Materials Research Proceedings 41 (2024) 1416-1425 https://doi.org/10.21741/9781644903131-157

Material-data-driven prediction of sheared surface tears of fine blanked parts

ORTJOHANN Lucia[1,a *], BECKER Marco[1,b], NIEMIETZ Philipp[1,c] and BERGS Thomas[1,2,d]

[1]Manufacturing Technology Institute MTI of RWTH Aachen University, Campus-Boulevard 30, 52074 Aachen, Germany

[2]Fraunhofer Institute for Production Technology IPT, Steinbachstr. 17, 52074 Aachen, Germany

[a]l.ortjohann@mti.rwth-aachen.de, [b]m.becker@mti.rwth-aachen.de, [c]p.niemietz@mti.rwth-aachen.de, [d]t.bergs@mti.rwth-aachen.de

Keywords: Fine Blanking, Non-Destructive Testing, NDT, Eddy Current, Quality Prediction

Abstract. Fine blanking is a cost-effective manufacturing technology for mass-producing sheet-metal components with high sheared surface quality. For steels with higher carbon content, the quality of fine blanking products is significantly influenced by microstructural characteristics, such as the morphology and distribution of carbides, which can be controlled through heat treatment [1]. Precisely, there is a relationship between spheroidization of carbides and the occurrence of tears at the sheared surface of fine blanked parts especially at the tip of a gear [2]. Furthermore, material characteristics can vary both along a sheet-metal coil and from coil to coil despite tight tolerances [3] leading to unpredictable tearing. To monitor the fluctuation of material characteristics at regular intervals along sheet-metal, non-destructive testing (NDT) is used before the process providing information about the microstructure. While in the state of the art, the data from NDT was used to calculate the mechanical properties and to optimize the process based on these properties [4], in this paper, NDT data is used to predict the sheared surface tears of fine blanked parts, without the reduction of the content-rich data to mechanical properties. For this purpose, an experiment was conducted on the fine blanking of the steel 42CrMo4+A to produce components resembling a gear shape. Prior to the manufacturing process, the material was measured using an eddy current sensor, and subsequently the tearing of the fine blanked parts was evaluated. For the prediction of sheared surface tears, linear regression methods were used, and a feature selection was done to find the excitation frequencies of the eddy current sensor with the highest impact on the tearing. It was shown that the eddy current measurements along the coil contain valuable information about the tearing of the fine blanked part.

Introduction and state of the art

Despite strict controls, stochastic fluctuations in material properties already occur during steel production [5]. During metal processing, these fluctuations are propagated all the way to the final sheet metal coil. One example of this is elongation at fracture, which can fluctuate by up to approximately 10% within a cold-rolled sheet metal coil [6], while the fluctuations between different batches can be in the range of 13% to 21% [3,6,7]. For different manufacturers, the elongation at fracture can even vary by up to 27% [7]. These fluctuations in the material properties of the input material are currently a significant problem leading to rejects and decreasing the process stability and thus, leading to expensive machine downtimes and time-consuming trial-and-error adjustment of sheet metal processes.

Fine blanking is one of those sheet metal processes used to manufacture high-accuracy sheet metal parts such as gears or sprockets [8]. Due to a blank holder, a counter punch and a vee-ring, the fine blanking process is operated with three independently acting process forces [9] (cf. Fig. 1 a). The process forces combined with a small die clearance (u ≈ 0.5% of the sheet thickness) and a vee-ring lead to a superimposed compressive stress (cf. Fig. 1 b) and enables the material to flow leading to a 100% smooth sheared surface, which can be used as a functional surface [2]. Die roll, tear-off and tears reduce the load-bearing proportion of functional surfaces and thus represent quality-influencing features [10].

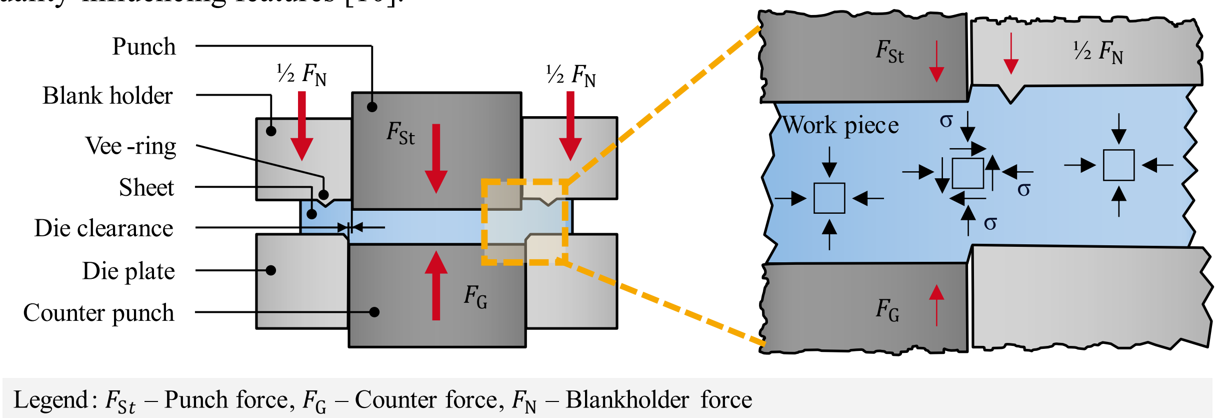

Fig. 1. a) Fine blanking setup and b) a detailed view of the shear zone

The influence of material properties on the plastic flow and the sheared surface quality is described in various places in the literature, for example in relation to carbides and cementite structures [9] and hardening [11]. For unalloyed carbon steels with a carbon content greater than 0.15% and steels with a higher alloy content without annealing on spheroidal cementite, lamellar cementite or carbides occur and, due to their brittle properties, these can lead to tears as well as tear-offs on the sheared surface [12]. However, the distribution and shape of the carbides fluctuates statistically along the coil, so that with additional small tip radii and tip angles of the part geometries, it is difficult to achieve a stable and economic fine blanking process especially for steels with high carbon content. Moreover, theses fluctuations in material properties especially microstructural differences in the distribution and shape of carbides lead to unpredictable tearing for high carbon steels. Nevertheless, material properties are typically measured only at the beginning and end of the coil using uniaxial tensile tests as well as metallographic analysis. Thus, there is no information about the exact material properties along the coil. In addition, uniaxial tensile tests cannot represent the complex stress state during fine blanking, as the material in the shear zone is subjected to three-dimensional compressive stress [13].

Monitoring the coil through non-destructive testing (NDT), such as eddy current (EC) measurements, can capture variations in material properties and create a digital shadow of the coil, referred to as Digital Coil. In sheet metal processing, electromagnetic methods are generally used for NDT, as there is a correlation between the mechanical and electromagnetic properties of sheet metal, as the microstructure influences both [14]. It has already been shown that sensors such as EC sensors, the 3MA sensor or the IMPOC sensor are successfully used for inline monitoring of coils. The data from these measurements correlate with mechanical properties and enable the prediction of tensile strength, yield strength, residual stress and hardness along the coil [14–16].

Various regressions and machine learning have been used to predict these parameters [17] and to detect cracks and material thinning [18]. Khan et al. showed a correlation between the EC measurements and austenite phase fractions [19]. Utilizing the mechanical parameters derived from EC measurements, a knowledge-based control approach was implemented to mitigate diverse factors affecting draw-in in the deep drawing process [20]. Furthermore, feedback control strategies were employed to minimize the impact of material variations [21]. Heingärtner et al. developed and tested an intelligent control system at an industrial scale. This system employed numeric simulations, mechanical properties obtained through EC, process settings, and draw-in measurements to optimize the deep drawing process of the production of kitchen sinks [22]. In a study for a stamping process, material fluctuations were recorded using EC measurements to analyse different motion sequences for a servo press [23]. Purr showed in a data analysis in a pressing plant that fluctuations in material properties, measured by IMPOC sensors, have a significant influence on the quality of car body parts [24]. A full overview of NDT methods for sheet-metal forming is given in [4].

The common theme of these publications regarding NDT in sheet metal processing is that first the mechanical parameters are derived from the sensor data and then the process is optimized based on these parameters. But only few studies measure material properties with NDT and relate them directly to the resulting part properties like quality or parameterization of the sheet metal processes. Since the reduction to mechanical parameters reduces the information content of the NDT data, the approach to directly combine NDT data with process information enables a big potential. Therefore, this paper answers the following research question:

(RQ) Do the eddy current measurements along the coil contain information about the expected quality of the fine blanked part, in particular about the tearing at a selected tip of the part?

To answer this question an experiment was conducted where strips from a coil were measured with an EC sensor, subsequently the strips were fine blanked and the quality of the resulting part was evaluated. The experimental setup and the resulting dataset are described in the following two sections. After the data acquisition a linear regression with a feedforward feature selection was fitted on the EC data to predict the quality of the fine blanked part, specifically the height and width of the tear on a selected tip. The feature selection also allowed to derive insights as to which excitation frequencies and evaluation harmonics are best suitable to predict the tearing. Section 4 is dedicated to the methodology of the regression. The results of the data analysis are presented in the fifth section.

Experimental setup

To investigate the relationship between the material data measured by EC and the quality of the fine blanked part, the sheared part geometry and the material was deliberately configured to align with conditions predisposing the occurrence of tears. Since tips with small angles and radii are challenging both in terms of the resulting part quality as well as punch edge load, the chosen part geometry, shown in Figure 2 a), consists of nine tips with different tip angles and tip radii representing an analogue application for tribologically stressed functional surfaces.

As material a coil of hot rolled and annealed 42CrMo4+A (EN 10132-3 respectively AISI 4140) with a sheet thickness of 6.95 mm was separated into numbered sheet metal strips. The material properties yield strength $\mathrm{R_{p0.2}}$, ultimate tensile strength $\mathrm{R_m}$, elongation at fracture $\mathrm{A}, \mathrm{A_{80}}$ are documented in Table 1. The medium carbon steel 42CrMo4+A finds application in critical components within the automotive and aircraft industries, such as gears, spindles, rods, and rams and it is often used in forming processes. However, the high thickness of the material combined with a high carbon level causes difficulties for the resulting part quality.

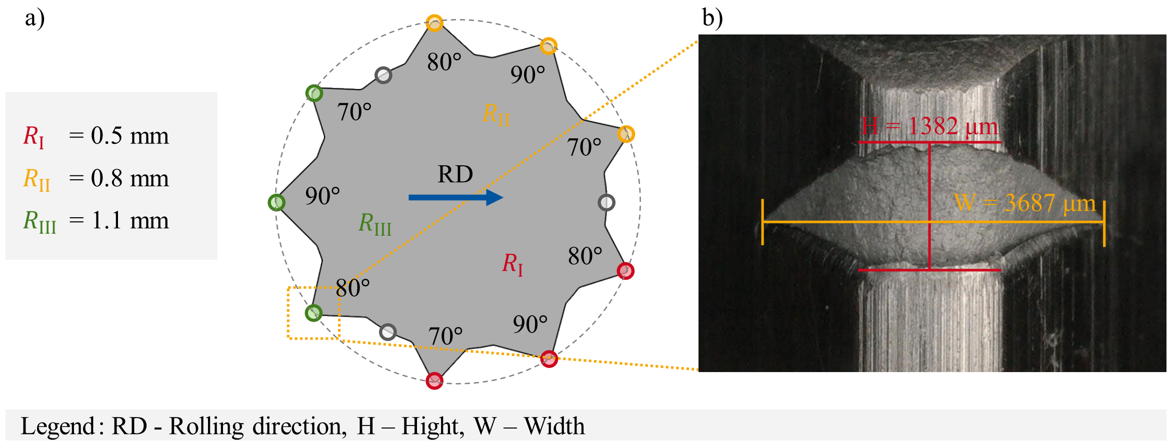

Fig. 2. Geometry of the sheared part (a) and height and width of the tear at the tip under the microscope (b)

After measuring the sheet metal strips with the *MAGNATEST D* from *Foerster*, the fine blanking experiments were conducted on a servomechanical fine blanking press *Feintool XFT 2500 speed*. Fine blanking was performed with a modular designed single part producing tool (one part per stroke). For each strip one fine blanked part was produced. The blanking punch and die were manufactured from *Böhler S390* powder metallurgical high-speed steel with a hardness of 65 HRC and coated with the *Platit FeinAl* coating (AlCrN-based nano-coating). The chlorine-free lubricant *Fuchs Wisura FMO 5020* was used for the experiments, further process and tool parameters are specified in Table 2.

Table 1. Mechanical properties of 42CrMo+A.

Material	$\mathbf{R_{p0.2}}$ **[MPa]**	$\mathbf{R_m}$ **[MPa]**	**A** [%]	$\mathbf{A_{80}}$ [%]
42CrMo4+A	381	591	29.1	26.5

The tool was initially designed for 5 mm material, leading to a relative die clearance u ≈ 0.3% of the sheet thickness. In the experiment, 245 valid parts were produced, and every tip of every part was torn. To evaluate the quality, the height and the width of the tears for the tip with tip angle 80% and tip radii 1.1 mm was measured manually as shown in Figure 2 b) using a *Keyence VHX-5000 digital microscope*.

Table 2. Process and tool parameters used for the fine blanking experiment.

Blanking velocity $\mathbf{v_B}$	45 mm/s	**Die chamfer angle**	35°
Vee-ring force $\mathbf{F_{VR}}$	440 kN	**Die chamfer height**	0.3 mm
Counter force $\mathbf{F_{CP}}$	170 kN	**Vee-ring distance**	2.5 mm
Die clearance u	20 µm	**Vee-ring height**	0.7 mm

Dataset description

The measuring system of the *MAGNATEST D sensor* consists of two electromagnetic coils. Applying a high frequency alternating current to the transmitting coil creates a primary field that induces eddy currents on the material. The secondary field generated by these eddy currents is then measured by the sensor's receiving coil and the data generated is represented as the amplitude (X-value) and phase shift (Y-value) between the transmitted and received signals. The sensor is used with an high frequency coil and can measure with excitation frequencies from 2 Hz to 128 kHz and it offers the flexibility to evaluate the measurements using higher harmonics [25]. This results in 48 features that are obtained for each measuring point, i.e. for each metal strip in the experiment. In Figure 3, two measurements with different frequencies are presented. The figure indicates the presence of collinearity in the dataset by showing exemplary that individual features are highly correlated.

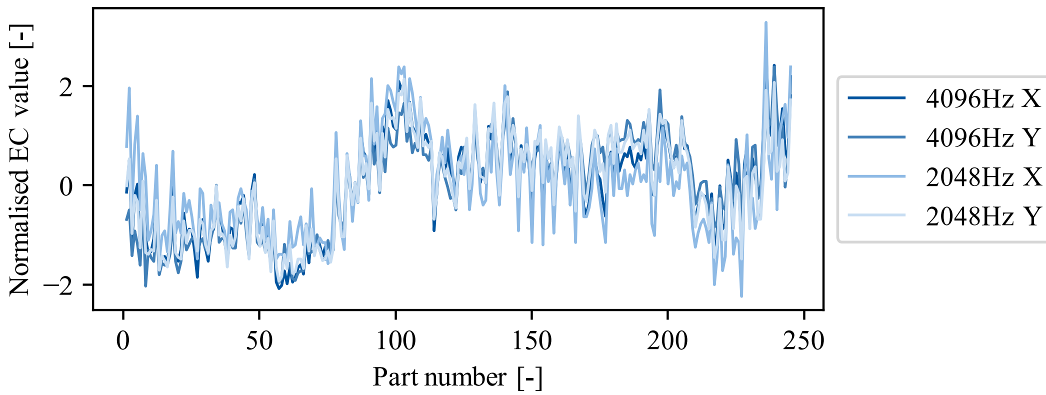

Fig. 3. Two different normalised EC measurements.

The height and width of the measured tears in the fine-blanked parts exhibit considerable variance throughout the dataset, as illustrated in Figure 4. This variability can be partly attributed to the inherent fluctuations of the manual measuring system. The standard deviation of nine measurements of one identical part is 13 µm for the height and 12 µm for the width of the tear of the part. The three parts with the highest and lowest values are highlighted in red for the evaluation in Section 4.

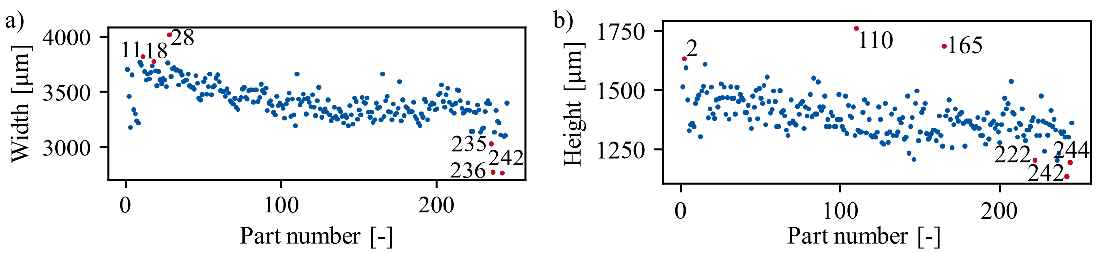

Fig. 4. Width (a) and height (b) of the tears for every measured part.

While the height displays a subtle drift across the coil length (part number), the width exhibits a discernible drift over the same coil length. In summary, the dataset consists of 245 data points for which there are 48 features (EC data) and two labels (quality data).

Methodology for the data analysis

To model the relationship between the EC data and the quality data linear regression is chosen. This choice is motivated by the model's high interpretability, facilitated by the availability of various statistical methods for example methods designed for testing assumptions or diagnostic methods for the model fit. Moreover, linear regression allows for the inclusion or exclusion of features based on their significance and contribution to the model. To evaluate the goodness of the fit of the linear model, it must be ensured that there is no collinearity, no overfitting, linearity between the features and labels, no correlation of error terms, constant variance of error terms and no outliers [26].

Because of the collinearity in the EC data, where multiple features display significant correlation, there is a risk of overfitting, leading to an increase in the standard error. Consequently, a forward feature selection method is employed, leveraging the Akaike information criterion (AIC) as the evaluation metric. The forward feature selection with AIC starts with the null model, i.e. the model that contains only the intercept, and then iteratively adds the feature that generates the model

Materials Research Proceedings 41 (2024) 1416-1425 https://doi.org/10.21741/9781644903131-157

with the smallest AIC [27]. The smallest AIC leads to the model with the best model fit compared to the true model fit, while also giving penalties for overfitting. The AIC is calculated as follows:

$$\mathrm{AIC} = 2\mathrm{p} - 2\ln\left(\hat{\mathrm{L}}\right), \quad (1)$$

where $\hat{\mathrm{L}}$ is the maximum of the likelihood function and p the number of features [28]. The feature selection is used to reduce overfitting and the selected features are less correlated than the total features of the dataset. Furthermore, this method directly identifies features with the most substantial impact on label.

To evaluate the performance and generalization of the linear regression model a k-fold cross-validation is used. Therefore, the dataset is randomly divided into k equal-sized subsets. Each subset is then used as test dataset and the rest of the data is used as a training dataset for the linear regression. Then the mean of the mean-squared error (MSE) and the mean of the coefficient of determination (R^2) of all linear regressions is computed. If the training and test errors, along with the coefficient of determinations, exhibit similar size, it indicates that the model can be generalized effectively, and there is no apparent issue with overfitting [27].

Residual plots can assess the relationship between the features and the label and whether the error terms do not correlate and have a constant variance. Ideally, a residual plot should not reveal any discernible pattern that would suggest a violation of these conditions [26]. To analyze outliers and data points with high influence the Cook's distance and the studentized residual can be calculated as well. The Cook's distance gives an estimate of the influence of a datapoint by evaluating how much the regression model changes when the datapoint is removed [28]. The studentized residual can be computed by dividing each residual by its estimated standard error. Data points with a studentized residual greater than 3 in absolute value are potential outliers [26].

Once it has been ensured that the model has approximated the data well, the F-test can be carried out. The F-test is a hypothesis test used to test whether there is a relationship between the features and the label of a linear regression. The null hypothesis is that all regression coefficients (except the intercept) are equal to zero, indicating that the features do not significantly contribute to explaining the variance in the label. It is tested against the hypothesis that at least one regression coefficient is non-zero. The F-statistic is calculated as follows:

$$\mathrm{F} = \frac{(\mathrm{TSS}-\mathrm{RSS})/\mathrm{p}}{\mathrm{RSS}/(\mathrm{n}-\mathrm{p}-1)},\ \mathrm{TSS} = \sum(\mathrm{y_i} - \bar{\mathrm{y}})^2,\ \mathrm{RSS} = \sum(\mathrm{y_i} - \hat{\mathrm{y}}_\mathrm{i})^2, \quad (2)$$

where y_i is the true value, $\hat{y}_i$ is the fitted value, $\bar{y}$ the mean of the label, n number of data point and p the number of features. From the F-statistic a p-value can be deduced and if this p-value is smaller than a selected significance level (e.g. 0.01) the null hypothesis can be rejected, and it can be concluded that the features contain relevant information about the label [26].

Results and discussion

To answer the research questions linear regressions were fitted with the EC data as features and the height and the width of the tears of the selected tip of the fine blanked part as labels. Moreover, to analyze the impact of different frequencies and different harmonics a feature selection was performed. Initially, a 5-fold cross-validation with a linear regression model fitted on the entire dataset showed that even the linear regression is not generalizable on this dataset (see Table 3a). Considering the high collinearity of the dataset, this result was to be expected. Thus, the feature selection approach presented in Section 4 was implemented and the linear model fitted on the selected features exhibited less overfitting in the cross-validation (see Table 3b).

The MSE is still quite high and the R^2 quite low, but considering the high variance in the labels, it is coherent with the dataset. Note that the R^2 values of the model of all features and the model with the selected features cannot be compared since R^2 is influenced by the number of features.

Table 3. Results of the cross-validation on all features (a) and on the selected features (b).

	a) Cross-Validation on all features		b) Cross-Validation on selected features	
	Height	**Width**	**Height**	**Width**
MSE **Train**	3,642	8,472	4,631	11,296
MSE **Test**	6,340	15,750	4,997	12,142
R^2 **Train**	0.46	0.69	0.32	0.58
R^2 **Test**	0	0.34	0.22	0.51

The selected features are shown in Table 4, here, “harmonic” is abbreviated by “h.”. Apart from the 8192 Hz 5th harmonic Y feature (phase shift of the 5th harmonic for the excitation frequency 8192Hz), the selected features of both labels have no overlaps. In addition, no frequency spectrum is particularly emphasized. However, it is noticeable that the 3rd and 5th harmonic were selected very frequently. Since the harmonics show the permeability of the material this suggests that the permeability has a stronger influence on the formation of tears and this again confirms the influence of the microstructure on the formation of tears, as the microstructure has a strong influence on the permeability of the material [25].

Table 4. Selected features of forward feature selection.

Label	**Selected features**
Height	8192 Hz 5th h. Y, 4096 Hz 5th h. X, 256 Hz X, 256 Hz 3rd h. X, 32 Hz Y
Width	8192 Hz 3rd h. X, 8192 Hz 5th h. Y, 2048 Hz Y, 2048 Hz 3rd h. X, 1024 Hz 3rd h. X, 512 Hz 3rd h. X and Y, 512 Hz Y, 256 Hz 3rd h. Y, 128 Hz Y

Fig. 5 shows the analysis of the model fit with the label height of the tear. The read line in the residual plot shows the smoothed curve for the residuals. The plot where the true values are plotted against the fitted values of the model highlights challenges in accurately predicting values with both low and high heights. This can be also seen in the residual plots and in the Cook’s distance since the highlighted data points have all very low or high height (cf. Fig. 4). The studentized residuals reveal data point (part) 110 and 165 as outliers, since these data points have an absolute studentized residual bigger than three. Thus, it might be that the EC data cannot predict tears with very high height. However, overall, the Cook’s distance is considerably smaller than 1 and the residual plots show no pattern, hence the model fit is valid.

In general, the fit of the model for the label width of tears is better than the fit for the height (cf. Fig. 6). Here again, the datapoints considered to be outliers are parts which have a low or a high tear width (cf. Fig. 4), nevertheless, it can again be concluded that the model fit is valid. Since both linear regressions have a good fit on the dataset, the F-test could be conducted (cf. Table 5).

Table 5. Results of the F-test.

	Height	**Width**
F-statistic	22.04	32.46
p-value (F-statistic)	$3.80e-18$	$6.05e-39$

Because the p-value of the F-test is considerably small, the result is that the null hypothesis can be rejected, and it can be concluded that the EC data contains valuable information about the tearing of the fine blanked parts.

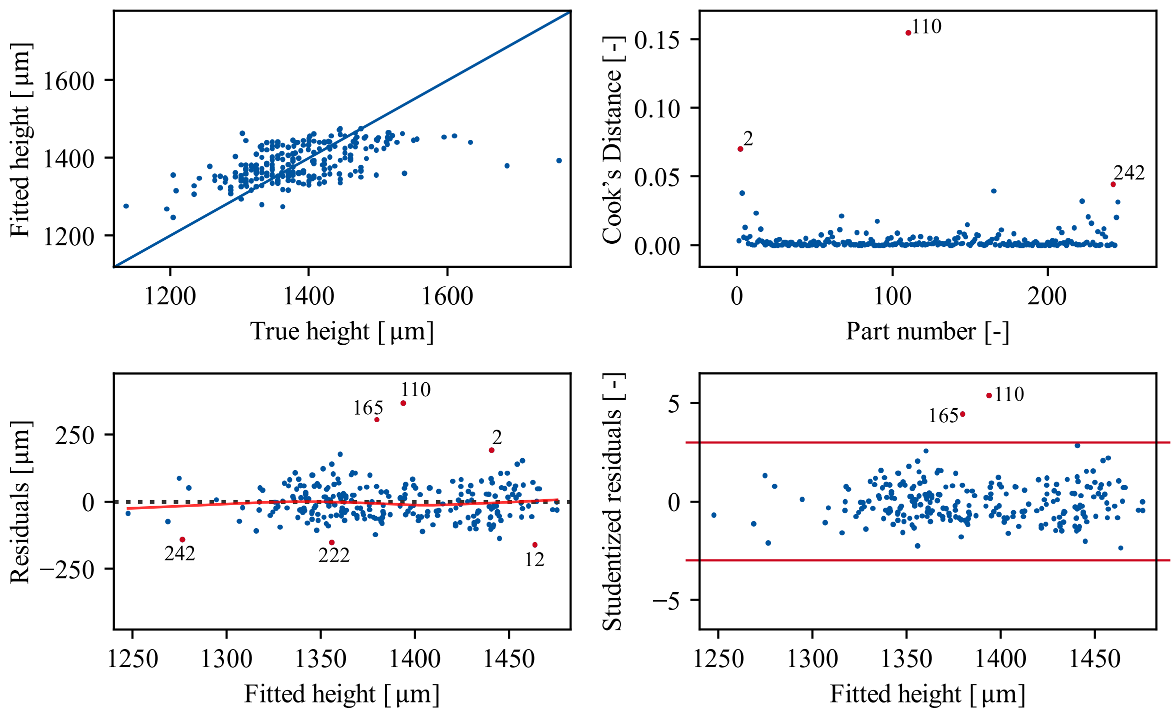

Fig. 5. Analysis of the model fit with the label height with different diagnostic plots.

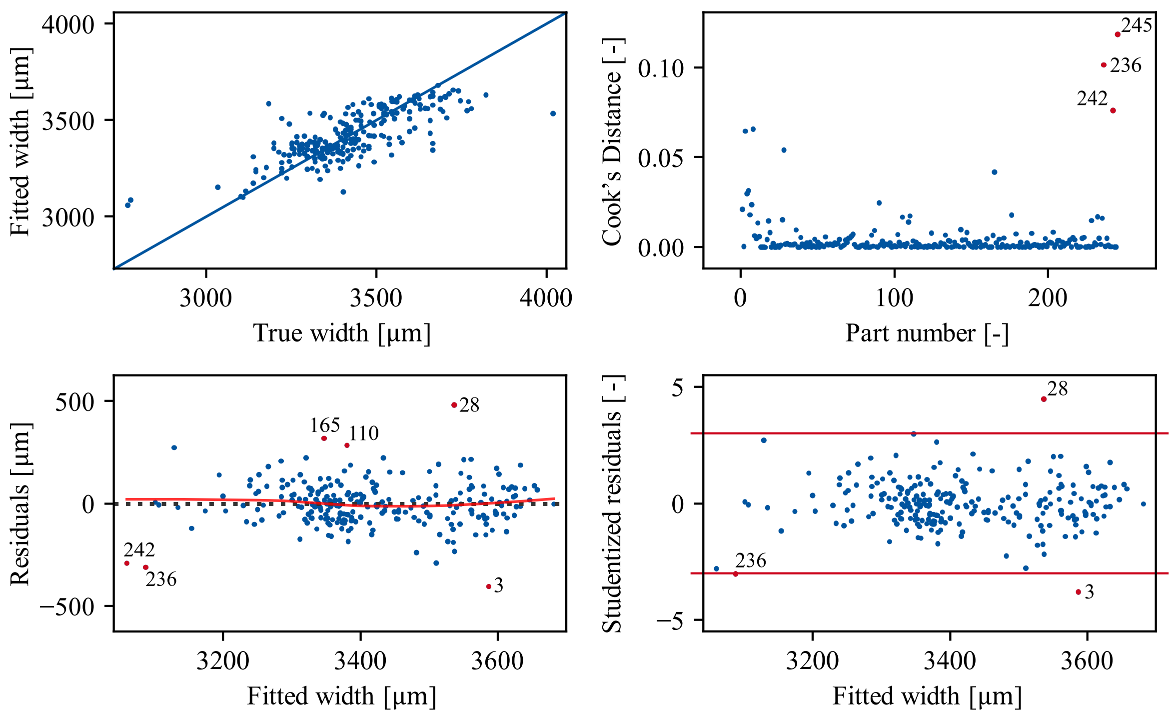

Fig. 6. Analysis of the model fit with the label width with different diagnostic plots.

Conclusion and outlook

In this paper, a forward feature selection and linear regression was used to investigate the influence of the material represented by eddy current data on the quality of fine blanked part particularly the tearing behaviour of a selected tip. In an experiment, sheet metal strips were measured non-destructively and a geometry analogue to gears was fine blanked. Subsequently the height and the width of the tear of a selected tip of the resulting parts was evaluated. It was shown that eddy current measurements along the coil contain information about the expected height and the width of the tear of the fine blanked part. Furthermore, a forward feature selection analysis indicated that no particular frequency spectrum contains the relevant information. However, the frequent choice of harmonics implies that the material's permeability likely has a significant impact on the tearing process.

As a next step, experiments are conducted in which the die clearance is designed for the thickness of the material but material with higher carbon is selected potentially resulting in tear-free parts and torn parts. The overall goal of this approach is to implement a control strategy in which the eddy current signals are evaluated by a model which analyses the tearing. Since tearing can be potentially prevented by an increased vee-ring force, which in turn accelerates wear, the model will adapt the vee-ring force based on the eddy current signals only if required.

Acknowledgements
Funded by the Deutsche Forschungsgemeinschaft (DFG, German Research Foundation) under Germany's Excellence Strategy – EXC-2023 Internet of Production – 390621612. Furthermore, the authors would like to thank the Federal Ministry for Economics and Climate Action for the kind support within the Project "NUMA 4.X" (Project ID: 13IK029B).

References
[1] Q. Zheng, X. Zhuang, Z. Zhao, State-of-the-art and future challenge in fine-blanking technology, Prod. Eng. Res. Devel. 13 (2019) 61–70. https://doi.org/10.1007/s11740-018-0839-7
[2] R.-A. Schmidt, Cold Forming and Fineblanking: A Handbook on Cold Processing Steel Material Properties Component Design, Carl Hanser, 2007.
[3] D. Harsch, P. Fischer, B. Berisha, J. Heingärtner, Y. Renkci, P. Hora, Considering fluctuations of material properties, stainless steel 1.4301, on manufacturability of kitchen sinks, IOP Conf. Ser.: Mater. Sci. Eng. 418 (2018) 12113. https://doi.org/10.1088/1757-899X/418/1/012113
[4] L. Ortjohann, M. Becker, P. Niemietz, T. Bergs, Monitoring of fluctuating material properties for optimizing sheet-metal forming processes: a systematic literature review, in: Materials Research Forum LLC, 2023. https://doi.org/10.21741/9781644902479-222
[5] J.M. Allwood, S.R. Duncan, J. Cao, P. Groche, G. Hirt, B. Kinsey, T. Kuboki, M. Liewald, A. Sterzing, A.E. Tekkaya, Closed-loop control of product properties in metal forming, CIRP Annals 65 (2016) 573–596. https://doi.org/10.1016/j.cirp.2016.06.002
[6] D. Banabic, G. Dragos, I. Bichis, Influence of Variability of Mechanical Data on Forming Limit Curves, Metal Forming 3 (2013) 858–863.
[7] V. Sturm, Einfluss von Chargenschwankungen auf die Verarbeitungsgrenzen von Stahlwerkstoffen. Zugl.: Erlangen-Nürnberg, Univ., Techn. Fak., Meisenbach, Bamberg, 2013.
[8] K. Gupta, N.K. Jain, R. Laubscher, Advanced Gear Manufacturing and Finishing: Classical and Modern Processes, Elsevier Academic Press, 2017. https://doi.org/10.1016/B978-0-12-804460-5.00004-3
[9] F. Klocke, Fertigungsverfahren 4, 6th ed., Springer Vieweg Berlin, Heidelberg, 2017. https://doi.org/10.1007/978-3-662-54714-4
[10] W. Volk, J. Stahl, Shear Cutting, in: L. Laperrière, G. Reinhart (Eds.), CIRP Encyclopedia of Production Engineering, Springer Berlin, Heidelberg, 2014. https://doi.org/10.1007/978-3-642-35950-7_16823-1
[11] F. Schweinshaupt, I.F. Weiser, T. Herrig, T. Bergs, Investigation of Combined Flat Coining and Fine Blanking of 16MnCr5 to Influence the Die Roll Formation, in: B.-A. Behrens, A. Brosius, W.-G. Drossel, W. Hintze, S. Ihlenfeldt, P. Nyhuis (Eds.), Production at the Leading Edge of Technology, Springer International Publishing, Cham, 2022, 112–121. https://doi.org/10.1007/978-3-030-78424-9_13

[12] H. Hoffmann, R. Neugebauer, G. Spur (Eds.), Handbuch Umformen, 2nd ed., Carl Hanser, München, 2012. https://doi.org/10.1007/978-3-446-43004-4
[13] M.D. Gram, R.H. Wagoner, Fineblanking of high strength steels: Control of material properties for tool life, Journal of Materials Processing Technology 211 (2011) 717–728. https://doi.org/10.1016/j.jmatprotec.2010.12.005
[14] J. Heingärtner, M. Born, P. Hora, Online Acquisition of Mechanical Material Properties of Sheet Metal for the Prediction of Product Quality by Eddy Current, 10th European Conference on Non-Destructive Testing, Moscow, Russia, 2010.
[15] B. Wolter, Y. Gabi, C. Conrad, Nondestructive Testing with 3MA—An Overview of Principles and Applications, Appl. Sci. 9 (2019) 1068. https://doi.org/10.3390/app9061068
[16] K. Herrmann, M. Irle, IMPOC: an online material properties measurement system, in: Flat-Rolled Steel Processes: Advanced Technologies, 2009.
[17] K. Lee, C. Hong, E.H. Lee, W. Yang, Comparison of Artificial Intelligence Methods for Prediction of Mechanical Properties, IOP Conf. Ser.: Mater. Sci. Eng. 967 (2020) 12031. https://doi.org/10.1088/1757-899X/967/1/012031
[18] A. Zoesch, T. Wiener, M. Kuhl, Zero Defect Manufacturing: Detection of Cracks and Thinning of Material during Deep Drawing Processes, Procedia CIRP 33 (2015) 179–184. https://doi.org/10.1016/j.procir.2015.06.033
[19] S.H. Khan, F. Ali, A. Nusair Khan, M.A. Iqbal, Eddy current detection of changes in stainless steel after cold reduction, Computational Materials Science 43 (2008) 623–628. https://doi.org/10.1016/j.commatsci.2008.01.034
[20] P. Fischer, D. Harsch, J. Heingärtner, Y. Renkci, P. Hora, A knowledge-based control system for the robust manufacturing of deep drawn parts, Procedia Eng. 207 (2017) 42–47. https://doi.org/10.1016/j.proeng.2017.10.735
[21] P. Fischer, J. Heingärtner, W. Aichholzer, D. Hortig, P. Hora, Feedback control in deep drawing based on experimental datasets, J. Phys.: Conf. Ser. 896 (2017) 12035. https://doi.org/10.1088/1742-6596/896/1/012035
[22] J. Heingärtner, P. Fischer, D. Harsch, Y. Renkci, P. Hora, Q-Guard – an intelligent process control system, J. Phys.: Conf. Ser. 896 (2017) 12032. https://doi.org/10.1088/1742-6596/896/1/012032
[23] H. Kim, J.C. Gu, L. Zoller, Control of the servo-press in stamping considering the variation of the incoming material properties, IOP Conf. Ser.: Mater. Sci. Eng. 651 (2019) 12062. https://doi.org/10.1088/1757-899X/651/1/012062
[24] S. Purr, Datenerfassung für die Anwendung lernender Algorithmen bei der Herstellung von Blechformteilen, FAU Studien aus dem Maschinenbau 338, 2020.
[25] Foerster Group, MAGNATEST D-HZP: Magnetinduktive Prüfung von Werkstoffen auf magnetische und elektrische Eigenschaften (2018).
[26] G. James, D. Witten, T. Hastie, R. Tibshirani, An introduction to statistical learning: With applications in R, Springer New York, NY, 2021. https://doi.org/10.1007/978-1-0716-1418-1
[27] T. Hastie, R. Tibshirani, J.H. Friedman, The elements of statistical learning: Data Mining, Inference, and Prediction, 2nd ed., Springer New York, NY, 2009. https://doi.org/10.1007/978-0-387-84858-7
[28] A. Agresti, Foundations of Linear and Generalized Linear Models, John Wiley & Sons, 2015.