Potential use of machine learning to determine yield locus parameters

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Abstract. The determination and validation of material parameters required for the finite element simulation of sheet metal forming processes can be realized by a full-field optical measurement of the deformation of a test specimen in combination with a simulation-based inverse approach. Development of such an inverse approach can be quite time consuming and requires programming skills and also expertise in FEM analysis and optimization. Emerging machine learning techniques offer a practical alternative to optimization and inverse approaches provided that the ground truth is completely known and generalized by the machine learning model. To be more precise, a machine learning model can directly compute the material parameters from the experimental measurements if the hypothetical mapping function between material parameters and deformation behavior is learned as ground truth. This paper presents such a machine learning based approach for the determination of validated yield locus parameters.

1. Introduction

Low margins and high equipment costs (e.g. for forming tools) mean that profitable production of sheet metal components can generally only be achieved through relatively high quantities and cost-efficient process development. Furthermore, the robustness of manufacturing processes of sheet metal components depends on a multitude of influencing factors, which requires a comprehensive process design and the most accurate determination of the correct input parameters. With regard to the implementation of robust production processes for new sheet metal components, manufacturing companies are therefore under constant time, cost and quality pressure. Today, these challenges towards robust production processes are overcome using process simulation by finite element method (FE). Implemented state of the art material models such as Barlat Yld2000-2d [1], Banabic BBC05 [2] and Vegter [3] are used to predict the material behavior during the forming process. However, for this purpose, the material parameters have to be determined and validated by a large number of tests to expect accurate simulation results [4].

The determination and validation of these material parameters (material characterization) for the selected material model thus represents an essential factor in the development and design of robust forming processes.

Thanks to the progress of full-field optical measurements, more and more inverse methods are being used for material characterization. There are two main approaches being pursued: One approach is to build a finite element model of the characterization experiment in order to identify accurate values for material parameters through simulation iterations [5, 6, 7, 8]. This approach is commonly known as finite element model updating (FEMU). One of the best known FEMU methods is the Inverse Parameter
Identification according to [8] shown in Figure 1. This method is based on experimental tensile tests with waisted tensile specimens of the selected material and the recorded strain distributions using optical measurement technology. Iterations with the corresponding FE simulations initialize with material parameters being set to isotropic values, namely 1.0 for the case shown. Subsequently, the calculated strain distributions are compared with the measured strain distributions. In case the deviation representing the difference between these two strain distributions does not meet the convergence criterion, optimization algorithms provide a new set of values for the material parameters and the FE simulation is repeated. Such iterations are repeated until the convergence criterion is met and thus the simulated strain distribution is as close as possible to the measured distribution.

Figure 1. Principle procedure of the Inverse Parameter Identification Method according to [8].

The second approach to determine material parameters is to evaluate the measured strain field directly by using equilibrium equations [9, 10, 11]. The Virtual Field Method (VFM) [12] is the most commonly used method based on this approach today. Recently, methods combining benefits of both approaches, such as iDIC, have also developed [13, 14]. All material characterization methods mentioned above are difficult, costly and time consuming for the users due to the necessity of simulation and optimization environments and the proper employment of these.

A novel approach to address the disadvantages described above can be developed on the basis of machine learning (ML) strategies. ML with its methods and algorithms has already been known for decades. In addition, the steadily increasing computer performance in recent years and the availability of more data have led to ML strategies becoming increasingly important in production. Likewise, new variants and adapted methods of ML are also being developed in the field of materials science. Artificial neural networks (ANN), which are in theory universally applicable and adaptable to approximate ("learn") any function buried in data, represent a major tool of ML [15, 16]. Feedforward neural networks (FFNN) represent a useful variant for regression analysis [17, 18]. In general, the signal traverses the network in a unidirectional manner, gradually converting the input signal into an output signal ("feedforward") [16]. Hereafter, examples of this method will be shown how such FFNN have already found application in materials science.

For example, Gorji et al. showed that using three hidden layer FFNN with 15 neurons per layer could accurately reproduce strain-rate and temperature-dependent yield curves \( (\sigma=f(e, e', T)) \) which were analytically generated using the Zerilli-Armstrong yield curve model. Furthermore, using various classical strain paths observed in Nakajima forming limit tests, an FFNN was trained for inputs \( \{d\varepsilon_{11}, d\varepsilon_{22}, d\varepsilon_{12}, e_{11}, e_{22}, e_{12}\} \) and outputs \( \{\sigma_{11}, \sigma_{22}, \sigma_{12}\} \). In this regard, the inputs and outputs were generated by virtual experiments of monotonic loading for a von-Mises plasticity model. In this way, the force-displacement curves of tensile tests could be reproduced using an FFNN with a prediction accuracy of 93% [19]. Koch et al. demonstrated the possible use of simple FFNN for the estimation of yield curve parameters from the force-displacement curve of a tensile test. For this purpose, the training database was created using FEM simulations of tensile tests modelled with only eight elements. All parameters of the Hockett-Sherby yield curve were varied between the symbolic range of values from 0.1 to 1 with 12 support values for each parameter. As a result, the input force-displacement curves and the force-displacement curves obtained by the predicted yield curve parameters were compared [20].
As another application of FFNN, a machine learning workflow for predicting forming limit curves based on chemical composition and rolling process parameters of sheet metals is presented in [21]. In this work, an ANN was developed that can predict the failure of a drawing test with a cross-cup geometry 5-10% before the maximum achievable drawing depth [21]. In [22], an ML model for modeling the complicated path-dependent plasticity behavior with a recurrent ANN is presented. Deliberately designed heterogeneous representative volume elements (RVE), were simulated under periodic boundary conditions by implicit static FEM. Both random and complicated deformation paths were generated. A sequence of strains, homogenized stresses and plastic energy served as the database for training of the recurrent ANN, which has a modified gated recurrent unit (GRU) architecture. The training database was built with 15,000 different deformation paths, each represented by 100 points (per deformation path). The promising predictive capability of the proposed ML model was additionally demonstrated by validation calculations. However, it should be noted that the effort to replace phenomenological material models with ML requires large amounts of datasets, which nowadays can only be generated numerically. The challenge in obtaining realistic phenomenological material models is that complicated deformation paths and local stresses are very difficult or almost impossible to capture accurately in reality. For example, accurate values for local stresses can be calculated using global forces only in case of uniformity of stress distribution. In reality, stress distributions are usually not uniform for experiments to generate comprehensive datasets with combined loadings, therefore local stresses cannot be calculated accurately from experiments. In contrast, uniformly distributed stresses can be calculated with sufficient accuracy using the measurable forces from experiments, but these deformation paths are very limited and do not provide a sufficient database for generalizing the ML model. Before taking such a pioneering but difficult step in substituting ML models for phenomenological material models, this paper aims to use ML models to assist in the determination of material parameters. Hence, a new approach is shown how ANN can accelerate the measurement, calibration and validation processes for finding the material parameters of phenomenological material models.

2. Modelling and design of the ANN

This study will demonstrate that ANN can be used to approximate the relationship between the strain distributions in a tensile specimen and the yield locus parameters for sheet materials of a selected material model. In order to keep the computation time and the amount of data for a desktop PC within manageable limits, the Barlat-3 parameter model was used here to define the anisotropic material behavior [23]. In combination with the exponent of the yield criterion $m$, the Barlat-3 parameter model requires a total of four parameters including the three anisotropy values ($r_0$, $r_{45}$, $r_{90}$). The value range of the material parameters was defined in such a way that the calculation effort is manageable and the generated data set contains sufficient information for the feasibility study of the approach presented here. Table 1 shows the defined value ranges of these material parameters.

| Material parameters | Unit | Value range       |
|---------------------|------|-------------------|
| Exponent of yield curve $m$ (Barlat 3-Parameter) | [-] | 4, 6, 8          |
| Anisotropy Parameter ($r_0$, $r_{45}$, $r_{90}$) | [-] | 0.7; 0.8; 0.9; 1.0; 1.1; 1.2; 1.3 |

The values in Table 1 were combined full factorially for the anisotropic Barlat 3-parameter material model, resulting in a total of 1029 different variants of material behaviour. Both the input (material parameters) and output (strain values) of the FEM simulation were stored in a database to be used for subsequent training of the ANN. For details of the finite element model chosen, see [8]. It is noted that all FEM simulations in this study were calculated using the Swift-Krupkowski yield curve $\sigma = 200 (0.01 + \varepsilon)^{0.2} \text{MPa}$ [24]. The specimens were stretched by 3 mm, giving a maximum value of...
about 0.1 for the equivalent plastic strain. As shown in Figure 2a), three tensile specimens were modelled at 0°, 45° and 90° to the rolling direction (RD). Due to the orthogonal symmetry of the material behaviour, only a quarter of the tensile specimen was modelled. The strain values of the elements located in the yellow area of the tensile specimen (see Fig. 2b)) were extracted. This element area of the tensile specimen is stretched the most. In each case, 18 elements per tensile specimen were considered. The elements at the edge were excluded from the dataset, as optical measuring instruments cannot record this area accurately. For each of the elements, the longitudinal strains (y) and transverse strains (x) were exported for 10-time steps. A total of 1080 strain values were thus obtained per FEM simulation. As an example, Fig. 2c) shows the numerically determined x and y strains of all-time steps in a diagram. It is observed that due to the anisotropy of the material, there is a different development of the strain values over time. The same can be observed for the elements considered within a tensile specimen, which is due to the position of the respective element.

![Figure 2](image)

**Figure 2.** a) Modelled tensile specimens with three different rolling directions (RD), b) considered elements of the respective tensile specimen, c) Example: strain distribution of the numerical calculations.

An FFNN with two hidden layers was used for the ML model in this study. The first layer of the FFNN has 20 neurons and the second has 7 neurons (see Figure 3a)). The input for this FFNN are the calculated 1080 strain values and the output vector is defined as the material parameters \(r_0\), \(r_{45}\), \(r_{90}\) and \(m\) in the given order. In the first half, the input vector maps the values of the x-strains and in the second half the values of the y-strains. Each third of these halves refers to a specimen with 18 elements. For each element, 10 consecutive strain values from 10 time steps are taken. These are followed by the 10 strain values of the next element, taken from the same 10 time steps (see Figure 3b)). This order was chosen because of the available data export routines. The order of the input values can be changed before training the ANN without adversely affecting the results. However, this is no longer possible after training. The two hidden layers of the FFNN are fully connected. The Rectified Linear Unit activation function (RELU activation function) \(f(x) = \max(0, x)\) was used for both the neurons in the hidden layers and the output layer. All strain values were entered as absolute values for the training in order to solve the problem of vanishing gradients for negative input values of the RELU activation function. Thus, only the signs of the transverse strains (x-strain) change, which are always negative, as shown in Fig. 2c). Since the ANN performs a multivariate-regression analysis for four output parameters, the output value of the exponent of the yield criterion \(m\) is normalized by dividing it by 10. As a result, a similar magnitude is achieved among all output values, increasing the prediction accuracy of the material parameters.
3. Results and discussion training phase of the ANN

The objective of this study is to demonstrate that the regression capability of an ANN can be used to obtain calibrated and validated parameters for anisotropic material models. As previously described, an ANN was first trained with numerically calculated strain distributions from tensile tests and the associated material parameters. In this way, the ANN is now able to determine the material parameters of the respective material in fractions of a second on the basis of experimentally determined strain distributions from tensile tests. These experimental strain distributions can be extracted automatically using mapping algorithms that have been available on the market for over 15 years. The introduced workflow above demonstrates how inverse parameter identification or validation procedures can be replaced by such a use of ANN, rather than replacing the phenomenological material model with data-based ANN models. For the training of the ANN, only 70% of the total amount of data was initially used for the training cycles. The trained ANN was tested with another 15% of the total data set. The remaining 15% were used as a validation data set to validate the performance of the training algorithm during the training cycles. The errors calculated during the training cycles were used to incrementally improve the previously randomly initialized weights of the ANN using the Levenberg-Marquardt optimization algorithm. The mean squared error was used here as a convergence criterion. In total, 200 epochs were performed to obtain convergence with a mean square error of $10^{-5}$. In this case, one epoch corresponds to training an ANN once with the entire data set. In Figure 4a) the prediction accuracy of the trained ANN for the different datasets (total, training, test, validation) is shown. The regression quality of the training and test datasets is $R = 0.9999$. When considering the prediction accuracy of the validation dataset, a very accurate regression quality result of $R = 0.99989$ is also obtained. In this context, it should be noted that the validation and test datasets consist entirely of interpolation values that were not used during training. Thus, the prediction accuracy for these datasets is a meaningful evidence of the high regression quality (for interpolating values) of the trained ANN.

Figure 3. a) ANN architecture, b) Sequence of values in a strain vector.

Figure 4. a) Prediction quality of the ANN for different datasets, b) Error histogram.
The maximum possible error that can occur in the prediction of any material parameter from the entire determined data set (training, test or validation) is estimated to be 0.015, as shown in the error histogram in Figure 4b). This is equivalent to a maximum error of 0.015 for the anisotropy values \((r_0, r_{45}, r_{90})\) and the normalized exponent of the yield criterion \(m\). Due to the normalization, the estimation of the maximum possible error of the exponent must be multiplied by 10 and is therefore 0.15. As is evident from this figure, about 90% of the prediction errors are below the value 0.004. Although the prediction accuracy for the validation data set has thus given a sufficient indication of the regression quality, the ANN was additionally checked by further parameter combination. For this purpose, the material parameters \(\{m=5.0 \quad r_0=1.05 \quad r_{45}=0.85 \quad r_{90}=0.95\}\) were selected, which represent interpolated values. Using these material parameters, a FEM simulation was performed to generate the strain distributions of the virtual experiment. As a result, using these strain distributions, the output values \(\{m=5.0480 \quad r_0=1.0536 \quad r_{45}=0.8583 \quad r_{90}=0.9507\}\) were computed. This gives a maximum error of 1% for all predicted material parameters.

The results presented here show that it is possible to determine directly validated material parameters for simple yield locus definitions by means of the ML approach introduced here, however, the same number of tensile tests as for the classical approach are still required for such a model. To demonstrate the potential of the presented ML approach, it was therefore additionally trained with a smaller number of experiments. In a first step, only the strain distributions of tensile specimens with only two rolling directions (0° and 90°) were considered. In the next step, only the strain distributions of tensile specimens with one rolling direction at 45° were examined. The tensile specimen variants with only one rolling direction at 0° or 90° were not considered. It was shown in [8] that these variants give worse results with respect to the material parameters for the corresponding transverse directions compared to the above-mentioned variants. The structure of the input data was kept as described above. Keeping the remaining architecture of the ANN, the input vector for two tensile specimens (0° & 90° RD) consists of only 720 and for one tensile specimen (45° RD) of only 360 strain values.

The variant with two tensile specimens (0° & 90° RD): The results of the training phase with two rolling direction tensile specimens are shown in Table 2, which were determined using 400 epochs. The regression quality for all data sets resulted in a value of \(R=0.99966\). Overall, a very high regression quality is also achieved for each of the training, test and validation data sets. Consequently, this ANN also has a very good prediction accuracy with respect to the material parameters to be determined. The maximum error of the anisotropy values \((r_0, r_{45}, r_{90})\) of the error histogram is only 0.03, while about 90% of the errors are below 0.02. The normalized exponent of the yield criterion \(m\) is predicted with a maximum error of about 0.02. In comparison with the original three-sample variant, the prediction error is slightly higher, but the lower experimental effort could make material characterization using the two-sample variant more efficient in the future.

| Table 2. Results of the training phase for the two- (0° & 90° RD) and one- (45° WR) tensile specimen. |
|---------------------------------------------------------------|
| Results of the training phase | 0° & 90° RD | 45° RD |
| Regression quality of all datasets | 0,99966 | 0,99819 |
| Regression quality of the training dataset | 0,99981 | 0,99889 |
| Regression quality of the test dataset | 0,99926 | 0,99629 |
| Regression quality of the validation dataset | 0,99942 | 0,99681 |
| Maximum error anisotropy values \((r_0, r_{45}, r_{90})\) | 0,03 | 0,06 |
| Maximum error exponent of yield curve criterion \(m\) (Barlat 3-Parameter) | 0,2 | 0,2 |
The variant with single tensile specimen (45° RD): Even when training with the data from only one tensile sample (45° RD), a high regression quality of $R= 0.99819$ is achieved for all data points (see Table 2). The maximum error of the anisotropy values ($r_{0}, r_{45}, r_{90}$) of the error histogram is about 0.06. Again, the maximum error of the normalized exponent of the yield curve criterion is $m= 0.02$. Since the exponent was normalized before, the actual maximum error is 0.2. Considering this error, validated material parameters can thus be determined from experimental strain distributions even by means of an ANN trained with the data set of only one tensile specimen (45° RD).

4. Conclusion

In the present paper, a new approach for determining phenomenological material parameters of sheet materials using an ANN for a simple yield locus description was presented. The aim of this study was to prove the proposed concept using a simple yield locus definition, namely Barlat 3-Parameter yield locus, which models the anisotropy using only three r-values and the yield locus exponent. It was shown that the mapping function between strain distributions and material parameters can be approximated relatively well by an ANN. This leads to the fact that the phenomenological material parameters can be determined with an excellent prediction accuracy. For this purpose, the value range of the data set of the considered material class must be sufficiently wide. In the subsequent training phase, the ANN is trained and its prediction accuracy is determined. As soon as the training phase of the ANN is completed, it can be used directly for the rapid calculation of the material parameters of the considered material. Thus, in the future, the presented approach could also be used to determine parameters of more complex yield locus descriptions by means of an ANN. The simultaneous determination of yield curve parameters is also probable.

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