PhD Thesis Offer

Hard and soft constraints in Scientific machine learning (SciML)

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Scientific context of the thesis

Physics-informed machine learning (PIML) [1] and Scientific machine learning (SciML) [2] aim to integrate prior physical knowledge into data-driven models in order to improve their generalization, robustness, and efficiency. In many applications across computational physics, engineering, and the natural sciences, this integration is achieved by embedding physical laws or *constraints* (conservation principles, symmetries, or governing partial differential equations) into the learning process.

A central methodological question in this area concerns how such constraints should be imposed. Soft constraints typically incorporate physical knowledge as penalty terms in the loss function [3], allowing violations that are balanced against data fidelity during training. This approach is flexible and easy to implement, but may lead to solutions that only approximately satisfy the underlying physics, especially outside the training regime. In contrast, hard constraints enforce physical laws exactly by construction, for example through constrained model architectures, parameterizations, or numerical solvers embedded within the learning framework[4, 5, 6]. While this can guarantee physical consistency, it may reduce model expressiveness or increase computational complexity.

Despite the widespread use of both paradigms, practitioners lack clear guidelines on when soft constraints are sufficient, when hard constraints are necessary, and how the two can be combined effectively.

Project objectives

The central objective of this PhD project is to develop a principled framework to compare, analyze, and combine soft and hard constraints in scientific machine learning. A key contribution will be the development of standardized benchmark problems and evaluation protocols that jointly assess data accuracy, physical consistency, stability, and generalization. This benchmarking effort will enable reproducible and meaningful comparisons across constraint-enforcement strategies and help identify fundamental trade-offs inherent to each approach.

Beyond comparison, the project aims to advance the state of the art by designing hybrid learning methods that integrate soft and hard constraints within a unified framework. Rather than viewing these approaches as competing alternatives, the project explores how exact enforcement of physical principles can be combined with flexible, data-adaptive penalties for secondary constraints. A particular emphasis will be placed on structured dynamical systems, including port-Hamiltonian formulations [7, 6], where physical principles such as energy conservation, passivity, and interconnection structure are important.

These new methods will be applied to practical problems, building on the experimental facilities of the host laboratory (FEMTO-ST Institute). In soft robotics, algorithms will, for instance, be tested on HASEL actuators [8] which exhibit highly nonlinear, coupled electro-mechanical dynamics. By embedding physical constraints, we aim to improve generalization and ensure physically consistent behavior under varying operating conditions. This is particularly relevant for control tasks, where stability guarantees are critical. In neuroscience, algorithms will be tested on system identification problems in electroencephalographic (EEG) data, where using such structured hybrid models can promote the learning of more interpretable dynamical representations while retaining the flexibility of data-driven approaches.

Overall, this research will contribute to a deeper understanding of constraint-based learning in scientific machine learning, provide concrete tools and benchmarks for the community, and enable the development of more reliable, physically consistent, and scalable learning algorithms.

About the environment

The recruited person will be hired by the SUPMICROTECH School of Engineering, and will conduct their research in the FEMTO-ST Institute, all co-located in Besançon, France. The PhD students will be supervised by Dr. Karim Cherifi (Junior professor @ SUPMICROTECH) and Dr. Jean-Julien Aucouturier (Directeur de recherche @ CNRS)

SUPMICROTECH-ENSMM, one of the founding members of the Université Marie et Louie Pasteur (UMLP), is a public higher-education institution training accredited multi-disciplinary engineers in mechanical systems, mechatronics and microsystems. Authorized by the French Ministry of Education, Higher Education and Research, the SUPMICROTECH diploma has been recognized by the Commission des Titres d'Ingénieur since 1934. SUPMICROTECH is part of a research consortium that constitutes the FEMTO-ST institute. With more than 750 researchers, FEMTO-ST was created just about 20 years ago, and has grown to become the country's largest public CNRS engineering lab, with expertise covering all fields of system science. FEMTO's Department of Automation and Robotics (AS2M), where this PhD project is located, hosts about 80 researchers active in the fields of robotics, mechatronics, automatic control and artificial intelligence.

This research environment comes together in Besançon, which is a world-heritage UNESCO site close to the French-Swiss mountains of Jura. Besançon is a vibrant, mid-size regional capital city regularly ranking best-in-France for its quality of life and surface green spaces per inhabitant, but also boasts a newly-federated university (Université Marie et Louis Pasteur) of more than 50k students.

Administrative information

This is a fully-funded PhD position, with a 3-year doctoral contract issued by Supmicrotech/ENSMM, that it is based fulltime in Besançon. The Ph.D. thesis will start in September 2026 or by arrangement. The ideal applicant for the position would have:

- A solid theoretical background in automatic control, applied mathematics or machine learning, as evidenced e.g. by a EE/Maths/Computer-Science MSc/Engineering diploma with specialization in these areas.
- A previous research experience in control or machine-learning applied to physical or experimental data, as evidenced e.g. by a MSc research internship.
- Practical programming skills in machine learning in the Python language, as evidenced e.g. by an active github profile or a portfolio of programming projects.

How to apply

Send the following documents:

- Detailed CV (including publications, if any).
- A concise cover letter describing your interest in the topic, written without LLM assistance.
- List of references

by email to karim.cherifi@supmicrotech.fr with the Subject "[PhD position] Your name".
Application deadline : 2026/06/15 - early applications encouraged!

References

[1] G. E. Karniadakis, I. G. Kevrekidis, L. Lu, P. Perdikaris, S. Wang, and L. Yang, "Physics-informed machine learning," *Nature Reviews Physics*, vol. 3, no. 6, pp. 422–440, 2021.

[2] A. Quarteroni, P. Gervasio, and F. Regazzoni, "Combining physics-based and data-driven models: advancing the frontiers of research with scientific machine learning," *Mathematical Models and Methods in Applied Sciences*, vol. 35, no. 04, pp. 905–1071, 2025.

[3] M. Raissi, P. Perdikaris, and G. Karniadakis, "Physics-informed neural networks: A deep learning framework for solving forward and inverse problems involving nonlinear partial differential equations," *Journal of Computational Physics*, vol. 378, pp. 686–707, 2019.

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[5] N. Chalapathi, Y. Du, and A. S. Krishnapriyan, "Scaling physics-informed hard constraints with mixture-of-experts," in *The Twelfth International Conference on Learning Representations (ICLR)*, 2024.

[6] K. Cherifi, A. El Messaoudi, H. Gernandt, and M. Roschkowski, "Nonlinear port-hamiltonian system identification from input-state-output data," *arXiv:2501.06118*, 2025.

[7] A. J. van der Schaft and D. Jeltsema, "Port-Hamiltonian systems theory: An introductory overview," *Foundations and Trends® in Systems and Control*, vol. 1, no. 2-3, pp. 173–378, 2014.

[8] Y. Yeh, N. Cisneros, Y. Wu, K. Rabenorosoa, and Y. L. Gorrec, "Modeling and position control of the hasel actuator via port-hamiltonian approach," *IEEE Robotics and Automation Letters*, vol. 7, no. 3, pp. 7100–7107, 2022.