Phd position 2025 - CEMEF

TITLE	***Development of digital twins of Zr alloys hot forming processes by deep learning***
Project acronym	AI-Zr-Forgemaster
Global objective of work	Developing digital twins of the hot forming processes of Zr alloys with state-of-the-art deep learning, based on finite element simulations, analytical models and industrial data.
Context	Within Framatome, the Fuel Business Unit designs, manufactures and sells nuclear fuel for power stations and research reactors. The Component Operations Division (DOC) masters all stages of zirconium metallurgy, from the ore to the production of zirconium alloy components: flat products, bars and tubes for the manufacture of nuclear fuel; some others products are also used in aeronautical and medical industries. The Component Operations Division has recognised expertise and the largest production capacity in the world with its five plants (Jarrie, Ugine, Rugles, Montreuil-Juigné and Paimboeuf). It also has a Research Centre (CRC) specialised in metallurgy and processes for manufacturing zirconium alloys. For 40 years, process modelling has been developed by Framatome/CRC and now covers the entire manufacturing process for zirconium components, from extractive metallurgy to ingot casting, including hot and cold forming, heat treatments and welding. These models, from the simplest to the most complex, are used to optimise manufacturing processes and accelerate the industrialisation of new alloys/products. Taking advantage of large industrial databases and recent developments in AI, a new generation of faster and/or more accurate models is being developed, combining physics-based models with purely data-based models. The CRC's current developments are moving in this direction, towards digital twins of processes, and particularly those of metal forming.
Detailed presentation with figure(s)	Framatome uses forming routes for zirconium alloys. In the first stages of deformation, the material is hot-formed through 3 main stages: open-die forging, extrusion and rolling. The research centre Famatome/CRC has been working for many years on the development of finite element (FE) numerical models to develop and optimise the forming routes. These models are accurate but time-consuming. There are also analytical models that have been developed as tools for rapid decision but with much less accuracy. There is a lack of intermediate complexity mechanical models that allow: (i) the integration of all available industrial data; (ii) identify in real time the mechanical properties of the material during its forming by inverse method analysis; (iii) update in real time the forming parameters according to the mechanical properties of the material. The available data is multimodal since it is of a

different nature. They come from databases derived from simulations using the finite element method, from forecasts made by simplified models and from industrial data from observations made during production.

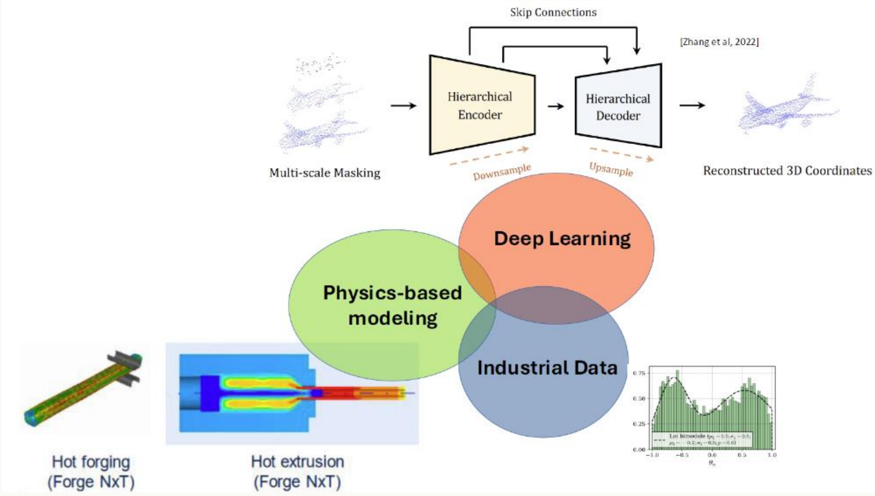

Figure 1: Deep learning for multimodal data in metal forming

The aim of the thesis is to develop deep learning models of increasing complexity by making the best use of all multimodal data, with the aim of creating digital twins of hot forming processes.

We will begin by developing models for the hot forging process, then the analysis will be gradually extended to the three processes.

The final objective is to develop digital twins capable of integrating industrial data during the manufacturing of products, in order to be able to adapt and optimise the forming processes (from forging to rolling) based on the information collected from the first stages of forging. These models could also be used as training tools for staff managing the processes, or even as virtual assistants if they are able to run in real time.

We assume that the synthetic data from FE modelling will help in learning the correlations between process parameters, industrial experimental data and material properties, as in [Pereira et al. 2021]. However, the FE model data has very large dimensions. We are talking here about the dimension of the state vectors, or degrees of freedom, calculated by an FE model [Ryckelynck et al. 2024]. The aim of this thesis is to develop a series of models, from the fastest to the most accurate, using deep learning methods. To facilitate the representation of FE data, a point cloud representation is adopted [Guo et al, 2020] [Saranti et al., 2024] and the aim is to model the deformation of this point cloud during deformation stages in contact with the forming tools. <u>There are still very few publications on AI for processing point cloud deformations.</u> We will focus our analysis on an area of interest with maximum deformation. During the thesis, we will look at the following three simplified models: an analytical model M0, a meta-model M1 of the deep learning type on point clouds, and a physics-informed deep learning model M2. M0 is an existing model that will be updated based on multimodal data. For the meta-model M1, it is proposed to develop a dimensional reduction of the multimodal data using a masked autoencoder on point clouds [Zhang et al, 2022] [Kaiming et al. 2021] or MLP-Mixer type [Dao et al. 2023][Ekambaram et al. 2023], with a self-supervised learning technique. The M1 model can be improved by the 'fine-tuning' technique on exclusively industrial data. For the M2 model, a physics-informed Graph Neural Network (GNN) will be used [Gao et al. 2022] [P. Garnier, E. Hachem 2025] developed at CEMEF by the CFL team since 2021 [Chen et al. 2021]. This work is intended to enrich models similar to ones developed by Transvalor for Forge® (TSV PyLab), without having to rewrite the equations of mechanics of materials. M2 will be the most accurate of the models excluding the FE model. In order to speed up the forecasts on GNN, an innovative submodelling method will be developed in the zone of maximum deformation, fed by deep learning [Launay et al., 2022]. The scientific animation of this work will be based on the PR[AI]RIE-PSAI programme of PSL University (https://psl.eu/actualites/ia-cluster).

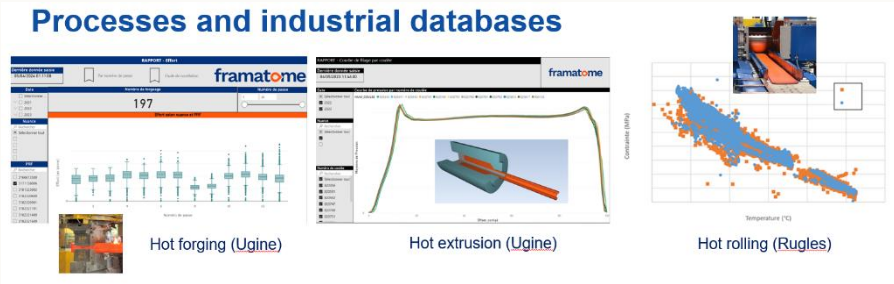

Figure 2: Forming steps and industrial database

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Tools	*Python, PyTorch, Forge NxT*
Key-words	Deep Learning, Autoencoder, Point Cloud, Graph Neural Network
Project type/ cooperation	The PhD is funded by Framatome, under an ANRT CIFRE Grant.
Skills, abilities requested	Master degree in Applied Mathematics or in Computational Mechanics. Rigor, dedication to a subject, aptitude to teamworking are important Mastering of the English language is necessary (level B2 minimum)
Gross annual salary	38,5 k€
Location	- MINES Paris, CEMEF, Sophia Antipolis (80%) - Framatome (20%)
CEMEF team(s)	CSM (Computational Solid Mechanics)
Supervisor(s)	- David Ryckelynck, Professor, MINES Paris, principal superviser David.ryckelynck@minesparis.psl.eu - Katia Mocellin, Research Director (HDR), co-supervisor Katia.mocellin@minesparis.psl.eu - Alexis Gaillac, senior expert, Framatome alexis.gaillac@framatome.com

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