

Experimental mechanics and fracture: Toward a big data approach?

O. Allix,^{1*} F. Chinesta,² F. Hild¹

¹ Univ. Paris-Saclay, Centrale-Supélec, ENS Paris-Saclay, CNRS, LMPS–Laboratoire de Mécanique Paris-Saclay, 4 avenue des sciences, F-91190 Gif Sur Yvette, France, olivier.allix@ens-paris-saclay.fr

² CNRS, Arts et Metiers, ESI Chair, PIMM, 151 boulevard de l’Hopital, F-75013 Paris, France

One of the main sources of data in experimental solid mechanics comes from the use of digital images and their registration via correlation techniques. Thanks to such measurements, one may state that experimental mechanics has entered the big-data world [1]. Adapted inverse techniques have been proposed to use such data for constitutive model identification [2]. In Ref. [3], the authors have inferred failure initiation criteria with an interior approach. It consisted in analyzing all the strain-stress pairs that did not generate failure. For a ductile Ti 6-4 alloy at a mesoscopic level, it was shown that Rankine’s criterion was well suited while criteria based on other quantities failed to give consistent results for both thin and thick notched samples submitted to tension.

The new possibilities associated with data-driven approaches, machine learning and artificial intelligence invite us to question and revisit the exploitation of data generated in such tests. Many data generated in mechanical tests are often not or not completely exploited. For example one may think of:

- all the set of images (partially exploited in the present case)
- micrographs of the surface of failure (not exploited yet)
- the shape of the broken specimen (not exploited).

In the presentation, we will first discuss the experiment itself [4, 3] before opening discussions on the type of approaches that could be used to merge all these different types of data. Another part of the discussion will concern the extension to the case of rupture of the work concerning the learning of behavioral laws [5]. A fundamental question concerns the introduction of physical knowledge

within learning processes, which could / should be performed when dealing with failure.

References

- [1] Neggers, J., Allix, O., Hild, F., Roux, S. Big Data in Experimental Mechanics and Model Order Reduction: Today’s Challenges and Tomorrow’s Opportunities, *Arch. Comput. Meth. Eng.*, 25(1), pp. 143-164, 2018
- [2] Mathieu, F., Leclerc, H., Hild, F., and Roux, S. Estimation of elastoplastic parameters via weighted FEMU and Integrated-DIC, *Exp. Mech.*, 55(1), pp. 105-119, 2015
- [3] Lindner, D., Allix, O., Hild, F., Pinelli, X., Paulien-Camy, O. I-DIC-based identification strategy of failure criteria: Application to Titanium and Nickel-based alloys, *Meccanica*, 51(12), pp. 3149-3165, 2016.
- [4] Lindner, D., Mathieu, F., Hild, F., Allix, O., Ha Minh, C., Paulien-Camy, O. On the evaluation of stress triaxiality fields in a notched titanium alloy sample via integrated DIC, *J. Appl. Mech.*, 82, 071014, 2015
- [5] Ibanez, R.; Gilormini, P.; Cueto, E.; Chinesta, F.; Numerical experiments on unsupervised manifold learning applied to mechanical modeling of materials and structures, *COMPOTES RENDUS MECANIQUE*, 348, issue 10-11, pp. 937-958, 2020