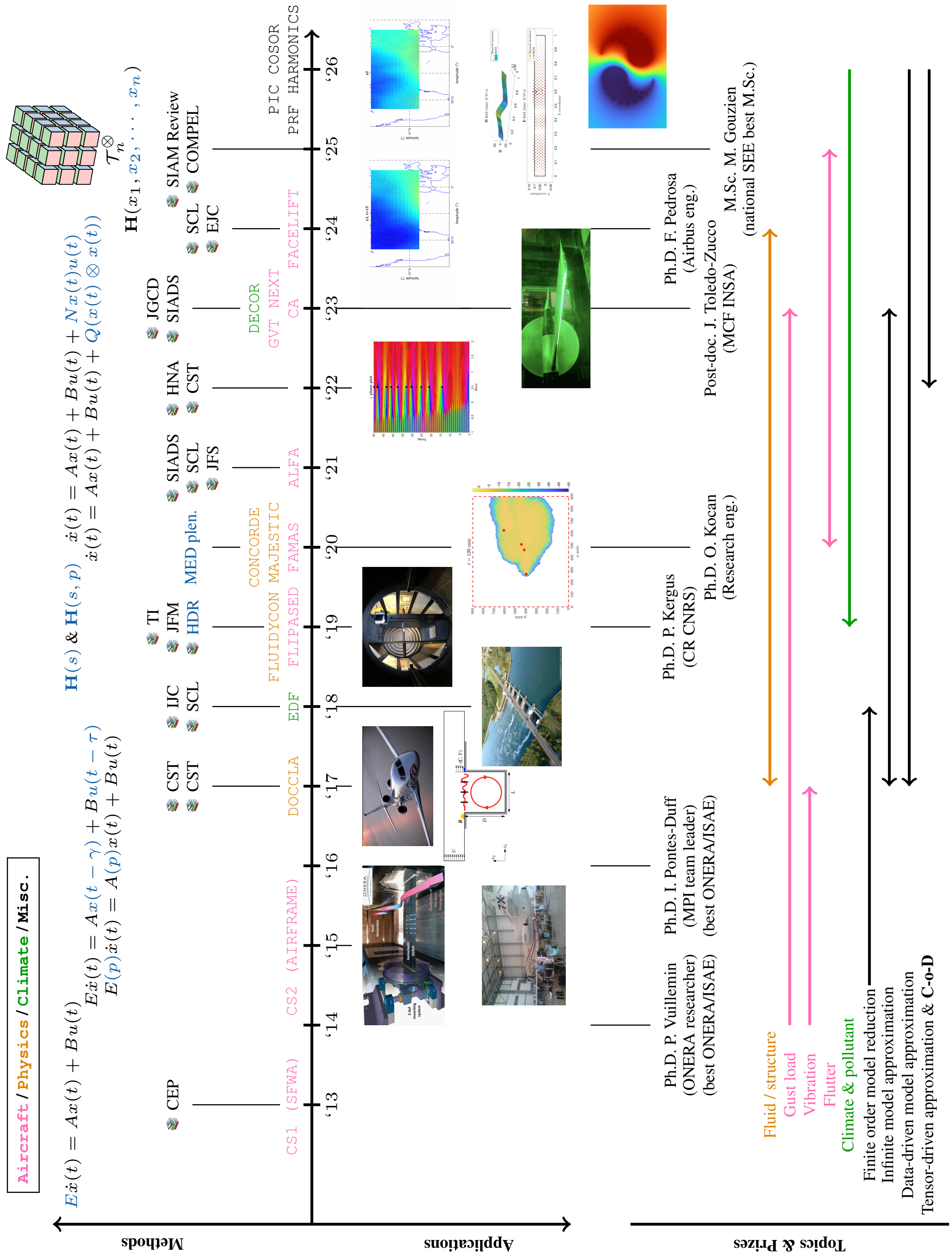
M.Sc. (2005) — **LTH** Lund Institute of Technology (Lund, Sweden).
- ***M.Sc. (with honors)** in control theory, embedded systems, numerical analysis.*

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

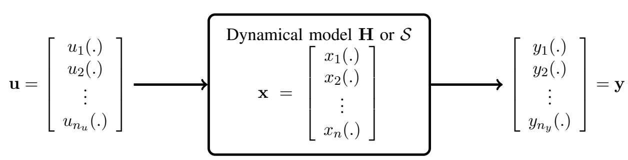


2 Research activities overview and ONERA outcomes

Forewords. My research belongs to the wide field of **approximation theory**, and more specifically to the so-called **data-driven (multivariate) rational approximation** one. My focus is on (static and dynamical time invariant) multivariate model construction, approximation & tensor data compression. The solutions I develop both address model- and data-driven approximation problems with a special emphasis on the latter. This research led to contributions in two domains: ($\mathbf{A_1}$) dynamical system realization theory, identification, large-scale (finite) & infinite model reduction and approximation; ($\mathbf{A_2}$) tensor data compression and multivariate rational approximation. The research I conduct covers both theoretical and practical matters, with a spotlight on numerical and computational issues. My contributions are threefold: (i) Model- and data-driven dynamical model reduction and approximation algorithms ($\mathbf{A_1}$, sections 3.2 to 3.4); (ii) Scalable tensor-driven multivariate rational approximation method ($\mathbf{A_2}$, section 3.1); (iii) Applications to industrial modeling, control & analysis problems, and software developments ($\mathbf{A_1}$ & $\mathbf{A_2}$, section 3.5). These contributions embrace a branch of applied mathematics and yield to numerous outcomes ranging from aeronautics to climate, antenna, fluids, etc., including many real-life industrial applications, impacting engineers and researchers workflows.

($\mathbf{A_1}$) Dynamical model- & data-based (single variable) reduction & approximation. A dynamical system $\mathbf{\Sigma}$ is a physical process evolving in time, linking inputs $\mathbf{u}$ to outputs $\mathbf{y}$. It can be described by evolution - difference or recursive - equations, being a mathematical operator explaining its inputs to outputs relation and/or its inputs to states ($\mathbf{x}$) to outputs evolution. The former is an external representation ($\mathbf{H}$), while the latter is an internal one ($\mathcal{S}$). If either $\mathbf{H}$ or $\mathcal{S}$ is available, related approximation methods refers to as **model-driven**. Alternatively, if only a discrete set of input-output are available either in time- ($\{t_i, \mathbf{\Sigma}(t_i)\}_{i=1}^N$) or frequency-domain ($\{z_i, \mathbf{\Sigma}(z_i)\}_{i=1}^N$), we refer to **data-driven** methods.

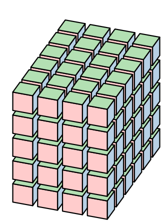
(**Internal time-domain model**) $\mathcal{S} \sim \mathbf{u} \to \mathbf{x} \to \mathbf{y}$
(**External frequency-domain model**) $\mathbf{H} \sim \mathbf{u} \to \mathbf{y}$ (Sections 3.3 and 3.4)



(**Time-domain data**) $\{t_i, \mathbf{\Sigma}(t_i)\}_{i=1}^N$
(**Frequency-domain data**) $\{z_i, \mathbf{\Sigma}(z_i)\}_{i=1}^N$ (Sections 3.2 and 3.5)

($\mathbf{A_2}$) Tensor-based multivariate approximation. An extension to the above data-driven case 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 / data-driven multivariate** approximation and compression methods.

$$\left.\begin{array}{rcl} \mathbf{x}_1 & = & \left[\begin{array}{cccc} x_1(1) & x_1(2) & \cdots & x_1(N_1) \end{array}\right] \\ \mathbf{x}_2 & = & \left[\begin{array}{cccc} x_2(1) & x_2(2) & \cdots & x_2(N_2) \end{array}\right] \\ \vdots & & \\ \mathbf{x}_n & = & \left[\begin{array}{cccc} x_n(1) & x_n(2) & \cdots & x_n(N_n) \end{array}\right] \end{array}\right\} \xrightarrow{\mathbf{H}} \mathcal{T}_n^{\otimes}$$



(Section 3.1)

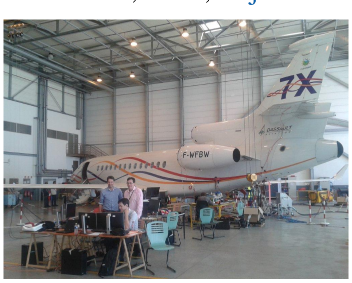
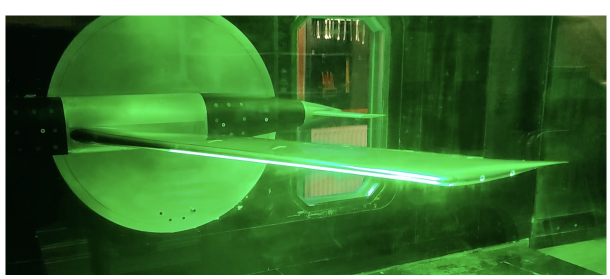
Surrogate modeling in the interpolatory framework. Based on the above presented ($\mathbf{A_1}$) and ($\mathbf{A_2}$) paradigms, my research seeks for **(multivariate) simplified surrogate (static or dynamical) models** of different structure: **L-DAE**, **B-DAE**, **Q-DAE** or **pL-DAE** (respectively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

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

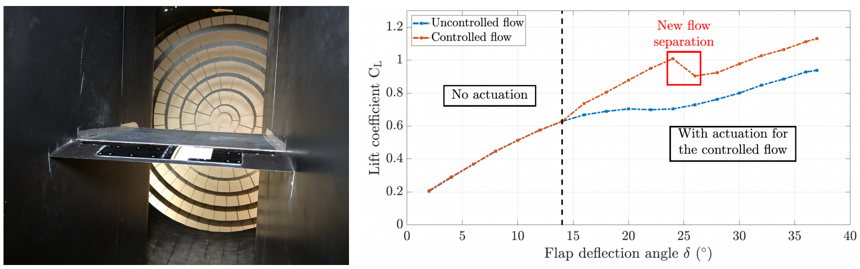
The surrogate should accurately capture the underlying original model, and eventually recover its intrinsic properties (*e.g.* complexity, stability, passivity, etc.). An objective is to use this surrogate in place to the original one to improve (both in time and quality) any many-query optimization process. In this quest, the main tool is the **rational interpolation**, essentially achieved by mean of the **Loewner matrix** proposed by Mayo and Antoulas (2007); Antoulas et al. (2020, 2025b).

ONERA's outcomes and skill overview. As data-driven modeling and simplification plays a pivotal role in many domains, this research led to numerous outcomes for **ONERA**. This includes its use in **industrially-driven projects** (European projects Clean Sky 1 & 2, Flipased, Facelift, Clean Aviation / DGAC projects Majestic, ALFA, DECOR, GVT-Next, etc.), but also **prospective** ones (Ph.D. thesis, PRF FluiDyCon & HARMONICS and AID projects). In addition, **advanced presentations** in scientific groups, teaching in engineering school (ISAE, INSA, ENAC) and continuous training (Ecole de l'X, EuroSAE, Summer schools) were held. It also contributes to open **ONERA** DTIS to internal exchanges with DAAA, DOTA, DMAE, and to build national (*e.g.* LAAS, ISAE) and international (*e.g.* Rice University, MPI Magdeburg, DLR, etc.) collaborations and researcher exchanges. Finally, it led to the creation of a cutting edge technological startup: **MOR Digital Systems**. Fundamental skills in **data-driven tensor approximation and realization theory** are now mastered at **ONERA**, at a high international level. These skills already irrigate (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.

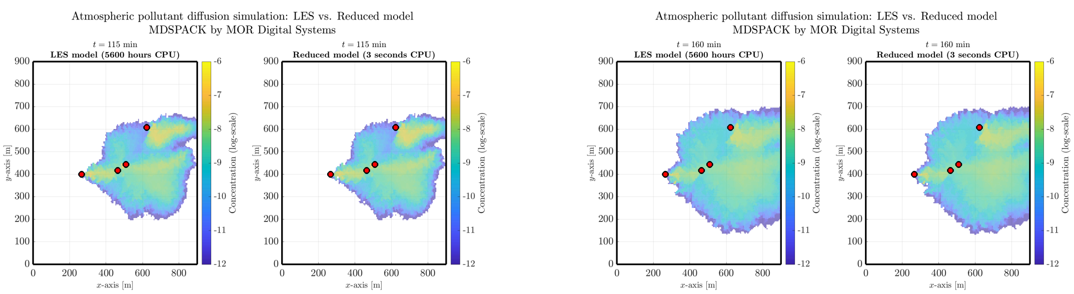
Industrial aircraft applications (Clean Sky 1 & 2, Majestic). Within these major projects, an important collaboration with Dassault-Aviation and Airbus has been consolidated. I did provide solutions on different aircraft topics, all involving approximation at its core: gust load modeling and control, 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 frame), and (ii) the validation of modeling and control methods for of gust load in transonic conditions over a 3D wing, at **ONERA** Meudon wind tunnel facility (right frame) (Meyer et al., 2017; Poussot-Vassal et al., 2021; Vojkovic et al., 2023).

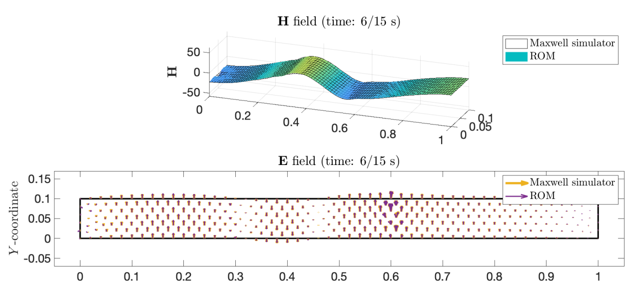
Fluid structure applications (FluiDyCon). Application at **ONERA** Lille wind tunnel facility of two flow separation strategies (a model-driven nonlinear positive and a data-driven linear one) involving interpolatory approximation methods. Left frame is the wind tunnel facility with the 2D wing; right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



Pollutant approximation (DECOR). The application of the interpolatory framework to construct a simplified **Q-DAE** model of a pollutant dispersion data computed from the high-fidelity **Meso-NH** software (implementing LES). Two time instants top views of pollutant plume. Left frames: original data obtained in 5,600 hours; right frames, approximated model data obtained in 3 seconds.



Waveguide approximation (coll. ISAE). The construction of a simplified passive dynamical model of a wave guide setup using data collected directly from a Maxwell's equation driven simulator. The reduced model recovers first the structure and properties, second the input/output behavior and third, enables the full state (approximate) reconstruction. The figure shows a wave guide magnetic (**H**, top) and electric (**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).



Publications, 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 researcher 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 teach control theory at INSA, and applied mathematics at ISAE. I also built 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 in 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. Whatever the given importance, 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[2].

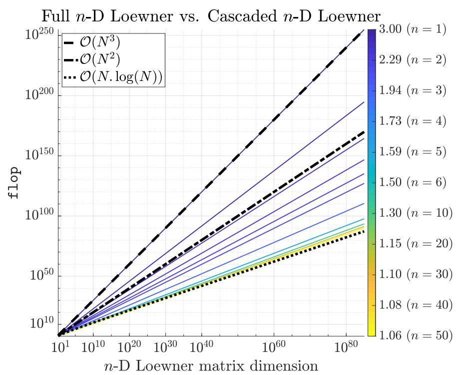
3.1 Tensor multivariate rational approximation & Kolmogorov Superposition Theorem

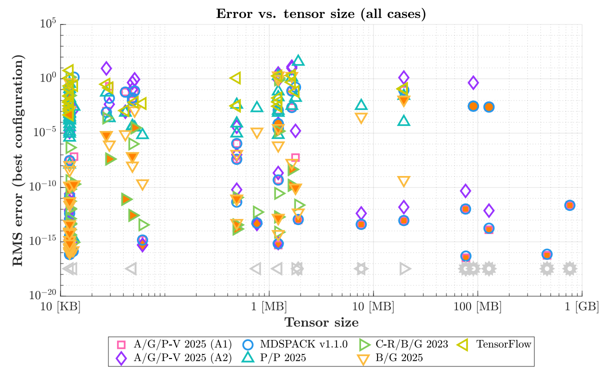
SIAM Review (Research Spotlight) (collaboration with Rice University & Max Planck Institute)
Antoulas et al. (2025b), https://doi.org/10.1137/24M1656657

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**. More specifically, 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 of the KST for this special function case (Pólya and Szegö, 1925). As a byproduct, **taming the curse of dimensionality** (**C-o-D**) 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 domain. In details, the following contributions are established (refer to Antoulas et al. (2025a) for details):
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 $x_2, \cdots, x_n$ 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.

Below left-hand frame shows the worst case `flop` for varying number of variables n, and compares with the full n-D Loewner approach and some standard references, showing the complexity huge drop thanks to the decoupling. Right-hand frame compares approximation error of the **mLF**[3] and its implementation in MOR Digital Systems (2025, MDSPACK)[4] 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
[2] See also: https://cpoussot.github.io/publications.html for full list and https://cpoussot.github.io/research.html for animated visuals.
[3] https://github.com/cpoussot/mLF.
[4] http://mordigitalsystems.fr/en/.



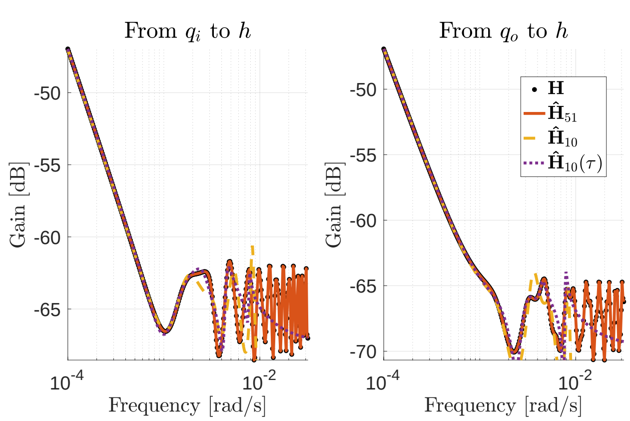


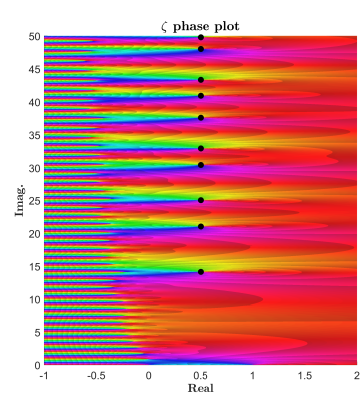
The above right frame exhibits the error as a function of the tensor size. One important point is that only the proposed solution is capable to accurately approximate very large-scale tensors, where other methods fail. Filled points the best method while grey symbol show un-converged ones.

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

In this contribution we discuss the modeling and model reduction framework known as the Loewner framework. This is a data-driven approach, applicable to large-scale systems, which was originally developed for applications to linear time-invariant systems. We detail how this can be extended to a number of additional more complex scenarios, including **linear parametric** or **non-linear** dynamical systems. We provide here an overview of the latter two, together with time-domain extensions. Additionally, 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). In particular, the below left frame illustrates the accuracy of the approximation by a rational function (without and with input delay) of a linear partial differential equation used by **EDF** to model an open-channel water level as a function of in and outflows. The right frame illustrates how it is possible to recover the functions and zeros of the infinite irrational **Riemann ζ function**. Both use-cases are solved with the Loewner framework.

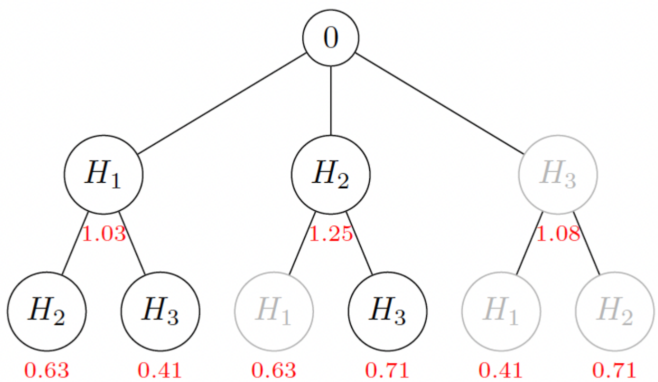




3.3 Optimal modal truncation method

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

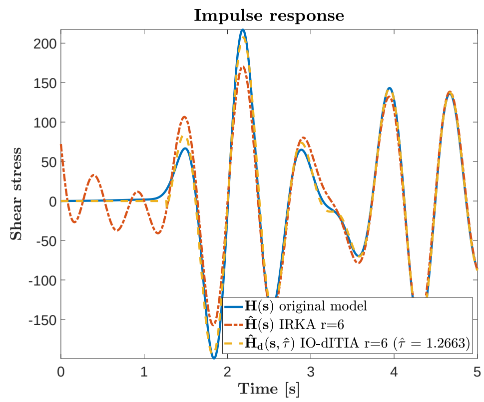
This paper **revisits - the old fashioned - modal truncation method** from an optimization point of view. In particular, the concept of dominant poles is formulated with respect to different system norms as the solution of the associated optimal modal truncation problem. The latter is reformulated as an equivalent convex integer or mixed-integer program. Numerical examples highlight the concept and optimization approach. The frame illustrates the combinatory nature of the optimization problem. One central element of this method is its acceptance and preference by industrial partners. Indeed, preserving the modal content is often required by structure and aero-engineers. This approach responds to a real demand from industrial collaborators.

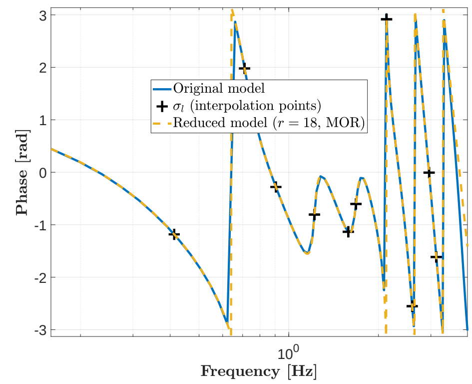


3.4 $\mathcal{H}_2$-optimal model reduction with input-output delays

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

In this paper, the $\mathcal{H}_2$-optimal approximation of a multi-input multi-output transfer function by a finite dimensional system **including input/output delays**, is addressed. This problem is of particular interest when the full order model represents a transport phenomenon. The contribution 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, the underlying $\mathcal{H}_2$ optimality conditions of the approximation problem are obtained as an extension of the tangential interpolatory conditions. It is also demonstrated that for fixed delay values, this problem can be recast as a rational function approximation one. An iterative algorithm is sketched out and numerical results assess the theoretical contributions. The bellow frames represent the impulse (left) and phase (right) responses 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! This theoretical result extends the well known IRKA algorithm, being the gold standard model reduction algorithm.

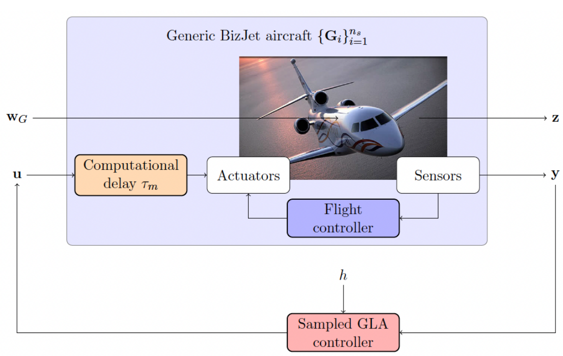


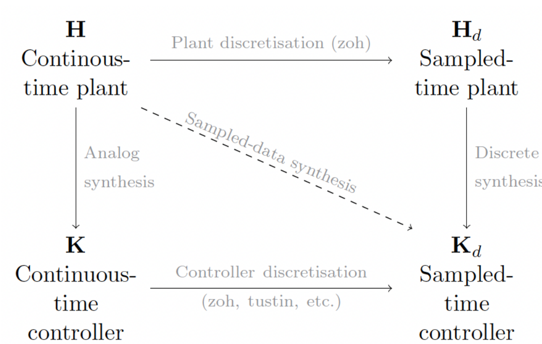


3.5 Gust load alleviation control applied on a Dassault-Aviation use-case

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

The main contribution concerns the use of interpolatory methods to solve an end-to-end industrial control problem proposed by **Dassault-Aviation**, involving a complex irrational delayed linear dynamical model. In more detail, contributions show how rational function interpolation is a pivotal tool (i) to construct **frequency-limited reduced-order dynamical models** appropriate for model-based control design and (ii) to **discretize controllers** with an improved accuracy, in view of onboard control implementation. This is illustrated along the paper through the design of an active feedback gust load alleviation function, applied on a **Dassault-Aviation** generic business jet aircraft use-case. The closed-loop validation and performance evaluation are assessed through the use of a dedicated industrial simulator and considering certification objectives. Although application is centered on aircraft applications, the method is not restrictive and can be applied to any linear dynamical system. The left frame shows the active closed-loop gust load control scheme with the generic complex (large-scale, delayed irrational) business jet model, while the right one shows the discretization process which is predominant is all real-life control applications. This works demonstrates how versatile the rational approximation is, applied in a complex industrial context.





4 Perspectives

After this research activities and main contributions exposition and illustration with heterogenous applications and problematics, reader may measures how versatile multivariate rational function 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:

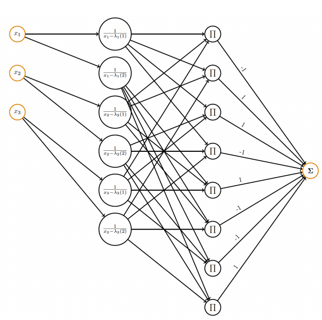
- Explore the linear **parametric and multivariate forms**. The recent results in tensor approximation ($\mathbf{A_2}$, Antoulas et al. (2025b) and section 3.1) are very promising as they demonstrate a breakthrough in simplifying the computational complexity for addressing very complex real life problems. They already show superiority with respect to multiple approximation via neural nets or rational form approaches. 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.

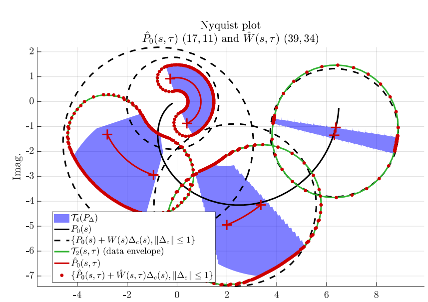
- Explore the **uncertain modeling**. One direct link with the previous item is the connection of the multivariate forms with the uncertain ones. One idea is to consider some variables as parameters and others as uncertainties. Connecting both would benefit to robust control, modeling and uncertainty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

- 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 first point, multivariate passive (and stable) models are also challenging targets.

- 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.

- **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.





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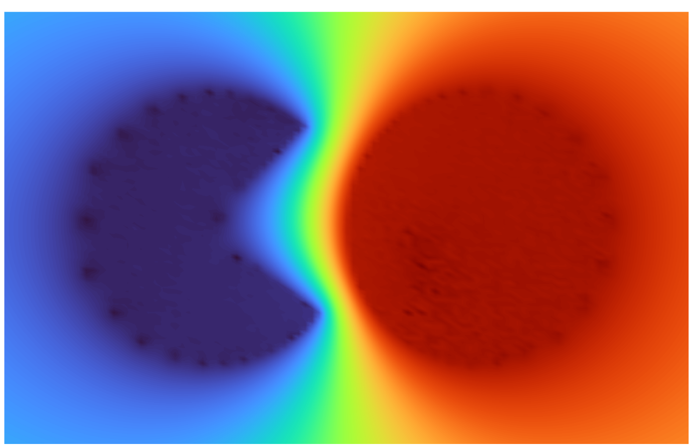

Artistic view of the Pac Man topology in Zolotarev 3rd and 4th problems (submitted in 2026).