Solid State Phenomena
ISSN: 1662-9779, Vol. 389, pp 125-133
doi:10.4028/p-8Tbjxt

Submitted: 2026-01-07
Revised: 2026-02-17
Accepted: 2026-02-24
Online: 2026-04-16

Multivariate Analysis of Scrap Web Sheared Surface Roughness for Punch Wear Indicators in Sheet-Metal Forming

MOON Jiyoung[1,a*], FRIGGE Alexander[1,b], NIEMIETZ Philipp[1,c], HERRIG Tim[1,d] and BERGS Thomas[1,2,e]

[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]j.moon@mti.rwth-aachen.de, [b]a.frigge@mti.rwth-aachen.de, [c]p.niemietz@mti.rwth-aachen.de, [d]t.herrig@mti.rwth-aachen.de, [e]t.bergs@mti.rwth-aachen.de

Keywords: Sheet-metal Forming, Punch Wear Assessment, Multivariate Analysis.

Abstract. In precise sheet-metal forming operations such as fine blanking, the closed tool design precludes direct observation during production, which makes indirect monitoring of punch wear necessary. Previous work has shown that the sheared surfaces of the scrap web can be used to infer the punch wear through spatial correlation analysis of areal roughness parameters. However, these correlations have so far each explained only a limited portion of the variance and have only been investigated for a single punch geometry, leaving their robustness and generalizability open to question. In this work, multivariate regression approaches and feature importance analysis are used to combine complementary areal roughness parameters and generate robust indicators of punch wear. The plausibility of these indicators is validated by linking the correlated scrap web sheared surface features to physically interpretable wear mechanisms, such as worn surface area or punch breakage. Furthermore, the approach is extended to multiple punch geometries to examine the extent to which the identified correlation patterns can be transferred to different tool designs and process conditions. The results demonstrate the generalizability of spatial correlation-based indicators across different geometries and process conditions.

Introduction

Unplanned downtime in manufacturing causes substantial economic losses. The world's 500 largest manufacturing companies lose approximately \$1.4 trillion annually through unplanned downtime, equivalent to 11% of their revenues [1]. As one of the manufacturing processes that are widely used across various industries, sheet-metal forming processes rely on tools that are subject to wear during operation. Among the various tool components, punches represent critical wear parts that require precise dimensional control throughout their lifetime. Particularly in processes such as fine blanking, the economic impact of punch wear intensifies. Since worn punches can no longer meet these tight tolerances, more frequent replacement is necessitated, and downtime costs increase. The closed tool design of fine blanking process prevents direct observation during production, making indirect monitoring of punch condition essential for preventing costly unplanned stops.

Indirect monitoring in sheet-metal forming processes commonly include process signals, such as force or acoustic emission (AE). Kubik et al. proposed a machine learning-based inline wear quantification workflow that relies on engineered process features and explicitly identifies which signal-derived descriptors are most relevant for wear-state discrimination [2]. Becker et al. applied explainable deep learning approach to fine blanking force time series to reveal which time regions drive the wear prediction [3]. To this extent, Niemietz et al. investigated representation learning methods for fine blanking force signals and demonstrated that the stability and variance of individual low-dimensional representation components can be interpreted as physically meaningful indicators of wear progression [4]. Most recently, Unterberg et al. demonstrated data-driven indirect punch wear monitoring where scrap web sheared surface roughness is treated as a proxy for punch condition and is linked to process signals such as acoustic emission features across shearing and stripping phase [5].

While these data-driven methods demonstrate the value of engineered features for wear monitoring, similar feature extraction principles have been applied to different process monitoring tasks as well. Frigge et al. employed sensor fusion techniques to combine statistical, temporal, and spatial features extracted from force and AE signals for crack prediction in fine blanking [6]. Similarly, Ortjohann et al. applied forward feature selection on eddy current measurements to identify the most informative frequency harmonics for predicting sheared surface tears [7]. Feature extraction methods have also been extended to spatial domain analysis. Recent research of Moon et al. revealed the spatial relationship between punch and scrap web sheared surface [8]. They demonstrated correlations between punch surface characteristics and scrap web sheared surface roughness, where individual parameters explained up to 60% of the variability. However, the previous analysis was limited to a single punch geometry from one experiment, leaving the transferability of these correlations unexplored. The goal of this work is to investigate influences of areal roughness parameters of scrap web sheared surfaces on those of the corresponding punches across different punch geometries and process setups, thereby establishing robust and generalizable indicators for punch wear monitoring in sheet-metal forming processes.

Methods

To systematically study how punch wear manifests in the sheared surface of scrap webs across different tool and process configurations, a series of fine blanking experiments was performed on a FEINTOOL XFT 2500 SPEED press. 12 punches with varying geometries, sheet materials, lubricants, and production lengths were investigated (see Table 1). The experiments covered three geometry families (Types A-C; see Figure *1*) and four sheet materials (58CrV4, 42CrMo4, 100Cr6, and C75S) processed at thickness of 5-6 mm under varying industrial lubrication conditions. Among these, three experiment sets {P1, P2}, {P3, P4}, and {P5, P6} were conducted with paired punches, producing two parts per stroke. All remaining experiments used a single punch configuration.

Table 1. Overview of punches and production conditions.

Punch index	Geometry type	Punch material	Coating	Sheet material	Sheet thickness	Lubricator	Number of production strokes
P1	Type A	BOEHLER K490	PLATIT FEINAL	58CrV4	5 mm	WISURA FMO 5020	41,410
P2	Type A	BOEHLER K490	PLATIT FEINAL	58CrV4	5 mm	WISURA FMO 5020	41,410
P3	Type Ba	BOEHLER S390	PLATIT FEINAL PLUS	42CrMo4	5 mm	RAZIOL CLF 48 HL	31,400
P4	Type Bb	BOEHLER S290	PLATIT FEINAL PLUS	42CrMo4	5 mm	RAZIOL CLF 48 HL	31,400
P5	Type Bc	BOEHLER S390	PLATIT FEINAL PLUS	42CrMo4	5 mm	BERUFORM STO 121 ZF	33,000
P6	Type Bd	BOEHLER S290	PLATIT FEINAL PLUS	42CrMo4	5 mm	BERUFORM STO 121 ZF	33,000
P7	Type Ca	BOEHLER S390	PLATIT FEINAL PLUS	58CrV4	6 mm	BERUFORM XFO 2577	10,800
P8	Type Ca	BOEHLER S390	PLATIT FEINAL PLUS	58CrV4	6 mm	RENOFORM FMO 5020	2,000
P9	Type Ca	BOEHLER S390	PLATIT FEINAL PLUS	100Cr6	6 mm	RENOFORM FMO 5020	2,000
P10	Type Cb	BOEHLER S390	PLATIT FEINAL PLUS	58CrV4	6 mm	RENOFORM FMO 5020	2,000
P11	Type Cb	BOEHLER S390	PLATIT FEINAL PLUS	C75S	6 mm	RENOFORM FMO 5020	700
P12	Type Cb	BOEHLER S390	PLATIT FEINAL PLUS	C75S	6 mm	RENOFORM FMO 5020	1,000

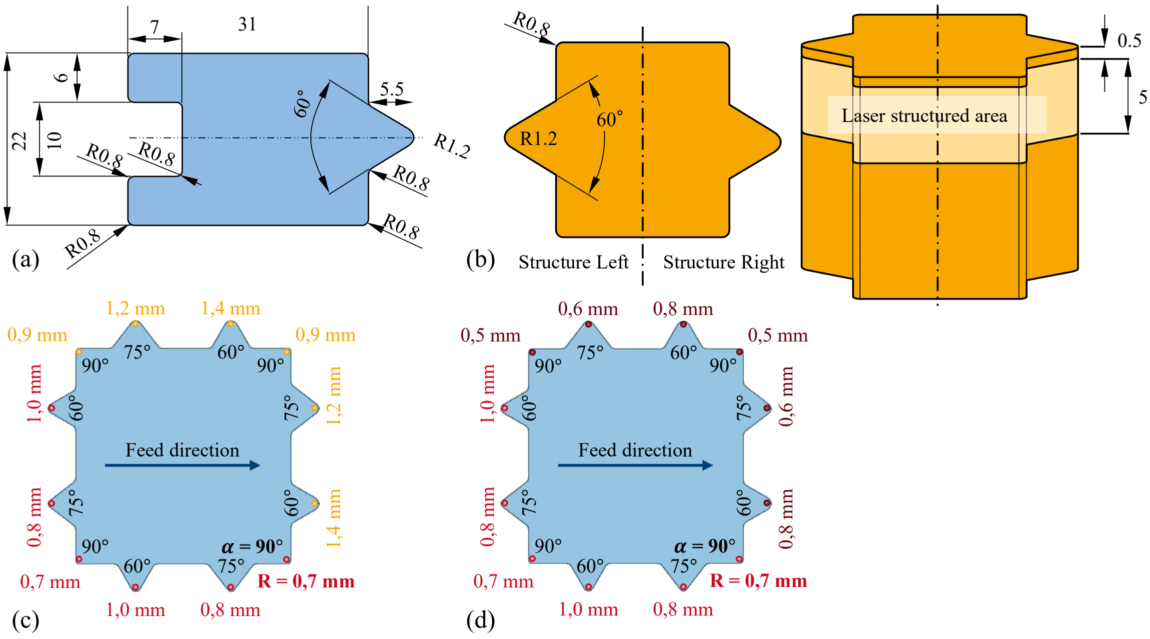

Fig. 1. Part geometry families: (a) Type A dimensional specifications, (b) Type B variants showing structure symmetry and laser-structured area in top view as well as the schematic 3D punch model. The left/right sides of punches feature different laser textures, which are not examined in this study. (c) Type Ca dimensional specifications, (d) Type Cb dimensional specifications.

Across all production runs, the last scrap web from each experiment was collected to represent the state of the shearing interface at the end of tool life or at the end of the experimental run. These scrap webs, together with the worn punches, were subsequently characterized using a KEYENCE VR-6000 3D optical profilometer to quantify wear morphology and to extract corresponding roughness parameters on both tool and sheared surfaces. Following rotation and leveling correction, the measurable flat regions along the shearing edges were segmented into uniformly distributed edge segments per punch, consistent with established procedures for spatially resolved wear characterization. Several segments exhibiting irregular production-induced artefacts, or severe mechanical damage that would bias the roughness statistics were excluded. Across all 12 punches, this yielded a total of 415 valid edge segments.

For each retained edge segment, surface regions were defined with punch surfaces extending 2 mm below the shearing edge as shown in Figure *2*. For each edge segment, 21 areal roughness parameters from ISO 25178 were extracted, and proportion of the worn area (Eq. (1) and normalized removed volume (Eq. 2) were measured.

$$\text{Worn area proportion} = \frac{\int_0^b \mathrm{W(x)dx}}{\mathrm{b \cdot 2\,mm}} \tag{1}$$

$$\text{Normalized removed volume} = \frac{\text{Removed volume}}{\mathrm{b \cdot 2\,mm}} \tag{2}$$

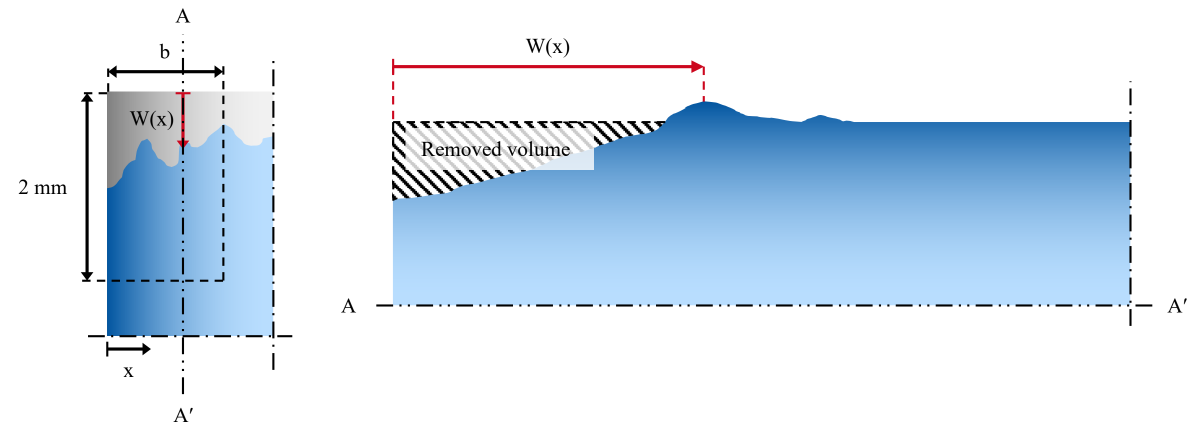

Fig. 2. Schematic representation of punch wear measurement methodology. Left: Cross-sectional view (A-A') showing segment width b, surface Region W(x), and 2 mm evaluation depth. Right: Longitudinal section illustrating the removed volume (hatched area).

To ensure one-to-one spatial correspondence between punch segments and scrap web segments, the corresponding scrap web sheared surface segments, representing the contact areas with the punch, were further subdivided into five equally spaced sub-areas along the shearing direction. Sub-area heights were 1 mm for 5 mm sheet thickness and 1.2 mm for 6 mm sheet thickness. 21 areal roughness parameters are extracted for each sub-area, yielded sequences of five values per roughness parameter for each segment, representing the spatial evolution of sheared surface features along the shearing direction. To characterize the shape and variability of these sequences, 27 statistical and temporal features were extracted using the Python TSFEL library, resulting in 567 sequence-derived features per scrap web segment.

Based on the spatially resolved measurements, the problem is formulated as two-step multivariate regression tasks in which a shared feature matrix **X** is used to jointly predict two punch wear indices. Specifically, the input Matrix $\mathbf{X} \in \mathbb{R}^{415\times p}$ contains either p punch areal roughness parameters or p scrap web sequence-derived features for 415 edge segments, while the output matrix $\mathbf{Y} \in \mathbb{R}^{415\times 2}$ comprises the worn area proportion and the normalized removed volume. The relationship is expressed as:

$$\mathbf{Y} = \mathbf{XB} + \mathbf{E}, \tag{3}$$

where $\mathbf{B} \in \mathbb{R}^{p\times 2}$ contains target-specific regression coefficients and **E** represents residual errors. The objective of this study is therefore twofold. First, it aims to identify which punch surface areal roughness parameters most robustly describe the spatial manifestation of wear on the shearing edge. Second, it seeks to determine whether these wear-relevant punch-parameters can subsequently be inferred from scrap web sequence-derived features, enabling indirect punch wear assessment.

Before using the defined wear indices as supervision targets for indirect monitoring, it is first assessed whether they can be consistently explained by plausible punch surface roughness descriptors (Task T1). Next, whether the same wear indices can be inferred from scrap web sheared surface features, enabling indirect wear assessment (Task T2). Therefore, the modelling framework must satisfy two following requirements:

1. The shearing process is influenced by several interacting factors, such as lubrication, contact conditions, and complex wear mechanisms. These mechanisms can interact in ways that may introduce nonlinear relationships between the measured scrap web features and the punch roughness parameters. A regression model therefore needs the capacity to capture potential nonlinear relationships and feature interactions, without requiring strong assumptions about their exact structure. Gradient-boosted decision-tree models, such as *CatBoost*, are well suited for this purpose, as they can represent nonlinear feature interactions, handle heterogeneous feature scales, and remain robust under limited sample sizes [9].

2. The dataset is composed of segments originating from different punches, materials, lubricants, and production campaigns, resulting in heterogeneous operating conditions and clustered data structures. A suitable modelling framework must therefore provide a reliable estimate of how well the learned relationships generalize across different experimental contexts. To meet this requirement, the evaluation strategy must explicitly respect the grouping structure of the data and ensure balanced representation of wear states across training and test sets, which is achieved by employing 5-fold group-stratified cross-validation (CV). For both tasks, SHAP values were therefore computed exclusively on out-of-fold predictions within the CV procedure and aggregated across folds, ensuring that the resulting feature attributions reflect robust and generalizable relationships rather than artefacts of a single model fit.

Results and Discussion

For the first task, all 21 punch areal roughness parameters were used as input features, while the proportion of worn area and the normalized removed volume served as target variables representing punch wear. Model training and evaluation were performed using a multitask *CatBoost* regression model, allowing both wear metrics to be learned jointly while exploiting shared structure between them. To ensure that the identifying wear-related punch parameters are not driven by a single train-test split, model evaluation was performed using 5-fold group-stratified CV. Table 2 summarizes the fold-wise cross-validated R^2 values for both wear metrics, demonstrating consistently high and stable predictive performance across all folds.

Table 2. Group-stratified cross-validated R^2 for predicting punch wear indices from punch areal roughness parameters (Task T1).

Fold	Worn area proportion	Normalized removed volume
1	0.919	0.975
2	0.927	0.955
3	0.912	0.942
4	0.824	0.930
5	0.864	0.925

Subsequently, SHAP values were computed in an out-of-fold manner for each fold and aggregated across folds, yielding robust global importance estimates that reflect contributions under unseen experimental conditions. Figure *3* shows the global SHAP importance for worn area proportion and normalized removed volume. While several roughness parameters contribute to both targets, a small subset consistently dominates across wear metrics. In particular, parameters related to material volume and bearing ratio (mostly *Vmc*, *Smr1*, and *Smr2*) exhibit the highest and most stable SHAP contributions. This indicates that volumetric surface characteristics are most informative for describing the spatial manifestation of punch wear.

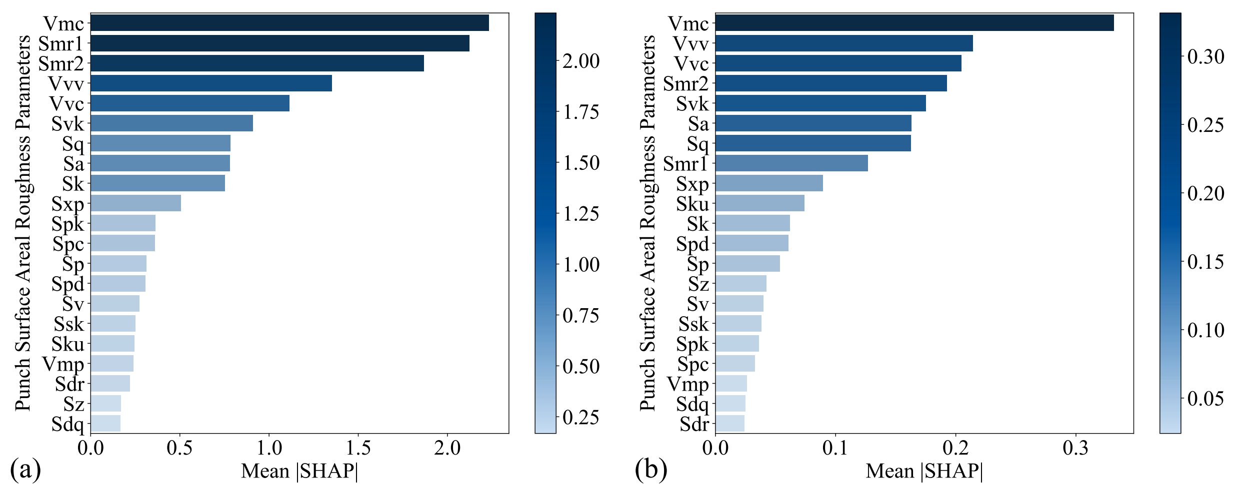

Fig. 3. Global SHAP importance plots for multitask prediction of (a) worn area proportion and (b) normalized removed volume from punch areal roughness parameters.

While several parameters contribute to both targets, Table 3 highlights those punch areal roughness parameters that combine high SHAP importance, cross-target relevance, and stable contributions across folds. The reported SHAP standard deviation (denoted as "SHAP std" in the table) quantifies the variability of the fold-wise mean absolute SHAP values across the 5 CV folds and therefore reflects the stability of each feature's contribution under changing training-test splits. Parameters related to material volume and bearing ratio (*Vmc*, *Smr1*, *Smr2*) dominate both target wear metrics. In particular, *Vmc* consistently exhibits the highest importance for both the worn area proportion and the normalized removed volume, indicating that the defined wear metrics align mostly with the core material volume of the punch surface.

Table 3. Punch roughness parameters with highest SHAP importance for both punch wear metrics.

Punch roughness parameter	Worn area proportion			Normalized removed volume		
	Mean |SHAP|	SHAP std	Rank	Mean |SHAP|	SHAP std	Rank
Vmc	2.333	0.255	1	0.331	0.031	1
Smr1	2.123	0.300	2	0.127	0.030	8
Smr2	1.867	0.584	3	0.192	0.069	4
Vvv	1.351	0.388	4	0.214	0.065	2
Vvc	1.113	0.197	5	0.204	0.044	3
Svk	0.910	0.175	6	0.175	0.018	5

The worn area proportion is primarily influenced by bearing-ratio-related parameters (*Smr1*, *Smr2)*, and by volumetric descriptors such as *Vmc* and *Vvv*, which together describe how the contact area grows and how material spreads along the punch edge as the surface wears. This indicates that the worn area proportion predominately captures the spatial spread of wear and surface flattening. In contrast, the normalized removed volume shows stronger associations with valley- and volume-related parameters, including *Vmc*, *Vvc*, *Vvv*, and *Svk*. These parameters characterize the amount of material available below the dominating surface level and the capacity of valleys to accommodate material removal. Accordingly, the removed volume index reflects the depth-related progression of wear, emphasizing material loss below the original surface.

While Task T1 demonstrates that the defined wear indices are consistently explained by physically plausible punch surface descriptors, the punch surface itself is not accessible for inline or in-process monitoring. Therefore, the subsequent task focuses on assessing whether the same wear indices can be inferred indirectly from the sheared surface characteristics of the scrap web.

For the second task, all 567 sequence-derived features extracted from scrap were used as input features, while the proportion of worn area and the normalized removed volume on the punch served as target variables. Similar to the task before, a multitask *CatBoost* regression model was employed to jointly learn both wear metrics, and model evaluation was again performed using 5-fold groupaware CV with substantial out-of-fold SHAP analysis. Table 4 reports the fold-wise cross-validated R^2 values for this indirect prediction task.

Table 4. Group-stratified cross-validated R^2 for predicting punch wear indices from scrap web sequence-derived features (Task T2).

Fold	Worn area proportion	Normalized removed volume
1	0.416	0.297
2	0.746	0.767
3	0.707	0.712
4	0.464	0.543
5	0.576	0.558

Compared to Task T1, the predictive performance is lower and exhibits higher fold-to-told variability. This behavior is expected, as Task T2 addresses a substantially more complex problem, that punch wear is not directly observed but must be inferred indirectly from surface features of the scrap web, which are influenced by additional factors such as local material flow, fracture behavior, lubrication and process variability. Consequently, moderate and variable R^2 values reflect the natural difficulty of the indirect mapping. Despite the reduced predictability, the cross-validated performance remains consistently positive across folds, providing sufficient signal for meaningful SHAP-based identification of wear-related scrap web features.

Figure *4* shows the resulting global SHAP importance of scrap web roughness parameters for normalized removed volume and worn area proportion. In contrast to the previous task, where a small set of volumetric punch parameters clearly dominated, the scrap web-based models exhibit a broader distribution of contributing features, reflecting the indirect and more entangled nature of the information transfer from scrap web to punch.

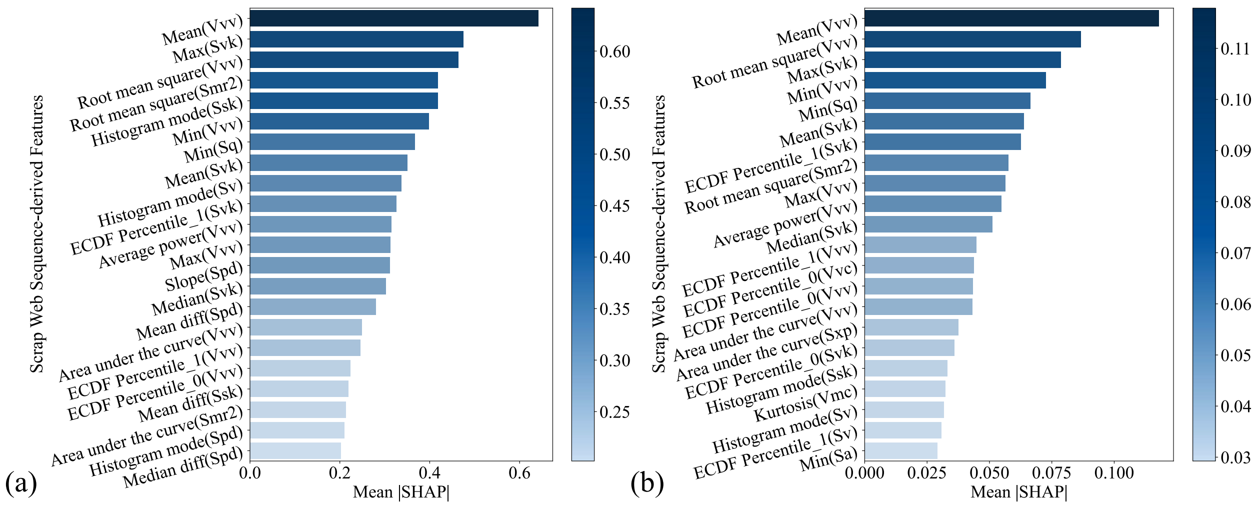

Fig. 4. Global SHAP importance plots for multitask prediction of (a) worn area proportion and (b) normalized removed volume from scrap web sequence-derived features.

Across both wear metrics, descriptors related to valley void volume and depth on the sheared surface of the scrap web characteristics (*Vvv*) consistently appear as the most influential features. Statistical measures such as mean and root mean square (RMS) of *Vvv* dominate the SHAP rankings for both targets, indicating that punch wear is strongly reflected in the scrap web through changes in valley formation during the shearing process. Beyond *Vvv*, parameters related to core roughness depth (*Svk*) and bearing-ratio characteristics (*Smr2*) also show relevant contributions, suggesting that wear progression affects not only the deepest valleys but also the transition region between plateaus and valleys. The presence of histogram-based and empirical cumulative distribution function (ECDF)-based descriptors among the top-ranked features further suggests that wear information is encoded in changes to the overall distribution of surface heights and depths on the sheared surface of the scrap web, rather than in simple shifts of average roughness alone. Table 5 summarizes those scrap web sequence-derived features that combine high SHAP importance, relevance across both wear metrics, and stable contributions across CV folds.

Table 5. Scrap web sequence-derived features with SHAP importance across both punch wear metrics.

Scrap web sequence-derived features	Worn area proportion			Normalized removed volume		
	Mean |SHAP|	SHAP std	Rank	Mean |SHAP|	SHAP std	Rank
Mean(Vvv)	0.642	0.291	1	0.118	0.047	1
Max(Svk)	0.475	0.240	2	0.079	0.041	3
RMS(Vvv)	0.463	0.247	3	0.087	0.045	2
RMS(Smr2)	0.418	0.153	4	0.058	0.022	8
Min(Sq)	0.367	0.194	7	0.066	0.035	5

The worn area proportion is most strongly influenced by features capturing the overall magnitude and spread of valley structures, such as *Mean(Vvv)* and *RMS(Vvv)*. These descriptors reflect how extensively deep valleys are formed along the sheared surface and how uniformly they are distributed across the sequence. Their prominence suggests that the worn area proportion is primarily sensitive to the spatial extent and consistency of surface degradation, rather than a few isolated deep scratches or peaks. In contrast, the normalized removed volume shows relatively higher sensitivity to features related to local depth irregularities and pronounced spatial variability of surface height, such as *Max(Svk)* and *Min(Sq)*. Increased material removal at the punch edge indicates a more advanced wear state, in which the punch no longer provides a sharp and well-defined shearing interface. It suggests that the initial shearing process becomes less uniform and less clearly localized due to weakened local shearing force, leading to a more irregular sheared surface on the scrap web. These effects are reflected in deeper valleys and increased depth variability rather than in changes of the overall contact extent.

Summary

This study investigated the spatially resolved measurements of worn punches and corresponding scrap web sheared surface across 12 punches with varying geometries, materials, lubricants, and production lengths to establish robust and physically interpretable indicators of punch wear. Two physically motivated wear indices, the worn area proportion and the normalized removed volume, were defined to describe representative aspects of punch wear. In Task T1, multitask regression analysis demonstrated that these wear indices can be consistently explained by a small set of punch surface roughness parameters, primarily related to material volume and bearing ratio. In Task T2, the same wear indices were inferred indirectly from scrap web sequence-derived features. Explainable SHAP analysis revealed stable and physically interpretable feature contributions, primarily related to valley depth and distribution, demonstrating that punch wear leaves a measurable and systematic imprint on the scrap web sheared surface across varying process conditions.

The presented approach has several limitations that point to directions for future work. First, while robust feature-level indicators were identified, the study does not yet provide a single aggregated wear index suitable for direct industrial deployment. Second, the indirect inference from scrap web surfaces remains sensitive to process variability, such as local material flow and fracture behavior, which were not explicitly modeled. Future research should therefore integrate additional process signals (e.g., force or AE) to further develop indirect wear inference. Moreover, extending the framework toward temporal modeling across tool life, rather than end-of-run characterization, would enable punch wear footprint assessment. Finally, validating the identified indicators in online or quasi-inline measurement setups will be essential to translate the proposed methodology into practical tool condition monitoring systems.

Acknowledgements

Funded by the Deutsche Forschungsgemeinschaft (DFG, German Research Foundation) under Germany's Excellence Strategy – EXC-2023 Internet of Production – 390621612.

References

[1] Siemens AG, The True Cost of Downtime 2024 (2024).

[2] C. Kubik, M. Becker, D.-A. Molitor, P. Groche, Towards a systematical approach for wear detection in sheet metal forming using machine learning, Prod. Eng. Res. Devel. 17 (2023) 21–36. https://doi.org/10.1007/s11740-022-01150-x.

[3] M. Becker, P. Niemietz, T. Bergs, Study on the explainability of deep learning models for time series analysis in sheet metal forming, Procedia CIRP 126 (2024) 727–732. https://doi.org/10.1016/j.procir.2024.08.298.

[4] P. Niemietz, M. Fencl, T. Bergs, Study on learning efficient stroke representations in clocked sheet metal processing: theoretical and practical evaluation, Prod. Eng. Res. Devel. 17 (2023) 279–289. https://doi.org/10.1007/s11740-023-01182-x.

[5] M. Unterberg, Data-driven indirect tool condition monitoring in sheet-metal stamping. Dissertation, 1st ed.

[6] A. Frigge, M. Unterberg, T. Kaufmann, P. Niemietz, T. Bergs, Enhancing Crack Prediction in Fine Blanking Through Multi-sensor Data Fusion, in: W.-G. Drossel, S. Ihlenfeldt, M. Dix (Eds.), Production at the leading edge of technology: Proceedings of the 14th Congress of the German Academic Association for Production Technology (WGP), Chemnitz University of Technology, December 2024, Springer, Cham, 2025, pp. 153–161.

[7] L. Ortjohann, M. Becker, P. Niemietz, T. Bergs, Material-data-driven prediction of sheared surface tears of fine blanked parts, in: Material Forming: ESAFORM 2024, Materials Research Forum LLC, 2024, pp. 1416–1425.

[8] J. Moon, M. Unterberg, P. Niemietz, T. Bergs, Spatial Correlation Analysis between Punch and Scrap Web Sheared Surface Roughness for Indirect Punch Wear Assessment in Sheet-metal Forming, in: Congress of the German Academic Association for Production Technology WGP 2025 (accepted).

[9] L. Prokhorenkova, G. Gusev, A. Vorobev, A.V. Dorogush, A. Gulin, CatBoost: unbiased boosting with categorical features (2017). https://doi.org/10.48550/arXiv.1706.09516.

The publication of this article was funded by the RWTH Aachen University 10.13039/501100007210