Comparison of full-field inverse identification methods for metal plasticity

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ABSTRACT

The simulation of deep drawing processes and its quality is intrinsically dependent on the accuracy of the constitutive model in reproducing the mechanical behaviour of the sheet metal material. Today, the calibration of elastoplastic models – correspondent to the inverse identification of the material parameters – often uses full-field measurements, through Digital Image Correlation (DIC) techniques, to capture non-homogeneous strain fields and states, coupled with non-straightforward numerical inverse methodologies. In the last decade, new parameter identification methodologies, such as the Finite Element Model Updating (FEMU), the Constitutive Equation Gap (CEG) method, the Equilibrium Gap Method (EGM) and the Virtual Fields Method (VFM) have been developed and have proven to be effective for non-linear plasticity models. From the latter list, the FEMU and the VFM have distinguished themselves from the others. More recently, supervised machine learning (ML) techniques have been also used as an inverse identification method. This artificial intelligence-based method uses a large data set of numerical tests to train an inverse model in which the input is the history of the strain field and loads during the test, and the output is directly the material parameters.

The goal of this communication is to analyse, compare and discuss these inverse identification methods, with a particular focus on the FEMU, VFM, and ML methodologies. A heterogeneous tensile-load test is considered to compare in detail the FEMU, VFM, and ML strategies.

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