Identification of hardening parameters using FEMU and DIC-levelled FEA data

João Henriques^{1,*}, Mariana Conde¹, António Andrade-Campos¹ and José Xavier²

¹TEMA, Department of Mechanical Engineering, University of Aveiro, Campus Universitário de Santiago, Aveiro, Portugal ²UNIDEMI, Department of Mechanical and Industrial Engineering, NOVA School of Science and Technology, NOVA University Lisbon, Caparica, Portugal * joaodiogofh@ua.pt



ENCONTRO COM A CIENCIA E TECNOLOGIA EM PORTUGAL

16 a 18 MAIO 2022 #ciencia2022PT

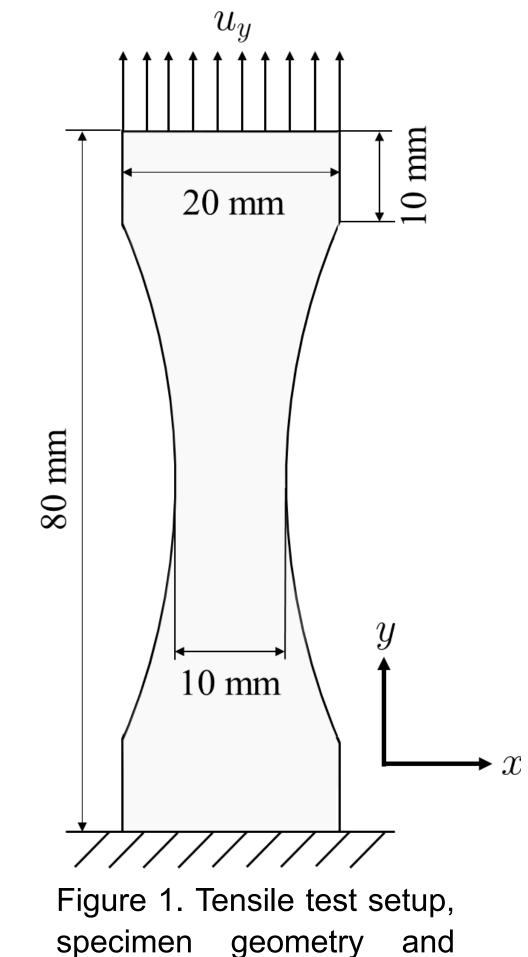
1. Framework

Computer-aided engineering systems role in the simulation of play a key manufacturing processes, to reduce costs and time waste in the development of highquality products. The material constitutive model and its parameters influence the reliability and accuracy of metal forming simulations. Although finite element analysis (FEA) is widely used to simulate processes, the accuracy of the simulation highly depends on the calibration of the model that describes the material behaviour. Classical approaches use simplified geometry and loading conditions, however, only a limited number of parameters can be identified per test configuration. There has been an increase in the use of novel optical, which are contact-free and provide full-field data, such as digital image correlation (DIC) [1]. This full-field measurement data when coupled with inverse identification techniques such as the finite element method updating technique (FEMU) has the potential to reduce the number of experimental tests required to accurately identify all material properties, assuming that the test configuration is rich enough that all material properties play a role in mechanical behaviour. Classically, experimental DIC measurements and FEA results were compared directly in the FEMU approach. However, numerous inconsistencies must be addressed before doing this comparison, including different coordinate systems, data locations, strain formulation, spatial resolutions, and data filtering. To address these issues, recent studies used an approach based on deforming the reference image of a DIC speckle pattern synthetically, using the FEA mesh and displacements [2,3,4]. This work aims to identify the Swift hardening law parameters of a DP600 steel using a virtual tensile test on a dogbone specimen with a non-constant section under uniaxial and quasi-static loading conditions using the FEMU technique. To simulate a real experiment, the numerical results were used to generate synthetic images, which were then processed by DIC and used as the reference in the identification procedure. Two identification approaches are used: first, by using the direct comparison between the DIC measurements and FEA results, and second, a comparison using DIC-leveled FEA data. The identification results of both approaches are compared.

2. Methodology

A virtual tensile test was carried out on a heterogeneous dogbone specimen with a non -constant section [4] assuming plane stress and uniaxial tensile loading conditions. The specimen geometry and boundary conditions of the tensile test are shown in Fig. 1. The test was conducted until the failure of the specimen, with a total of 10 time stages. The material used in this study is the DP600 steel, and the constitutive model chosen assumes an isotropic linear elastic behaviour according to Hooke's Law, isotropic hardening described by Swift law and anisotropic behaviour described by Yld2000-2d criterion. The goal of this was to identify the material constitutive parameters related to the hardening behaviour. Therefore, the linear elastic parameters and the Yld2000-2d

coefficients are fixed during the identification procedure. The reference numerical results, including the mesh and displacement fields, were used to generate synthetic images based on a real speckle pattern image, which were then processed by DIC. In the FEMU method, the main goal was to match the iterative numerical results to the experimental data, which was usually processed by DIC. However, to address the inconsistencies between both data sets. iterative numerical results were used synthetically deform the reference image of a real DIC speckle pattern, resulting in a set of synthetically images. Afterwards, the synthetically deformed deformed images can be processed with DIC using the same DIC parameters as the experimental images, ensuring that data filtering, spatial resolution, and strain formulation are consistent across both data sets. Fig. 2 shows a diagram of the virtual experiment (VE) methodology. The cost function used describes the difference in strain fields and the load between the reference and the iterative numerical results.



Experimental Numerical results test DIC filter DIC-levelled DIC measured Comparison FEA results experimental results Experimental Synthetic images images

Figure 2. Diagram of the virtual experiment (VE) methodology.

3. Results

Figure shows convergence study of the identified parameters, cost function value, strain and values force terms throughout the identification the for process identification run of each methodology. The results significant show the improvement in accuracy of the parameters identified when using the VE methodology, with a $\frac{4}{5}$ 10^{-6} maximum relative error of 0.16% for the most accurate identification run, whereas the maximum relative error for the FEA methodology is 28.48% for the same initial set of parameters.

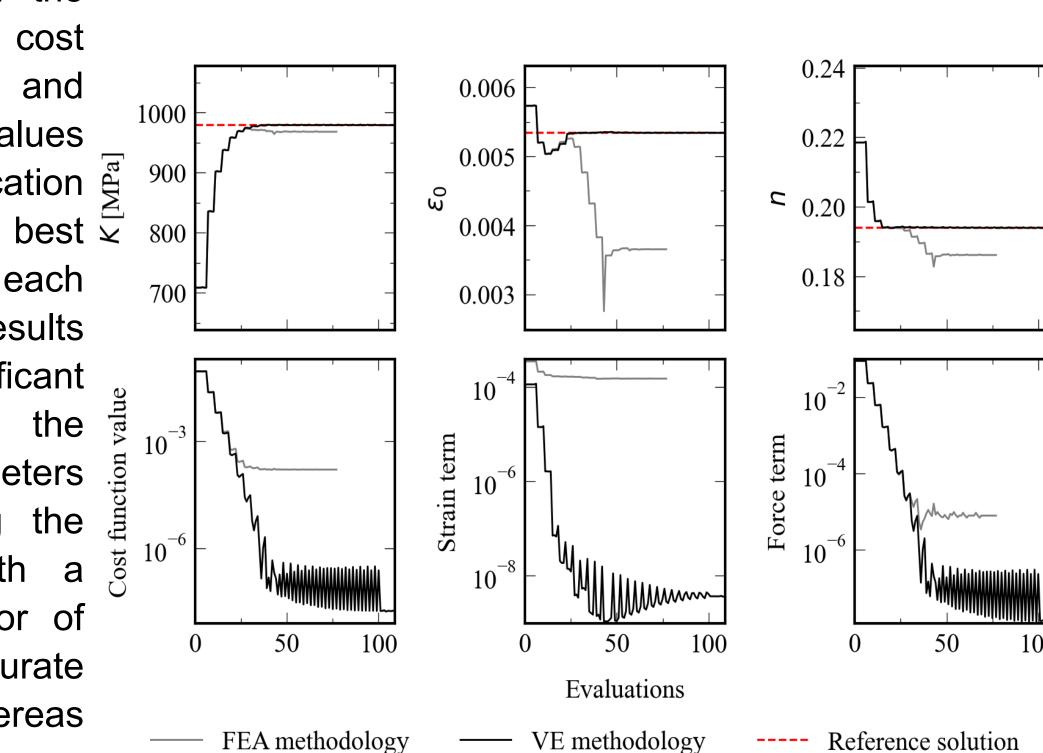


Figure 3. Evolution of the identified parameters, cost function value, strain and force terms values throughout the identification process, for the best identification run of each methodology.

4. Conclusions and future work

- Improvement in the identification accuracy when using the DIC-levelled FEA data in the identification procedure mainly due to the accurate minimisation of the differences between the strain results.
- Increased accuracy comes at the expense of increased computational time.
- In future work, the VE methodology can be used on more complex constitutive models using other heterogeneous test configurations, allowing all material parameters to be identified using a single test configuration.

Acknowledgements

J. Henriques is grateful to the FCT for the PhD grant 2021.05692.BD. This project has received funding from the Research Fund for Coal and Steel under grant agreement No 888153. The authors also gratefully acknowledge the financial support of the Portuguese Foundation for Science and Technology (FCT) under the projects CENTRO-01-0145-FEDER-029713, POCI-01-0145 FEDER-031243 and POCI-01-0145-FEDER-030592 by UE/FEDER through the programs CENTRO 2020 and COMPETE 2020, and UIDB/00481/2020 and UIDP/00481/2020-FCT under CENTRO-01-0145-FEDER-022083. Authors also acknowledge FCT - MCTES for its financial support via the projects UIDB/00667/2020 (UNIDEMI).

References

- [1] H. Schreier, J.-J. Orteu, M.A. Sutton, Image correlation for shape, motion and deformation measurements: Basic concepts, theory and applications, 1st ed., Springer 2009.
- [2] P. Lava, E. Jones, L. Wittevrongel, F. Pierron, Strain 2020, 56(4).
- [3] J. Henriques, M. Conde, A. Andrade-Campos, J. Xavier, *Esaform* **2022** 25th International Conference on Material Forming (Braga, Portugal).
- [4] J. Henriques, J. Xavier, A. Andrade-Campos, *Materials* **2022**, 15(2).
- [5] J. M. P. Martins, S. Thuillier, A. Andrade-Campos, AIP Conference Proceedings 2018, 1960(1).







boundary conditions.





















