XVIII International Conference on Computational Plasticity, COMPLAS 2025
September 2-5, 2025, Barcelona, Spain

AUTOMATIC LEARNING OF CONSTITUTIVE RELATIONS IN SOLID MECHANICS

E. BARANGER*, L. CHAMOIN*
AND L. DE LORENZIS†

* Université Paris-Saclay, CentraleSupélec, ENS Paris-Saclay, LMPS-Laboratoire de Mécanique Paris-Saclay, 91190 Gif sur Yvette, France
{emmanuel.baranger,ludovic.chamoin}@ens-paris-saclay.fr

† Department of Mechanical and Process Engineering, ETH Zürich, 8092 Zürich, Switzerland
ldelorenzis@ethz.ch

ABSTRACT

The art of modeling in mechanics of solid materials, quite often guided by the general principles of thermodynamics, is mainly a craft where the researcher or the engineer is seeking a good description (variables and functions) of a partially observed phenomenon. This active field of research has been recently renewed with the help of machine learning tools, especially neural networks [1] and sparse or symbolic regression [2].

This session aims to overview the topic of automatic learning of constitutive relations in solid mechanics. Applications, as well as more fundamental research, are welcome. In the literature, two main applications are currently developed: synthesizing macroscopic constitutive relations of numerical representative volume elements, and modeling macroscopic stress-strain curves; this mini-symposium includes, but is not limited to these applications. Note that, while synthetic data are most often used, the evaluation of strategies based on real data obtained from various experimental techniques is highly welcome.

The different topics covered by this session are related to the following keywords:

- Data: synthetic/real data, frugality, informational content…
- Learning strategies: supervised, unsupervised, reinforcement learning…
- Physics framework and integration: GENERIC, PINN, PANN, TANN…
- AI: dedicated loss functions, structure, initialization, hyper-parameter tuning, explicability, robustness…

The experimental/model/simulation triptyc being a whole, the interactions between the modeling itself and experimental or simulation constraints are of interest in this session.

REFERENCES

[1] Benady, A., Baranger, E., Chamoin, L. Unsupervised learning of history-dependent constitutive material laws with thermodynamically-consistent neural networks in the modified Constitutive Relation Error framework. *CMAME*, vol. 425, 2024.

[2] Flaschel, M., Kumar, S., De Lorenzis, L. Unsupervised discovery of interpretable hyperelastic constitutive laws. *CMAME*, vol. 381, 2021.