Ph.D. proposal – CIFRE funding

Physically informed machine learning for manufacturing technologies optimization : from architecture design to online and in-situ implementation

Funding: 36 months, CIFRE (https://www.anrt.asso.fr/fr/le-dispositif-cifre-7844)

Starting date : November / December 2025

Key words : Physically informed machine learning, Industrial manufacturing process, Online process monitoring, Condition based maintenance

Hosting institution : PIMM Laboratory, 151 Boulevard de l'Hôpital, 75013 Paris

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 urban life.

Partner company : OCTO Technology, 34 Avenue de l'Opéra, 75002 Paris

OCTO Technology, a subsidiary of Accenture, is a consulting firm with over 700 employees, including 120 specialists in Data and AI technologies. Serving clients across a wide range of industries, OCTO has established strong partnerships with leading manufacturing companies. Committed to open source, it both utilizes and contributes to open-source software. OCTO fosters an internal culture that encourages growth and continuous learning — employees have access to a comprehensive training catalog covering both foundational and advanced topics, from data science and AI to coding best practices, cloud platforms, green IT, and soft skills. OCTO Technology is proudly certified as a BCorp® and recognized as a Great Place to Work®.

Ph.D. project in a nutshell:

The **digital transformation of industrial processes** relies on sophisticated instrumentation. Machines must be equipped in-situ with smart sensors and supported by systems that can process such as images and time series, in real time. Machine learning and AI have become essential for driving intelligent decisions. In particular, when low latency is critical, these models are deployed directly on devices at the edge, close to the equipment itself — a necessary condition for smarter, faster operations.

In general,, **decision-taking models** can be integrated in two ways:

- In an ***open-loop fashion***, by triggering alerts that are processed by human operators who make the actual decisions;
- Or in a ***closed loop*** , by feeding back the decisions into the processes when their criticality allows such unsupervised behavior.

Conventional machine learning models suffer from significant limitations in both scenarios:

- They require large ***amounts of field data*** for training, and collecting this data can cause delays
- Their ***memory footprint*** may not be compatible with edge computing, especially when high precision and low latency are required.

- Their ***precision often degrades in the field***, when the environment is too noisy, or the equipment is subject to regimes not seen during the data collection phase. This issue can have safety implications, particularly in closed-loop setups.

Physically Informed Machine Learning (PIML), and in particular Physics-Informed Neural Networks (PINN), are less dependent on data and less energy-intensive, while their predictions remain consistent with physical laws. They offer a promising solution to the triple challenge outlined above. However, their contribution to advanced industrial process control remains under-explored; the current approach relies on statistical tests or conventional machine learning.

One of the manufacturing processes addressed in this thesis is **injection molding**. In light of environmental concerns, global policies are moving toward greater use of recycled polymers. Reusing polymers that have already been used reduces the carbon footprint of the product. In order to help the automotive industry reduce its carbon emissions, numerous regulations have been enacted to accelerate the use of recycled polymers. However, two major problems remain. First, global production of premium polymers varies greatly depending on the type of polymer. This production volume varies even more widely across industrial sectors. As a result, recycled polymers are made up of elements of different chemical natures. In addition, mechanical recycling, which is currently the most widely used process, causes chain breaks and thus alters the rheological and mechanical behavior of the polymer. For these two reasons, it is essential to monitor the injection process parameters in real time in order to adapt to the rheological behavior of recycled polymers, with the aim of ensuring optimal and repeatable part quality. Initial work has been carried out at PIMM laboratory to add new measuring instruments in order to determine the viscosity of the polymer in real time. The aim now is to use these measurements in addition to the information obtained from the manufacturing process to achieve closed-loop control based on PIML/PINN models.

In order to strengthen OCTO's offerings with scientifically grounded innovations, OCTO Technology and the PIMM laboratory at ENSAM are jointly sponsoring this PhD thesis. The research will focus on the application of Physics-Informed Machine Learning (PIML) and Physics-Informed Neural Networks (PINNs) in industrial settings, particularly for edge computing, with the outcomes contributing to open-source software.

Ph.D. Objectives:

The objectives are the following;

- Evaluate the eligibility of PIML / PINN models in both open and closed-loop contexts;
- Derive the necessary conditions for that eligibility (data to collect, model architectures, training procedures, …);
- Implement PIML / PINN models on actual equipment, and evaluate their performance against both simulations and field measurements;
- Extend OCTO Technology's open source software (https://github.com/octo-technology/VIO) with new process control capabilities, beyond its current specialization in visual inspection.

Required skills : If you hold a **Master's degree in machine learning**, artificial intelligence or applied mathematics with a strong interest in industrial process or you hold a **Master's degree related with applied physics or instrumentation** and would like to deepen your expertise in machine learning, this Ph.D. offer is for you.

Application process : You can apply for this PhD position by sending a CV, a cover letter, your transcripts from the master's degree and/or engineering diploma, and a list of two or three people who can recommend you at marc.rebillat@ensam.eu, nazih.mechbal@ensam.eu and thomas.vial@octo.com.

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