Material Forming - ESAFORM 2024 Materials Research Forum LLC
Materials Research Proceedings 41 (2024) 1836-1840 https://doi.org/10.21741/9781644903131-203

Constitutive model validity evaluation for MT 2.0 applications

PESHAVE Amar[1,a *], LAVA Pascal[1,b], COPPIETERS Sam[2,c] and PIERRON Fabrice[1,d]

[1]MatchID NV, Leiekaai 25a, 9000 Ghent, Belgium

[2]KU Leuven, Mechatronic System Dynamics (LMSD), Celestijnenlaan 300, 3001 Leuven, Belgium

[a]amar.peshave@matchid.eu, [b]pascal.lava@matchid.eu, [c]sam.coppieters@kuleuven.be, [d]fabrice.pierron@matchid.eu

Keywords: Digital Image Correlation, Virtual Fields Method, Material Testing 2.0, Model Validity Evaluation

Abstract. This paper demonstrates a methodology to discriminate between the performances of different material models within the framework of Material Testing 2.0, which consists in coupling heterogeneous test configurations, full-field measurements using for instance Digital Image Correlation (DIC) and inverse identification like the Virtual Fields Method (VFM). The methodology relies on using a set of different virtual fields for parameter identification with a selected model, and to evaluate the performance of the model. The paper illustrates this methodology on anisotropic metal plasticity.

Introduction

The necessity to identify ever more complex plasticity model in sheet metal forming leads to extensive and costly experimental campaigns, sometimes requiring up to more than ten different test configurations [1,2]. There is therefore a need to speed up the process by revisiting classical testing. This is now facilitated by the wide availability of camera-based deformation measurements like Digital Image Correlation (DIC), providing a map of deformation with spatial density comparable to that of simulation. This allows for the use of more complex test geometries and loadings that lead to heterogeneous stress and strain states. The downside of this new test paradigm is that an inverse identification technique has to be used, like the Virtual Fields Method (VFM, [3]) for instance, which in turn requires an *a priori* choice of a constitutive model. There have been recent efforts in the literature to circumvent this limitation. For instance, Flaschel *et al.* [4] consider a library of terms in a generic constitutive model. For plasticity, they use a Fourier expansion of the yield surface and they simultaneously identify the parameters and the number of terms. To do so, their cost function uses an equivalent of the VFM with local FE-based virtual fields, akin to the Equilibrium Gap Indicator (EGI) described below. Another approach, Data-Driven Identification [6], consists in using advanced statistical tools to build up a manifold relating stress to strain to identify stress fields directly. As opposed to the above, this technique is purely non-parametric. The downside is that the results can be difficult to handle as they are provided as point clouds in the stress/strain space. Finally, under the condition of isotropy, thus using the fact that stress and strain have the same principal directions, Cameron and Tasan [6] directly integrate stress equilibrium to obtain stress fields. None of the above however have tackled anisotropic plasticity so far.

The present approach is akin to that of Flaschel *et al.* [4] except that the two steps, model formulation and identification, are conducted in series rather than in parallel. Different models are first identified with a set of virtual fields, and then a second set of virtual fields ranks them lead to a final choice of models. This procedure extends from initial work aimed at hyperelastic laws [7].

Materials Research Proceedings 41 (2024) 1836-1840 https://doi.org/10.21741/9781644903131-203

Methodology

Test configuration. The selected test is similar to that in [7] and is shown on Fig. 1. It is an asymmetric double notch tensile specimen first considered by Meuwissen *et al.* [8] to create heterogeneous stress and strain fields for elasto-plastic identification. The specimen dimensions are provided directly in Fig. 1.

Synthetic data. The methodology is illustrated here using simulated data. This is a necessary first step for which the ground truth is known (model and parameters) and the procedure can be verified. A finite element model of the test was performed on Abaqus using a Hill48 yield surface and Swift hardening. The parameters are listed in Tab. 1. To simulate the experimental process robustly, synthetic image deformation has been performed using a numerically generated speckle pattern that is numerically deformed to encode the finite element displacement data. This was first imagined by Lava et al. [9] and refined later for small strain by Rossi et al. [10]. Grey level camera noise can then be added to the images directly for realistic simulations of actual image recordings. The complete procedure was performed using the MatchID FEDEF module (www.matchid.eu).

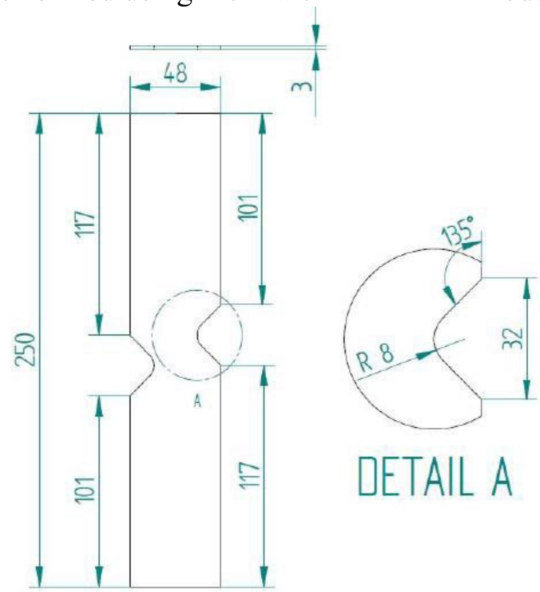

Fig. 1. Test configuration.

Table 1. Test parameters.

Elastic behaviour		
	E (GPa)	219
	ν (-)	0.3
Hill48 yield surface		
	F (-)	0.23
	G (-)	0.35
	H (-)	0.65
	N (-)	1.41
Swift hardening		
	ϵ_0 (MPa)	0.0059
	K (MPa)	563
	n (-)	0.276

Materials Research Proceedings 41 (2024) 1836-1840 https://doi.org/10.21741/9781644903131-203

Data processing. The numerically deformed images were processed with DIC to produce strain maps. The DIC parameters used are reported in Tab. 2. 50 load steps have been simulated. From the strain and load data, the VFM with Sensitivity-Based Virtual Fields (SBVFs, [11]) was used to identify the parameters of both Von Mises and Hill48 criteria, with the correct formulation of hardening (Ludwick).

Table 2. DIC parameters.

Parameter	Value
Virtual camera resolution	2448×2048
Software	MatchID 2024.0
Pixel to mm conversion	0.016 $mm.pixel^{-1}$
Subset size	15 pixel
Step Size	5 Pixel
Interpolation	Cubic spline
Shape function	Quadratic
Correlation criterion	ZNSSD
Pre smoothening	Gaussian 5×5 pixel
Strain window	21 data points

Model ranking

Equilibrium Gap Indicator (EGI). The EGI corresponds to a particular case of the VFM with local piecewise virtual fields. It was first used in [12] to identify damage maps in composites tested in-plane, then adapted to plate bending to identify barely visible damage in impacted composite plates. It was also used to detect heterogeneities in thin paper webs loaded in-plane. More recently, it was used to discriminate between hyperelastic constitutive models [7]. The EGI can detect inconsistencies in the local distribution of stresses leading to a violation of local stress equilibrium, suggesting that the constitutive model is inadequate. This paper is the first to apply this concept to anisotropic plasticity.

Force Reconstruction Error (FRE). This is obtained using piecewise virtual fields deforming one row of data across the specimen. In [14], this was used to identify elasto-plastic parameters. Here, it is used to rank the performance of material models, as in [7] for hyperelastic materials. It can also be seen as comparing the globally applied load measured by the load cell to individual cross- sectional loads reconstructed from the measured strains and the identified model. This indicator provides a 1D plot along the specimen loading axis.

Compared to the procedure in [4], where EGI virtual fields are used to select and identify the models, here, the models are identified with a set of virtual fields (SBVFs) and ranked with another set of virtual fields. It would be interesting to benchmark the two techniques to get an insight into respective efficiency.

Results

Figs. 2 and 3 show stress maps obtained from the FEDEF module. The conference presentation will provide EGI and FRE results as these are currently being processed.

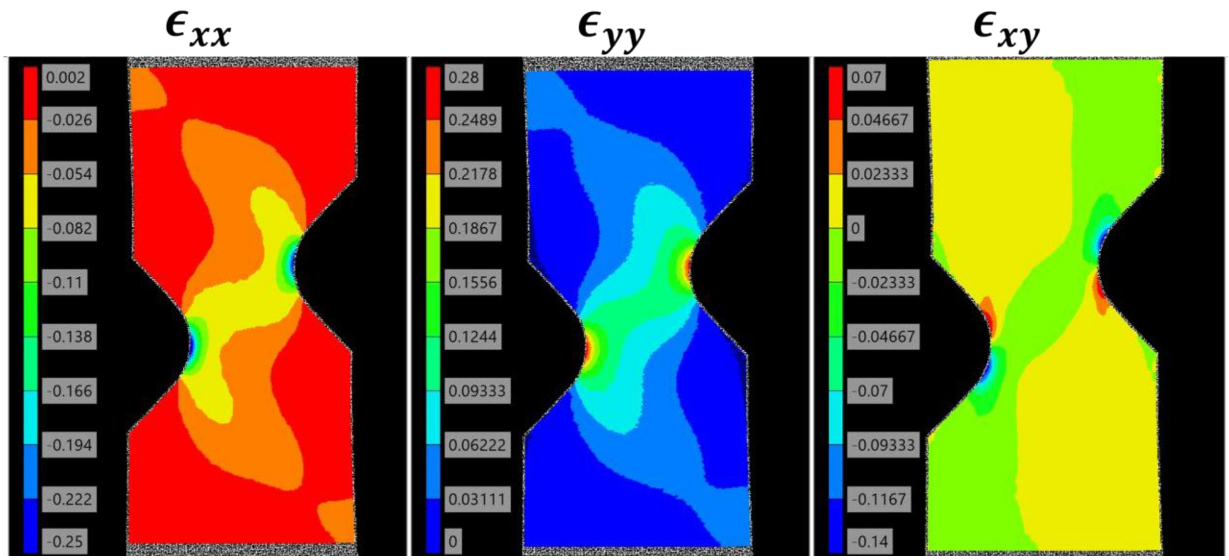

Fig. 2. Strain.

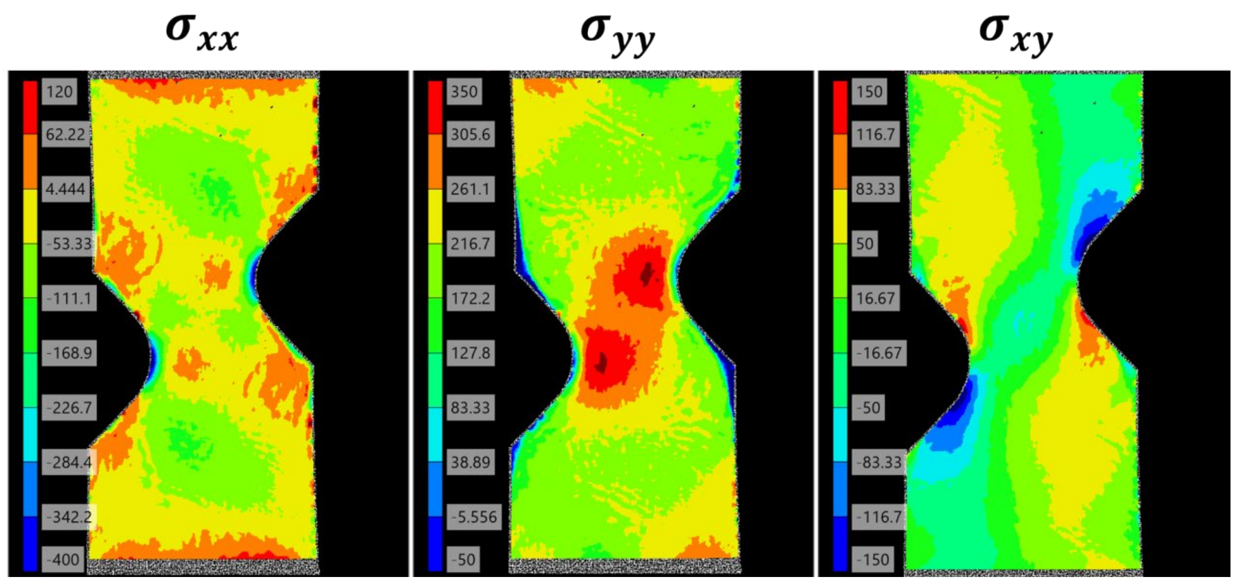

Fig. 3. FRE for Von Mises (left) and Hill48 (right) models.

Conclusion

This study is part of a larger corpus of work aiming at not only using MT2.0 for faster identification of anisotropic plasticity models, but also at evaluating the performance of each model to select the most appropriate. To this purpose, specific metrics have been developed (EGI and FRE). The presentation will propose different results combining increasing levels of complexity (Von Mises, Hill48, Yld2000-2D) and show how these metrics can discriminate between these models.

References

[1] Y. Zhang, A. Yamanaka, S. Cooreman, T. Kuwabara and S. Coppieters, S., Inverse identification of plastic anisotropy through multiple non-conventional mechanical experiments, Int. J. of Sol. and Struct., 285 (2023) 112534. https://doi.org/https://doi.org/10.1016/j.ijsolstr.2023.112534

[2] M. Rossi, A. Lattanzi, L. Morichelli, J.M.P Martins, S. Thuillier, A. Andrade-Campos and S. Coppieters, Testing methodologies for the calibration of advanced plasticity models for sheet metals: A review. Strain, 58(6) (2022) e12426. https://doi.org/10.1111/str.12426

[3] F. Pierron and M. Grédiac, The Virtual Fields Method, Springer, New York, 2012. https://doi.org/10.1007/978-1-4614-1824-5

[4] M. Flaschel, S. Kumar and L. De Lorenzis, Discovering plasticity models without stress data, Comp. Mat., 8(1) (2022) 91. https://doi.org/10.1038/s41524-022-00752-4

[5] R. Langlois, M. Coret and J. Réthoré, Non-parametric stress field estimation for history-dependent materials: Application to ductile material exhibiting Piobert–Lüders localization bands, Strain, 58(4) (2022) e12410. https://doi.org/https://doi.org/10.1111/str.12410

[6] B.C. Cameron and C.C Tasan, Full-field stress computation from measured deformation fields: A hyperbolic formulation. J. Mech. Phys. Sol., 147 (2021) 104186. https://doi.org/https://doi.org/10.1016/j.jmps.2020.104186

[7] A. Peshave, F. Pierron, P. Lava, D. Moens, D. Vandepitte, Metrics to evaluate constitutive model fitness based on DIC, in revision, Strain (2023).

[8] M.H.H Meuwissen, C.W.J. Oomens, F.P.T. Baaijens, R. Petterson, and J.D. Janssen, Determination of the elasto-plastic properties of aluminium using a mixed numerical–experimental method, J. Mat. Proc. Tech., 75(1–3) (1998) 204-211. https://doi.org/10.1016/S0924-0136(97)00366-X

[9] P. Lava, S. Cooreman, S. Coppieters, M. De Strycker and D. Debruyne, Assessment of measuring errors in DIC using deformation fields generated by plastic FEA. Opt. Las. Eng., 47(7- 8) (2009) 747-753. https://dx.doi.org/10.1016/j.optlaseng.2009.03.007

[10] M. Rossi, P. Lava, F. Pierron, D. Debruyne and M. Sasso, Effect of DIC spatial resolution, noise and interpolation error on identification results with the VFM, Strain, 51(3) (2015) 206-222. https://doi.org/10.1111/str.12134

[11] D. Claire, F. Hild, F. and S. Roux, A finite element formulation to identify damage fields: The equilibrium gap method. Int. J. for Num. Meth. in Eng., 61(2) (2004) 189-208. https://doi.org/10.1002/nme.1057

[12] C. Devivier, F. Pierron, and M. Wisnom, Impact damage detection in composite plates using deflectometry and the Virtual Fields Method, Comp. A, 48 (2013) 201–218. http://dx.doi.org/10.1016/j.compositesa.2013.01.011

[13] J. Considine, F. Pierron, K. Turner, P. Lava, and X. Tang, Smoothly varying inplane stiffness heterogeneity evaluated under uniaxial tensile stress, Strain, 53(5) (2017) e12237. http://dx.doi.org/10.1111/str.12237

[14] Y. Pannier, S. Avril, R. Rotinat and F. Pierron, Identification of elasto-plastic constitutive parameters from statically undetermined tests using the virtual fields method, Exp. Mech., 46(6) (2006) 735-755. http://dx.doi.org/10.1007/s11340-006-9822-x