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Determining the residual formability of shear-cut sheet metal edges by utilizing an ML based prediction model

GÖRZ Marcel[1,a *], SCHENEK Adrian[1], VO Trong Quan[1], RIEDMÜLLER Kim Rouven[1] and LIEWALD Mathias[1]

[1]Institute for Metal Forming Technology, University of Stuttgart, Holzgartenstr. 17, 70174 Stuttgart, Germany

[a]marcel.goerz@ifu.uni-stuttgart.de

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Abstract. When forming high-strength steel sheet material, premature failure can occur at shear-cut component edges because formability of the base material is reduced due to work hardening caused by the previous punching process. Here, the digitization of production processes provides new possibilities for quality monitoring of such forming and stamping processes. In this context, the present paper deals with a novel machine learning (ML) based method for determining the residual formability of sheet metal materials from measured punching force curves. The specific objective of the study carried out was to develop an efficient and accurate method for predicting the residual formability of shear-cut edges. The methodology proposed for this purpose involves collecting a comprehensive dataset comprising experimental measurements of material properties, cutting conditions and punching-force curves measured during blanking. To determine the residual formability of the sheet metal materials investigated, hole tensile tests were performed and the maximum major and minor principal strain at initiation of cracking were measured. This dataset was then used to train and validate different AI prediction models, which employ machine learning algorithms to establish complex relationships between input parameters and residual formability.

Introduction and State of the Art

Shearing is generally one of the most economically important manufacturing processes in sheet metal working industry [1]. During its production process, almost every sheet metal component is cut as a blank from a semi-finished product, trimmed or perforated prior to forming [2]. In addition to constantly increasing demands on the quality of formed sheet metal components, the component edges produced during shear cutting therefore also have to meet ever higher quality requirements. These quality requirements for cut edges and surfaces are characterised by a small edge radius, a high proportion of smooth cuts, freedom from burrs, low fracture surface heights and tight manufacturing tolerances [3]. Furthermore, the quality criterion of the residual formability of shear-cut edges of sheet metal components is becoming increasingly important, especially with regard to modern lightweight materials such as high-strength aluminium grades [4] or dual-phase steel sheets [5]. The residual formability of sheared sheet metal component edges is reduced due to the high plastic deformations and strain hardening within the shear affected zone (edge effect). Low residual formability can lead to edge cracks during the subsequent forming of cut and punched sheet metal components, emanating from the edge of the component or from the cut-outs. The formation of edge cracks on shear cut component edges crucially depends on the selected cutting parameters and the wear condition of the cutting elements used [6].

The only standardised method for determining the susceptibility to edge cracking is the hole expansion test described in DIN 16630 [7]. This two-stage process consists of a hole punching operation followed by a forming operation to expand the punched hole. The hole expansion ratio achieved up to crack formation provides a value for assessing the edge crack sensitivity of a sheet metal material. The crack initiation during these tests is usually detected using a camera system.

However, due to the wide range of parameters (punch diameter and radius on the drawing die) allowed by the standard, it is often difficult to compare different tests with each other. Other methods for determining edge crack sensitivity include the Diabolo Test developed at the IFU Stuttgart, which can only be used for open cut edges, and the Edge-Fracture-Tensile-Test (EFTT) method, which allows for analysis of both open and closed cut edges [8]. Watanabe developed the Open Hole Tensile Test (OHTT) method [9], which was adapted from the field of composite materials to metallic materials. In this method, a hole is punched in a rectangular specimen with a closed cutting line and subsequently subjected to uniaxial tensile loading. The tests thereby are analysed using a DIC capable camera system. However, a major disadvantage of the testing methods mentioned in this section is that none of them can be directly integrated into production processes for inline monitoring.

Based on the guidelines of Industry 4.0, meanwhile also the value chain in the stamping sector has been digitized, e.g. by integrating sensors into the stamping tools to collect large amounts of process data. Combined with analysis using machine learning (ML) methods, this enabled the development of new systems for monitoring stamping and forming processes. As a result, parameters that previously had to be determined in time-consuming procedures can now be measured inline during the process using ML methods. For example, the wear condition of a punch can be characterized by evaluating cutting force-displacement curves [10, 11]. Molitor was also able to predict the wear state of the punch from images of the stamped parts using convolutional neural networks [12]. Schenek et al. showed that the regression capability of artificial neural networks (ANN) enables material properties to be determined from cutting force-displacement curves [13]. In another study, the same authors showed that ANN can also be used to determine cutting surface quality parameters (edge draw-in height, clean cut height, fracture surface height, and burr height) from punching force curves measured during the stamping process [14].

The current state of the art shows that a number of properties that could previously only be measured offline can now be determined inline by using measuring systems based on ML models. In this context, a novel ML based method for determining edge crack sensitivity will be presented in this paper. Investigations will be described, which were performed to examine whether an ML model can be used to predict the maximum achievable major and minor principal strain at the onset of fracture based on cutting force displacement curves measured inline during punching. In these investigations, training data was determined experimentally in a first step. Here, cutting tests were carried out to determine the punching force and OHTT were performed to determine the major and minor principal strains. This data set subsequently was used to train and compare ML models with increasing complexity. The models considered here were linear regression (LR), support vector machine regression (SVM), random forest (RF) and artificial neural network (ANN).

Experimental Setup

A data set consisting of input and output data is required to create an ML model. The following section describes how this data set was determined experimentally. Punching force curves recorded during a stamping process were used as input data for training the ML models. The experimental investigations for recording the punching force curves were carried out using a modular test tool. Figure 1 shows a 3D rendering and cross-section of the tool used. The tool was equipped with a load cell for direct force measurement (Kistler 9104a) and an additional displacement measurement system (TR 8710-100). The measurement was performed with measuring frequency of 10 kHz, ensuring a high resolution of the measured punching force curves. During the experimental investigations, the punch was firmly clamped in the shank area of the punch over a length of 22 mm. The shank diameter of the punch was 13 mm in all tests performed in this study, in accordance with the ISO8020 standard. The initial cutting edge radius of the punch was approx. 50 µm and was determined using an optical microscope. The parameters used in the tests are shown in Table 1. The 90 punching force curves measured during the tests are shown in Figure 1 (a). The output data for training the ML models were recorded through open-hole tensile tests. The tests carried out according to the method proposed by Watanabe [9]. Described tests were performed on a Roell + Korthaus RKM 100 material testing machine. The ARAMIS 12M digital image correlation system was used to measure the specimen strains. Figure 1 (b) shows two exemplary images of the Aramis 12M system taken out of the test series. Here, the left image shows the distribution of the major principal strain at the start of the test and the right image shows the major principal strain at the initiation of the crack. The maximum tolerable major and minor strain up to failure is determined at a distance of 1 mm from the edge of the introduced hole. Figure 1 (c) shows an overview of the results of all OHTTs performed.

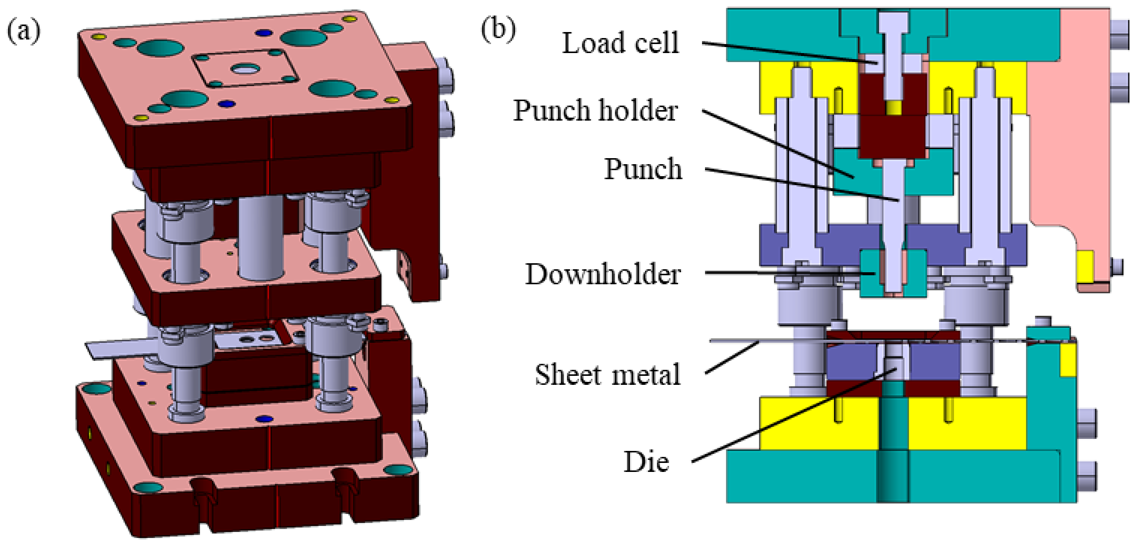

Fig. 1. 3D rendering of the modular test tool (a); sectional view of the modular test tool.

Table 1. Punching parameters investigated in the present study.

Parameter	Value
Length of punch	80 mm
Cutting clearance	10%, 15%
Sheet Thickness	1 mm
Punch diameter	10 mm
Material	DP600, DP1000, DC03

Feature Engineering, Model Design and Training

The data-specific investigations described in this paper were carried out using the Python programming language. The deep learning library TensorFlow (TF) was used to correlate features with the major and minor principal strain at crack initiation. TF was developed by researchers at Google specialising in artificial intelligence. Other Python libraries used in the research presented were Numpy for data preparation, Matplotlib for plotting, Pandas for reading data from measurement logs and Scikit-learn for performing the hyperparameter tuning, standardization and the training of the RF, SVM and LR Model.

In the first step of the data processing, the punching force curves recorded in the experiments were processed with a proprietary script and the shearing process itself was extracted from the time series data (Figure 1a). In addition to reducing the amount of data to be processed, this extraction also improved the prediction quality of the models, as only the relevant physical regions of the recorded measurement signal were taken into account. Previous studies have shown that the prediction quality of an AI model is strongly dependent on the quality and preparation of the training data. The process of systematic preparation of the training data is also referred to as feature

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engineering od feature extraction. Feature engineering is based on domain-specific expert knowledge and feature extraction on algorithms for the statistical analysis of the data. For the research presented in this contribution, only feature extraction based on Principal component analysis (PCA) was used.

PCA was applied to the resulting data set, as it provides a method to summarise the training data and extract features that represent the individual differences in the process. PCA was thus used to identify a reduced data set based on components that still represent the original training data in a lower dimensional subspace, but with minimal loss of information [15]. Here, it was ensured that the calculated components described 95% of the variance of the original data set, which could be accomplished with ten components. This data set, reduced to 10 components, was used for the following model training. To train the ML model, the data set was divided as follows: 80% of the total punch force curves and the associated parameters from the hole tensile tests were used as the training data set. The remaining 20% of the total data set were further split in a validation (10%) and a test data set (10%).

In order to determine optimal hyperparameters for the models the validation data set was used The ANN was tuned with the "Hyperband" tuner integrated into Keras. The aim of the optimization was to minimize the validation loss of the model. Table 2 shows an overview of the parameters varied and the range of parameters varied during the hyperparameter tuning of the ANN and the results of the tuning process. The SVM was tuned by varying the kernel functions. The model with the best R2 Score was choosen. Table 3 shows an overview of the varied kernel functions and the results of the tuning process. The RF model was optimized by using the “GridSearchCV” function of Scikit-learn. The aim of the optimization was to minimize the validation loss of the model during the tuning process. The parameters varied and the range of parameters varied during the hyperparameter tuning of the RF are shown in

Table 2. Hyperparameter tuning ANN.

Parameter	Parameter range	Results of tuning
Number of Hidden Layers	3 to 6	6
Neurons per Hidden Layer	32 to 512 (steps of 32)	320, 286, 192, 416, 32, 32
Activation function	Sigmoid, ReLU	ReLU

Table 3. Hyperparameter tuning SVM.

Parameter	Parameter range	Results of tuning
Kernel	sigmoid, rbf, poly, linear	sigmoid

Table 4. Hyperparameter tuning RF.

Parameter	Parameter range	Results of tuning
Number of Tress	10,50,100	50
Depth of the Tree	10,50,100	10
Number of samples at leaf node	1,2,4	2
Samples to split an internal node	2,5,10	2

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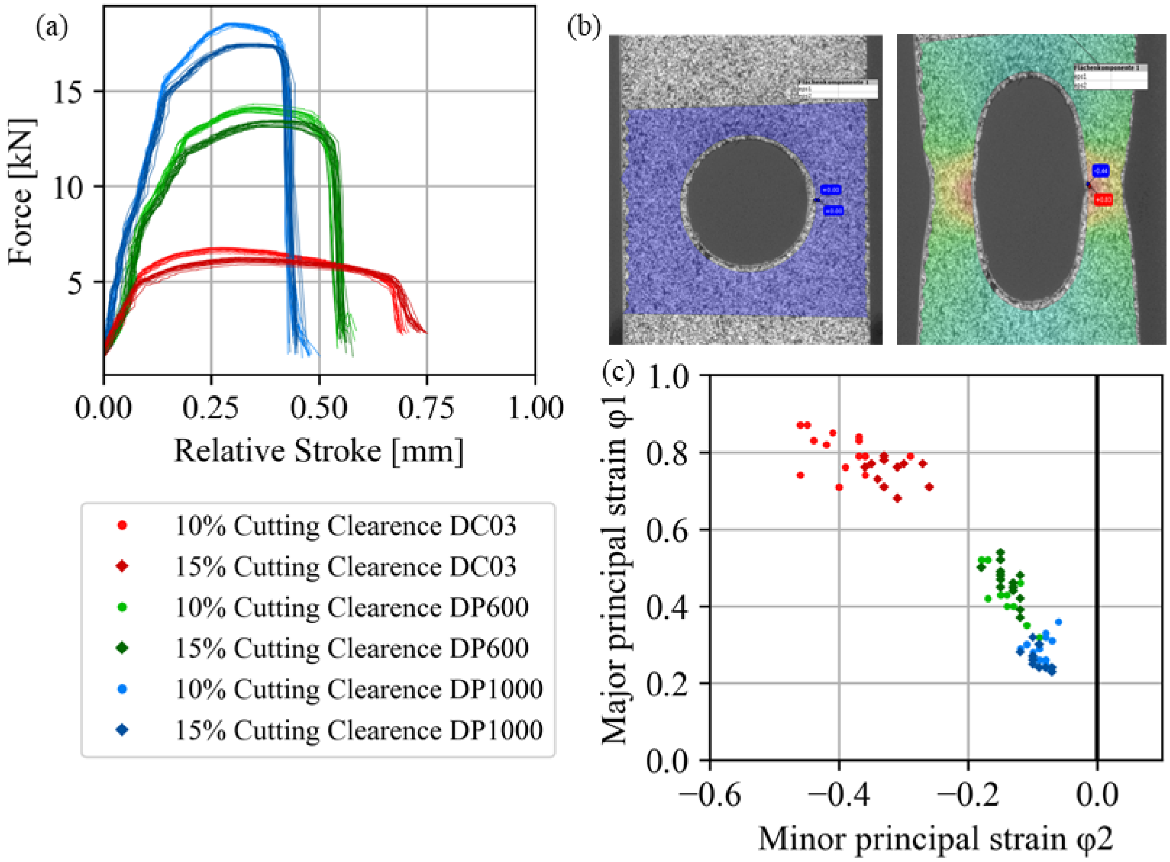

Fig. 2. Experimentally determined punching force curves (a), Strain distribution at the beginning and during crack initiation in an OHTT (DC03, cutting clearance: 10%)(b), Results of the OHTT(c).

Results and Discussion

Figure 2 shows a comparison of the model training results for the different ML models examined. The bar plot shows the mean squared error (MSE), mean squared error (MAE) and the R2-Score for all models. These results were determined for the training data set Figure 2 (left) and the test data set not used for training or hyperparameter tuning Figure 2 (right). Due to the small difference in model error between the training and test datasets, overfitting and underfitting of the generated models is not observed. Because Support Vector Machine models can only predict one parameter due to their particular characteristics, two separate models were trained for each model type for major and minor principal strain at crack initiation. In order to achieve better comparability, the results for the ANN were also presented separately for major and minor principal strain. The comparison of the results shows that all trained models achieve a high Pearson correlation coefficient (>0.8), demonstrating the models' fundamental industrial applicability [16]. The comparison of prediction quality shows that the RF model has the highest regression quality and the lowest MAE for both predicted variables. The LR model has the second best prediction quality. The SVM model and the ANN are comparable in their performance. Both models show a significant difference in regression quality when comparing the predictions for major and minor principal strain. This shows that increasing model complexity does not improve the prediction results. At first this result seems surprising as the sheet metal forming process is characterized by strong non-linearities. It is expected that the ANN performs best and LR worst due to the higher model complexity. We assume that this might be due to two factors. The use of PCA leads to a type of linearization that simplifies the problem and may have a positive effect on the less complex model. Furthermore, the data set used is relatively small and contains just 90 force curves. This means that the optimum result may not be achieved during hyperparameter tuning or subsequent training. In conclusion, the objective of the study was achieved. By using an RF model, it is possible to determine the maximum principal and minor strains at crack initiation from cutting force curves measured during punching operations.

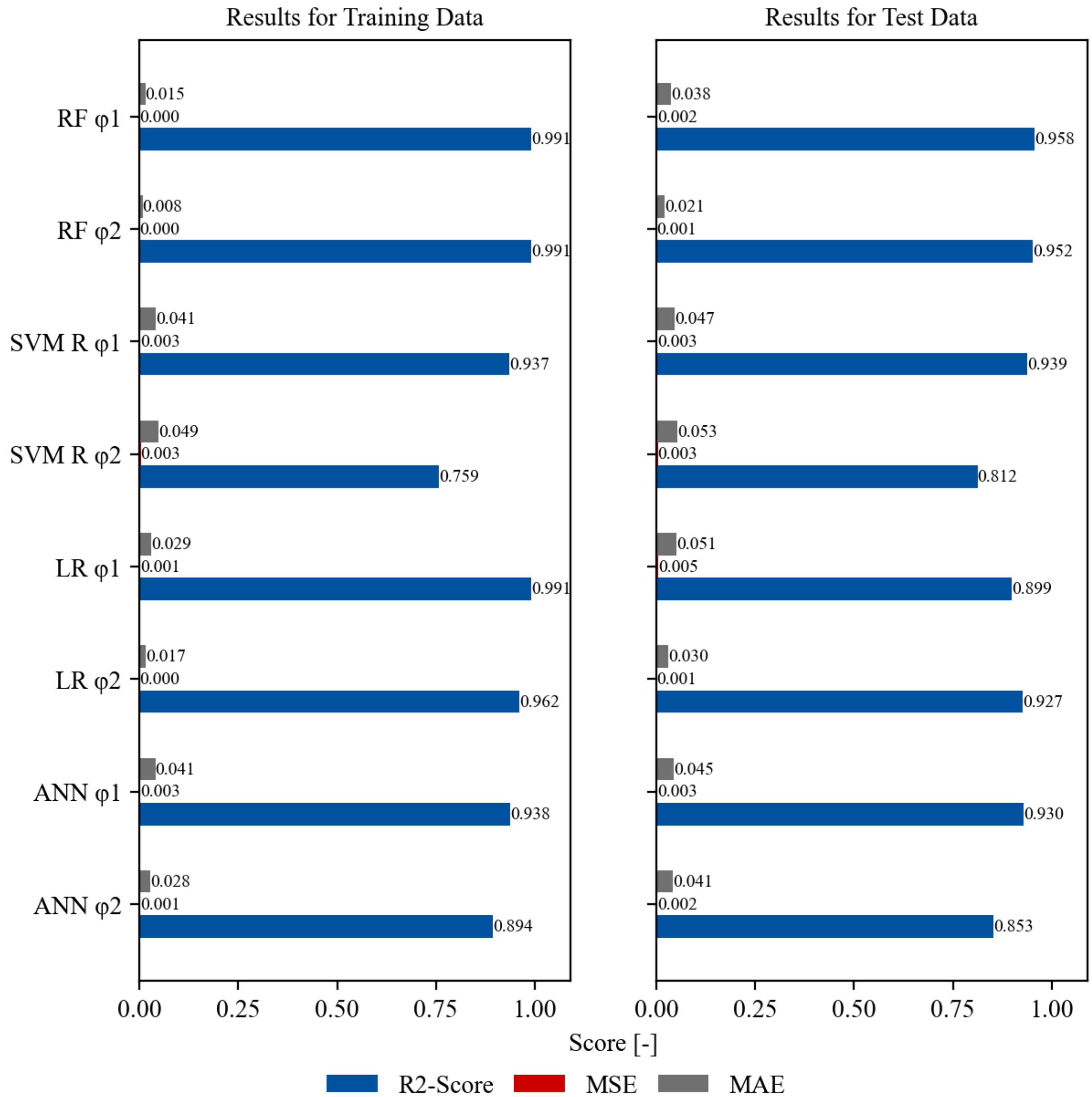

Fig. 3. Comparison of the prediction quality of the different models for the major and minor principal strain at crack initiation for the training data set (left) and the test data se (right).

Summary and Outlook

During the processing of high strength steel and aluminium sheet metal materials, premature failure can occur at the shear cut edges of components. This is due to the reduced formability induced by the punching process, particularly when compared to the inherent formability of the base material. Conventional testing methods are unable to measure the resulting residual formability inline during the blanking or punching process. In this contribution a novel method for characterising the maximum tolerable major and minor strain in combined shearing and forming processes based on ML was presented. As part of the investigations, it was shown that the regression capability of an Random Forrest model is able to predict the maximum residual formability after punching on the basis of inline measured cutting force-displacement curves.

To advance the research presented in this publication, further investigations will be undertaken at IFU by transferring the results to other material classes such as copper or aluminum. Additionally, the influence of batch-related fluctuations in the semi-finished product properties will also be investigated. Future research will also investigate transfer learning methods to reduce the amount of data required for model training. Furthermore, the influence of wear of the tool parts on the prediction quality of the models will be investigated through endurance tests.

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