# Shear cutting: Model-based prediction of material parameters based on synthetic process force signals

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**Abstract.** Data-driven process monitoring is an approach in the field of forming technology for increasing process efficiency. In shear cutting processes surrogate models based on process force signals can be used for process monitoring. Currently, the data basis for developing such models has to be generated within experiments. The generation of synthetic training data using numerical methods seems to be a more efficient alternative approach. In this work, it is investigated whether virtual training data for the prediction of material properties can be generated by numerical methods. An FE model of the investigated shear cutting process has been designed and validated based on experiments. It is shown that especially the consideration of the tool stiffness has a significant influence on the simulated process force signal. The validated FE model is used to generate synthetic training data. Based on this data, different prediction models are trained to predict the material model parameters based on the force signals. Different model types are compared and the hyperparameters are optimized for the preferred model.

## Introduction

In the field of forming-based production of sheet metal components, increasing component complexity and the use of novel materials are leading to narrow process windows [1]. On the one hand, this requires a highly accurate process design and, on the other hand, leads to reduced process robustness due to transient scattering of process inputs and conditions. The sources of scatter can be divided into the categories of material variability, tooling variability, process variability, lubrication and random variabilities like incorrect positioning of the sheet [2]. One of the most essential category on process robustness are fluctuating material properties [3]. Process robustness can be increased by restricting the material and process specification. However, this results in significantly increased production costs. Another approach to increase process robustness is model-based process monitoring and model-based adaptive process control using process-data based digital twins [4]. Acquiring the material properties of the semi-finished product being processed is an essential prerequisite for implementing these digital twins. Ideally, this should be done directly in the process (inline). Currently, the use of eddy current sensors is an established inline-capable method. This method is based on the correlation between local electromagnetic properties and the mechanical properties of the sheet metal [5]. One disadvantage of this method is the high calibration and hardware integration effort. An alternative method, investigated by

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Scheneck and others, involves predicting the mechanical properties of semi-finished sheet metal products by analyzing the cutting force curves during shear cutting [6]. This method has the advantage that shearing operations are carried out on almost any sheet metal component. The approach's in-line capability is guaranteed, and only the appropriate measurement technology needs to be integrated. Surrogate models are used to derive the mechanical parameters from the recorded force-displacement curves. In Scheneck's study, an artificial neural network (ANN) was used to predict several mechanical properties, including tensile strength ($R_m$), yield strengths ($R_{p0.2}$), elongations at break ($A_t$) and strain hardening exponent (n) of different sheet materials. The results showed a high level of agreement between the predicted values from the cutting force curves and the actual measurements obtained from the tensile test. However, generating training data with sufficient quantity and high variance remains a significant challenge in this approach. The overall objective is to investigate to what extent prediction models can be generated on the basis of virtual training data to predict the material parameters by analyzing the cutting force curve. To achieve this, three different material batches of micro-alloyed fine-grained structural steel S500MC (1.0984) were used to determine experimentally both the cutting force curves for the punching operation as well as the mechanical material properties in conventional tensile test. An FE model was established for the punching operation and calibrated using experimental data from one of the material batches. The training database is developed by running simulations with varied material model parameters. Prediction models are then trained using this data to predict mechanical characteristics. At the end, various prediction models are trained and their performance is compared.

**Material Characterization and experimental investigations**

The tests were conducted using S500MC material with a nominal thickness of t = 3.2 mm. The material batches analyzed were obtained from an actual production line and are available in a strip width of b = 78 mm. Initially, conventional tensile tests were performed on the available material batches according to ISO 6892-1:2016. Figure 1 shows the resulting stress-strain diagrams. Test specimens were taken only in the rolling direction due to the dimensions of the available semi-finished products. Each batch of material was tested with four samples. Table 1 summarizes the mean values of the mechanical properties determined for each batch. Batches 1 and 3 show fundamentally similar behavior in the tensile test, but the samples from batch 3 experience has higher stress levels. Batch 2, on the other hand, shows significantly different deformation behavior and slight hardening.

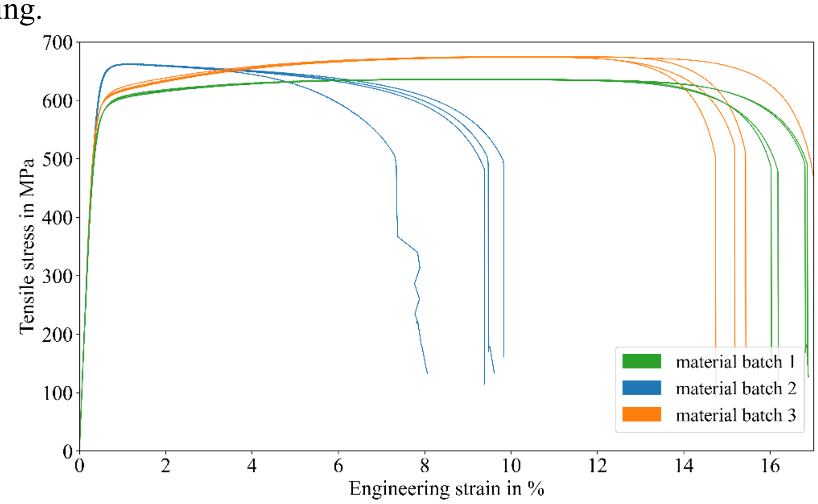


*Fig. 1: Stress-strain curves from tensile tests for the investigated material*

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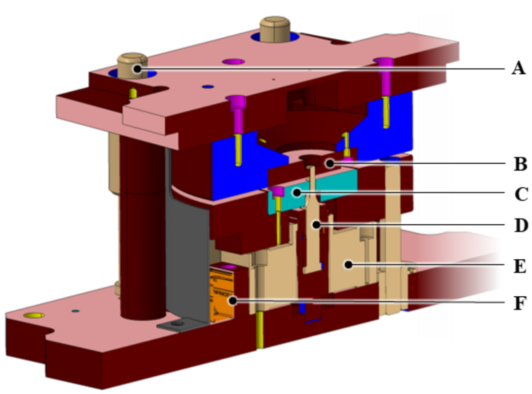
*Table 1: Material characteristics for the investigated material batches*

| Material Batch | t (mm) | E (GPa) | $R_{p0.2}$ (MPa) | $R_m$ (MPa) | $r_{2-20/Ag}$ | $A_t$ (%) |
|---|---|---|---|---|---|---|
| Batch 1 | 3.17 | 189 | 571 | 636 | 0.66 | 16.4 |
| Batch 2 | 3.22 | 180 | 640 | 662 | 0.67 | 9.1 |
| Batch 3 | 3.13 | 187 | 593 | 675 | 0.64 | 15.5 |

Shear cutting tests were conducted on the three material batches under consideration, and the resulting force-displacement curves were recorded. The tests were performed on a test press at the Fraunhofer IWU using a specialized measuring tool. The tool incorporates a load cell directly into the force flow of the cutting punch, while displacement is measured using a laser triangulation sensor. Figure 2 displays used the tool and the main process parameters. Figure 3 shows five force-displacement curves for each material batch. The graph shows the cutting force in relationship to the displacement of the punch relative to the specimen. It includes both the actual working stroke (positive forces) and the back stroke (negative forces). The curves recorded for the different batches exhibit significant differences. This indicates that the force-displacement curves are fundamentally suitable for detecting the different deformation behavior of the material batches.




| tool components | |
|---|---|
| A | tool guidance |
| B | die |
| C | blank holder plate |
| D | cylindrical punch |
| E | load cell MEGATRON KMC100K 200kN |
| F | laser triangulation sensor MICRO-EPSILON optoNCDT 1420 |

| experimental parameters | |
|---|---|
| punch diameter | 5.8 mm (material: HSS) |
| clearance | 0.125 mm |
| die velocity | 3.5 mm/s |
| blank holder force | 21 kN |

*Fig. 2: Section view of used cutting tool and main experimental parameters*

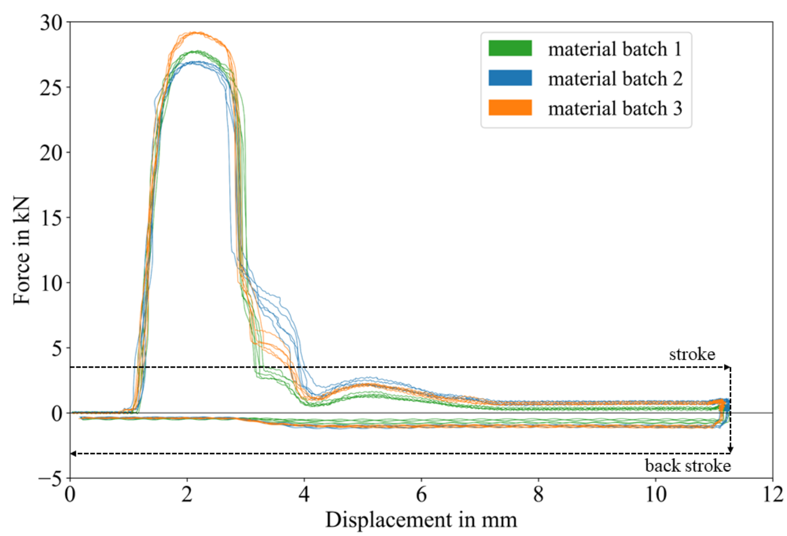



*Fig. 3: Experimentally obtained cutting force signals for the 3 investigated material batches*

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**FE-based Generation of Synthetic Training Data**

To generate synthetic training data, a 2D FE model was created (see Fig. 3) in LS-Dyna® using axial symmetry in 2D. The process parameters, blank holder force ($F_{BH}$), and die velocity ($v_y$), were selected according to the experiments. The isotropic material model MAT024 was used to model the deformation behavior of the investigated material. We approximated the flow curve using the Hockett-Sherby approach (refer to Eq. 1), where C1 indicates the start of flow and C2 the maximum yield stress. The expression $exp$ ($-C3 \cdot \varphi$^$C4$) describes the non-linear hardening behavior.

$$k_f = C2 - (C2 - C1) \cdot e^{-C3 \cdot \varphi^{C4}} \quad (1)$$

The yield curve parameters were determined based on the tensile test results for material batch 1 (see Table 3). The damage and failure behavior is modelled using the keyword ADD_DAMAGE_DIEM with the option DITYP = 1 where the damage is a function of the maximum shear stress.

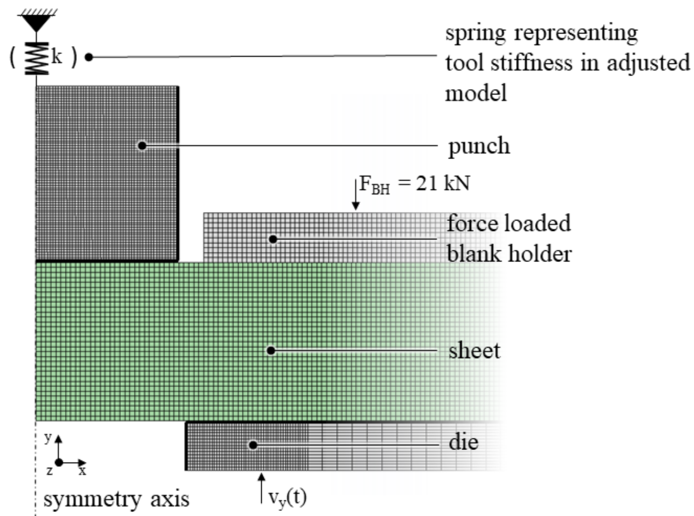


*Fig. 4: FE model for the generation of synthetic training data*

The initial set of parameters was used to simulate the cutting process, resulting in the cutting force curve shown in Fig. 5. A significant deviation from the experimentally determined curve was observed, particularly in the area of elastic deformation ($P_1$ to $P_2$ (FEM 1)). This deviation was caused by the tool element being modeled as a rigid body. To address this, a spring element with the stiffness k was introduced into the model to represent the tool stiffness. The spring constant k was determined to k = 60 kN/mm through inverse identification. The resulting cutting force curve shows a much better match in the range from $P_1$ to $P_2$ (FEM 2). However, there is still a deviation between the experiment and simulation in the range from $P_2$ (FEM 2) to $P_3$ (FEM 2). When the yield point ($P_2$ (FEM 2)) is reached, the sheet material begins to flow. Due to the progressive deformation and the associated work hardening of the sheet metal material, the cutting force continues to increase. To achieve better fit in this range, the flow curve parameters C1 and C4 were adjusted inversely using the experimental cutting force curve. The FEM3 simulation model and the experiment show good agreement. Table 2 displays the adjusted flow curve parameters.

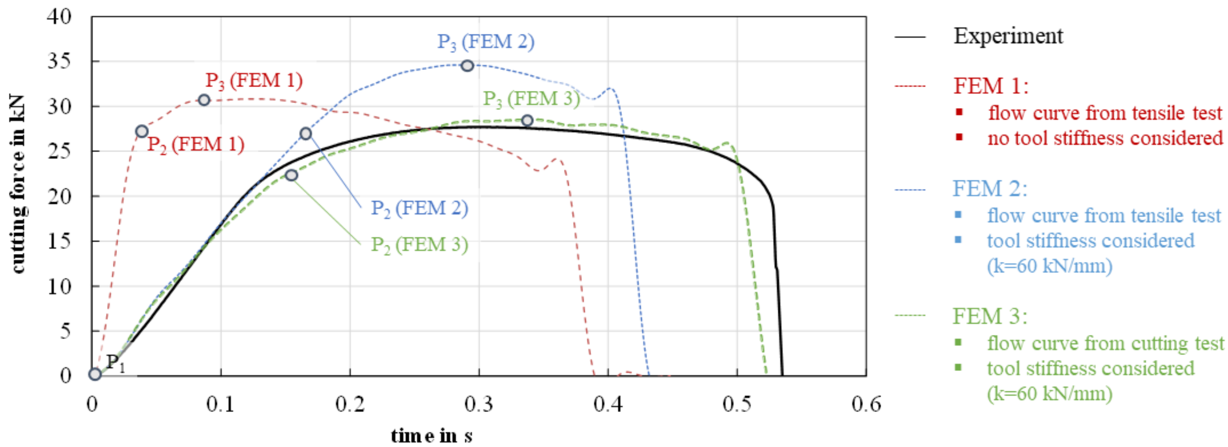


*Fig. 5: Comparison of experimental and simulated cutting force*

The simulation model FEM3 was used to generate the synthetic training data for the surrogate modelling. The varied parameters and the variation limits are summarized in Table 2.

*Table 2: Identified model parameters and variation limits for generating the synthetic training data*

| Parameter | flow curve approximation based on | | Range for synthetic training data | |
|---|---|---|---|---|
| | tensile test | cutting force | lower bound | upper bound |
| C1 in MPa | 575.3 | 431 | 400 | 460 |
| C2 in MPa | 756.5 | 756.5 | 700 | 800 |
| C3 [-] | 3.5376 | 3.5376 | 2,5 | 4,5 |
| C4 [-] | 0.5369 | 1.0738 | 0,53 | 1,2 |

**Surrogate machine-learning models based on synthetic training data**

The 163 synthetically generated force-displacement curves were then used to derive mechanical properties. We approached this in a two-fold approach. Firstly, characteristic quantities were extracted from each force displacement curve. We limit ourselves to the elastic gradient, maximum force, work and length of the punch phase [3]. Prior to extracting these quantities, we smoothed the force-displacement curves using the Savitzky-Golay-filter [7] to reduce the severe oscillations. The correlations between all input and extracted parameters can be seen in Fig. 6. Subsequently, we used these characteristic quantities as input for three different machine-learning algorithms: the decision tree based random forest (RF) [8] and XGBoost (XGB) [9] as well as a polynomial regression (PR) [8]. All models were trained using the scikit-learn package [10].

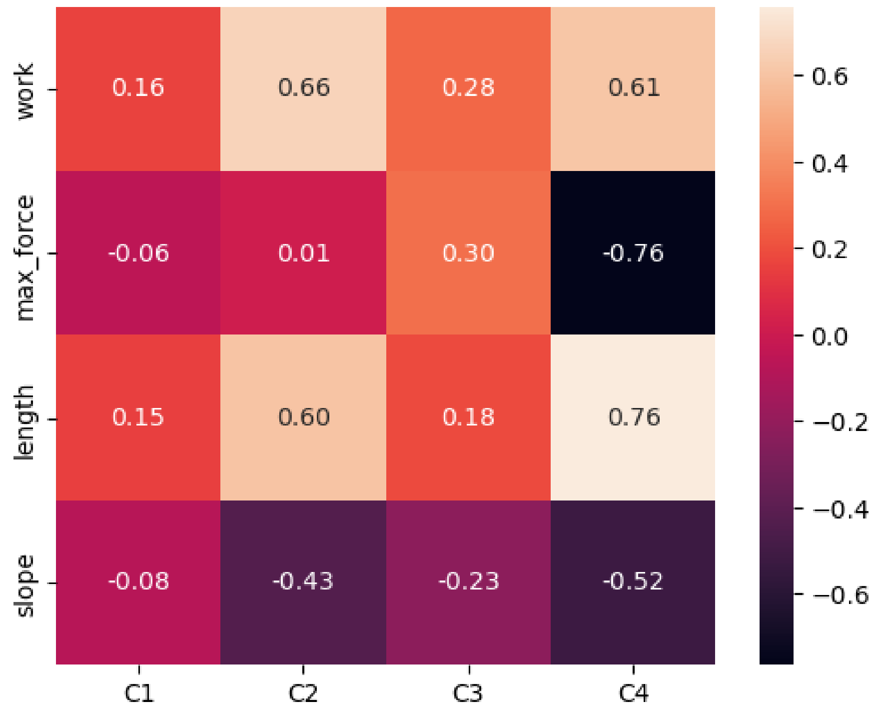


*Fig. 6: Correlation between input- (y-axis) and output-parameters (x-axis) for the ML-algorithms.*

To obtain a statistically well-behaved data set and improve convergence we normalized our data set using the min-max normalization they are scaled to values of [0,1]. Then, we split our dataset into a training and a test set with a ration of 0.9 to 0.1. Hyperparameters (HP) for the tree base algorithms were determined using a Bayesian optimization (BO) and generalization was improved with a 10-fold cross-validation. The 10 models with the lowest mean-squared-error on the training set were used to predict the test set. The resulting root-mean-squared-error (RMSE) was compared to results of a model with default HPs and finally, the lowest RMSE model was chosen. For the RF the default set of HPs yielded the best results while best HPs for XGB are: 'colsample_bytree' = 1.0, 'learning_rate' = 0.07404622431244764, 'max_depth' = 10, 'n_estimators' = 48, 'subsample' = 0.6675843330634745. We trained the PR with degrees of 1 to 8 and again used the test set as metric to choose an appropriate model. As a result, a first-order-degree polynomial fit was chosen.

Overall, the XGB gives the best fitting result while yielding similar RMSE values as the RF for the test set separately. The polynomial fit clearly underperforms compared to the other regression methods. The relevant values are shown in Table 3 and Table 4.

*Table 3: RMSE values for the total data set for all three ML-algorithms*

| RMSE Full Dataset | C1 | C2 | C3 | C4 |
|---|---|---|---|---|
| XGB | 4.68 | **8.34** | 0.17 | 0.05 |
| RF | **5.57** | **9.21** | 0.22 | 0.06 |
| PR | 12.51 | **16.97** | 0.44 | 0.10 |

*Table 4: RMSE values the test set for all three ML-algorithms*

| RMSE Test Dataset | C1 | C2 | C3 | C4 |
|---|---|---|---|---|
| XGB | 10.83 | 23.12 | 0.45 | 0.12 |
| RF | 9.6 | 23.23 | 0.5 | 0.16 |
| PR | **10.78** | 27.64 | 0.48 | 0.15 |

As the XGB algorithm gave the best results for the training and test set Figure 7 shows the one-to-one correspondence of all output quantities. Both the training and test set are depicted. Clearly the general trend is predicted well for all four material parameters. C1 shows reduced regression accuracy for measured values around 400 and 460, i.e. the lowest and highest simulated values. A similar effect can be seen for the remaining parameters. This is readily explained by the low data density in these intervals. The test set shows some larger outliers in all four cases.

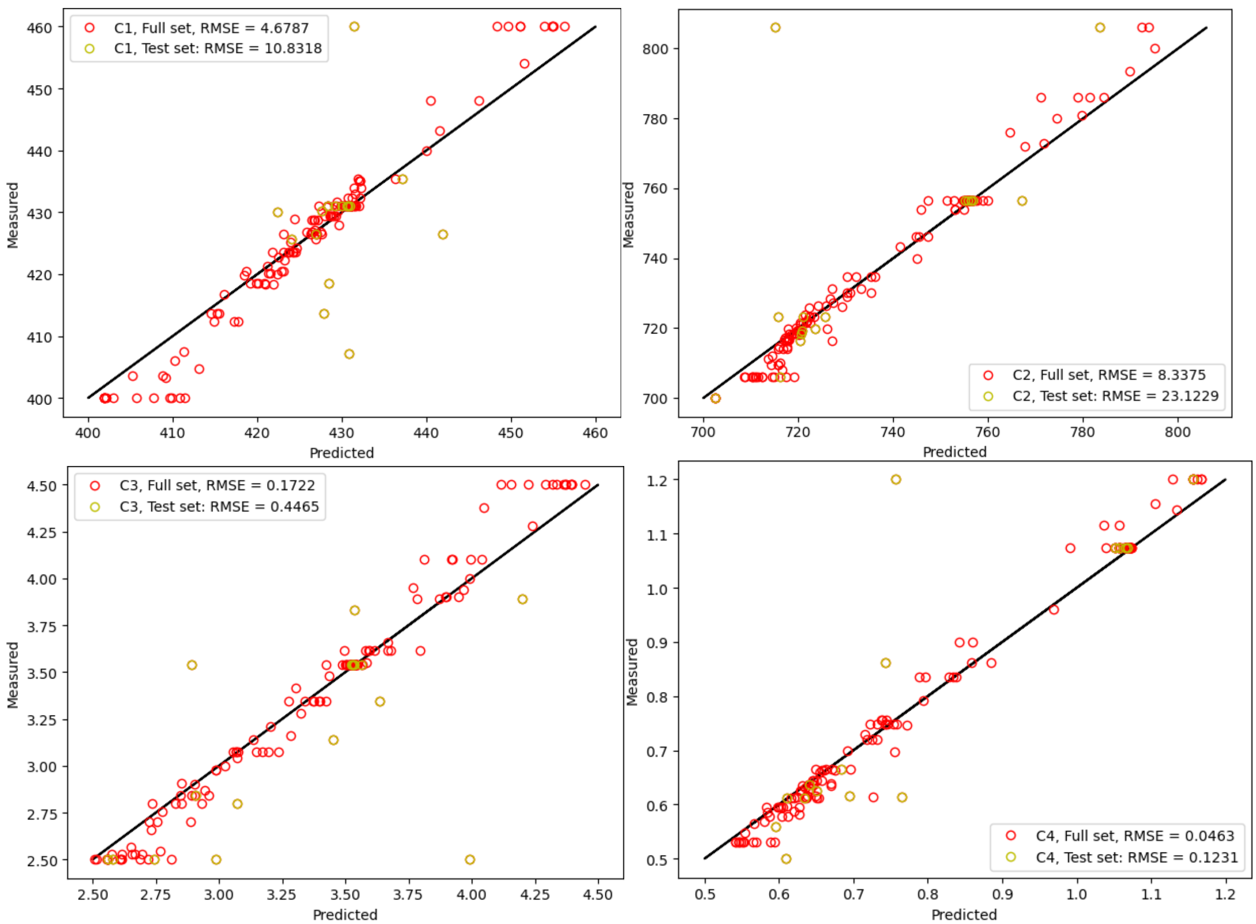


*Fig. 7: One-to-one correspondence between predictions by the XGB algorithm and measured values for the parameters C1 to C4. The training set is indicated by red and the test set by yellow circles*

For a more intuitive evaluation, Table 5 shows the relative absolute deviation (RAD) for the XGB algorithm defined as

$$\mathrm{RAD} = \frac{1}{N}\Sigma_i^N \left|(x_i - y_i)/y_i\right| \tag{2}$$

where $x_i$ are the predicted and $y_i$ the expected values and N is the total number of data points. The larger error within the test set is not surprising, as these values are predicted, not fit and the test set is small, whereby outliers statistically have a larger impact on the metric. Additionally, we provide the $R^2$-score in Table 6. This metric quantifies how much of the variance of a dependent variable can be explained by an independent variable of a trained regression model. For the full dataset we find high values of 0.88 to 0.96, indicating a good fit. As expected, the test set performs worse, C1 even yielding a negative value of -0.06. The variable C4 yields a relatively high value of 0.75.

*Table 5: RAD for the XGB on full and test dataset*

| **RAD** | **C1** | **C2** | **C3** | **C4** |
|---|---|---|---|---|
| XGB (full dataset) | 0.08 | 0.07 | 0.16 | 0.17 |
| XGB (test dataset) | 0.12 | 0.11 | 0.31 | 0.28 |

*Table 6: $R^2$-score for the XGB on full and test dataset*

| **$R^2$** | **C1** | **C2** | **C3** | **C4** |
|---|---|---|---|---|
| XGB (full dataset) | 0.88 | 0.89 | 0.90 | 0.96 |
| XGB (test dataset) | -0.06 | 0.42 | 0.21 | 0.75 |

Overall, we have shown using relatively easily accessible synthetic data from Fe-simulations in combination with ML-algorithms that force-displacement curves from shear-cutting processes are a valid approach to predict various material parameters. The XGB algorithm fits and predicts the data well, but few significant outliers remain, which significantly impacts the prediction of variance. This issue may be resolved using a larger data set with a more homogeneously distributed input parameter space and by finding further input parameters, which have a significant influence on the material parameters. One such example could be the sheet thickness or other parameters extracted using feature-extraction or -engineering. Finally, a comparison with experimental data is necessary to validate this approach. These issues will be covered in future research.

**Summary**

The experimental results demonstrate that the deformation behavior of the investigated material varies significantly between different batches. The cutting force curves obtained from the punching tests also vary depending on the material batch. Therefore, analyzing the cutting force curves can provide valuable information about the mechanical properties of the semi-finished products used. Furthermore, a FE model was developed for the shear cutting process being studied. A material model was parameterized based on the results of the tensile test and validated using the experimentally determined cutting force curves. This demonstrated the importance of considering tool stiffness. The optimized FE model was then used to perform variant calculations and generate synthetic training data to build predictive models to predict the flow curve and its parameters. Several machine learning algorithms were trained and evaluated using this data. The XGB algorithm demonstrated the best performance, accurately predicting the flow curve parameters. Future work will focus on optimizing and validating the prediction models using real experimental data.

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