









# Master Internship (Stage de fin d'étude) — Physics-aware Representation Learning for Turbulent Dynamo Data (leading to a potential PhD position within the project)

#### Context

Understanding and modeling magnetohydrodynamic (MHD) dynamos—flows of electrically conducting fluids that spontaneously generate magnetic fields—remains a central challenge in geophysics and astrophysics. These systems exhibit multi-scale, turbulent behavior, and their numerical simulation produces massive 3D datasets that are difficult to store, interpret, and reuse for modeling and data assimilation.

The ANR project MilaDy aims to bridge this gap by developing machine-learning models that respect the underlying physics of MHD flows. The internship will focus on the development of physics-aware data representations that compress turbulent dynamo states while preserving their essential physical structures (energy distribution, coherent flow patterns, and parameter dependencies).

# Objective of the internship

The goal is to design and evaluate representation learning methods that capture the relevant physical degrees of freedom of dynamo systems within a low-dimensional latent space. The resulting compressed representation should:

- Maintain key physical invariants and global quantities (such as energy balance and field topology).
- Encode variations across control parameters (e.g., Reynolds number, magnetic Reynolds number, material properties, precession rate, or geometry).
- Enable robust reconstruction of 3D fields and serve as input for reduced-order models or data assimilation frameworks developed elsewhere in the project.

The intern will explore combinations of deep-learning techniques and physical constraints to obtain interpretable and transferable latent spaces.

# Scientific and technical work

The work will include:

Data processing and analysis: handle 3D simulation outputs from dynamo configurations

used in two experiments in Cadarache (France) and in Dresden (Germany), visualize structures, and extract physical diagnostics for ML training and validation.

- Design of physics-aware compression models: implement and test several encoder–decoder architectures to compress full velocity and magnetic field datasets. Architectures will include convolutional or attention-based networks, but with an emphasis on how to embed physical information rather than on network complexity itself.
- Latent-space organization and physical meaning:
- Introduce latent-space regression so that the reduced representation correlates with physical parameters of the flow.
- Use contrastive learning to ensure that latent representations of physically similar regimes cluster together, improving generalization across dynamical transitions.
- Physics-informed training and evaluation: evaluate models not only by reconstruction error but also by physical consistency metrics (energy spectra, helicity, divergence control, topology preservation).
- Comparison and reporting: quantify trade-offs between compression rate, interpretability, and physical fidelity; document results for integration into the MilaDy modeling framework.

## **Expected outcomes**

- A comparative study of physics-aware compression strategies for turbulent MHD data.
- A concise technical report and reproducible code integrated into the MilaDy project toolbox.
- Successful candidates will have the opportunity to disseminate their research in leading international journals or top machine learning conferences.
- Depending on the intern's performance, a **fully funded PhD position** within the MilaDy project may be offered.

#### **Profile**

- Master 2 or final-year engineering student in Applied Mathematics, Computer Science, Physics or equivalent.
- Solid skills in Python and machine learning frameworks (PyTorch or equivalent) are necessary.
- Interest in physical modeling, fluid mechanics, or dynamical systems.
- Familiarity with data visualization and basic numerical methods is appreciated.

# **Supervision and environment**

The internship will mainly take place at CEREA (ENPC / Institut Polytechnique de Paris) under the supervision of Dr. Sibo Cheng (ENPC) and Dr. Didier Lucor (LISN, Université Paris-Saclay) in collaboration with Pr. Caroline Nore (LISN) and Dr. Yannick Ponty (Observatoire de la Côte d'Azur, CNRS) within the MilaDy consortium.

## **Practical information**

- Duration: 5–6 months (in spring 2026).
- Location: ENPC, Champs-sur-Marne, with possible remote work up to 1-2 days per week.
- Compensation: standard ENPC internship allowance and transport support.

# **Application**

Send a single PDF (CV + short motivation letter + **Master's transcripts** + at least 2 reference information (e.g., previous supervisor, course teachers), in french or english) to <a href="mailto:sibo.cheng@enpc.fr">sibo.cheng@enpc.fr</a>, <a href="mailto:didier.lucor@lisn.fr">didier.lucor@lisn.fr</a>, <a href="mailto:caroline.nore@lisn.fr">caroline.nore@lisn.fr</a>, <a href="mailto:yannick.ponty@oca.eu">yannick.ponty@oca.eu</a> email subject: [Application – MilaDy Internship, <a href="mailto:your name">your name</a>], feel free to write in english or french

# References (recommended to read before application)

Fukami, K. and Taira, K., 2023. Grasping extreme aerodynamics on a low-dimensional manifold. *Nature Communications*, *14*(1), p.6480.

Brandstetter, J., Worrall, D. and Welling, M., 2022. Message passing neural PDE solvers. *arXiv* preprint arXiv:2202.03376.

Bousquet, R., Nore, C., Lucor, D., 2025. AutoEncoders latent space interpretability in the light of Proper Orthogonal Decomposition: machine learning of periodically forced fluid flows, Computer Physics Communications, vol. 315, 109728