EDF R&D (Paris Chatou) and Mines ParisTech (Centre des Matériaux, Evry) internship

Physically-Informed Neural Networks for residual stress distribution assessment applied to high-temperature industrial manufacturing processes

Keywords: Computational Engineering, Applied Mathematics, Residual Stress, Welding, Finite Element Analysis, Data Assimilation, Machine Learning, Deep Learning, Neural Network, Industry 4.0

EDF is currently investigating the capabilities of emerging data-driven solutions to assess residual stress distribution induced by high-temperature manufacturing processes.

Industrial context:

Residual stresses are generated during manufacturing due to creation of permanent strain during material processing. For instance, during a welding operation, high thermal gradients spread through the welded component. The difference in cooling rates experienced in different parts of the component results in localized variations in thermal expansion and contraction. As a result, these phenomena develop non-compatible strains leading to-residual stresses.
Residual stresses can negatively affect structural integrity. For example, thick-walled structures in the as-welded condition are more prone to brittle fracture than a structure that has been stress-relieved. The undesired stresses may also influence the fatigue performance. Hence, assessing the level of residual stress at the end of manufacturing can reduce design engineering justifications as their level and state may affect the fit for service of metal parts in pipes and pressure vessel.

Scientific context:

In this context, *Numerical Simulation* allows to provide accurate estimations of residual stresses. Indeed, *Finite Element Methods* (FEM) are well-suited to solve the ***non-linear transient thermo elasto-plastic PDE system*** associated with industrial high-temperature manufacturing processes.
However, accurate simulations of representative industrial cases remain computationally expensive. What is more, the simulation set-up and the tuning of simulation parameters is out of reach for

engineers who do not have skills in numerical simulation. On the contrary, *online inference* stemming from ***deep learning neural networks*** offers straight-forward predictions almost in real-time. Yet, the complexity of such methods is left to the *offline learning process* whose design strongly affects the accuracy of the predictions.

Internship objective:

The objective of the internship is to design a neural network able to predict the residual stress tensor field within a given welded body considering the spatial and temporal evolution of temperature as input.

Methods and guidelines:

The architecture of the neural network will be guided by the concept of ***Physics-Informed Neural Networks*** (PINNs) introduced by Raissi, Perdikaris and Karniadakis in [1]. Such networks are trained to solve supervised learning tasks while respecting any given laws of physics described by general nonlinear partial differential equations. In the present case, the predicted residual stress tensor should abide by the *mechanical equilibrium law*.
What is more, the design of the Neural Network should lean on the fact that residual stresses result from *cumulative plastic deformations* of the material in reaction to *cyclic thermal loads*.
Integration of thermal history or other historical variables is thus of prime importance. Recent works that use PINNs or LSTM neural networks to approximate solutions of history dependent processes can be found in the literature (see [2], [3], [4]).

The technical outlines of the internship:

1. The candidate will spend one-month building a strong bibliography around PINNs and potential other alternatives

2. The candidate will define a Design of Experiments (DOE) to generate a space-filling dataset of numerical simulations. These simulations will be based on a given simple test case (Constrained dilatometry “Satoh” experiments). This test case is known to be representative of the residual stress generation in metallic heavy section metallic components submitted to cyclic high range thermal loads. Simulations will be achieved by using EDF’s open source solid mechanics finite element code code_aster.

3. The candidate will implement a robust PINN (or another alternative) that will be trained and tested using simulations of the previous step. The procedure will be validated against its ability to blindly predict a physically-relevant residuals stress distribution within the computational domain on a wide range of thermal loads calibrated to represent the welding effects and inherent experimental bias.

4. If there is time left, the candidate will try to extent its learning process to more representative industrial cases. He will try to improve the transferability of the calibrated deep learning algorithm over a wider range of materials, manufacturing conditions and part geometries.

Candidate's profile :

Core skills:

The candidate should have strong skills in **applied Math** and more specifically in **Statistics**, **Machine Learning** and **Deep Learning**. Proven experience in **supervised and unsupervised learning methods** will be asked. Besides, the candidate should be familiar with classical optimization algorithms. Fluency in Python programming is also a plus.

Additional skills:

The candidate should have knowledge in numerical simulation for Mechanics. Learning methods developed during this internship will be applied to computational welding mechanics (solid mechanics for welding applications). Hence, the candidate should show a strong interest in this field and more generally in the domain of manufacturing.

Transversal skills:

Internship success depends on the candidate's scientific curiosity, his/her strong interest in digital industry as well as his/her ability to easily work in an interdisciplinary team.

Internship set up:

The work will be hosted by EDF Lab Chatou and in partnership with Mines ParisTech (Centres des Matériaux). The duration of the stage is 6 months minimum, up to 9 months (expected start: spring 2021).

You can send a CV to David iampietro (EDF lab Chatou) david.iampietro@edf.fr, and put Pierre Kerfriden in copy pierre.kerfriden@minesparistech.fr.

Bibliography:

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[4] Zhu, Q., Liu, Z., & Yan, J. (2021). Machine learning for metal additive manufacturing: predicting temperature and melt pool fluid dynamics using physics-informed neural networks. Computational Mechanics, 67(2), 619-635.