

Internship:

Learning Beyond Backpropagation Hybrid AI Meets Industrial Simulation

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Location: Inria team MALICE, Laboratoire Hubert Curien, Saint-Etienne, France

Level: 1st or 2nd year Master

Keywords: Scientific modeling; physics-guided machine learning; optimization; deep learning

Context: In many scientific and industrial applications, physical knowledge is neither absent nor complete: an approximate partial differential equation (PDE) and a corresponding numerical solver are available, but they fail to capture part of the observed dynamics. Rather than asking a neural network to relearn the complete dynamics, we seek to learn only what the available numerical solver fails to explain, leading to *hybrid models* that combine physical modeling and machine learning [2, 1]. However, in cutting-edge industrial applications, such as aerospace, energy, and advanced manufacturing, numerical solvers are often highly sophisticated computational tools, designed to simulate complex physical phenomena with exceptional accuracy and efficiency. Their complexity makes backpropagation through them technically impractical, raising a fundamental question: *How can we train hybrid models that leverage state-of-the-art industrial numerical solvers without backpropagating through them?*

Mission: The objective of this internship is to investigate and develop new training strategies for hybrid physics–AI models involving complex, black-box numerical solvers. The internship will combine theoretical investigations, algorithmic developments, and numerical experiments through the following tasks:

- **LITERATURE REVIEW.** Conduct a bibliographic survey on hybrid physics–AI models and backpropagation-free learning algorithms.
- **ALGORITHMIC DEVELOPMENT.** Extend the recently proposed lifting-based training framework [3] to hybrid AI models incorporating black-box numerical solvers, without requiring differentiation through the solver.
- **IMPLEMENTATION AND NUMERICAL VALIDATION.** Implement the proposed approach and evaluate its performance on challenging scientific and industrial simulation benchmarks.
- **SCIENTIFIC DISSEMINATION.** Document the theoretical and experimental findings. The internship may lead to a publication at a leading international machine learning venue.

References

- [1] A.-R. Mezidi et al. “Proximal splitting methods for hybrid differentiable Models”. In: ICML (2026).
- [2] K. Um et al. “Solver-in-the-loop: Learning from differentiable physics to interact with iterative PDE-solvers”. In: NeurIPS (2020).
- [3] D. Pinto-Suarez et al. “Principled Backpropagation-Free Training via Layerwise Fenchel-Young Lifting”. Submitted to: ICLR (2027).