PhD (CNRS) – Structural Health Monitoring using sparse sensor networks and signature-informed modeling

Practical information

- **Duration:** 36 months
- **Starting date:** flexible between May and September 2026 (ANR funding secured)
- **Location:** PIMM Laboratory, ENSAM, Paris, France
- **Supervisors:** Dimitri Goutaudier (CNRS Research Scientist) and Marc Rébillat (Associate Professor, HDR, ENSAM)
- **Salary:** according to legal regulations
- **International collaboration:** possible with EPFL (Switzerland), short research stays could be organized

The PIMM Laboratory is a joint research unit of CNRS, Arts et Métiers and Cnam, dedicated to innovation in the fields of mechanical engineering, materials science and advanced numerical simulation. Located in the heart of the 13th arrondissement of Paris, the laboratory offers a privileged balance between dynamic university life and lively city life.

To apply, please send a complete application (CV, motivation letter, transcripts, and recommendation letter) to dimitri.goutaudier@ensam.eu.

Profile

- Engineering diploma or Master 2 involving at least one of the following disciplines: computational mechanics, scientific computing, physics-informed artificial intelligence.
- Interest in smart monitoring for mechanical systems, model order reduction, data assimilation, artificial intelligence.
- Motivation for joining an interdisciplinary research project including theoretical, numerical and experimental activities.

Expected skills

- Solid background in scientific computing (numerical methods for PDEs, linear algebra)
- Proficiency in one scientific programming language: MATLAB or Python.

Context

The task of **Structural Health Monitoring (SHM)** is to assess the integrity of a structure from in-situ sensor measurements [1]. This raises three important questions. The first is to define **what information** is an indication of structural integrity. It is common practice to focus on physically interpretable parameters which may characterize: a damage, a mechanical

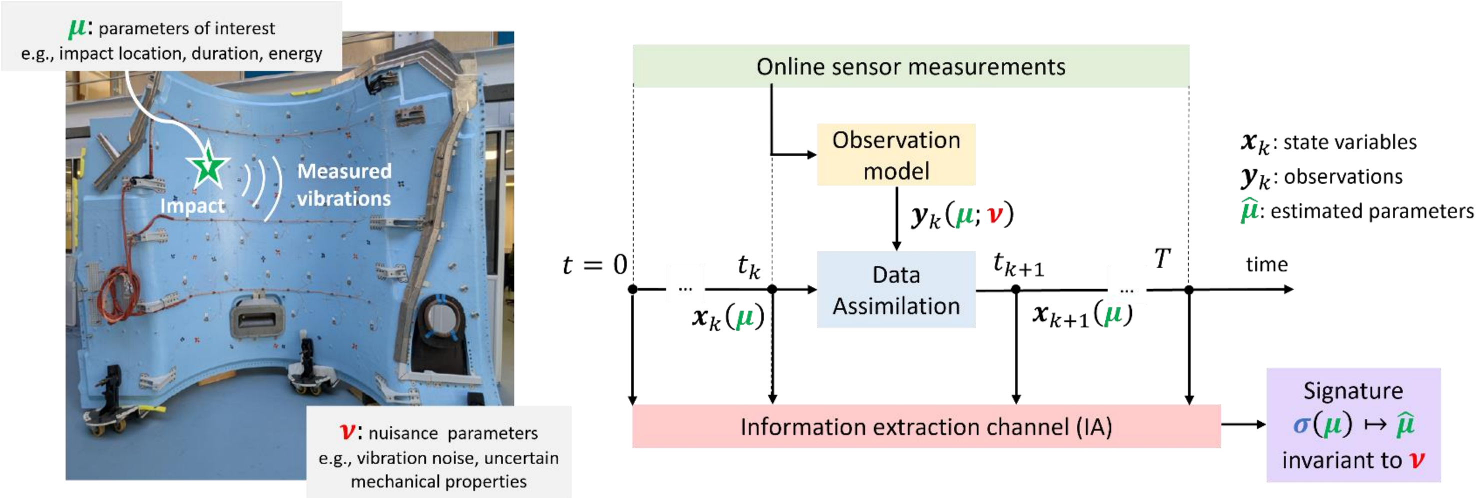

Figure 1. (Left) SHM demonstrator to be developed for localizing impacts on a A380 aircraft nacelle. (Right) Illustration of the data assimilation/IA pipeline. A signature is defined as a time-history aware, low dimensional representation of the parameters of interest, invariant to nuisances unmodeled in the simplified physical model.

property, boundary conditions, an external loading, the onset of an instability, etc. Importantly, complex monitoring problems, involving engineering structures under uncertain operational conditions, require these parameters to be identified within statistical confidence intervals. The second is to determine **what prior knowledge** on the studied structure is to be used. Relying on a mechanistic model or on a data-base of in-situ measurements leads, in some sense, to orthogonal approaches [2]. On the one hand, mechanistic models are physically explainable, but are limited to relatively simple systems. On the other hand, data-driven models may capture more complex phenomena, but are hardly interpretable. The last is to determine **what sensing technology** is to be installed on the structure given the constraints. Several criteria may drive the selection process, including: number and location of sensors, overall size and weight, durability and reliability in harsh environment, frugality, compliance with sector-specific regulations, and benefit-cost ratio.

In **industrial applications**, the **benefit-cost ratio** often represents a critical barrier to the widespread adoption of SHM. For example, in the context of commercial aviation, the use of SHM remains limited, partly due to challenges in establishing clear business cases [3]. Deploying a dense network of sensors to monitor large areas of an aircraft is not only expensive, but also difficult to reconcile with the stringent regulations governing sensor installation. In addition, achieving **high reliability** is of paramount importance. Developing **minimally intrusive** yet reliable smart monitoring systems is therefore a critical and urgent challenge of SHM. Successfully addressing these challenges could unlock economically viable applications for a wide range of applications across various industries (aeronautics, turbomachinery, industrial processes, etc.).

This PhD is part of the **funded ANR JCJC project *SPARSE-SHM*** (*Sparse structural health monitoring using signature-informed hybrid modeling*). The goal will be to develop an innovative SHM framework capable of operating with a **very limited number of sensors**. The core concept relies on **signature-informed modeling**. The principle is to develop a reduced-order model capturing just enough spatial and temporal information to estimate parameters of interest with uncertainty quantification. A proof of concept has been demonstrated in [4] for the industrial problem of localizing impacts on composite aircraft fuselages. To further improve the approach and open new smart monitoring applications, data assimilation [5, 6] and artificial intelligence techniques [7, 8] will be used to enhance **adaptability to varying operational conditions**.

PhD objectives

This PhD opportunity involves theoretical developments, numerical methods, and experimental validation. The candidate will:

1. **Formalize the concept of signature** within a reduced order modeling framework, enabling the development of fast surrogate models that encode critical parameter information.
2. **Implement data assimilation techniques** to enhance model adaptability, particularly in the presence of nuisance factors such as unmodeled operational variability.
3. **Design an artificial intelligence pipeline** to efficiently extract signatures from online measurements.
4. **Validate the SPARSE-SHM concept** on realistic experimental demonstrators, such as the A380 aircraft nacelle structure displayed on Figure 1.

The proposed methods will be tested across a spectrum of numerical models relevant to smart monitoring, from dissipative vibratory systems (passive SHM) to wave-dominated systems (active SHM).

References

[1] C. R. Farrar and K. Worden. *An introduction to structural health monitoring*. In: Philosophical Transactions of the Royal Society A: Mathematical, Physical and Engineering Sciences (2007).

[2] R. Liu et al. *Dynamic load identification for mechanical systems: A review*. In: Archives of Computational Methods in Engineering (2022).

[3] D. M. Steinweg and M. Hornung. *Cost and Benefit of Scheduled Structural Health Monitoring for Commercial Aircraft*. In: Proceedings of ICAS 2021, Shanghai, China (2021).

[4] D. Goutaudier et al. *Long-range impact localization with a frequency domain triangulation technique: Application to a large aircraft composite panel.* In: Composite Structures (2020).

[5] Y. Maday and T. Taddei. *Adaptive PBDW approach to state estimation: noisy observations; userdefined update spaces*, In: SIAM Journal on Scientific Computing (2019).

[6] G. Revach et al. *KalmanNet: Neural network aided Kalman filtering for partially known dynamics*. In: IEEE Transactions on Signal Processing (2022).

[7] Le-Khac et al. *Contrastive representation learning: A framework and review*. In: IEEE Access (2020).

[8] E. J. Cross et al. *Physics-informed machine learning for structural health monitoring*. In: Structural Health Monitoring Based on Data Science Techniques (2022).