FE analysis and parameter optimisations of anisotropic material models for sheet metal materials using Full-Field-Calibration

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1 Introduction

Forming simulation models and the associated material characterisation are important factors when representing the increasingly complex deep drawing operations. Especially in context of automotive components, the finite element analysis ensures producibility prior to pilot series and minimises the risk of wasting resources by predicting the material behaviour as accurately as possible, such as plastic, thermal and anisotropic behaviour. For the representation of the plastic material deformation during forming, material models like Barlat or Hill, representing the real material behaviour as precisely as possible, must be implemented in the simulation. For this purpose, the model needs to describe occurring effects of the material such as anisotropy or further effects. Despite the great importance of the material model for the result of the forming simulation, its calibration by determining the correct parameters is still a challenge. In order to identify material parameters and to calibrate complex material models, digital image correlation can be used. This method enables recording the three-dimensional deformation of components under different load conditions so that the entire strain fields can be evaluated and verified using FE analysis. Based on the experimental strain fields created conducting tensile tests of metal sheet specimens, material parameters in the simulation model can be optimised to match the component deformations both locally and globally. This Full-Field-Calibration (FFC) method enables the identification of parameters not only describing the plastic deformation but also the non-isotropic behaviour [1]. The calibrated material model can be used to simulate complex components and predict the close-to-reality component behaviour during forming.

Compared to the conventional approach, creating a flow curve on the basis of a fixed reference length, the FFC method enables a better capture of the experimental strain field [2]. Besides that, with using the FFC method it is possible to identify the Lankford coefficients describing the non-isotropic behaviour of the material in one optimisation run with the flow curve parameters, based on the same experimental data [3]. However, shortcomings in the optimisation time of this method interfere with the industrial applicability. Therefore, in this paper a non-isotropic material model for sheet materials is calibrated using the FFC method by optimising the yield curve parameters according to the Hockett & Sherby approach as well as the Lankford coefficients. Furthermore, investigations of the used element formulation in the FE-model as well as different optimisation approaches in LS-OPT are investigated with respect to accuracy and economy.

2 Methodology

2.1 Material parameter identification using Full-Field-Calibration

For parameter optimisation of the material model MAT_3-PARAMETER_BARLAT or MAT_36 in LS-DYNA, tensile tests are conducted on a metal sheet material with different orientations to the rolling direction [4]. The respective tensile specimen is prepared with a stochastic pattern, which allows recording the deformation of the specimen's surface using the GOM-Aramis stereo camera system [5,6]. Using Digital-Image-Correlation DIC, two-dimensional strain fields containing the true strains can be calculated and output from the captured deformations of the specimen. The evaluation of the local strains being contained in the strain field is performed at discrete points, which can be exported as a multihistory using the DIC-software Aramis Professional [5]. In a multihistory, global tensile force is plotted as ordinate over true strains as abscissa for each discrete point of the strain field individually. By recording the strain in two spatial directions, a multihistory is output in each case of the transverse and

longitudinal direction. The strain field of a tensile specimen is calculated not only experimentally, but also in a simulation model using a finite element solver. Parallel to the experiment, a multihistory results from the simulation containing the local strains plotted over the global tensile force. For the calibration of the material model, the experimental strain field has to be aligned with the simulation model using LS-OPT, so it can be compared to the simulation results. In this paper, the interpolation method *Element* is used, so the FE-model is evaluated exactly at the positions of the experimental strain field's discrete data points. Accordingly, the correct alignment of the experimental data points in the simulation model as well as low noise multihistory-curves are important for the optimisation results [7]. An experimentally determined strain field with discrete data points (black) aligned in the simulation model (red) is shown in Fig. 1.

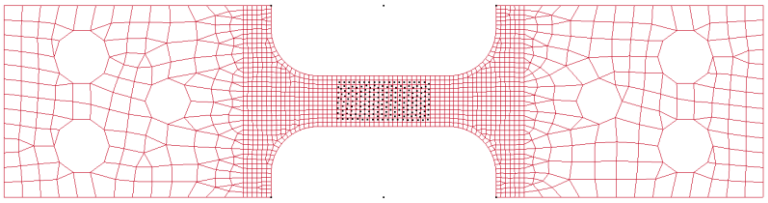


Fig. 1: Aligned experimental strain field (black) in the simulation model (red)

For the identification of suitable material model parameters, also the software LS-OPT is used. The identification follows an iterative approach, where selected material model parameters of the FE-model are adjusted so that the behaviour of the tensile specimen in the simulation corresponds in a close-to-reality manner to that of the experiment. The comparison of the deformation behaviour of the specimens is based on the force-strain multihistory of simulation and experiment. In this investigation, *Partial Dynamic Time Warping p-DTW* is used as curve matching algorithm for the multihistory comparison. The deviation of the curves is determined by the residual, which decreases as the match increases. In the calculation of the residuals using p-DTW, different curve lengths are considered computing the residual, allowing the comparison of differently dimensioned curves [8]. Therefore, the following residuals can be directly compared. An overview of the Full-Field-Calibration approach using simulatively and experimentally determined data in the form of multihistories and strain fields is shown in Fig. 2.

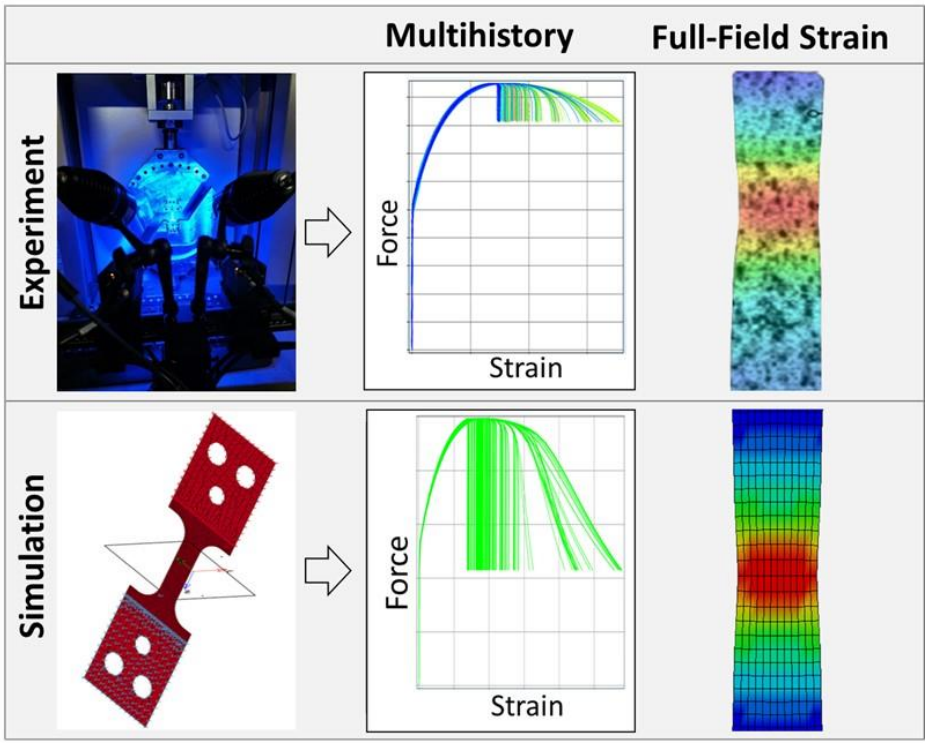


Fig. 2: Overview Full-Field-Calibration FFC approach

2.2 Material Model

Since the behaviour of a sheet metal material is to be represented in this paper, the model MAT_3-PARAMETER_BARLAT or MAT_36 in LS-DYNA is used. It's a material model for metal sheets, which represents the typical non-isotropic behaviour via the Lankford coefficients r_{00}, r_{45} und r_{90} in three directions 0°, 45° and 90° with respect to the rolling direction of the sheet [9]. The Lankford coefficient is characterised by logarithmic strain along the width φ_w and thickness φ_t direction of the tensile sample [10].

$$r = \ln(\varphi_w/\varphi_t) \tag{1}$$

Further, the plastic material deformation outside the range of uniform elongation is also integrated, whereby the yield criterion according to Barlat'89 applies. For the extrapolation of the yield curve, the approach according to Hockett & Sherby is used in this investigation in order to represent the relationship between the yield stress k_f and the degree of deformation φ [11].

$$k_f(\varphi) = A - B \cdot \exp(-c \cdot \varphi^n) \tag{2}$$

For a complete description of the material, the yield curve parameters A, B, c and n, as well as the associated Lankford coefficient r must be determined for each orientation to the rolling direction. Accordingly, there are three optimisations with five parameters each. In order to limit the optimisation range and thus the required computational effort, a relationship between the parameters A and B at the yield strength σ_y with no deformation $\varphi = 0$ is established.

$$A = B + \sigma_y \tag{3}$$

The yield strength σ_y can thus replace the yield curve parameter A as an optimisation parameter so the optimisation range can be aligned and restricted on the basis of the experimentally determined value. By recording the specimen's deformation in two dimensions, the thickness decrease of the specimen during the test can be calculated based on the major and minor principal strain under the assumption of volume constancy [12]. The knowledge about the three-dimensional deformation allows to output the Lankford coefficient to characterize the anisotropy. The coefficient values determined from the experiment using DIC, can be used as initial values for the optimisation. Using the yield strength allows a further limitation of the optimisation range due to its experimental value rather than using the yield curve parameter. The optimisation of the material model parameters is performed in the LS-OPT software.

2.3 Element formulation of the FE-models

For the consideration and simulation of sheet metals, it is common to discretise the thin-walled structures with shell elements. They reduce an initially three-dimensional sheet to a two-dimensional reference surface. In this study, the use of element formulations "2" (based on Belytschko-Tsay) and element formulations "16" (fully integrated shell elements) are used and investigated for parameter identification with the Full-Field-Calibration method. Both element formulations are based on the Reissner-Mindlin kinematic assumption and therefore exhibit a shear soft formulation. Element formulation 2 is the default shell formulation in LS-DYNA. It is characterised by high efficiency with the shortest computation times due to a one-point integration, but it tends to warp and is therefore not used for coarse models. Element formulation 16 is a fully integrated element with a 2x2 integration. It has a low susceptibility to the Hourglass effect and is suitable for large deformations. In comparison to formulation 2, it is up to three times more computationally expensive, but yet the most efficient fully integrated element [13]. Fig. 3 shows a comparison between both element formulations with five integration points over the thickness.

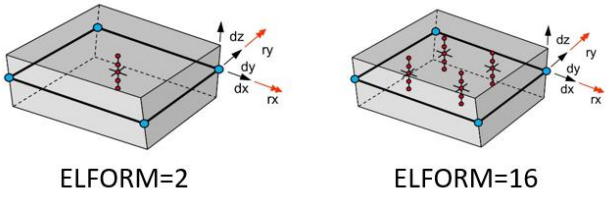


Fig. 3: Comparison of Shell element formulation 2 (left) and Shell element formulation 16 (right) [13]

2.4 Metamodels

For the identification of the material parameters in LS-OPT, a metamodel-based optimisation is used. This type of optimisation approximates the objective function using a less computationally intensive function. The aim of the optimisation, the determination of the global minimum of the objective function, is conducted using the approximated function, which is adapted with each further iteration of computation to precisely match the objective. An exact approximation of the objective is crucial for the optimisation results, since otherwise false assumptions or local minima can distort them [7]. The metamodel-based optimisation approach allows a more efficient identification of material model parameters due to using this simplified approximation function, which is mandatory because of the high computational effort with a high number of iterations. In this study, three in LS-OPT implemented metamodels are compared. For a local consideration of the objective function, a linear polynomial approach with the *Sequential with Domain Reduction (SRSM)* strategy is used. In contrast, for a global consideration the neural networks *Feedforward Neural Network FNN* and *Radial Basis Function Network RBNF* are applied using the strategy *Sequential*. For a global consideration, the metamodel approximates the entire optimisation domain, which is why complex metamodels are necessary to approximate the entire objective function accurately. For a local approach, the optimisation domain is restricted after each iteration, further considering the region of the prior global minimum only. Due to the continuous restriction of the optimisation domain, simple approximation functions can be used to represent the objective function in the region of the minimum. The response surfaces of the metamodels are shown and compared in Fig. 4 with an increasing number of iterations in a two-dimensional optimisation domain.

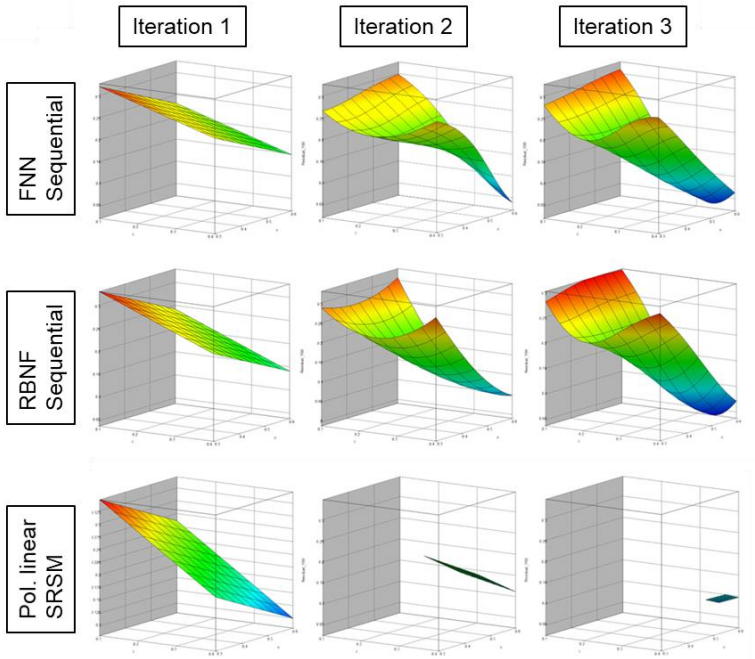
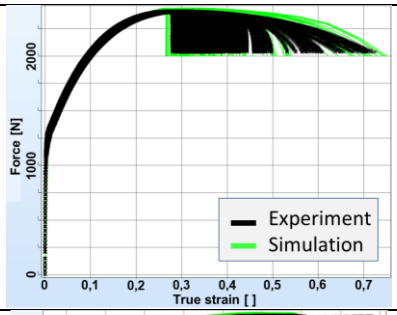
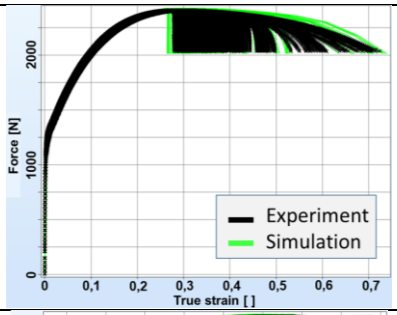
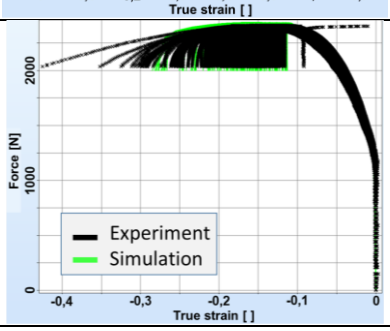
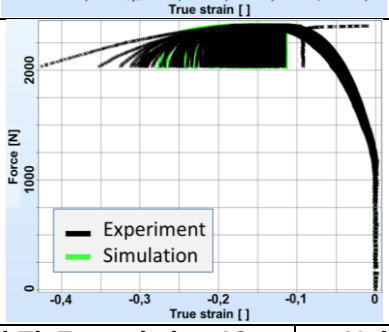


Fig. 4: Response surfaces of the metamodels FNN, RBNF and linear Polynomial

3 Optimisation results

3.1 Influence of the element formulation on the optimisation result

For the investigation of the influence of the element formulation using Full-Field-Calibration method, two identical optimisations are carried out with only the element formulation changed in the simulation model. The results of the investigation are shown in Table 1. The comparison is based on the force-strain multihistories in x- and y-direction, optimisation parameters, residuals and the optimisation times. The results show no significant difference in the optimisation results using different element formulations. It is noticeable that the optimisation duration for element formulation 2 is only 33 minutes. This is about 70% faster than element formulation 16. Due to the shorter times, element formulation 2 is used in further investigations only.

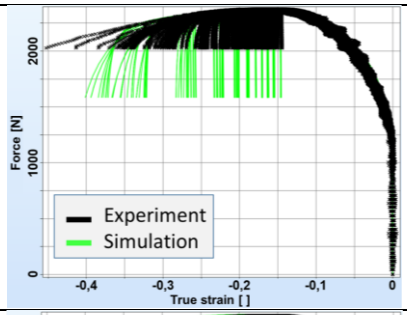
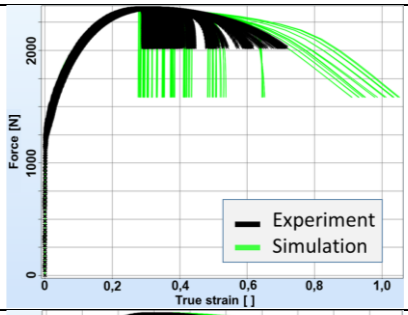
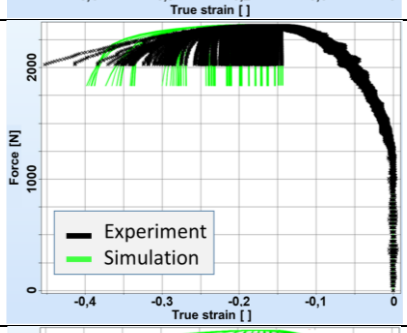
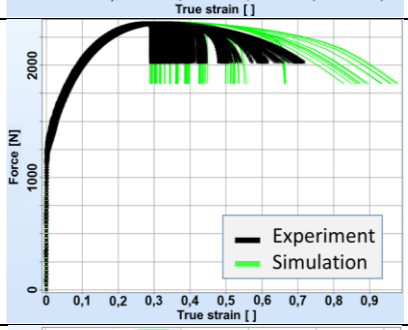
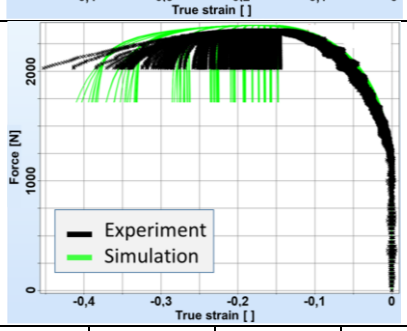
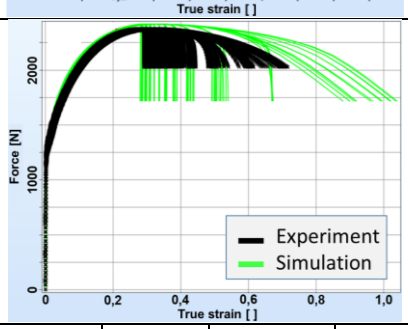
	Element Formulation 2	Element Formulation 16
Multihistory Y-direction		
Multihistory X-direction		

Parameter	Shell El. Formulation 2	Shell El. Formulation 16	Unit
A	414.81	412.53	*MPa*
B	315.92	314.03	*MPa*
c	2.56	2.57	-
n	0.82	0.82	-
σ_y	102.89	102.51	*MPa*
r	0.89	0.85	-
Res	0.046	0.043	-
t	33	105	*min*

Table 1: Results of the shell element formulation comparison

3.2 Influence of the metamodel on the optimisation results

Table 2 shows the optimisation results comparing different metamodels using otherwise identical settings. A linear polynomial approach using *Sequential with Domain Reduction SRSM* and the neural networks *Feedforward Neural Network FNN* as well as *Radial Basis Neural Network RBNF* using the *Sequential* strategy are compared.The results are benchmarked using the force-strain multihistories in x- and y-directions, optimisation parameters, residuals and optimisation duration. Those results show that the force-strain histories differ in the length of the vertical course. Based on the results, the Feedforward Neural Network FNN achieves the highest and the linear Polynomial approach the second highest accuracy in terms of the residual in this study. Due to the highest accuracy while having just a 4% higher optimisation duration, the Feedforward Neural Network is the most suitable metamodel for the Full-Field-Calibration method. Therefore, FNN is used for further optimisations only.

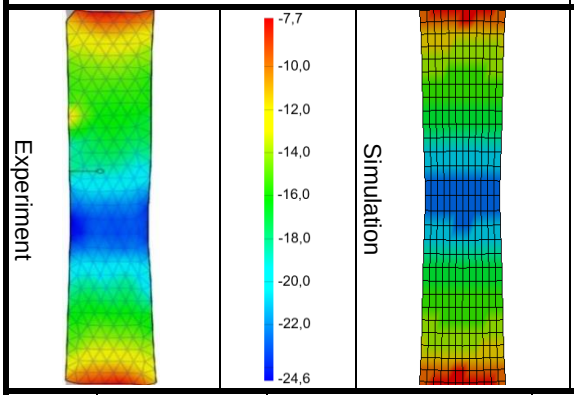
	Multihistories X-Direction	Multihistories Y-Direction
Linear Polynomial Pol.lin (SRSM)		
Feedforward Neural Network FNN (Sequential)		
Radial Basis Neural Network RBNF (Sequential)		

	A [MPa]	B [MPa]	c	n	σ_y [MPa]	r	Res	t [min]
Pol.lin.	770.43	666.41	0.68	0.59	104.02	1.17	0.030	110
FNN	817.82	713.82	0.65	0.60	104.00	1.19	0.026	117
RBNF	883.54	778.19	0.58	0.58	105.36	1.17	0.048	112

Table 2: Results of the metamodel comparison

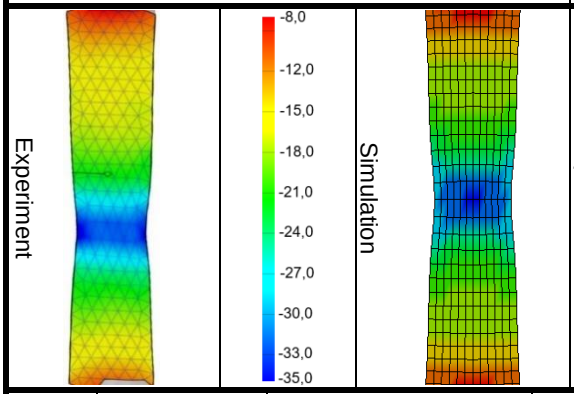
3.3 Calibration of an anisotropic material model using Full-Field-Calibration

In the following, Table 3 to Table 5 show the results of the parameter optimisation for the orientations 0°, 45° and 90° with respect to the rolling direction. The optimisation is carried out based on the results of chapters 3.1 and 3.2 using element formulation “2” and the Feedforward Neural Network FNN metamodel. In each case, the experimental values and strain fields determined with the Aramis Professional software are compared to the simulation results. This also contains the yield strength, maximum strain values and Lankford coefficients. Furthermore, the values of the optimised yield curve parameters according to Hockett & Sherby are shown. The comparison of the strain values in the x-direction shows a maximum deviation between experimentally and simulatively determined values of 3.6% at an orientation of 45° to the rolling direction. In the y-direction the maximum deviation of the strain value is 1.2% at an orientation of 90°. The maximum strain values are consistent with the high visual correspondence of the strain fields. The deviation of the Lankford coefficients is in the range of 10.2% around the experimentally determined values with a maximum deviation value of 0.11 at 45°. The yield strength of the optimised material models, with a maximum deviation of 7.73MPa at 90°, is in the range of 7% around the experimentally determined values.

Full-Field Strain – X-direction φ_x [%]	Full-Field Strain – Y-direction φ_y [%]
	

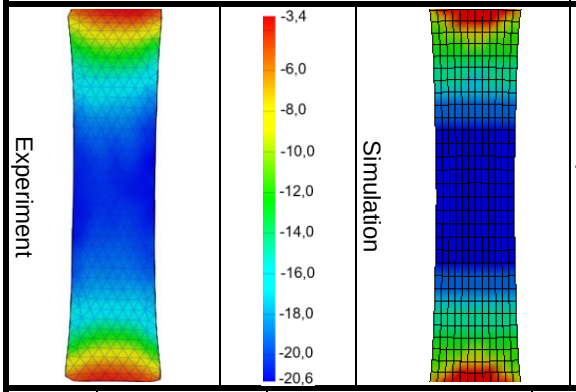
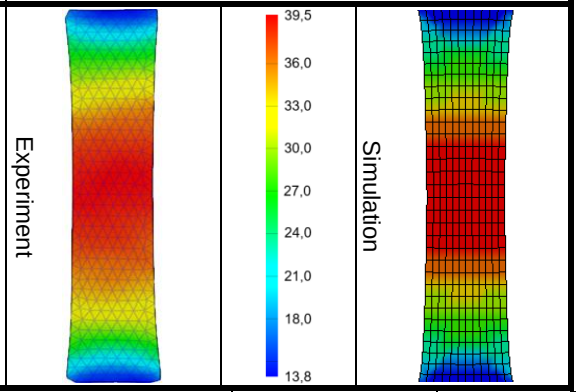
	Param.	Simulation	Experiment	Δ	Unit
0° w.r.t. the rolling direction	σ_y	109.82	107.16	2.66	MPa
	A	1195.75	-	-	MPa
	B	1085.93	-	-	MPa
	c	0.38	-	-	-
	n	0.60	-	-	-
	r_{00}	0.81	0.87	0.06	-
	Res	0.025	-	-	-
	$\varphi_{x\,min}$	-23.1	-24.6	1.5	%
	$\varphi_{y\,max}$	50.7	50.5	0.2	%

Table 3: Optimisation result - 0° w.r.t. the rolling direction

Full-Field Strain – X-direction φ_x [%]	Full-Field Strain – Y-direction φ_y [%]
	

	Param.	Simulation	Experiment	Δ	Unit
45° w.r.t. the rolling direction	σ_y	104.00	105.36	1.36	MPa
	A	817.82	-	-	MPa
	B	713.82	-	-	MPa
	c	0.65	-	-	-
	n	0.60	-	-	-
	r_{45}	1.19	1.08	0.11	-
	Res	0.026	-	-	-
	$\varphi_{x\,min}$	-33.6	-37.2	3.6	%
	$\varphi_{y\,max}$	63.8	64.5	0.7	%

Table 4: Optimisation result - 45° w.r.t. the rolling direction

Full-Field Strain – X-direction φ_x [%]	Full-Field Strain – Y-direction φ_y [%]
	

	Param.	Simulation	Experiment	Δ	Unit
90° w.r.t. the rolling direction	σ_y	102.58	110.31	7.73	MPa
	A	579.35	-	-	MPa
	B	476.78	-	-	MPa
	c	1.23	-	-	-
	n	0.74	-	-	-
	r_{90}	1.03	1.02	0.01	-
	Res	0.023	-	-	-
	$\varphi_{x\,min}$	-19.4	-20.6	1.2	%
	$\varphi_{y\,max}$	38.3	39.5	1.2	%

Table 5: Optimisation result - 90° w.r.t. the rolling direction

Fig. 5 shows the associated flow curves for the Hockett & Sherby flow curve parameters listed in Table 3 to Table 5 for the 0°, 45° and 90° orientations. It can be seen that the yield curves only differ noticeably for degrees of deformation >1, since the curves increase more sharply with decreasing angle in relation to the rolling direction.

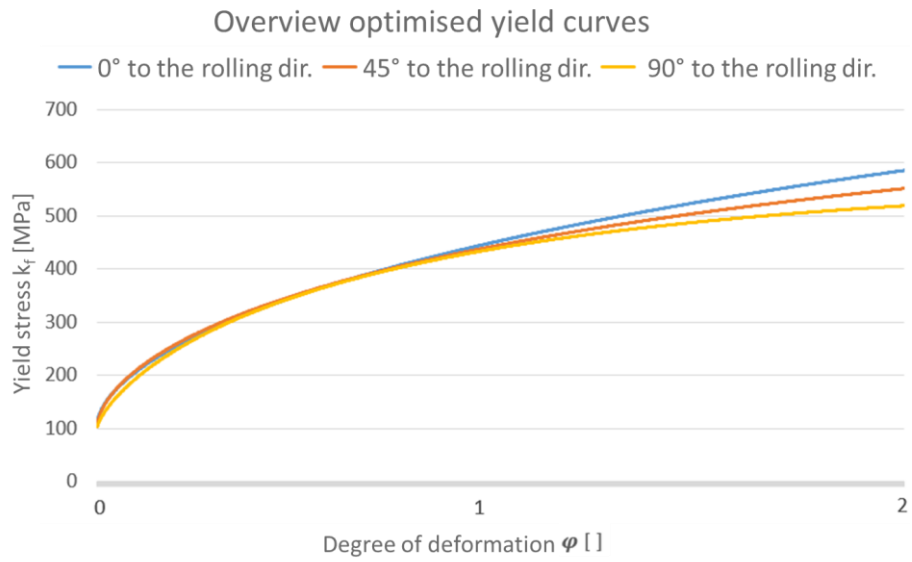


Fig. 5: Optimised strain curves w.r.t. the rolling direction using the Hockett & Sherby approach

4 Conclusion

In this paper, an anisotropic material model for metal sheet materials was calibrated using the Full-Field-Calibration method in LS-OPT. This included the optimisation of yield curve parameters according to Hockett & Sherby and the Lankford coefficients based on experimental data from tensile tests of sheet specimens with 0°, 45° and 90° orientations to the rolling direction. Further investigations were conducted on the use of different optimisation approaches in LS-OPT with the metamodel algorithms a) linear polynomial, b) Feedforward Neural Network (FNN) and c) Radial Basis Neural Network (RBNF) in terms of accuracy and optimisation time. With respect to the varied element formulation, no significant difference was found between the optimisation results, with element formulation 2 proving to be more economical without significant loss of accuracy. When comparing the metamodels, the Feedforward Neural Network turns out to be the most accurate due to the lowest deviation between simulated and experimentally determined force-strain curves. The combination of best agreement and only 4% higher optimisation time leads to the FNN being determined as the most suitable metamodel for the Full-Field-Calibration method.

The calibrated material model shows high correspondence with the experimental values, therefore it could be shown that the Full-Field-Calibration method is suitable for identifying Lankford and yield curve parameter according to Hockett & Sherby using experimentally determined plane strain fields at economically reasonable conditions. However, it is also shown that the convergence of the solution and thus the accuracy of the calibrated material model depend on the quality of the experimental data, which influences the choice of the metamodel used. The divergent optimisation results of different metamodels in this paper can be attributed to noise in the experimental date due to e.g. faulty image correlation. In the future, further investigations regarding the ratio of efficiency and convergence of several metamodels need to be carried out. In this context, the data sets used should get prepared using various filters, for example the SAE Filter.

5 Literature

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