Scientific challenges for the development of hybrid modeling / optimization / control strategies of complex fluid systems

Chair PROVE (Green Aeronautical Propulsion)

Denis Sipp, Angelo Iollo

Chair PROVE (Green Aeronautical Propulsion)
Co-chairs: D. Sipp & A. Iollo

- **Collaboration between ONERA and Région Nouvelle Aquitaine (academic & industry)**

- **Subject: Innovative methods to design low-emission propulsion (hybrid modeling, optimization and control strategies)**

- **Funding for PhD (6+), Post-docs (2+) and Interns (10+)**

- **Partners:**
  - **Research centers: ONERA, CEA CESTA**
  - **Academic: Bordeaux (MEMPHIS, CARDAMOM), Poitiers (PPRIME), Bidart (ESTIA)**
  - **Industry: Safran HE, Safran T, Ingeliance, AKIRA**

Outline

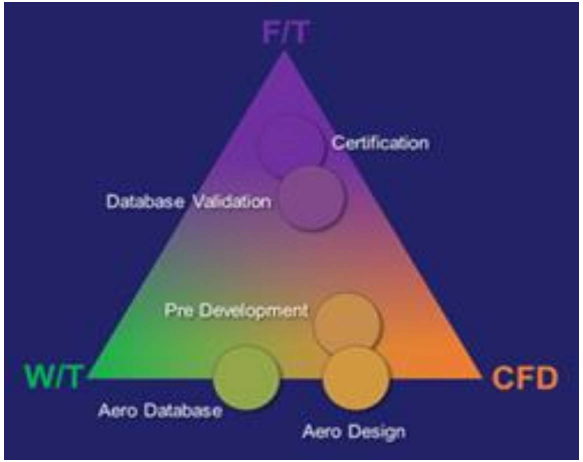
1) Context and objectives of the PROVE chair

2) Scientific challenges

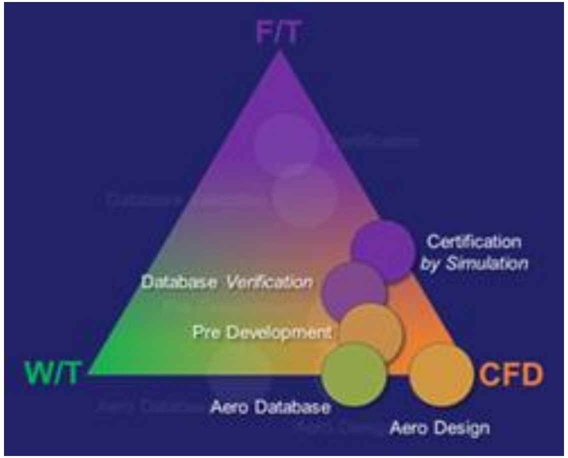
3) Partnership

The digital transformation of the aerospace industry
The case of aerodynamics

Today



Objective



« Mix of data » in various phases of aircraft development. Left: today, Right: tomorrow

Emerging opportunities for predictive CFD for off-design commercial airplane flight characteristics, J. Slotnick/Boeing, G. Heller/Airbus, 54th A3F, 25-27 mars 2019

Digitalisation of aeronautical industry

Setting up digital twins

- Numerical models accompanying the development of an aircraft from the pre-project phase to operation and withdrawal
- Multi-fidelity and evolutionary models
  - Quick "low-fidelity" models at the pre-project stage
  - Accurate "high-fidelity" models for the later phases
- Hybrid models built by combining
  - Physical models (conservation principles)
  - Data from various sources (engine test benches, numerical simulations, flight tests, etc.) and characterized by different uncertainties
- AI techniques to manage the mass of data
- Modeling, Optimization and Control techniques (objective=low emissions) under constraints (high level of flight safety)

Outline

1) Context and objectives of the PROVE chair

2) Scientific challenges

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Scientific Challenges

- Challenge 1: Input to Output ROM with large-dimensional input space
- Challenge 2: Input to State ROM with few CFD evaluations
- Challenge 3: Data-based Turbulence Modeling for accurate and fast CFD computations
- Challenge 4: State reconstruction with sparse measurements
- Challenge 5: Dynamic ROM with finite-amplitude perturbations

Challenge 1: Input to Output ROM with large-dimensional input space

- **Objective:** considering the optimisation problem, $\min_p J(p)$, adapt response surface-based optimization tools to take into account the gradient information $\nabla_p J$, routinely provided by new CFD codes.
- **State of the art:**
  - Surrogate models (Kriging)
  - Clustering (Gaussian mixtures)
  - Design of experiment (DoE), adaptive enrichment (EM)
  - Reduction of the dimension of the input space (Active sub-spaces U_1, P. Constantine):

$$\begin{pmatrix} \nabla_{p_1} J & \nabla_{p_2} J & \cdots \end{pmatrix} = \begin{pmatrix} U_1 & U_2 \end{pmatrix} \begin{pmatrix} \Sigma_1 & 0 \\ 0 & \approx 0 \end{pmatrix} \begin{pmatrix} V_1 & V_2 \end{pmatrix}^* \approx U_1 \Sigma_1 V_1^*$$

$$J(p) = J(U_1[U_1^* p] + U_2[U_2^* p]) \approx J(U_1[U_1^* p])$$

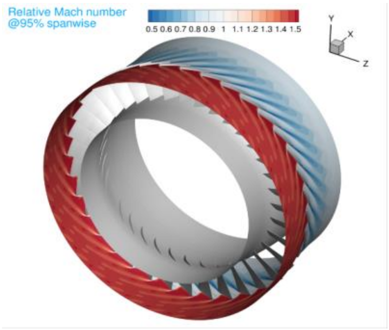
- **People involved**: M. Chapron (PhD student), Ch. Blondeau (DAAA/MSAE), I. Salah El Din (DAAA/H2T), M. Bergmann (MEMPHIS)
- **Related project :** UE NEXTAIR
- **References:**

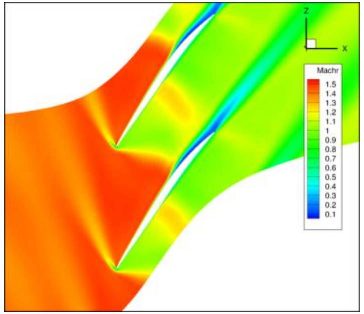
  - Constantine, P. G., Dow, E., & Wang, Q. (2014). Active subspace methods in theory and practice: applications to kriging surfaces. SIAM Journal on Scientific Computing, 36(4), A1500-A1524.
  - Bettebghor, D., Bartoli, N., Grihon, S., Morlier, J., & Samuelides, M. (2011). Surrogate modeling approximation using a mixture of experts based on EM joint estimation. Structural and multidisciplinary optimization, 43(2), 243-259.
  - Bouhlel, M. A., Hwang, J. T., Bartoli, N., Lafage, R., Morlier, J., & Martins, J. R. (2019). A Python surrogate modeling framework with derivatives. Advances in Engineering Software, 135, 102662.

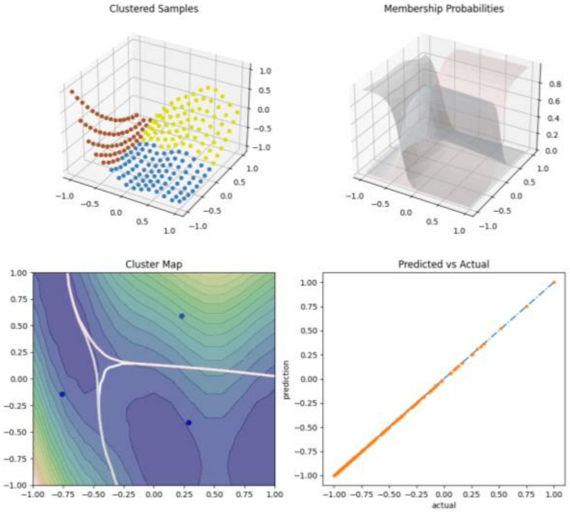
Challenge 1: Input to Output ROM with large-dimensional input space

- **Scientific challenge:** efficient exploration and compact representation of the surrogate $J(p)$ when p is high dimensional (in an industrial process one can typically have 100 to 10000 parameters!) in the case where there are several local minima (multi-modality)
- **Approach considered:** Combination of the "Active Subspace" technique due to the availability of $J(p)$ and $\nabla_p J$ in new CFD solvers + clustering (Gaussian mixture, EM)

Cas d'étude 3D
ROTOR 37





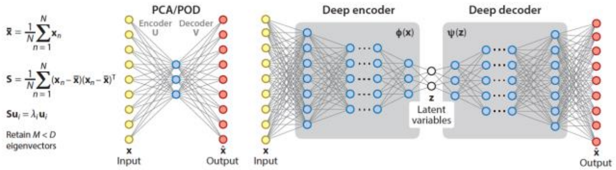


- **Expected results:**
  - Methodology for surrogate models and robust optimization in the case of a very high dimensional input space (≈10000)
  - Implementation of the clustered Active Subspaces approach in SMT

PhD of Maxime Chapron=> see poster

Challenge 2: Input to State ROM with few CFD evaluations

- **Industrial need:** in the design phase, need to optimize a very large number of parameters (the shape of a blade) with objectives on the state of the system (suppression of a vortex for example)
- **Objective:** From realizations of the state as a function of parameters, identify a subspace and build a reduced-order model representing the input - state - output relationships.
- **State of the art**:
  - Identification of a reduced dimensional subspace in the output space:
    - POD
    - Auto-Encoder
  - Reduced-Order model:
    - Physics-based : Galerkin projection, DEIM, hyper-reduction, …
    - Data-based : Clustering, GP, ML, SINDY, …

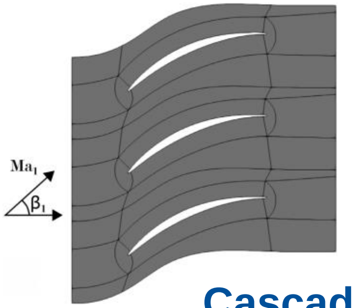


- **People involved:** J. Labatut (thésard), J.-B. Chapelier (DAAA/NFLU), A. Remigi (ST), T. Taddei (IMB/MEMPHIS)
- **Related projects:** UE ARIA (A. Iollo)
- **References :7**

- **Iollo, A.**, & **Taddei, T.** (2022). Mapping of coherent structures in parameterized flows by learning optimal transportation with Gaussian models. Journal of Computational Physics, 471, 111671.
- **Chapelier, J. B.**, De La Llave Plata, M., Renac, F., & Lamballais, E. (2014). Evaluation of a high-order discontinuous Galerkin method for the DNS of turbulent flows. Computers & Fluids, 95, 210-226.
- **Sipp, D.**, de Pando, M. F., & Schmid, P. J. (2020). Nonlinear model reduction: a comparison between POD-Galerkin and POD-DEIM methods. Computers & Fluids, 208, 104628.
- Cordesse, P., **Remigi, A.**, Duret, B., Murrone, A., Ménard, T., Demoulin, F. X., & Massot, M. (2020). Validation strategy of reduced-order two-fluid flow models based on a hierarchy of direct numerical simulations. Flow, Turbulence and Combustion, 105(4), 1381-1411.

Challenge 2: Input to State ROM with few CFD evaluations

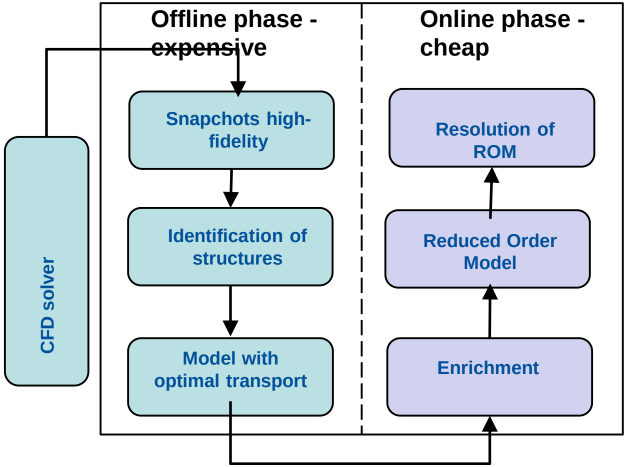
- **Scientific challenge** : compression of a compact structure (vortex) that moves (depending on the parameters), taking into account the boundary conditions during the optimal transport phase, feature selection, enrichment of the basis, ...
- **Approach considered:** non-linear interpolation (registration-based)
- **Test case:** reduction of the DG Aghora code on the following data set



Cascade V103

Flow conditions for various compressor cascade scenarios.

Scenario	S_1	S_2	S_3	S_4
β_1	36.99°	39.97°	44.09°	49.2°
Ma_1	0.654	0.674	0.666	0.65
Re_1	302K	302K	298K	289K
Tu (%)	2.9	3.4	3.4	3.5



- **Expected results:**
  - Methodology for setting up a parameterized ROM
  - Model for a rotor-stator channel, multi-channel coupling for the representation of an entire stage, then multi-stage coupling for the representation of a compressor (Post-Doc)
  - Module for model reduction in a python library

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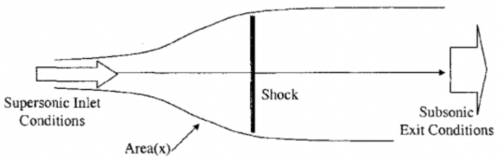
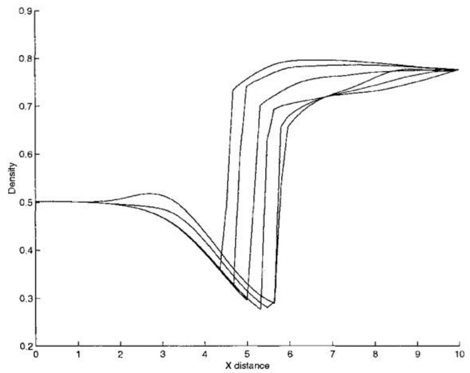
de Zordo-Banliat, M., Merle, X., Dergham, G., & Cinnella, P. (2020). Bayesian model-scenario averaged predictions of compressor cascade flows under uncertain turbulence models. *Computers & Fluids*, *201*, 104473.

Challenge 2: Input to State ROM with few CFD evaluations

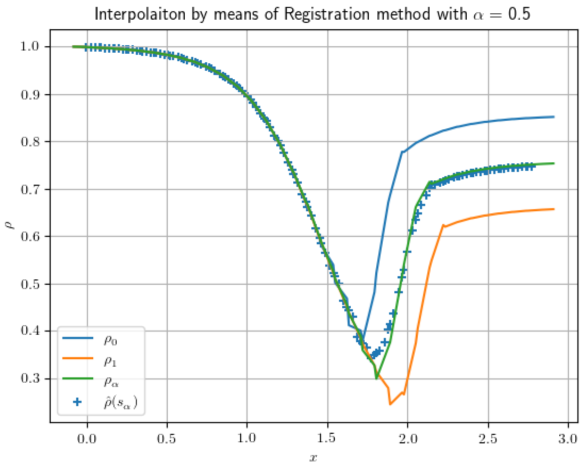
Parametrized nozzle flow: $p_{out} \in [0,1]$



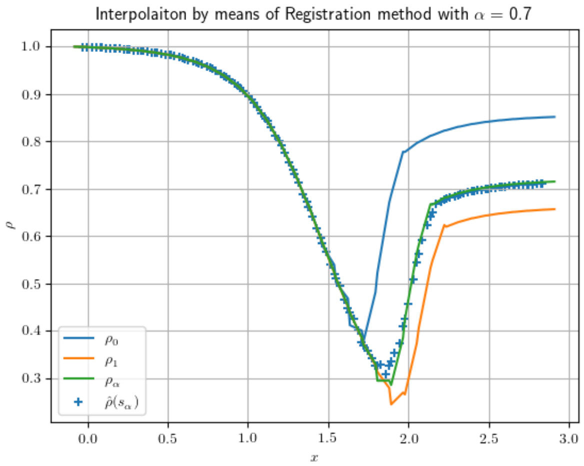


CFD solver
$\hat{\rho}(p_{out}, x)$

Two solutions for $\rho_0(p_0 = 0.85, x)$ and $\rho_1(p_1 = 0.65, x)$.
Approximation: $\hat{\rho}(s_\alpha, x)$ which gives a prediction of the solution at low cost.
Relative error: $\varepsilon_\alpha = \left|\left|\hat{\rho}_{s_\alpha} - \rho_{obj}\right|\right|_2^2 / \left|\left|\rho_{obj}\right|\right|_2^2$



$\varepsilon_\alpha = 0.013$
$p_{out} = 0.75$



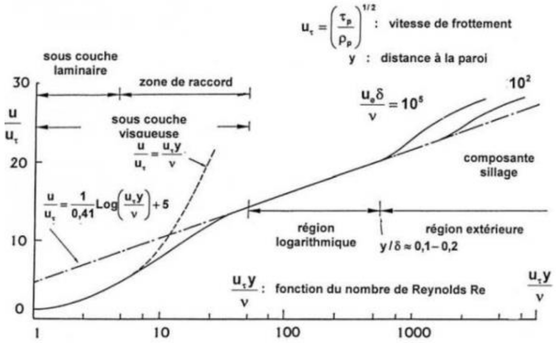
$\varepsilon_\alpha = 0.017$
$p_{out} = 0.71$

PhD of Jon Labatut => see poster

Challenge 3: Data-based Turbulence Modeling for accurate and fast CFD computations

- **Objective:** improve fidelity and reduce the cost of RANS aerodynamic simulations used in design offices
- **State of the art:**
  - Improvement of turbulence closure models
  - Improvement of wall laws
  - Empirical wall laws : Musker, Afzal ...
- **Model for internal region:**

$$\frac{\bar{u}(y)}{u_\tau} = f\left(\frac{\rho_w u_\tau}{\mu_w} y, \frac{\mu_w}{\rho_w^2 u_\tau^3}\partial_x \bar{p}\right),\ u_\tau = \sqrt{\frac{\mu_w \partial_y \bar{u}|_{y=0}}{\rho_w}}$$



- **People involved:** M. Romanelli (PhD) S. Beneddine (ONERA/MASH), I. Mary (ONERA/DEFI), H. Beaugendre (INRIA/CARDAMOM), M. Bergmann (INRIA/MEMPHIS)
- **Related projects:** ANR NEWMAC (with SAFRAN TECH and DLR)
- **References:**

  - **Beneddine, S.** (2022). Nonlinear input feature reduction for data-based physical modeling. arXiv preprint arXiv:2206.07400.
  - Constant, B., Péron, S., **Beaugendre, H.**, & Benoit, C. (2021). An improved immersed boundary method for turbulent flow simulations on Cartesian grids. Journal of Computational Physics, 435, 110240.
  - Péron, S., Benoit, C., Renaud, T., & **Mary, I.** (2021). An immersed boundary method on Cartesian adaptive grids for the simulation of compressible flows around arbitrary geometries. Engineering with Computers, 37(3), 2419-2437.
  - Volpiani, P. S., Meyer, M., Franceschini, L., Dandois, J., Renac, F., Martin, E., ... & **Sipp, D.** (2021). Machine learning-augmented turbulence modeling for RANS simulations of massively separated flows. Physical Review Fluids, 6(6), 064607.

Challenge 3: Data-based Turbulence Modeling for accurate and fast CFD computations

- **Approach followed:**
  - Steady RANS resolved up to the wall=reference
  - Identification of inputs by physical approach and by data-based approach (mutual information, determination of the most influential parameters)

$$\frac{\bar{u}(y)}{u_\tau} = f\left(\frac{\rho_w u_\tau}{\mu_w} y, \frac{\mu_w}{\rho_w^2 u_\tau^3} \partial_x \bar{p}, \text{Compressibility, Geormetry, Non-locality, ...}\right)$$

$$\bar{v}(y) = ???$$
$$\bar{\rho}(y) = ???$$
$$\bar{\nu_t}(y) = ???$$

2. GAN (image based approach) ?
3. Separated flows, LES data or experimental data-base

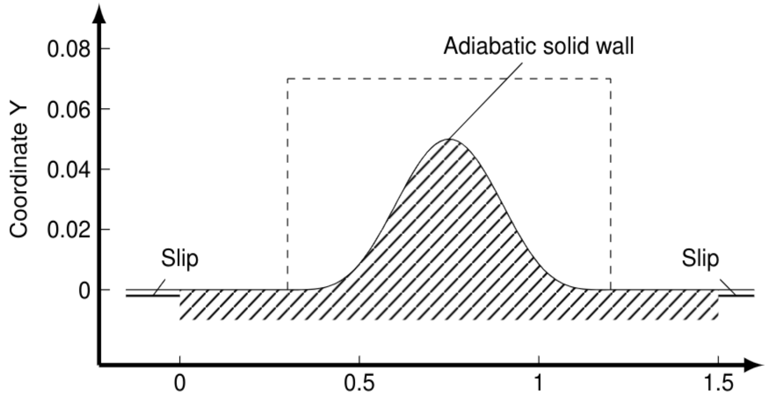
  - Unsteady LES resolved up to the wall=reference
    - Modeling of fluctuations

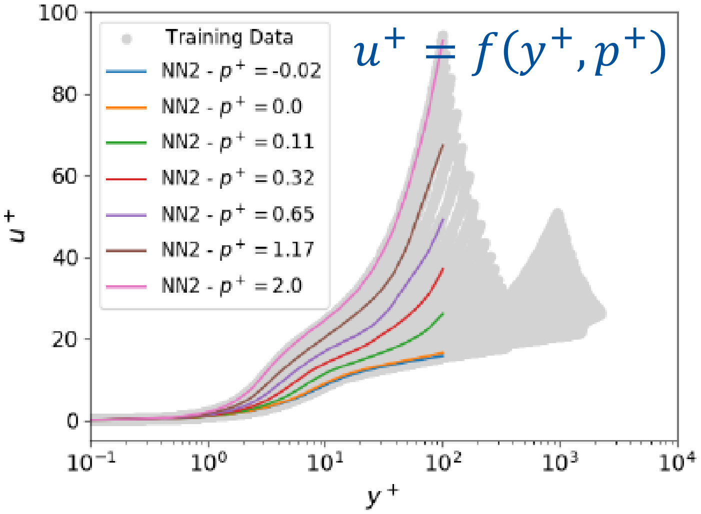
- **Expected results**
  - More accurate and more robust laws of the wall for RANS and LES simulations
  - Data-based methodology to determine best input / output features (Mutual information)

Beneddine, S. (2023). Nonlinear input feature reduction for data-based physical modeling. *Journal of Computational Physics*, *474*, 111832.

Challenge 3: Data-based Turbulence Modeling for accurate and fast CFD computations

- High-fidelity database: 2D RANS
- Bump flows: $Re \in [10^6, 10^7],\ h/L \in [0{,}05; 0{,}08]$
- Moderate pressure gradients without separation





RANS interface at $y^+ \approx 10$					
	$h = 0$	$h = 0.05$	$h = 0.06$	$h = 0.07$	$h = 0.08$
$Re = 1 \cdot 10^7$			0.72%		0.88%
$Re = 8 \cdot 10^6$			0.75%		
$Re = 6 \cdot 10^6$		0.77%	0.8%	0.85%	
$Re = 3 \cdot 10^6$	0.61%	0.84%	0.93%	0.92%	
$Re = 1 \cdot 10^6$		1.26%	1.35%	1.54%	
RANS interface at $y^+ \approx 30$					
	$h = 0$	$h = 0.05$	$h = 0.06$	$h = 0.07$	$h = 0.08$
$Re = 1 \cdot 10^7$			1.68%		2.09%
$Re = 8 \cdot 10^6$			1.92%		
$Re = 6 \cdot 10^6$		1.94%	2.27%	2.53%	
$Re = 3 \cdot 10^6$	1.21%	2.94%	3.41%	3.76%	3.98%
$Re = 1 \cdot 10^6$		5.54%	6.28%	6.84%	

Learning

PhD of Michele Romanelli => see poster

Challenge 4: State reconstruction with sparse measurements

- **Industrial need:** reconstruction of the flow in a confined system with moving parts, in which measurements are difficult and scarce
- **Objective:** to be able, from sparse measurements, to reconstruct the large-scale state of a system
- **State of the art:**

$$\min_{\boldsymbol{w}} \|\boldsymbol{y}(\boldsymbol{w}) - \bar{\boldsymbol{y}}\|^2_{\boldsymbol{M}^{-1}} + \|\boldsymbol{w} - \bar{\boldsymbol{w}}\|^2_{\boldsymbol{F}^{-1}}$$

  - Ensemblistic methods (EnKF): non-intrusive, very expensive, covariances OK, generation of ensemble members?
  - Variational methods: intruisive, expensive, covariances KO
  - Nudging : almost non-intrusive, not expensive, covariances KO
- **Persons involved :** R. Villiers (thésard), V. Mons (DAAA/MAPE), E. Lamballais (PPRIME/Poitiers), M. Meldi (LMFL/Lille)
- **References :**

  - **Mons, V.**, Chassaing, J. C., Gomez, T., & Sagaut, P. (2016). Reconstruction of unsteady viscous flows using data assimilation schemes. *Journal of Computational Physics*, *316*, 255-280.
  - **Meldi, M.**, & Poux, A. (2017). A reduced order model based on Kalman filtering for sequential data assimilation of turbulent flows. *Journal of Computational Physics*, *347*, 207-234.
  - Dairay, T., **Lamballais, E.**, Laizet, S., & Vassilicos, J. C. (2017). Numerical dissipation vs. subgrid-scale modelling for large eddy simulation. Journal of Computational Physics, 337, 252-274.
  - Franceschini, L., **Sipp, D.**, & Marquet, O. (2020). Mean-flow data assimilation based on minimal correction of turbulence models: Application to turbulent high Reynolds number backward-facing step. *Physical Review Fluids*, *5*(9), 094603.

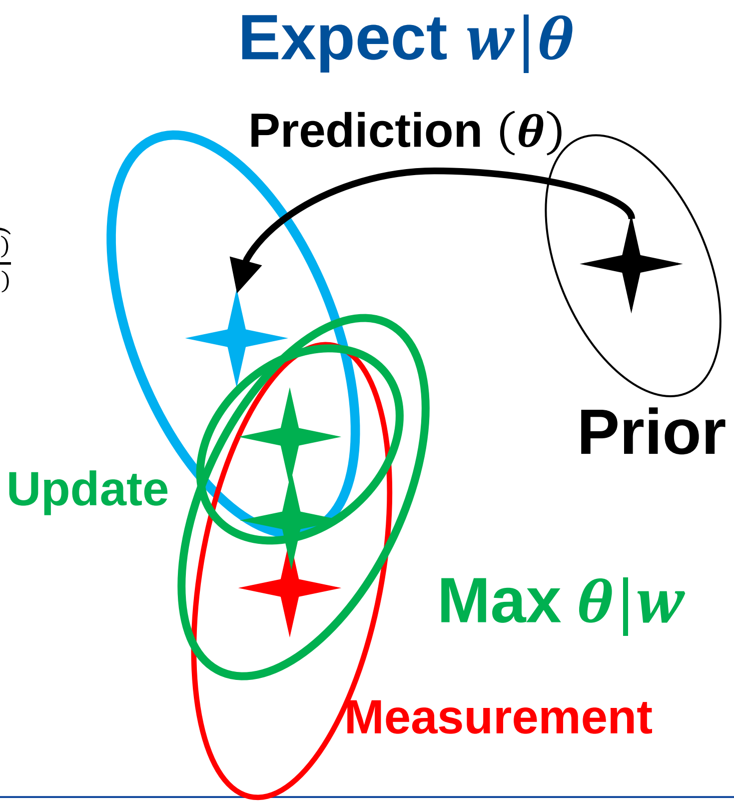
Challenge 4: State reconstruction with sparse measurements

- **Scientific challenge:** best combine statistical information from sparse observations with an imperfect predictive model to be improved
- **Approach considered:** Expectation-Maximization (EM) algorithm provides the best estimate of the state w (ensemble-based method), parameters θ and state-covariance F (machine learning)

Maximisation of probability likelihood: $p(w,\theta,F|y,M) = p(y|w,M)p(w|\theta,F)\frac{\overbrace{p(w,F)}^{K}}{p(y,M)}$

$$p(y|w,M) = \exp\frac{\left(-\frac{1}{2}\|y-y(w)\|^2_{M^{-1}}\right)}{\sqrt{(2\pi)^{N_y}|M|}} \quad p(w|\theta,F) = \exp\frac{\left(-\frac{1}{2}\|w-w(\theta)\|^2_{F^{-1}}\right)}{\sqrt{(2\pi)^{N_w}|F|}}$$

- **Reference:** Bocquet, M., Brajard, J., Carrassi, A., & Bertino, L. (2020). Bayesian inference of chaotic dynamics by merging data assimilation, machine learning and expectation-maximization. Foundations of Data Science, 2(1), 55.
- **Test-cases:** unsteady turbulent flows (turbulent boundary layer, cylinder at Re=12000), then ROTOR 37
- **Expected results:**
  - Methodology for estimating (w,θ,F)
  - Improved URANS model and LES subgrid model correction with explicit filtering

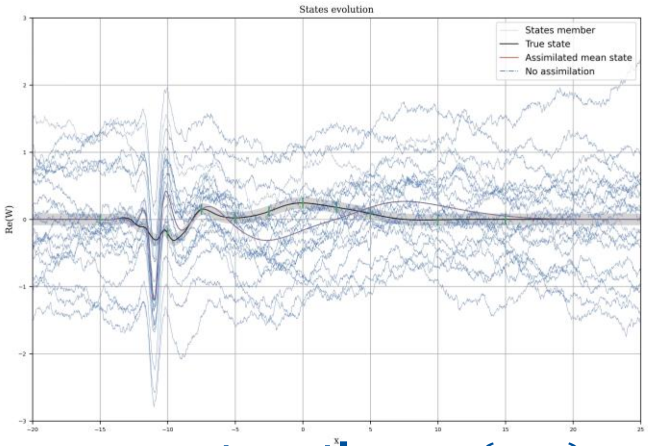


Challenge 4: State reconstruction with sparse measurements

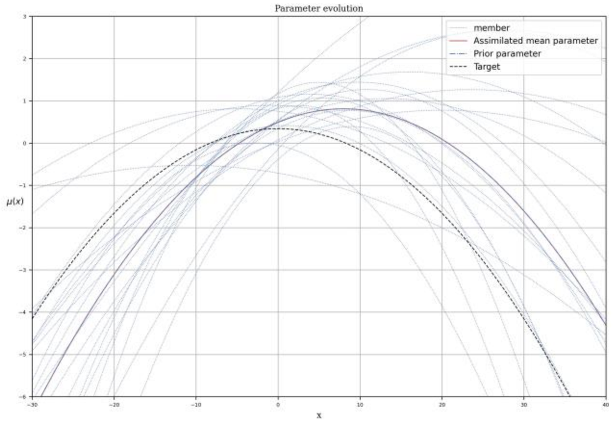
1D model $w(x,t)$ (which mimicks NS) :

$$\partial_t w + U\partial_x w + w|w|^2 = \left(\mu_0 - c_u^2 + \frac{\mu_2 x^2}{2}\right) w + \nu\partial_{xx} w + \eta(x,t)$$

Imperfect model : $\partial_t w + U\partial_x w = \mu_\theta(x) w + \nu\partial_{xx} w$
Measures : $w(x_i,t)$
Assimilation technique : Sequential Kalman



State reconstruction $w(x,t)$



Parameter reconstruction $\mu_\theta(x)$

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PhD of Raphaël Villiers => see poster

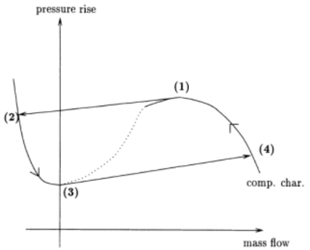
Challenge 5: Dynamic ROM with finite-amplitude perturbations

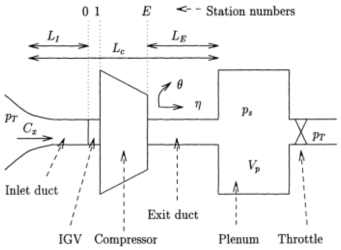
- **Industrial need:** in a compressor, monitoring and control of the pumping phenomenon (strongly non-linear)
- **Objective** From sparse measurements, build a predictive model of the state of a system (with strong nonlinearities) and control it
- **State of the art:**
  - Reduced-order models:
    - Model-based linearized approches: BPOD, résolvant
    - Data-based linearized approaches: Identification, Loewner (Ch. Poussot-Vassal), …
    - Hybrid nonlinear approaches: POD+Projection and variants (L. Cordier), coupling of physical models and data (APHYNITY=>N. Thome, P. Gallinari, CD-ROM=>A. Bucci, L. Mathelin, M. Schoenauer)
    - Data-based nonlinear approaches : Koopman, DMD, Reservoir-computing (L. Magri)
  - Linear control : synthèse robuste Hinf (P. Apkarian), MPC, …
  - Joint learrning of model & control with data: RL (Mathelin, Cordier, Beneddine, thèse R. Paris)
  - Alternative: iterative procedure with robust linear controllers based on linear models (Leclercq et al, 2019)
- **People involved:** PhD student (?), C. Leclercq (DAAA/MASH), L. Cordier (PPRIME), L. Magri (Imperial College), J. Marty (DAAA/H2T)
- **Related projects:** PhD of N. Lepage with N. Thome & I. Mortazavi by combining a physical model and data
- **References:**

  - Leclercq, C., Demourant, F., Poussot-Vassal, C., & Sipp, D. (2019). Linear iterative method for closed-loop control of quasiperiodic flows. *Journal of Fluid Mechanics*, *868*, 26-65.
  - Bucci, M. A., Semeraro, O., Allauzen, A., Wisniewski, G., Cordier, L., & Mathelin, L. (2019). Control of chaotic systems by deep reinforcement learning. *Proceedings of the Royal Society A*, *475*(2231), 20190351.
  - Menier, E., Bucci, M. A., Yagoubi, M., Mathelin, L., & Schoenauer, M. (2022). CD-ROM: complementary deep-reduced order model. *arXiv preprint arXiv:2202.10746*.
  - Yin, Y., Le Guen, V., Dona, J., de Bézenac, E., Ayed, I., Thome, N., & Gallinari, P. (2021). Augmenting physical models with deep networks for complex dynamics forecasting. *Journal of Statistical Mechanics: Theory and Experiment*, *2021*(12), 124012.

Challenge 5: Dynamic ROM with finite-amplitude perturbations

- **Scientific challenge:** control of bifurcations (nonlinearity)
- **Approach considered:**
  - ✓ Representation of the surge phenomenon in the framework of dynamic systems





Plenum pressure coeff.

$$\begin{aligned}
\dot{\Psi} &= \frac{W/H}{4B^2}\left(\frac{\Phi}{W} - \frac{1}{W}\Phi_T(\Psi)\right)\frac{H}{l_c} \qquad (1.16)\\
\dot{\Phi} &= \frac{H}{l_c}\left(-\frac{\Psi-\psi_{c0}}{H} - \frac{1}{2}\left(\frac{\Phi}{W}-1\right)^3 + 1 + \frac{3}{2}\left(\frac{\Phi}{W}-1\right)\left(1-\frac{J}{2}\right)\right)\\
\dot{J} &= J\left(1-\left(\frac{\Phi}{W}-1\right)^2-\frac{J}{4}\right)\varrho,
\end{aligned}$$

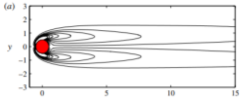
Annulus average mass flow coeff.

Rotating stall amplitude squared

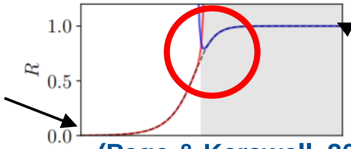
Moore & Greitzer (1986)

- ✓ Linearized model obtained by DMDc (fully data-driven) to replace the solver (partially data and physics based)
- ✓ Learning a nonlinearity by machine learning to augment a linear DMDc model (Khodkar et al. 2021)

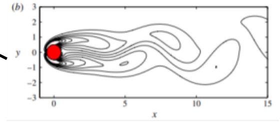
$\dot{x}_1 \approx A_1 x_1$ $\qquad$ $\dot{x}_2 \approx A_2 x_2$



(de Jager,1995)



(Page & Kerswell, 2019)



$$\dot{x} = Ax + f(x)$$

Cross-over problem between two DMD representations

- ✓ Predictive control, adaptive control

Khodkar, M. A., & Hassanzadeh, P. (2021). A data-driven, physics-informed framework for forecasting the spatiotemporal evolution of chaotic dynamics with nonlinearities modeled as exogenous forcings. *Journal of Computational Physics*, *440*, 110412.)

Challenge 5: Dynamic ROM with finite-amplitude perturbations

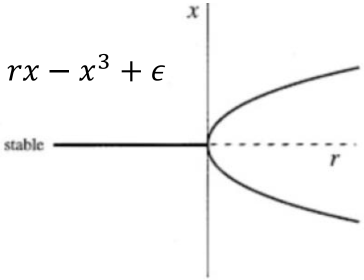
- **Expected results:**
  - Representation of the surge phenomenon as a dynamic system
  - Data-based control methodology to detect and suppress surge
  - Module in a software library for the identification and control of a bifurcation

Challenge 5: Dynamic ROM with finite-amplitude perturbations

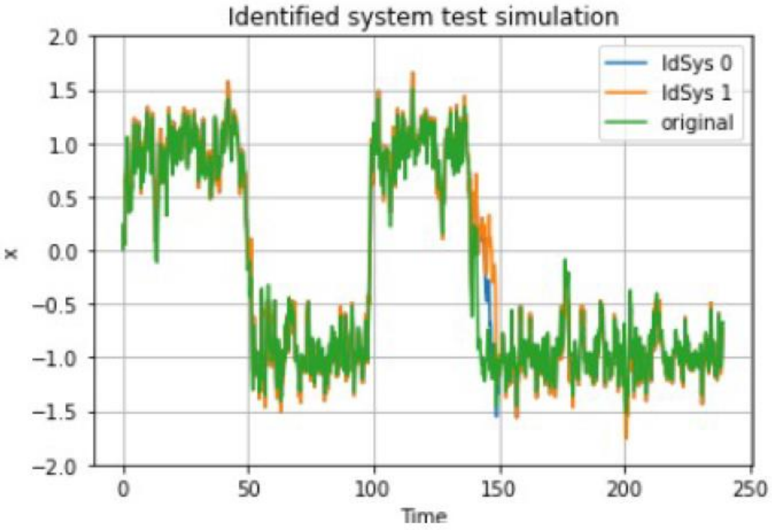
<u>Normal form of a supercritical fork bifurcation</u>

5 ARX composite models capable of tracking ~30% of branch changes

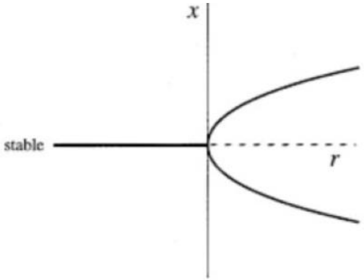
$$\dot{x} = rx - x^3 + \epsilon$$

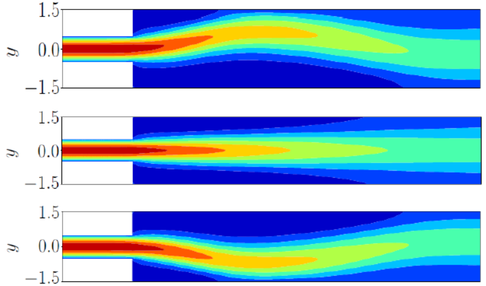


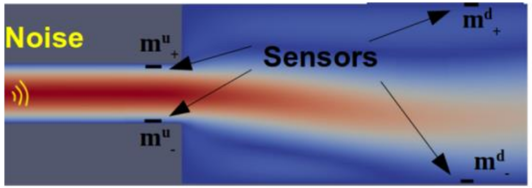
$$
\begin{aligned}
x_{k+1} = &\left[\sum_{i=0}^{n_a} a_i^{\sqrt{\mu}} x_{k-i} + \sum_{i=0}^{n_b} b_i^{\sqrt{\mu}} u_{k-i} + \left(\sum_{i=0}^{n_a} a_i^{\sqrt{\mu}} - 1\right)\sqrt{\mu}\right] \mathbb{1}_{[0.73<x_k]} \; + \\
&\left[\sum_{i=0}^{n_a} a_i^{\sqrt{\mu/3}} x_{k-i} + \sum_{i=0}^{n_b} b_i^{\sqrt{\mu/3}} u_{k-i} + \left(\sum_{i=0}^{n_a} a_i^{\sqrt{\mu/3}} - 1\right)\sqrt{\mu/3} + \frac{2}{3}\sqrt{\frac{\mu}{3}}\Delta t\right] \mathbb{1}_{[0.6<x_k\leq 0.73]} \; + \\
&\left[\sum_{i=0}^{n_a} a_i^{0} x_{k-i} + \sum_{i=0}^{n_b} b_i^{0} u_{k-i}\right] \mathbb{1}_{[-0.6\leq x_k\leq 0.6]} \; + \\
&\left[\sum_{i=0}^{n_a} a_i^{-\sqrt{\mu/3}} x_{k-i} + \sum_{i=0}^{n_b} b_i^{-\sqrt{\mu/3}} u_{k-i} - \left(\sum_{i=0}^{n_a} a_i^{-\sqrt{\mu/3}} - 1\right)\sqrt{\mu/3} - \frac{2}{3}\sqrt{\frac{\mu}{3}}\Delta t\right] \mathbb{1}_{[-0.73\leq x_k<-0.6]} \; + \\
&\left[\sum_{i=0}^{n_a} a_i^{-\sqrt{\mu}} x_{k-i} + \sum_{i=0}^{n_b} b_i^{-\sqrt{\mu}} u_{k-i} - \left(\sum_{i=0}^{n_a} a_i^{-\sqrt{\mu}} - 1\right)\sqrt{\mu}\right] \mathbb{1}_{[x_k<-0.73]}
\end{aligned}
$$



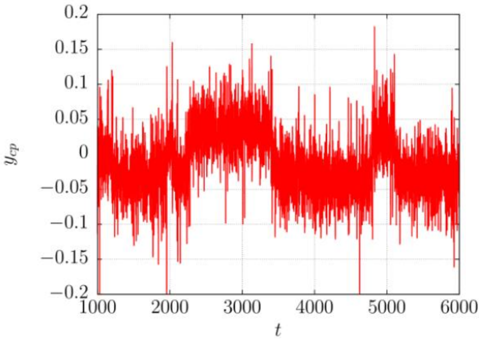
Challenge 5: Dynamic ROM with finite-amplitude perturbations

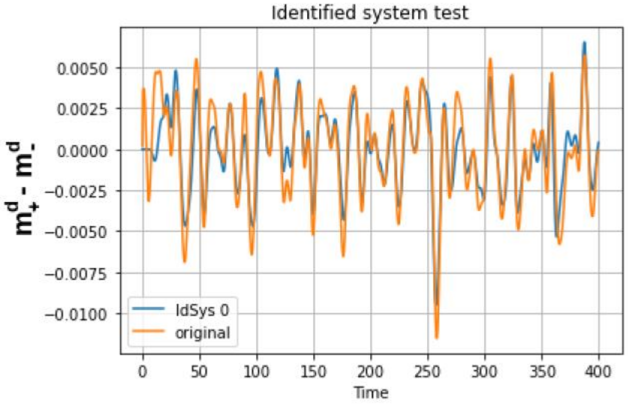






+ finite amplitude noise





No PhD yet, but see poster of N. Lepage

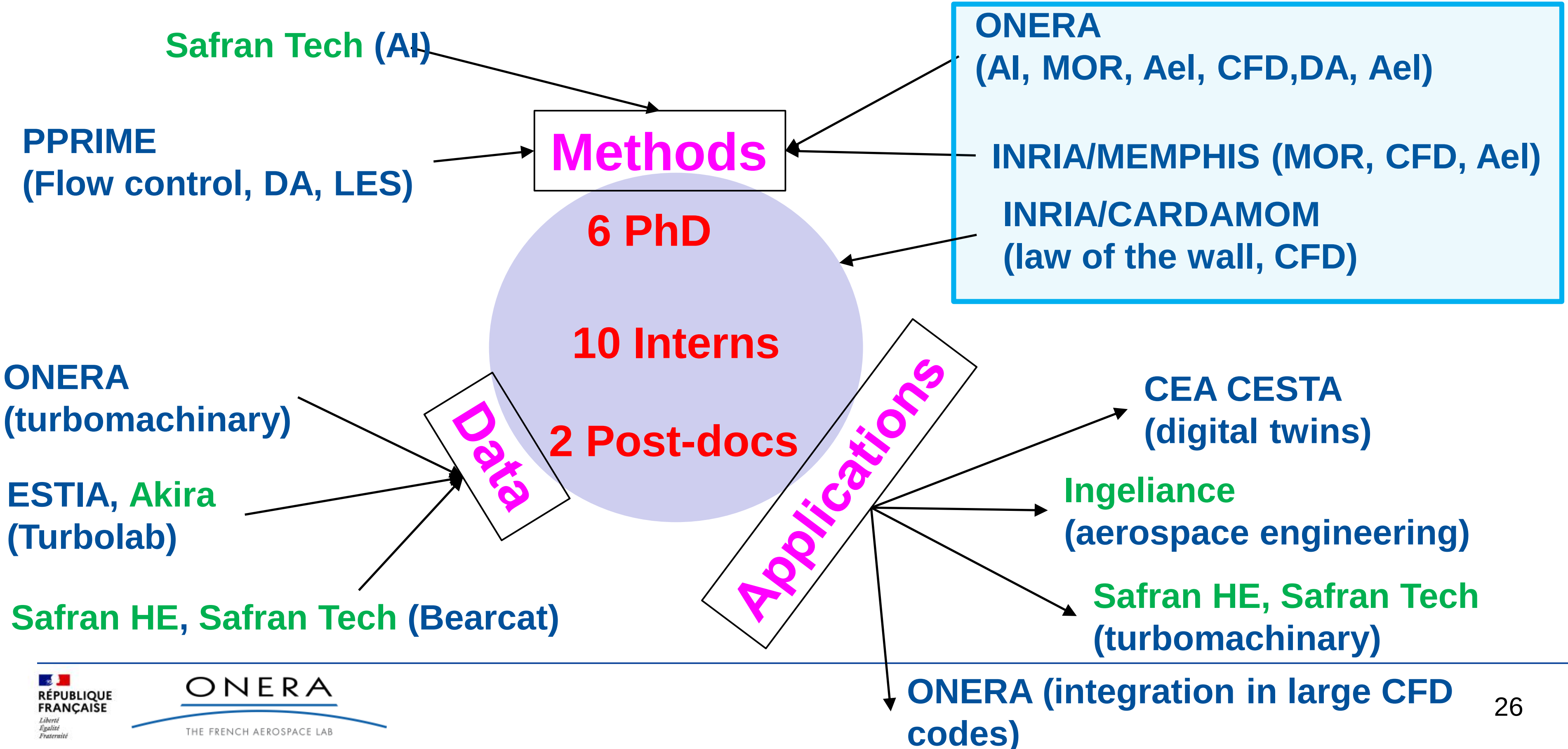
Outline

1) Context and objectives of the PROVE chair

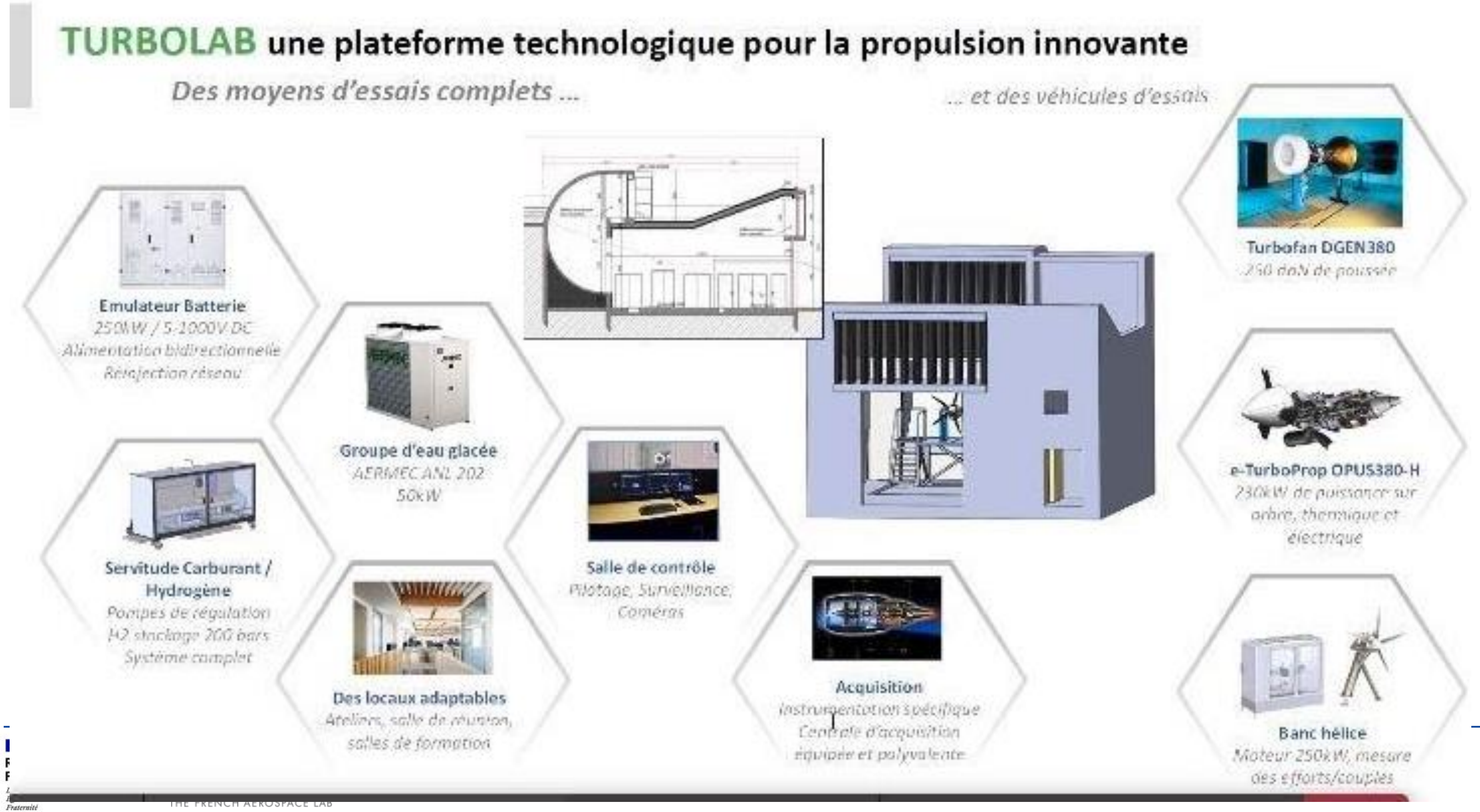
2) Scientific challenges

3) Partnership

PROVE Chair (co-funded by Région Nouvelle-Aquitaine)

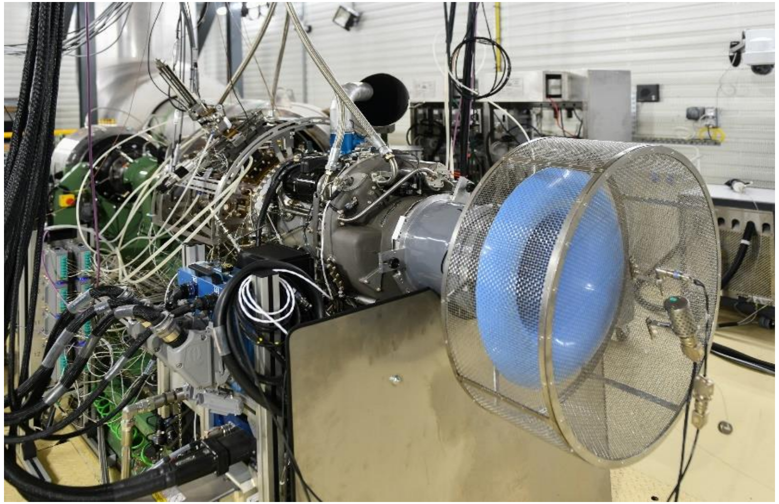


Data from representative experimental test-benches TURBOLAB (ESTIA, AKIRA)



Data from representative experimental test-benches BEARCAT (Safran HE & Safran Tech)

Le banc « BEARCAT » (Banc d'Essai Avancé pour la Recherche en Combustion et Aérothermique des Turbomachines) est un turbomoteur basé sur le moteur MAKILA. Il est dédié à la caractérisation fine des phénomènes aérothermiques se produisant dans la chambre de combustion et la turbine haute pression ainsi qu'à leurs interactions.



BEARCAT

People involved

DAAA:
- MAAA : Denis Sipp
- MAPE : Vincent Mons, Olivier Marquet
- MASH : Samir Beneddine, Colin Leclercq
- H2T : Itham Salah el Din, Julien Marty, Raphaël Barrier
- DEFI : Ivan Mary
- MSAE : Christophe Blondeau
- NFLU : Jean-Baptiste Chapelier, Florent Renac
- ACI : Pedro Stefanin Volpiani

DTIS:
- IVA : F. Champagnat

MEMPHIS :
- Angelo Iollo
- Michel Bergmann
- Tommaso Taddei

CARDAMOM :
- Heloise Beaugendre

PPRIME :
- Eric Lamaballais
- Laurent Cordier
- Lionel Agostini
- Guillaume Lehnasch
- Nassim Razaaly
- Vincent Jaunet

LMFL :
- Marcello Meldi

CEA CESTA :
- Pierre-Henri MAIRE
- Sébastien Esquieu

SafranT :
- Alberto Remigi
- Grégory Dergham
- Alessandro Bucci

SafranHE :
- Jerome Maynadier
- Franck Mastrippolito

Ingéliance :
- Matthieu Puyo
- Guillaume Ruiz
- Mathias Truel

PhD students:
- Michele Romanelli
- Raphael Villiers
- Maxime Chapron
- Jon Labatut
- Bartolomeo Fanizza
- Thomas Philipert

Thank you for your attention