Key Engineering Materials
ISSN: 1662-9795, Vol. 1049, pp 107-114
doi:10.4028/p-jZ5Rxd

Submitted: 2026-01-19
Revised: 2026-02-17
Accepted: 2026-03-02

Towards Single-Test Anisotropy Calibration: Sensitivity, Identifiability and Validation of YLD2000-2d

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Keywords: MT2.0, finite element model updating, DIC, material characterization, anisotropy.

Abstract. This paper revisits the long-standing question of how to fully characterise the in-plane plastic anisotropy of sheet metals without assembling evidence from multiple standardised tests. The central idea is pragmatic: a single, well-designed heterogeneous biaxial experiment can replace the conventional combination of uniaxial and equibiaxial tests if the specimen and the inverse identification method are co-designed to (i) activate informative stress states and (ii) maintain low strain gradients for accurate digital image correlation measurements. The proposed cruciform specimen is deliberately conceived as a benchmark configuration for full-field inverse identification, with known locations and stress-strain states at which relevant material information is embedded. The approach is coupled with a Finite Element Model Updating framework, enabling all anisotropy parameters of the YLD2000-2d model to be identified from a single full-field dataset. Sensitivity and identifiability analyses demonstrate that a physically based parameter formulation significantly improves the conditioning of the inverse problem. Virtual experimentation confirms the robustness and accuracy of the proposed “one-test” identification strategy.

Introduction

The predictive capability of numerical simulations in sheet metal forming critically depends on the accurate identification of constitutive model parameters, particularly those governing in-plane plastic anisotropy. Traditionally, these parameters are obtained from a collection of standardised mechanical tests, including uniaxial tensile tests performed along multiple material directions and equibiaxial loading experiments. While such procedures are well established, they rely on assembling information from several independent tests, each probing only a limited subset of the material response, and typically assume homogeneous stress and strain states.

The rapid development of full-field optical measurement techniques, most notably digital image correlation (DIC) [1], has fundamentally changed the landscape of material characterisation. Full-field measurements provide access to heterogeneous displacement and strain fields over an entire region of interest, thereby offering significantly richer experimental information than conventional pointwise measurements. This has motivated the emergence of so-called *Material Testing 2.0* (MT 2.0) [2,3], in which heterogeneous tests are deliberately designed and combined with inverse identification techniques to determine constitutive parameters from a reduced number of experiments, ideally from a single test.

Within this framework, a wide range of inverse identification strategies has been proposed, including the Virtual Fields Method (VFM) [4,5], Finite Element Model Updating (FEMU) [6], equilibrium-gap-based approaches [7], and integrated DIC formulations [8]. Among these, FEMU and nonlinear VFM have become the most widely used methods for identifying plasticity parameters in sheet metals. FEMU relies on iterative finite element simulations coupled with optimisation algorithms, whereas VFM exploits the principle of virtual work to extract parameters directly from measured fields. Despite their conceptual differences, both approaches critically depend on the interplay between the chosen constitutive model, the design of the heterogeneous specimen, and the quality of the measured full-field data, which ultimately determines whether the inverse problem is well or ill conditioned.

A key limitation that continues to hinder broader industrial adoption of MT 2.0 is the lack of *systematic benchmarking of a complete identification chain from specimen design, full field measurement to inverse identification process*. While many studies demonstrate successful parameter identification using carefully designed heterogeneous tests [9], fewer explicitly address whether a given test configuration truly contains sufficient and well-conditioned information to uniquely identify all targeted parameters [10,11]. In particular, parameter correlation, low sensitivity, or insufficient activation of specific stress–strain states may lead to ill-posed inverse problems, non-unique solutions, or poor characterisation of the targeted material behaviour. As highlighted in previous identifiability studies, the apparent success of an inverse algorithm does not necessarily guarantee that all identified parameters are physically meaningful or robust [12].

In this work, we revisit the long-standing question of whether the in-plane plastic anisotropy of sheet metals can be fully characterised without assembling evidence from multiple standardised tests. We propose a single, purpose-designed heterogeneous biaxial experiment intended to replace the conventional combination of three uniaxial tensile tests (rolling, transverse, and diagonal directions) and an equibiaxial test. The specimen is conceived as a tailored cruciform geometry that simultaneously activates well-defined uniaxial stress states in multiple orientations while maintaining low strain gradients to ensure reliable DIC measurements.

Beyond serving as a practical “one-test” alternative, the proposed configuration is deliberately designed for comparative analysis of inverse identification methods utilising different cost function formulations. The specimen and the inverse identification pipeline are co-designed such that the locations and loading stages containing the relevant information for parameter identification are known *a priori*. This enables a rigorous assessment of whether full-field inverse methods, such as FEMU and VFM, are able to correctly extract the embedded information from the measured data. The benchmark nature of the test thus allows the inverse algorithms themselves to be scrutinised, rather than merely demonstrating successful parameter fitting.

The proposed design is used within a FEMU framework, in which all material parameters are identified from a single full-field dataset. While the concept of heterogeneous testing is well established in the scientific community, its practical applicability in industrial sheet metal forming remains limited. Consequently, the specimen design also reflects pragmatic considerations related to manufacturability, test execution, and measurement robustness, thereby bridging the gap between academic MT 2.0 developments and industrial practice.

A benchmark Cruciform Specimen for Robustness Analysis of Full-Field Inverse Identification

To intrinsically incorporate the key data obtained from uniaxial tensile tests-namely the uniaxial yield stresses and R-values-a natural approach is to combine the three uniaxial test orientations into a single heterogeneous test configuration, as shown in Fig. 1. The proposed biaxial test employs a cruciform specimen with four individual ligaments converging in the central region. This configuration enables simultaneous plastic deformation in regions aligned with the rolling, transverse, and diagonal directions. Consequently, the testing procedure if needed can be simplified, as a single experiment suffices to characterise the uniaxial response in all three material directions. Furthermore, the configuration is designed such that the identification outputs are clearly defined, allowing the results to be post-processed also analytically. This makes the setup particularly suitable for evaluating full-field inverse identification methods, such as Finite Element Model Updating (FEMU) and the Virtual Fields Method (VFM). Importantly, the test is conceived such that the locations and load frames containing the relevant information are known a priori, ensuring that the appropriate data can be measured and exploited by full-field inverse identification methods.

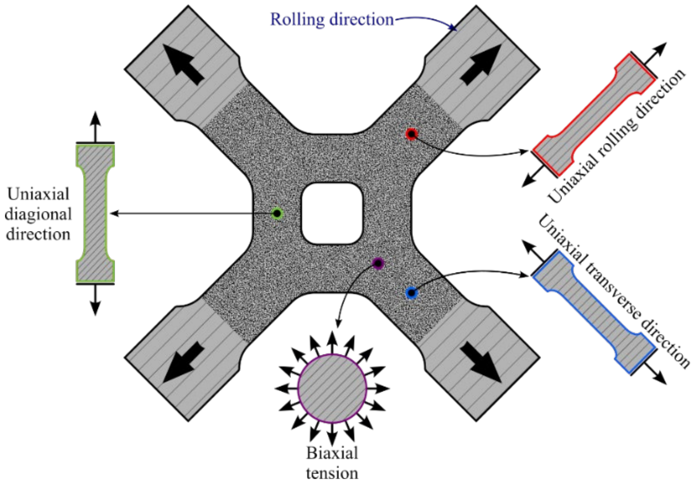


Fig. 1. Design of the biaxial tensile specimen. Predominantly uniaxial tensile stress states develop in the ligaments, whereas a biaxial tensile stress state occurs at the ligament junction.

As shown in Fig. 1, the outer ligaments predominantly experience a uniaxial tensile stress state aligned with the rolling and transverse directions, whereas the inner ligaments primarily represent a uniaxial stress state in the diagonal direction. A biaxial stress state develops at the junction of the ligaments; however, this region typically enters the plastic regime at later loading stages than the ligaments. *A key design requirement is therefore that all ligaments yield simultaneously and attain comparable plastic strain levels*. This condition is satisfied by enforcing force equilibrium between the outer and inner ligaments while maintaining identical yield stresses. Under these assumptions, force balance dictates that the width of the inner ligaments should be reduced by a factor of √2/2 relative to that of the outer ligaments.

The *fillet regions are designed to minimise stress and strain gradients*, enabling efficient convergence of DIC measurements. In addition, the ligaments are sufficiently elongated to maintain an approximately uniaxial stress and strain state, which is essential for analytical post-processing. With the proposed geometry, each ligament allows the determination of the uniaxial yield stress and the corresponding R-value, resulting in six independent quantities. The equibiaxial yield stress also influences the strain evolution within the ligaments, and its effect is therefore implicitly captured by the test. In contrast, the equibiaxial R-value is not strongly represented, as the plastic strains at the ligament junction remain significantly lower than those developing in the ligaments.

YLD2000-2d: Alpha-Based Versus Physical-Based Parameter Formulation

The quality of parameter identification critically depends on the interplay between the constitutive model formulation and the heterogeneous test design. To illustrate this relationship, two formulations of the YLD2000-2d plastic anisotropy model are revisited. In the first formulation, the material parameters are expressed in their original form as proposed by Barlat et al. [13]. In the second formulation, a physically based interpretation is adopted, in which uniaxial yield stresses and R-values-associated with standard tensile testing procedures—are treated as model parameters.

The α formulation.

The equivalent stress of the original model is formulated as

$$2\,\sigma_{eq}^{m} = |X'_1 + X'_2|^m + |2X''_2 + X''_1|^m + |2X''_1 + X''_2|^m, \tag{1}$$

where m is a material parameter determine the curvature of the yield surface. The quantities X'_i and X''_i are the eigenvalues of the transformed stress tensors $\mathbf{X}'$ and $\mathbf{X}''$, respectively. These tensors are obtained through linear transformations of the Cauchy stress tensor $\boldsymbol{\sigma}$, namely $\mathbf{X}' = \mathbf{L}'\boldsymbol{\sigma}$ and $\mathbf{X}'' = \mathbf{L}''\boldsymbol{\sigma}$. The transformation matrices $\mathbf{L}'$ and $\mathbf{L}''$ are defined as

$$\mathbf{L}' = \frac{1}{3}\begin{pmatrix} 2\alpha_1 & -\alpha_1 & 0 \\ -\alpha_2 & 2\alpha_2 & 0 \\ 0 & 0 & \alpha_7 \end{pmatrix}, \mathbf{L}'' = \frac{1}{9}\begin{pmatrix} -2\alpha_3 + 2\alpha_4 + 8\alpha_5 - 2\alpha_6 & \alpha_3 - 4\alpha_4 - 4\alpha_5 + 4\alpha_6 & 0 \\ 4\alpha_3 - 4\alpha_4 - 4\alpha_5 + \alpha_6 & -2\alpha_3 + 8\alpha_4 + 2\alpha_5 - 2\alpha_6 & 0 \\ 0 & 0 & 9\alpha_8 \end{pmatrix} \quad (2)$$

In this formulation, the model contains eight independent parameters α_{1-8} that must be calibrated. These parameters have a coupled influence on the shape of the yield surface and cannot be directly interpreted in physical terms. Consequently, an alternative formulation is introduced in the following, in which the mathematical structure of the model is retained while the parameters are expressed in terms of physically meaningful quantities associated with tensile testing.

Formulation with physical interpretation of parameters.

In the original work by Barlat et al. [13], a calibration procedure for the parameters α_{1-8} based on standard uniaxial test results—namely normalised yield stresses and R-values—was proposed. This procedure requires solving a system of eight nonlinear equations, with the normalised yield stresses $Y_{0°}, Y_{45°}, Y_{90°}, Y_b$ and the corresponding R-values $r_{0°}, r_{45°}, r_{90°}, r_b$ as inputs. The system is solved for α_{1-8} using the Newton–Raphson algorithm and typically converges within three to five iterations.

From this perspective, the material model may alternatively be formulated in terms of the physically interpretable parameters $Y_{0°}, Y_{45°}, Y_{90°}, Y_b$ and , $r_{0°}, r_{45°}, r_{90°}, r_b$, while the transformation to the internal parameter set α_{1-8} and the associated solution of the nonlinear system are regarded as an integral part of the constitutive model. From a computational standpoint, this implies that the parameter transformation can be implemented directly within the Abaqus UMAT subroutine, where the nonlinear system is solved only once per parameter update iteration, rather than during every stress update at each material integration point.

Direct-Levelling-Based Finite Element Model Updating

FEMU is adopted in this work as the inverse identification framework for exploiting the full-field measurements obtained from the proposed benchmark cruciform experiment. It is selected due to its simplicity and flexibility cost function modification, and its ability to incorporate heterogeneous strain fields without requiring spatial convergence of the measured data.

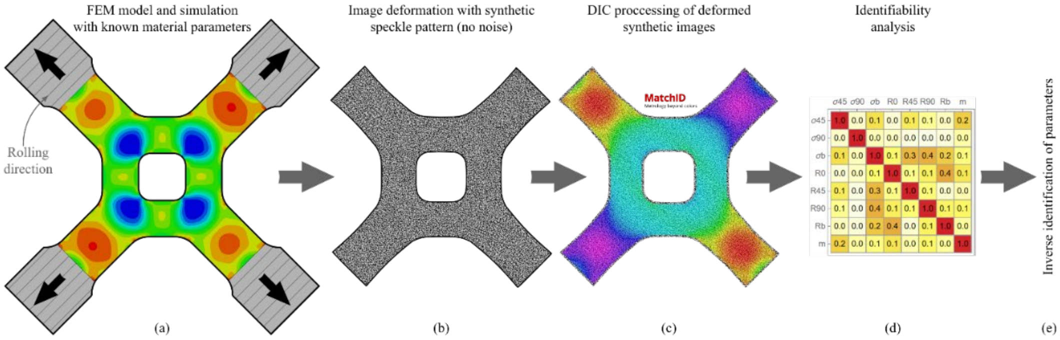
Within the FEMU framework, the mechanical test is reproduced numerically using a finite element model, and the resulting displacement and strain fields are compared with those measured experimentally by DIC. The material parameters are iteratively updated by minimising a cost function that quantifies the discrepancy between experimental and numerical fields. However, FEM and DIC inherently differ in the manner in which kinematic fields are computed and spatially filtered. While FEM can resolve sharp strain gradients through mesh refinement, DIC measurements are affected by spatial filtering governed by subset size, interpolation scheme, and strain window parameters. If not properly accounted for, this mismatch may introduce systematic bias into the inverse identification procedure [14].

To mitigate this issue, a direct-levelling-based FEMU strategy is employed, following the methodology established in previous work. In this approach, FEM-computed nodal displacement fields are post-processed using the same strain reconstruction procedure as applied to the DIC data. Specifically, the FEM displacements are interpolated onto the DIC measurement grid and subsequently converted into strains using an identical strain window. By enforcing equivalent spatial filtering on both experimental and numerical data, the direct-levelling procedure ensures consistency between the compared strain fields, while avoiding the computational overhead associated with full DIC levelling via synthetic image generation.

Methodology

The classical approach to assessing a heterogeneous specimen design is to first conduct a digital virtual twin (DVT) of the real experiment [15]. The purpose of the DVT is to simulate the experiment using known material parameters, generate deformed images from the calculated displacement fields, and process these images with a DIC engine to obtain strain fields. The resulting strain fields are then used as inputs for the FEMU procedure. It should be emphasised that, during the creation of the DVT, the user has full control over the speckle pattern characteristics, image resolution, DIC parameters, and noise level, enabling a systematic investigation of the influence of image noise and measurement settings.

In the present study, the finite element model used to generate the DVT was built with a dense spatial discretisation comprising approximately 50,000 quadrilateral elements and 100 load frames to ensure a converged solution. The material parameters of the YLD2000-2d model were adopted from Coppieters et al. [16]. Furthermore, the speckle pattern, image resolution, noise level, and DIC settings were selected to closely match those used in the real experiment. Using this procedure, synthetic DIC results were generated that are representative of measurements obtained under experimental conditions.



	σ45	σ90	σb	R0	R45	R90	Rb	m
σ45	1.0	0.0	0.1	0.0	0.1	0.1	0.0	0.2
σ90	0.0	1.0	0.0	0.0	0.0	0.0	0.0	0.0
σb	0.1	0.0	1.0	0.1	0.3	0.4	0.2	0.1
R0	0.0	0.0	0.1	1.0	0.1	0.1	0.4	0.1
R45	0.1	0.0	0.3	0.1	1.0	0.1	0.0	0.0
R90	0.1	0.0	0.4	0.1	0.1	1.0	0.1	0.1
Rb	0.0	0.0	0.2	0.4	0.0	0.1	1.0	0.0
m	0.2	0.0	0.1	0.1	0.0	0.1	0.0	1.0

Fig. 2. Flowchart illustrating the virtual experiment based on known material parameters. The procedure starts with a finite element simulation, whose displacement fields are used to generate synthetic deformed images. These images are subsequently processed with DIC to obtain virtual experimental inputs for FEMU.

The post-processed DIC results were then supplied to the FEMU engine as measured data. For the purpose of numerical optimisation, a second finite element model with a coarser mesh was constructed. The rationale behind this approach is that, in real experiments, the optimal mesh density cannot be determined a priori, and a coarser mesh is typically adopted to ensure reasonable computational efficiency. This choice inevitably introduces a certain level of systematic error, which is also expected under real experimental conditions. Further details regarding the formulation of the optimisation problem are provided in Zhang et al. [11].

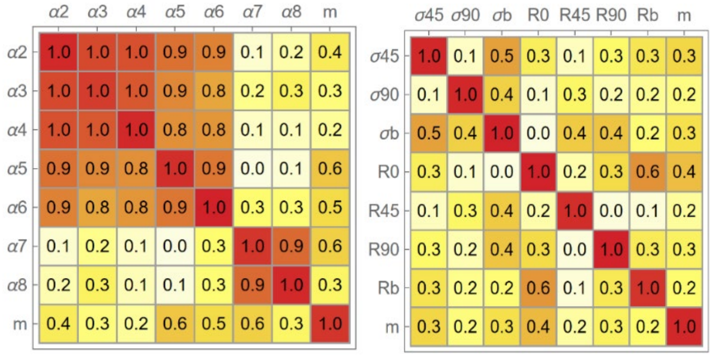
Finally, prior to performing the actual optimisation, an identifiability analysis was conducted to assess whether the inverse problem is well or ill conditioned. This step is particularly important when the numerical response exhibits low sensitivity to variations in certain parameters, or when variations in multiple parameters lead to similar responses, in which case a unique solution cannot be obtained. For this reason, sensitivity maps were computed and an identifiability study was performed. Most importantly, this analysis reveals the underlying structure of the optimisation problem for both material model formulations considered in this work, namely the α-based formulation and the physically based parameter formulation of YLD2000-2d.

Results

Sensitivity maps and identifiability study.

For both formulations of the YLD2000-2d yield function-the α-based formulation and the physically based parameter formulation—the sensitivity of the cost function was calculated and analysed. The results indicate that, for both parameter sets, the strain fields exhibit good sensitivity to variations in most parameters. The main exceptions are the yield function exponent and the biaxial R-value, whose sensitivities are less pronounced. This behaviour is expected, as the shape of the yield function primarily governs the evolution of plastic strains in regions between the control points defined by $Y_{0°}, Y_{45°}, Y_{90°}, Y_b$ and slopes , $r_{0°}, r_{45°}, r_{90°}, r_b$. These intermediate stress states correspond to relatively low strain levels, as they predominantly develop at the junction of the ligaments. A similar argument applies to r_b, since plastic strains under equibiaxial tension remain smaller than those developing under uniaxial tension.

Further analysis focused on the interaction between individual parameters. When two parameters have a similar influence on the spatial distribution of the strain field, they cannot be uniquely identified from the experimental data [12]. To assess this interaction, a correlation matrix was constructed based on the sensitivity information. The resulting correlation matrices for both formulations of YLD2000-2d are shown in Fig. 3. For the α-based formulation, it can be observed that the parameters α_{1-6} are highly correlated and therefore cannot be uniquely determined from the experimental data. A similar correlation is observed between the parameters α_7 and α_8. In contrast, the physically based parameter formulation enables a unique identification of all parameters.



	α2	α3	α4	α5	α6	α7	α8	m
α2	1.0	1.0	1.0	0.9	0.9	0.1	0.2	0.4
α3	1.0	1.0	1.0	0.9	0.8	0.2	0.3	0.3
α4	1.0	1.0	1.0	0.8	0.8	0.1	0.1	0.2
α5	0.9	0.9	0.8	1.0	0.9	0.0	0.1	0.6
α6	0.9	0.8	0.8	0.9	1.0	0.3	0.3	0.5
α7	0.1	0.2	0.1	0.0	0.3	1.0	0.9	0.6
α8	0.2	0.3	0.1	0.1	0.3	0.9	1.0	0.3
m	0.4	0.3	0.2	0.6	0.5	0.6	0.3	1.0

	σ45	σ90	σb	R0	R45	R90	Rb	m
σ45	1.0	0.1	0.5	0.3	0.1	0.3	0.3	0.3
σ90	0.1	1.0	0.4	0.1	0.3	0.2	0.2	0.2
σb	0.5	0.4	1.0	0.0	0.4	0.4	0.2	0.3
R0	0.3	0.1	0.0	1.0	0.2	0.3	0.6	0.4
R45	0.1	0.3	0.4	0.2	1.0	0.0	0.1	0.2
R90	0.3	0.2	0.4	0.3	0.0	1.0	0.3	0.3
Rb	0.3	0.2	0.2	0.6	0.1	0.3	1.0	0.2
m	0.3	0.2	0.3	0.4	0.2	0.3	0.2	1.0

Fig. 3. Correlation matrices for the α-based formulation (left) and the physically-based parameter formulation (right) of YLD2000-2d.

The identified parameters.

The identified parameters obtained for three different mesh sizes-0.3 mm, 0.5 mm, and 0.75 mm-are reported in Table 1. As expected, the largest discrepancies are observed for the coarsest mesh and for the least sensitive parameters, namely the R-values and the yield function exponent. For these parameters, the relative error is in the order of 2–3%. It should be emphasised that, for the physically based formulation of YLD2000-2d, the solution converges within three to five iterations. In contrast, for the α-based formulation, the optimisation either fails to converge or converges to a local minimum.

Table 1. Target and identified parameters used in the study.

parameter [-]	target value	el. mesh size 0.3 mm	el. mesh size 0.5 mm	el. mesh size 0.7 mm
Y_{0° (fixed)	1.00000	1.00000	1.00000	1.00000
Y_{45°	1.09977	1.09972	1.09992	1.09942
Y_{90°	1.00383	1.00351	1.00377	1.00269
Y_b	1.05596	1.05554	1.05787	1.0527
r_{0°	1.71111	1.70429	1.71083	1.66433
r_{45°	1.88974	1.88727	1.8809	1.85759
r_{90°	2.7824	2.78347	2.78561	2.74348
r_b	1.16131	1.16972	1.17107	1.18151
m	6.555	6.53253	6.60417	6.39339

Physical testing on fully calibrated materials.

A well-known limitation of virtual testing is its inability to fully replicate all uncertainties present in real experimental conditions. Consequently, the ultimate validation of the proposed specimen design and inverse identification strategy requires application under real experimental conditions. For this reason, future work will focus on experimental measurements performed using an in-house-designed biaxial tensile testing machine and fully calibrated materials for which the anisotropy parameters are known. The planned experimental campaign will include different materials, such as SPCE [16], AISI304 [17], and AA5754-H22 [18]. The actual measurements and DIC results are presented in Fig. 4.

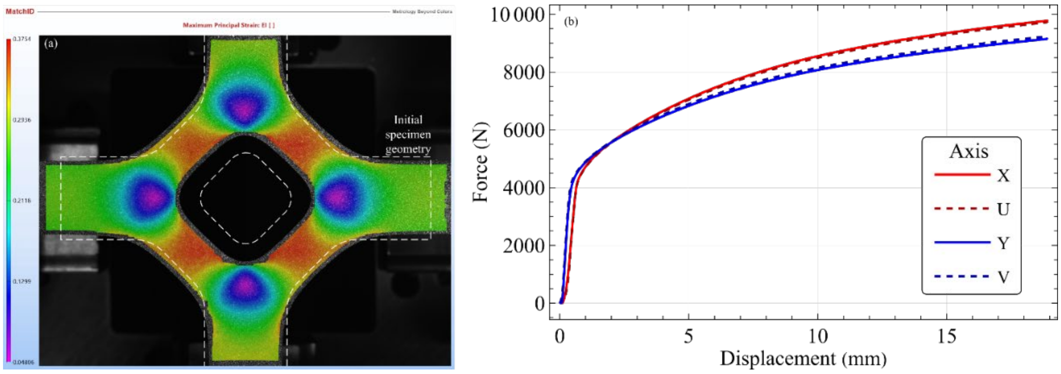


Fig. 4. Actual experimental test of AISI304 stainless steel sheet metal: the measured strain field on deformed configuration (left), force-displacement response of each individual loading arm (right). The quantities X,Y,U and V present a displacement of individual arm.

Conclusion

Based on the specimen design, sensitivity and identifiability analyses, and virtual experimental validation presented in this work, the following conclusions can be summarised:

- A purpose-designed cruciform specimen was proposed to enable single-test characterisation of in-plane plastic anisotropy in sheet metals, replacing the conventional combination of multiple uniaxial and equibiaxial tests.
- A physically based parameter formulation of the YLD2000-2d yield function, expressed in terms of uniaxial yield stresses and R-values, was shown to significantly improve the conditioning and identifiability of the inverse problem compared to the classical α-based formulation.
- Sensitivity and identifiability analyses demonstrated that, for the proposed specimen, the physically based parameter set can be uniquely identified, whereas strong parameter correlations prevent reliable identification in the α-based formulation.
- FEMU combined with a direct-levelling strategy enabled robust exploitation of heterogeneous full-field strain measurements while accounting for spatial filtering effects inherent to digital image correlation. Virtual experimentation confirmed that the proposed approach yields accurate parameter identification, with relative errors typically limited to a few percent, even in the presence of mesh-induced modelling discrepancies.
- Future work will focus on experimental validation using fully calibrated materials tested on a biaxial tensile testing machine, with the aim of demonstrating the practical applicability of the proposed benchmark configuration under real testing conditions.

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The publication of this article was funded by the KU Leuven 10.13039/501100004040