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Towards a systematical approach for wear detection in sheet metal forming using machine learning

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Abstract
Wear is one of the decisive factors for the economic efficiency of sheet metal forming processes. Thereby, progressive wear phenome lead on the one hand to a poor workpiece quality and on the other hand to tool failure resulting in high machine downtimes. This trend is intensified by processing high-strength materials and the reduction of lubricant up to dry forming. In this context, data-driven monitoring methods such as machine learning (ML) provide the potential of detecting wear at an early stage to overcome manual and cost-intensive process inspections. The presented study aims to provide a ML based inline quantification of wear states within sheet metal forming processes. The development of this monitoring approach is based on a procedure model the Knowledge Discovery in Time series and image data in Engineering Epplications (KDT-EA) which is validated on two forming processes, blanking and roll forming, that strongly differ in their physical process behavior and their acquired process data. The presented inline quantification allows an estimation of wear states with a deviation of less than 0.83% for the blanking process and 2.21% for the roll forming process from the actual wear state. Furthermore, it is shown that combining different feature extraction methods as well as a compensation of unbalanced data using data augmentation techniques are able to improve the performance of the investigated ML models.

Keywords Sheet metal forming · Roll forming · Blanking · Machine learning for forming · Wear detection

1 Introduction

Forming processes represent one of the most economical steps in the value-added chain in manufacturing industry. Compared to additive manufacturing or machining, forming processes are characterized by an optimum utilization of material and lower specific energy costs per manufactured workpiece [1, 2]. Even with these technical and economic advantages, forming companies are under high cost pressure caused by low margins per product. As a result, manufacturers are faced with the challenge of optimizing the degree of utilization of their processes while ensuring high quality standards [3]. In this context, one of the main cost drivers of forming processes is the wear-related failure of machines or tools and the resulting deteriorated quality of the workpiece. The impact of wear on the profitability in such processes increases through the environmental sustainability demanded by the automotive industry. This forces companies to process high-strength materials using only low amounts of lubricant, which especially accelerates abrasive wear phenomena [4, 5]. Due to this trend, wear is identified as the major cause for unplanned machine downtimes [6], required removal of tools [7] or the failure of the whole system [8]. In order to achieve an inline estimations about the actual wear state within a sheet metal forming process and to plan maintenance properly, data driven techniques like ML help to generate this process knowledge by identifying highly complex and non-linear patterns in given data sets [9]. Especially in sheet metal forming processes, where a description of the interdependencies between wear, process parameters and workpiece properties is no longer possible by analytical and empirical models, ML offers the potential to describe and even predict these correlations. As a framework for the application of such ML approaches, trustworthy holistic procedure models play a crucial role. Fayyad's Knowledge Discovery in Databases (KDD) approach was developed as one of the first procedure models to support the systematic implementation of ML models in practice and

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to assist personnel in extracting useful information (knowledge) from the rapidly growing volumes of data, taking the overall data management of the process into account [10]. This KDD approach was extended in the following years by Chapman et al. as well as Huber et al. for the use in engineering applications, considering the underlying database as well as the related process knowledge [11, 12]. Kubik et al. extended the existing procedure model with the KDT-EA to include the step of data acquisition and adapted the steps of data preparation, data transformation as well as modelling to the boundary conditions of manufacturing processes [13]. Thereby, the KDT-EA focuses on the use of process-related time series and image data, and allows an adaptation of each single step by inserting domain knowledge. Even though the use of holistic procedure models in combination with ML models offers major advantages for inline estimation of the actual process state, few authors have investigated the actual application of such models in practice. In particular, establishing ML models for inline wear estimation in sheet metal forming processes are rarely found in the literature. Especially, no study demonstrates that the application of holistic procedure models is transferable to multiple processes, taking highly divergent time series characteristics into account. But especially sensorial acquired data in sheet metal forming process show a heterogeneous characteristic from stationary to highly dynamic and transient profiles. Therefore, the aim of this study is to demonstrate that knowledge from sheet metal forming processes can be generated by the systematic procedure model KDT-EA, despite the heterogeneity of the physical process sequence and the characteristics of the underlying data. As use cases, a blanking process characterized by a transient, stroke-related force signal and a roll forming process characterized by continuous and stationary torque signal are considered. In both cases abrasive wear states are to be estimated inline by an artificial neuronal network (ANN). Special attention will be paid to the selection of features extracted during the transformation phase of the KDT-EA. The aim is to validate the accuracy and reliability of different feature types (model-based features and engineered features) as well as combine them in order to increase the model's ability to inline estimate the current wear state. Since the data from the roll forming process is not generated in sufficient quantity and shows an unbalanced characteristic, a data augmentation technique is performed in the data preparation step of the KDT-EA to expand the data set and thus increase the model performance. Therefore, the study is structured as follows and orients itself on the procedure of the KDT-EA. Section 3 discusses the experimental set up of this study and the characteristics of the given time signals during blanking and roll forming. In Section 4, features are extracted from the given time series. This transformation is done on the one hand by a feature engineering approach and on the other hand by a model-based dimension reduction approach using a principal component analysis (PCA). Finally, in Section 5 the ability to estimate abrasive wear states depending on the extracted set of features and their combination is quantified.

2 Data-driven methods for tool wear estimation in sheet metal forming processes

2.1 The blanking and roll forming process

Blanking is generally one of the most frequently used manufacturing processes in sheet metal forming and represents the most efficient step in the process chain. Nearly every manufactured workpiece is trimmed in its intermediate contour and separated from the semi-finished product [14]. As shown in Fig. 1, a blanking process is divided into three phases according to the force–displacement curve. In the punch-phase (I), the punch impacts on the sheet metal and starts to elastically deform the material. If the occurring stresses exceed the maximum shear strength of the material, it tends to deform plastically. When the shearing stress finally exceeds the shear fracture limit, the material tears and the stored elastic energy is abruptly released. In the following push-phase (II), the workpiece or the grid-shaped discard is completely pushed out of the die and the punch passes through the bottom dead center. Finally, the punch is pulled out of the die in the withdraw-phase (III) and withdrawal forces occur as a result of jamming between the sheet and the punch.

Roll forming is a continuous forming process with a potentially high output rate. In roll forming, the sheet metal is transported through several forming steps by rotating tools and formed according to the tool shapes. Since the diameters of the tool vary along the rolls width due to their given tool shape, the circumferential speeds deviate locally from the sheet speed, resulting in various slip conditions. As a result,

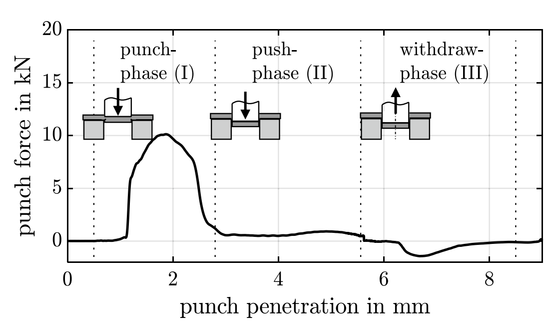

Fig. 1 Force-displacement curve during blanking of sheet metals separated in three characteristic phases [15]

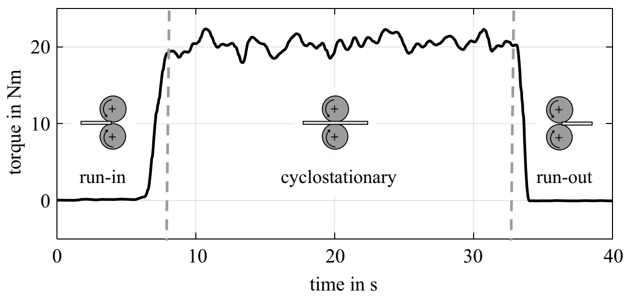

Fig. 2 Torque-time curve during roll forming of the lower roller tool with cyclostationary phase between move in and out phases

both rolling friction and sliding friction occur, whereas the sliding friction lead to tool wear [16].

Figure 2 shows the torque over time curve of the lower forming roll. The cyclostationary phase characterizes the continuous roll forming process, whereas its duration depends on the sheet or coil length. During the move in and move out phases, the torque increases or decreases linearly.

2.2 Wear phenomena during blanking and roll forming processes

In sheet metal forming, a trend towards the processing of Advanced High-Strength Steel (AHSS) is emerging. Especially in the automotive industry, such materials are used to reduce weight or optimize crash performance [17]. In addition, driven by the demand for sustainable production, the manufacturing industry has set itself the goal of avoiding lubricants as far as possible in the processing of AHSS [18]. However, the low-lubricant processing of high-strength materials has led to an increase in abrasive wear phenomena. A significant correlation between the strength of the sheet material and the resulting abrasive wear is observed. Hohmann et al. discovered this dependency in their work investigating force–displacement curves extracted from a blanking process in long-term experiments. While soft coil material (< 400 MPa) is prone to adhesive wear, a significant increase in wear volume was observed when processing high-strength materials (> 850 MPa) [19]. In addition to these findings, a geometric change of the tool contour caused by abrasive wear significantly affects the quality of the formed workpieces [20].

To ensure the resilience of the process despite increased wear caused by low-lubricant processing of AHSS, it is necessary to obtain real time information on the tool wear conditions without stopping the process or performing time-consuming and costly inspections. In the literature, this challenge is mainly faced by estimating the wear state by analytical or empirical models. An example for this approach is the model according to Archard, which estimates the wear volume as a function of the wear coefficient, the normal force, the tool hardness and the sliding distance [21]. While the tool hardness and sliding distance are constant or pre-known parameters, the normal force (depending on the machine and tool parameters, wear condition, etc.) as well as the wear coefficient (depending on the material pairing, temperature, lubricant, etc.) are estimated.

Over the last decade, many experimental and empirical studies have been conducted to understand wear in blanking and roll forming processes. On the one hand, they investigated the influence of tool parameters (e. g. forming [22] or cutting [23] edge radii) and machine parameter (e. g. stroke rate [24, 16] or feeding speed [16]) as well as properties of the semi-finished product (e. g. sheet-metal thickness [25]) on the wear evolution. On the other hand, the influence of occurring wear on the quality of the manufactured workpieces was investigated [8, 26]. In addition to these empirical and experimental investigations, great progress has been made in the 2D and 3D numerical simulation of wear phenomena. Using computational methods in blanking, several authors tried to predict tool wear and the resulting form errors on the blanked workpieces [27] to optimize process parameters and reduce these errors [28]. In roll forming by contrast, to the knowledge of the authors only one analytical approach to predict wear based on the prevailing contact normal stresses is known [16].

Since wear and its characteristics depend on a large number of parameters, a quantitative description of wear by simulations is only possible to a limited extent. This also applies to analytical or experience-based models, which cannot estimate temporary wear events at all and progressive wear only to a limited extent. A detailed description of wear states requires the process to be stopped and the tools to be disassembled and visually inspected. In order to avoid this step of manual inspection and to enable a quantitative description of the wear state in real time, an intelligent analysis of available in-process data is necessary.

2.3 Data-driven methods for tool wear prediction

In practical application, the identification of wear in sheet metal forming processes is limited to condition monitoring systems, which focus on the detection, isolation and identification of errors as they occur [29]. In these systems, domain specific knowledge is necessary to determine thresholds and envelopes. In this case, the full potential of the data is not used and is limited to identifying discrete faults [30, 31]. These error types describe a binary condition (ok/nok) of the machine and tool (e. g. protecting the press by achieving maximum process force to prevent overload and system failure) as well as the quality of the manufactured workpieces. Identification of error-cause dependencies, derived from time signals recorded by inline process sensors, does not take place in industrial practice. In contrast, studies are found in the literature that show approaches to fully exploit the potential of existing process data to identify faulty process conditions and assign them to a specific cause [32]. From a theoretical point of view, this data-driven fault diagnosis fits a model to describe the system behavior by acquired process data. These approaches are either use engineering or numerical models, such as sensitivity analyses, linear regressions or Kalman filters, or ML models such as neural networks, decision trees or support vector machines [33]. As an example for an engineering model, Klingenberg and de Boer identified the length of the punch phase during a blanking process and correlated this feature with the onset of wear on the cutting edge of the punch [34]. Hohmann et al. extended these investigations, deriving ten engineered features from force-displacement graphs to quantify different wear states in a blanking process. Thereby, a correlation was found between the extracted features and the number of strokes conducted in the endurance test. This sensitivity analysis proved a dependency between the blanked material, the number of strokes conducted and the type of wear occurring [19]. In their study, Kubik et al. established correlations between the parameters of a blanking tool and 12 handcrafted engineered features determined from a force signal. These correlations served as basis for a decision tree to assist in the detection of varying system properties. In addition, the influence of the blanking tool parameters on the characteristics of the cutting edge surface was investigated [20]. Another paper in this field presented by Hoppe et al. compared engineered features with model-based features extracted by a PCA. These features were used to estimate the abrasive wear state on a blanking tool and the angle in a bending process using a least absolute shrinkage and selection operator regression. Furthermore, the study ranked the extracted features according to their importance for the modelling procedure. However, an analysis and interpretation of why PCA features provide better performance than engineered features, taking into account the physical boundary conditions of the process, was not given. In addition, the influence of combining engineered features with model-based features on the performances was not considered [35].

Regarding wear prediction in roll forming, the authors are not aware of any publication on the topic of consisting data-driven methods. Becker and Groche investigated correlations between tool positions and process data such as driving torques and workpiece geometry to train a classification model of discrete failure classes [36]. Based on a limited amount of data, wear detection was not considered in this approach.

Due to the highly non-linear behavior of sheet metal forming processes, a detailed description of process conditions by means of engineering or numerical models is only possible to a limited extent [25]. In contrast, ML models enable a classification, evaluation as well as prediction of process conditions and have become an important part of the current literature in the domains of machining and health monitoring [37, 38]. The most common regressive ML models for predicting process states that are not analytically describable include polynominal regression analysis, artificial neural networks (ANN), support vector regression (SVR), random forest (RF) and Gaussian process regression (GPR) [39].

Polynominal regression analysis is the simplest ML technique to predict an outcome variable based on the value of one or more input variables. Al-Momani et al. presented a multiple regression analysis (MRA) to predict burr height during a blanking process. The inputs of the MRA model consist of force-displacement graphs generated by a finite element model considering different clearances, sheet metal thicknesses and blank holder forces as well as the simulated burr height. The results showed that the trained MRA model provides an accurate prediction of the burr height [40]. Kirchen et al. developed a model for predicting the homogeneity of the thickness of tailored blanks during a rolling process using an incremental regression method. Experimental results showed that the regression model was able to accurately predict the sheet thickness with a maximum deviation of 5% [41]. Hao et al. developed an interaction model that uses a linear regression model to quantify the onset of wear during a multistage manufacturing process, considering product quality degradation and the interaction between a current stage and a subsequent stage [42].

The RF algorithm is an aggregation of several decision trees and is characterized by fast training procedure, especially with large data sets, and its simple “out of the box” implementation [43]. However, prediction accuracy on complex problems is usually inferior to advanced regression models. Patil et al. used a RF to estimate the quality of a blanked workpiece based on the value of the surface roughness. The model was able to assigned the quality of the blanked surfaces to three different classes with an accuracy of 96% [44]. Even though the implementation process of this model type is very simple, there are only few studies in the area of manufacturing which applied RF for regression.

Another ML technique which has been attracting the interest of researchers for several years are support vector machines (SVM) and its adaption to regression problems (SVR). Ge et al. presented in their work SVMs with different kernel functions to classify erroneous states during a blanking process. The experimental results showed that SVM can achieve a 99% success rate in detecting these faults [45]. Singh und Gupta developed an SVM to classify the spring-back in a W-bending process. Considering the material and tool parameters, the dimensional accuracy and forming quality of the bended workpieces, a relative error between the predicted values and the experimental values of 0.3% was determined [46]. In their study, they presented a one-class SVM for detecting abnormal health conditions (ok/nok) of a progressive stamping machine. To achieve a desirable performance considering a trade-off relationship between the false alarm rate and miss detection rate, hyperparameter of the SVR had to be optimized [47]. Kubik et al. classified five abrasive wear states in a blanking process. However, the focus of this study was not on optimizing the model performance but rather on quantifying the influence of the individual phases of a procedure model on the performance of the SVM. The authors were able to show that the type of sensor used to capture the database and the speed of the process have a significant influence on the performance of ML models.

The Gaussian process regression (GRP) is nonparametric kernel-based probabilistic model which describes probability distributions over functions. The GPR algorithm offers the possibility to directly determine a distribution for the prediction value, rather than just a single prediction value but requires a great computational effort. In literature only a few applications for the GPR in the field of manufacturing and especially in the field of forming are found.

Using ANN in sheet metal forming has been part of the literature for several decades. Many studies are concerned with the spring-back behavior in bending processes [48–50], the error diagnosis and process control in incremental forming [51], and characterization of material properties [52–54]. In contrast, ANN approaches are rarely applied to the identification of wear states in sheet metal forming. Hambli presented a backpropagation neural network algorithm for predicting the burr height formation on blanked workpieces, considering tool clearance and wear state. The inputs of the ANN were generated by a finite element analysis of the circular blanking process. Validating the results from the ANN showed a good agreement with a deviation of 10% between predicted and experimentally determined burr height [55]. A similar procedure was chosen by Stanke et al., who compared the performance of an ANN and SVM for prediction of the die roll height in fine blanking. They demonstrated, that an ANN is able to predict the die height with high accuracy even considering a small data set [56]. Li et al. developed an ANN to predict friction resistance and to estimate wear states considering different surface roughness conditions. Here, the ANN results showed high agreement with the experimentally recorded frictional resistances [57].

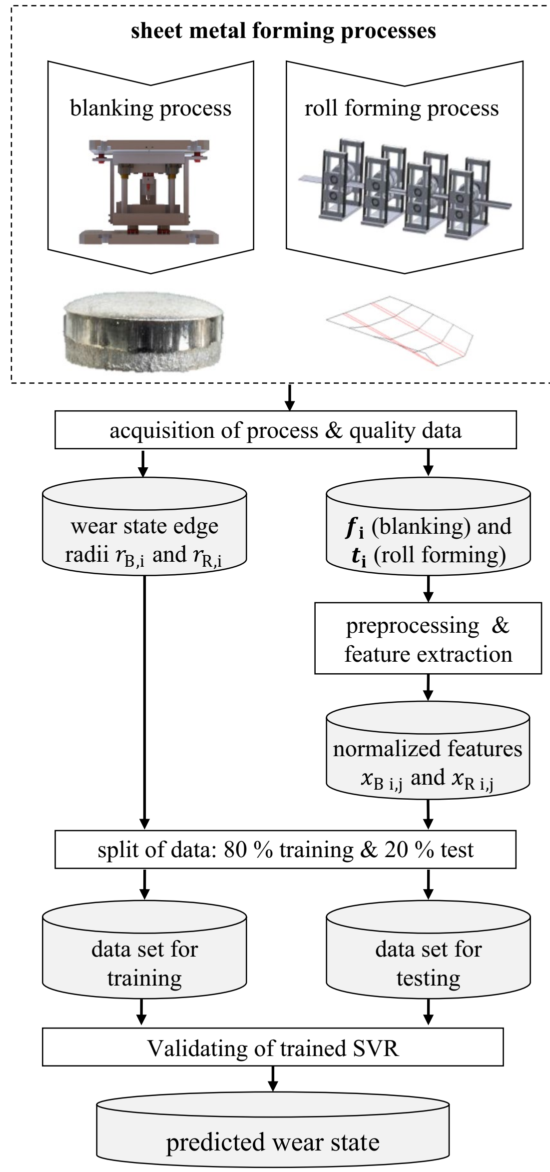

Fig. 3 The required steps for predicting the abrasive wear states including data acquisition, feature extraction and application of ML model

3 Experimental setup and procedure

The procedure to inline estimate abrasive wear states in sheet metal forming processes based on the KDTE-EA is shown in Fig. 3. First, a labled data set consisting of process (force and torque signals) and quality (abrasive wear state) data is generated. While stroke related force signals are measured during the blanking process, torque signals are captured continuously during roll forming. The quality data described by a wear-dependent rounding of the cutting edge radii of the blanking tool and of the roll edge radii is measured offline by an optical system. Subsequently, the acquired time series are preprocessed and characteristic values are extracted by an engineering feature as well as a model-based feature approach. The extracted features are normalized and serve as an input for the modelling step which is carried out with the regression learner toolbox of the software MATLAB 2021b [58]. To choose a suitable regression model a twostep grid search is conducted. In the first step, various regression model types are trained based on their initial hyperparameter configuration. 12 features extracted by a PCA serve as an input for the training process during the first step of selecting a suitable model. The accuracy of each model is quantified by a five-fold cross validation which is 30 times repeated to statistically secure the prediction quality. In the second step, the best model is optimized via a hyperparameter variation. Thereby, the data is split into three subsets. The first subset (training data), which is used for computing the parameters of the model. The second subset (validation data), which is used to monitor the error on the validation data. The third subset (test data), which is used to validate the model with unseen input via the root mean square error (RMSE). Further on the labeled data set is described by the force during blanking $\boldsymbol{F}_i$ and the torque during roll forming $\boldsymbol{T}_i$ as well as the cutting edge radii of the punch r_i^{B} and the edge radii of the roller r_i^{R}. The extracted and normalized features from the labeled data set are described by $r_{\mathrm{PCA},i}^{\mathrm{B}}$ for the model-based features and $r_{\mathrm{ENG},i}^{\mathrm{B}}$ for the engineered features during blanking as well as $r_{\mathrm{PCA},i}^{\mathrm{R}}$ for the model-based features and $r_{\mathrm{ENG},i}^{\mathrm{R}}$ for the engineered features during roll forming.

3.1 Experimental tool and setup

In the case of the blanking process, all experiments for the acquisition of process data were conducted on a Bruderer high-speed mechanical press (BSTA 810). The machine parameters for the experiment were set to a stroke distance of 35 mm and stroke speeds of 300 spm. The geometry of the punch was chosen to be cylindrical with a diameter of 6 mm. In terms of wear investigations, the punch edge radius was varied over five different states. The gap between punch and die is set to 0.15 mm, which results in a clearance of 7.5% using a sheet thickness of 2 mm. A cold rolled steel 1.0347 was used. In case of the roll forming process all experiments were conducted using a Dreistern GmbH roll forming line with four forming steps (P3.070.04). The stand distances are 150 mm and the incremental bending angles of the four stages are 12°, 14°, 16° and 12° to achieve a final flange angle of 56°. The sheet metal has an initial width of 100 mm and is formed in a 2:1 ratio between web and flanges. The tool parameters are 112 mm diameter for the upper and 80 mm diameter for the lower forming rolls. The initial bending radius is 1.0 mm at each forming roll. In terms of wear investigations, the roll edge radius of the upper roll in the last forming stage was varied over four different states. The feed speed of 75 mm/s and the sheet length of 2000 mm were constant for all experiments. A cold rolled dual phase steel 1.0936 with a sheet thickness of 1.0 mm was used.

Table 1 shows the tool and machine parameters as well as the properties of the sheet metal for the blanking and roll forming process.

For data acquisition in the blanking process, a multisensory tool consisting of a lower and an upper workpiece connected by four guide columns is used. The cylindrical punch is connected to the adapter plate in the upper tool via a plunger. A piezo electrical force washer (Kistler 9051C) is integrated into the direct force flux. The distance of the upper tool during the stroke is measured by an eddy current sensor (Micro-Epsilon EU8). Figure 4a shows the detailed design of the tool, its integration into the press and the positioning of the sensor.

For data acquisition in the roll forming process, a strain gauge-based sensor is integrated into a cardan shaft, recording the torque load on the shaft and transmitting the data to a receiver via bluetooth low energy as shown in Fig. 4b. The pre-calibrated cardan shaft measure the torques in both directions of rotation. During roll forming, negative torques often occur at individual rolls due to interactions between neighboring stands caused by different rotational speeds, slip behavior and contact conditions between forming roll and workpiece. The position of the sensor is set to the last upper forming roll where the different wear states are investigated. Since a change of the roll radius is expected to move the position of the highest contact normal stresses between tool

Table 1 Tool and machine parameters and the properties of the sheet metal for conducting the experiments

Blanking		Roll forming	
Tool properties			
Punch diameter in mm	6	Upper roll diameter in mm	112
Clearance in %	7.5	Lower roll diameter in mm	80
Cutting edge radii in µm	7 …358	Roll edge radii in mm	1…4
Tool steel punch	1.2379	Tool steel rolls	1.2379
Machine properties			
Stroke speed in spm	300	Feed speed in mm/s	75
Stroke distance in mm	35	Sheet length in mm	2000
Material properties			
DC03	1.0347	DP 600	1.0936
Tensile strength in MPa	299 ± 2.9	Tensile strength in MPa	651 ± 4.9
Sheet thickness in mm	2 ± 0.02	Sheet thickness in mm	1 ± 0.02

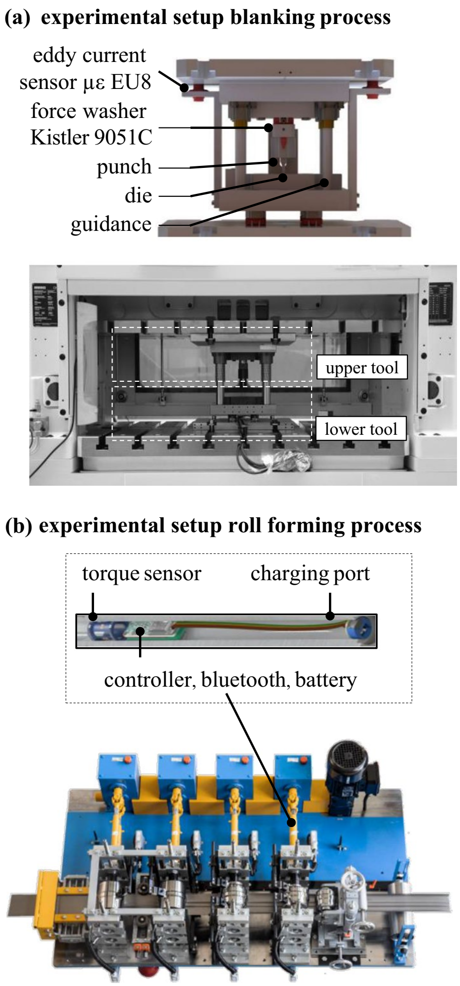

Fig. 4 Experimental set up of the blanking tool (**a**) [15] and the sensorial equipped roll forming line (**b**) [59]

and sheet metal, this slightly changes the driving diameter of the forming roll. In roll forming, the driving diameter is defined as the section of the forming roll where the slip is considered zero and static friction occurs. Former investigations by Traub et al. show that even though a change of the driving diameter at one single forming roll influences the roll torques at several stages of the roll forming line, the major influence occurs at the varied stage [60].

3.2 Acquisition of quality and process data

Quality data described by the abrasive wear states of the punch and the upper roll are optically measured by a confocal white light microscope (NanoFocus AG type µsurf explorer). It is assumed that abrasive wear causes a rounding of the cutting edge radii of the punch in the blanking process and of the roll edge radii in the roll forming process. In order to approximate the reproducible abrasive wear conditions without the need for time-consuming long-term experiments,

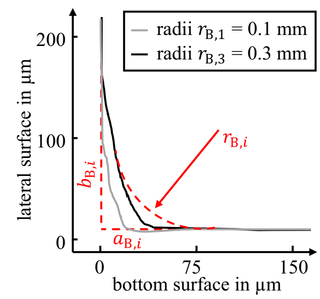

Fig. 5 Actual geometry of the artificially worn blanking tool for the wear sates $r_{B,1}$ and $r_{B,3}$

the edge radii are mechanically rounded by pre-machining. For the blanking process the edge radii is varied in five steps, starting from a sharp cutting edge $r_{B,0}$ to a critical wear state $r_{B,4}$. In case of the roll forming process, the roll edge radii is varied in four steps starting from an unworn roll $r_{R,0}$ to a critical wear state of the roll $r_{R,3}$. In the following discussion of the results, the index *B* stands for the blanking process, the index *R* for the roll forming process using the index 0 for the reference state and the unworn tool condition. For the blanking process, literature suggests differing magnitudes for reaching an excessive wear state. The bearable amount of wear described by the cutting edge radii of the blanking tool is individual for the underlying process configuration and depends on the acceptable degradation of the workpiece quality. Since a critical wear state at the cutting edge has to be specified individually for each process configuration in this study a range up to $r_{B,4} = 358.154$ µm shall be estimated by the developed ML model. This meets the maximum limit of excessive wear which is assumed in the literature in a range of 0.1 mm to 0.4 [34, 55, 61]. Since the cutting edge radii of the punch is artificially generated, its geometry is inspired by a real abrasive wear pattern. Figure 5 shows the actual geometry applied to the punch for $r_{B,1}$ and $r_{B,3}$ measured by a confocal microscope. It demonstrates that the radius gradually tapers off with increasing distance to the bottom of the punch [26]. This results in radial $a_{B,i}$ (face ware) and axial $b_{B,i}$ (flank wear) length of punch, where $a_{B,i} < b_{B,i}$. In order to aggregate the wear lengths to a single label, an approximated value quantified by the edge radii $r_{B,i}$ is defined. Due to the asymmetric distribution of $a_{B,i}$ and $b_{B,i}$ the measured cutting edge radii tends to be smaller as the intended target edge radii (see Table 2). In roll forming, the state of the art provides no empirical data so far on the extent of wear under long-term conditions. Therefore, wear radii of $r_{R,0} = 1$ mm to $r_{R,3} = 4$ mm are selected as to be classified even though the range is larger than the tolerance specifications of the final manufactured profile radius. This is due to intermediate profile deviations within the roll forming process are usually being eliminated by successive forming stages, and thus the contour of a single roll is not regarded as a criterion for the tolerance compliance of the manufactured profile. In addition, the regressive ML model is adaptable to various tool configurations since the model is able to estimate the actual wear state over an extended range of the roll edge radii. By optimizing the selected ML model in this study (see Section 5), a deviation of the roll edge radii < 22 µm is detectable.

Table 2 shows the results of the optically measured wear states represented by the edge radii.

The process data for training the ML model are obtained in both processes by a CompactRIO (NI 9047) with an integrated measuring modul NI 9220 (analog input ± 10 V). During blanking, the vertical process forces are acquired by a piezoelectric force washer with a sampling frequency of 50 kHz. Assuming five wear conditions and 100 experiments conducted per wear state, this results in 500 independent time series. This determines a complete stroke cycle of the Bruderer press from top dead center through bottom dead center back to top dead center. The actual tool engagement time only takes place in a limited angular range. Assuming a stroke speed of 300 spm and an angular range of 160°–210°, this results in a time during data acquisition of 0.07 s per stroke. This leads to approximately 3395 data points per time series. Hence, the raw data for the blanking process are stored in a dimensional matrix $\mathbf{F} \in \mathbb{R}^{500\times3395}$. To keep the amount of data as small as possible, features are extracted from the dimensional matrix F (engineered features and model-based features) by dividing the force signal into three phases according to Kubik et al. (see Section 4). Figure 6 shows the mean and the standard deviation of the acquired force signals including the dimension of the raw data as well as the dimension of the extracted engineered features.

During roll forming, the torque is measured at the upper forming roll in the last pass of the line where mostly abrasive wear occurs. Assuming four wear conditions and five experiments conducted per wear state, this results in 20 independent time series. Thereby, a sheet with a length of 2000 mm was run through the four passes of the roll

Table 2 Experimentally measured wear states

Wear state	Cutting edge radii $r_{B,i}$ in µm	Roll edge radii $r_{R,i}$ in mm
No abrasive wear edge radii r_0	7.624	1.021
Small abrasive wear edge radii r_1	66.717	2.018
Medium abrasive wear edge radii r_2	127.281	3.007
High abrasive wear edge radii r_3	258.459	4.006
Critical abrasive wear cutting edge radii r_4	358.154	–

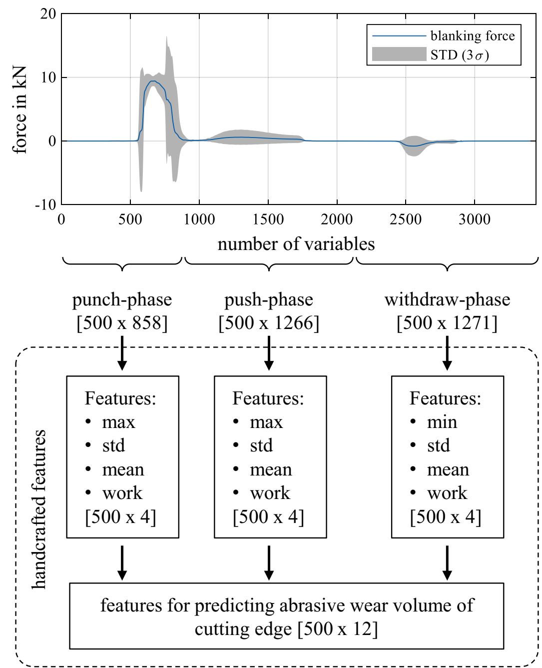

Fig. 6 Extracted features from force signals of the blanking process

forming machine. As a result, each time series consists of a run-in and run-out section as well as a section in which the sheet is fully entered in all stages. Assuming a feed speed of 75 mm/s, a length of 2000 mm of the sheet and a sampling rate of 40 Hz, this results in approximately 1266 data points per time series. Since 20 time series are not enough to train a ML model, a data augmentation technique is used to increase the amount of data. For this purpose, the Synthetic Minority Over-sampling TEchnique (SMOTE) according to Chawla et al. was applied to the data. The SMOTE approach generates synthetic data between each data point of its k nearest neighbors. For each of the samples, the k nearest neighbors are located and new synthetic data is generated between the sample and each of its neighbors. It should be noted, that on the one hand, continuous data is necessary for the SMOTE approach, and on the other hand, the generated synthetic data is linearly dependent. With respect to the SMOTE approach, the amount of data for the roll forming process is increased and stored in a dimensional matrix $\mathbf{T} \in \mathbb{R}^{400\times1266}$. As with blanking, to keep the amount of data as small as possible, engineered features are extracted from the dimensional matrix $\mathbf{T}$. Figure 7 shows the mean and the standard deviation of the acquired torque signals including the dimension of the raw data as well as the dimension of the extracted features.

A Comparison of the data sets for blanking and roll forming demonstrates strongly different time series characteristics, which depend on both the forming process and the sensor type.

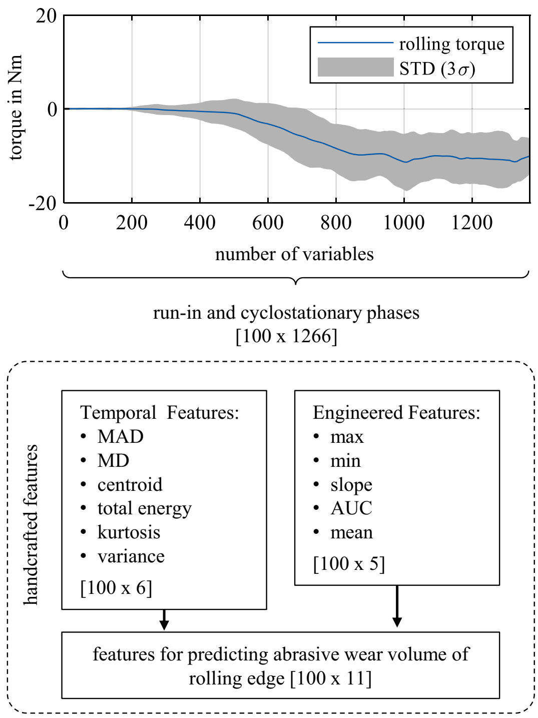

Fig. 7 Extracted features from torque signals of the roll forming process

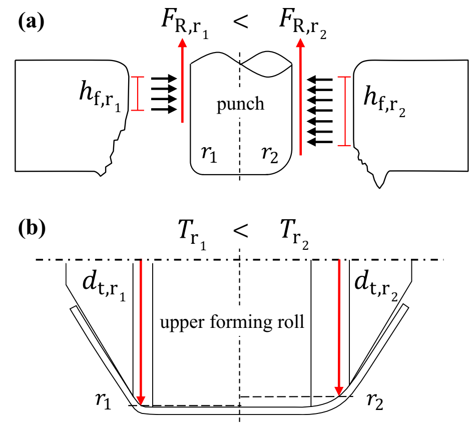

Fig. 8 Dependency of the frictional length h_f and the contact normal force on the frictional force F_{R,r_i} due to a rounding of the cutting edge radii during blanking (**a**) and dependency of the of the driving diameter $d_{t,ri}$ on the torque load T_{ri} due to a rounding of the forming edge radii during roll forming (**b**)

In contrast, the time series for blanking are characterized by a nonlinear, transient and stroke-related profile. Especially, the dynamic effects resulting from the impact of the punch on the sheet metal and the material breakage show up in form of superimposed oscillations. Furthermore, the force signal increases in the push- and withdraw-phase, caused by reinforced frictional forces. After material breakage, there is an elastic spring-back of the sheet metal, which leads to increased contact normal stresses between the lateral surface of the punch and the sheet metal. In addition, the frictional forces in the push- and withdraw-phase are determined by the frictional length. The frictional length is directly correlated to the quality of the cutting edge of the blanked workpiece. In case of a wear-induced rounding, the cutting edge radius of the punch increases. Kubik et al. were able to show that the height of the burr and the shear zone increases with increasing cutting edge radii [20]. The enlarged height of the shear zone increases the frictional length h_f as shown in Fig. 8a. Due to the combination of elastic spring-back of the sheet metal and enlargement of the frictional length, the absolute maximal force in the push- and withdraw-phase increases.

At the sensorial equipped roll forming tool, a negative torque occurs while the sheet runs in. The running-in process is characterized by a transient phase in which the sheet initially enters all forming stages without tensile or compressive stresses. Due to the tensile and compressive stresses that subsequently develop between the interacting forming stages, the sliding and contact conditions initially change until a cyclostationary phase is reached. At this point, the torque reaches a uniform level with oscillations in the range of the rotational frequency of the tool rolls. This process condition is characterized by a continuous industrial roll forming process using sheet metal coils. In case of a wear-induced rounding, the tool edge radius increases. An increasing radius moves the position of the highest contact normal stresses between the tool and the sheet metal outwards. Consequently, the driving diameter $d_{t,ri}$ of the forming roll decreases as shown in Fig. 8b. At this local spot the lower circumferential speed of the forming roll leads to increased slip between the tool and the sheet metal due to the remaining sheet feed of the lower forming roll and the neighboring forming stages. The measured process data show an increased absolute torque level in comparison to the initial unworn state with smaller edge radius.

4 Data transformation

Section 3.2 illustrates that blanking and roll forming processes are characterized by heterogeneous time series. However, in order to show that the KDT-EA is capable of predicting the wear states in this study even for these heterogeneous time series, the data must be transformed . Thus, data transformation aims to reduce dimensionality as well as remove noise and redundancy of given data without removing relevant information [62]. In addition to the feature extraction step, the number of features can be further reduced by a feature selection step to generate an optimal feature subspace for the ML model. Since a large dataset results in high model complexity which leads to poor generalizability of the model and high computational times, feature extraction and selection are a key factor for successful ML projects [63]. According to Li, extracting features from time signals is done either from the time domain, the frequency domain, the time–frequency domain or based on a model approach [64]. In this context, feature from the time domain is straight forward and widely used in sheet metal forming process monitoring, as features can be extracted directly from the time signal. Mostly, these features are statistical parameters such as maximum values, mean values, standard deviations, skewness, kurtosis or the root mean square [65]. Next to these statistical moments of first to fourth order several studies extract engineered features depending on the characteristic of the process-related time series [34]. The feature engineering approach for the blanking process used in this paper is based on the results of Kubik et al. and is shown in Fig. 9a [20]. Therefore, the force signal is initially divided into three phases and characteristic points are identified to define the start and end points as well as the extrema during each phase. Finally, these characteristic points are used to derive the features that can be described by the length $l_{j,i}$, the maximum force $F_{\max j,i}$ and the work done $W_{j,i}$ at each point. In this case, the index j describes the respective phase of the cutting process (punch-phase (p), push-phase (pu), withdraw-phase (w)) and i the number of obervations in the experiments.

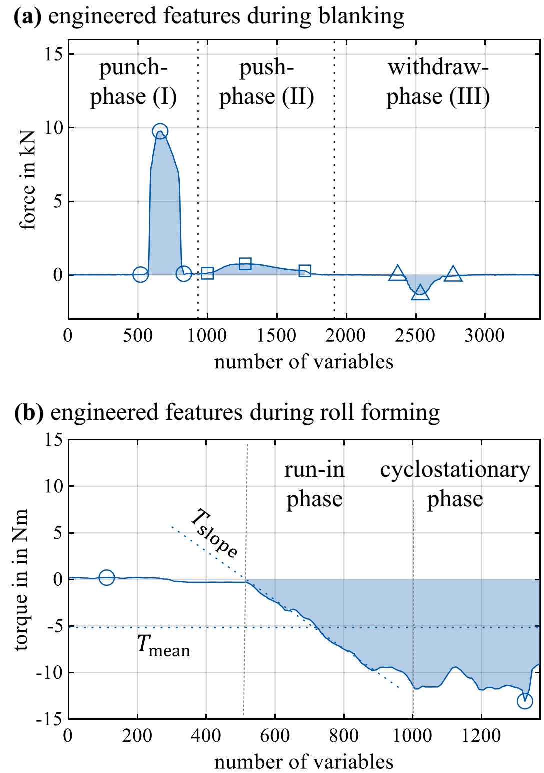

Fig. 9 Extraction of engineered features from blanking (**a**) and roll forming process (**b**)

The features used in this study for the roll forming process are divided into two categories: temporal features and engineered features. The temporal features consider the two mathematical moments of second order *variance* and fourth order *kurtosis*, as well as the mean of the absolute deviations of the data around the mean *MAD* and the mean of the deviations of the data around the mean *MD*. In addition, the area under the squared magnitude of the considered signal *totalenergy* and the center of mass of the time signal *centroid* are taken into account. In the second category, engineered features are extracted based on the results of Becker and Groche as shown in see Fig. 9b [36]. The mean values of the measured data are dependent on many process parameters during the cyclostationary phase. In former investigations, Traub et al. used mean values of the cyclostationary phase to find correlations between the torque data and the driving diameter respectively the circumferential velocity of the tools [60]. During the run-in process, the *slope* and the *area under the curve* change depending on the contact conditions between the roll forming tools and the sheet metal.

In addition to the engineered features, model-based features are automatically extracted from time series using a PCA. In this context, PCA is one of the commonly used data transformation techniques in the literature [66]. In engineering applications, PCA is used for the purpose of quality control [67], condition monitoring [68] and predictive maintenance [69]. PCA is a multivariate statistical technique that handles large amounts of data via orthogonal projection. It reduces the dimensionality of a data set by projecting original data into a lower dimensional space defined by significant eigenvectors. Applied to a blanking and roll forming process, this means searching for a compact representation of the measured force and torque signals that still contains the information about relevant variations. The features of the PCA are derived from the two dimensional matrices $\mathbf{F} \in \mathbb{R}^{m \times p}$ and $\mathbf{T} \in \mathbb{R}^{m \times p}$ in which each row vector $\boldsymbol{f}_i$ is a complete cycle of a force signal and $\boldsymbol{t}_i$ is a complete cycle of a torque signal with p measurement points, and m is the total number of observations. The principal components are computed by solving the eigenvalue problem of the covariance matrix $\boldsymbol{\Sigma} \in \mathbb{R}^{p \times p}$ of the dimensional matrices. The received vector $\boldsymbol{v}_j \in \mathbb{R}^{p \times 1}$ $(j = 1, \ldots, p)$ determines the normalized eigenvector of the covariance matrix. Calculating the dot product between the eigenvector and each row vector in the dimensional matrix results in the feature $f_{\mathrm{Bi,j}}$ from the force signal during blanking and the features $f_{\mathrm{Ri,j}}$ from the torque signal during roll forming. Projecting the data on the eigenvectors, it is often found that only the first few eigenvectors, corresponding to the largest eigenvalues, are associated with the physical-related process variations.

All remaining eigenvectors reflect more and more the variations of the process noise. Therefore, the p features of the original PCA are reduced to ensure that more than 99% of the variance in the force signal can be explained by the p_{opt} largest eigenvalues in this study. This leads to 11 features for the roll forming process $f_{Ri,j}$ with $j \in \{1, \ldots, 11\}$ and to five features for the blanking process $f_{Bi,j}$ with $j \in \{1, \ldots, 5\}$.

In order to compare the different features with each other, two criteria must be met. On the one hand, the features must be normalized by the Z-score. On the other hand, the performance of the ML model must be quantified on the basis of an equal number of features. This is mainly due to the fact that with a growing number of features the informational content of the input to the model increases and thus model performance is expected to improve. For this reason, model-based features determined by PCA and engineered features are reduced to a fixed value of five. In case of the PCA features, this is achieved by selecting the five largest principal axes. On the other hand, the five engineered features with the highest informational content are selected. For this purpose, a feature selection method, the minimum redundancy maximum relevance algorithm (MRMR) is used. The algorithm measures how much uncertainty of one variable A is reduced by knowing the other variable B. Thereby, the mutual information I of the discrete random variable A and B is defined as

$$I(A, B) = \sum_{i,j} P\left(A = a_i, B = b_j\right) \log \frac{P\left(A = a_i, B = b_j\right)}{P\left(A = a_i\right) P\left(B = b_i\right)} \tag{1}$$

The objective of the MRMR algorithm is to find an optimal set S of features that maximizes V_S the relevance of S with respect to a response variable y, and minimizes W_S, the redundancy of S.

$$V_S = \frac{1}{|S|} \sum_{x \in S} I(x, y) \ and \ W_S = \frac{1}{|S|^2} \sum_{x,z \in S} I(x, z) \tag{2}$$

At this point, it should be noted that the procedure of feature selection risks losing essential information for predicting process with an ML model [35]. Figures 10 and 11 show the feature importance for the blanking and the roll forming process.

In summary, the features kurtosis, MAD, mean, variance and centroid are used for further modelling in case of the roll forming process. For the blanking process, the engineered features work done in each phase W_j as well as the absolute maximal force in the punch phase $F_{max,p}$ and withdraw phase $F_{max,w}$ are used as input the ML model. In addition to these engineered features the five most relevant PCA features are considered in both processes for the modeling step.

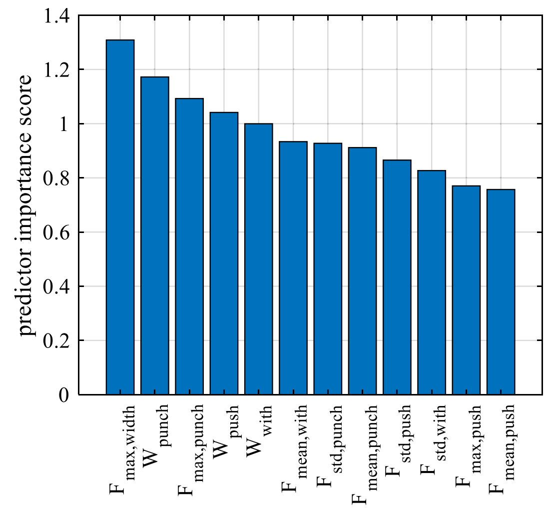

Fig. 10 Importance of engineered features extracted from the force signal during blanking

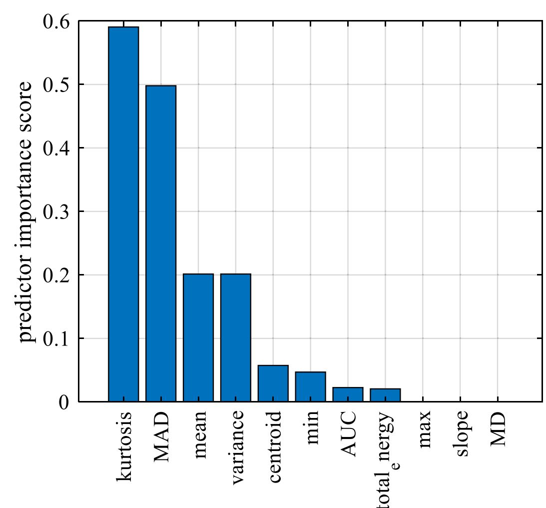

Fig. 11 Importance of features extracted from the torque signal during roll forming

5 Tool wear prediction using ANN

5.1 Selection of regressive ML model

To inline estimate the wear states of the blanking as well as roll forming process a suitable regression model has to be selected. Therefore, various regression model types are trained based on their initial hyperparameter configuration. As reference input data, to compare the ability of the regressive ML models, 12 features extracted by a PCA as well as 12 engineered features (see Section. 4) are fixed for the training procedure. During this selection step the accuracy of each model is quantified by a five-fold cross validation which is 30 times repeated to statistically secure the estimation results. Since there are many different model types for regression tasks the most common one based on the regression learner toolbox of the software MATLAB 2021b are chosen. These include eight models trained with their initial parameter configuration considering linear regression (LR), quadratic regression (QR), linear SVR (lSVR), quadratic SVR (qSVR), cubic SVR (cSVR), RF, GPR and a simple one-layer neuronal network (NN1). Figure 12a shows the performance of each model estimating the wear state of the blanking tool quantified by the RMSE of the cutting edge radii based on PCA features as well as engineered features. For the blanking process, the one-layer neural networks (NN1) delivers the best results on average. However, it should be noted that a higher model complexity does not necessarily correspond with an improved performance. For example, the cSVR with a high polynomial kernel function tends to overfit starting at a degree of three, while the qSVR delivers the best results, especially when using engineered features. In general, regressive ML model trained with engineered features tend to show a better performance than the models trained with model-based features. This is mainly due to the fact that the force signal of the blanking process shown in Fig. 6 is closely linked to the physics of the forming procedure. Thus, wear-induced increasing of the cutting edge radii supposes hydrostatic stress in the forming zone, resulting in an extension of the plastic deformation phase. As a result, the rupture of the material is shifted to a later point in time and the length of the punch-phase and thus the work performed in the punch-phase increases. As Fig. 8 shows, a higher frictional length also causes the absolute maximum force and the work done in the push- und withdraw phases to increase. Thus, the engineered features strongly depend on the current wear state of the blanking process, which strengthens the model performance achieved by these feature type. One exception is given for of the RF in combination with PCA features which provide the best model performance. The suitability of the RF is probably due to the simple structure of the algorithm, which is composed of uncorrelated decision trees. Since the RF shows worse model performance when using the PCA features and only provides a single hyperparameter (depth of the tree structure) to be optimized, ANNs are recommended as suitable regressive ML type.

Figure 12b shows the performance of each model estimating the wear state of the roller quantified by the RMSE of the edge radii based on PCA features as well as engineered features. In contrast to the blanking process, all model types show better results if they are trained with the PCA features. This is due to the constant signal of the torque, which merely changes even under significant fluctuating process conditions. While each phase of the blanking process has its own

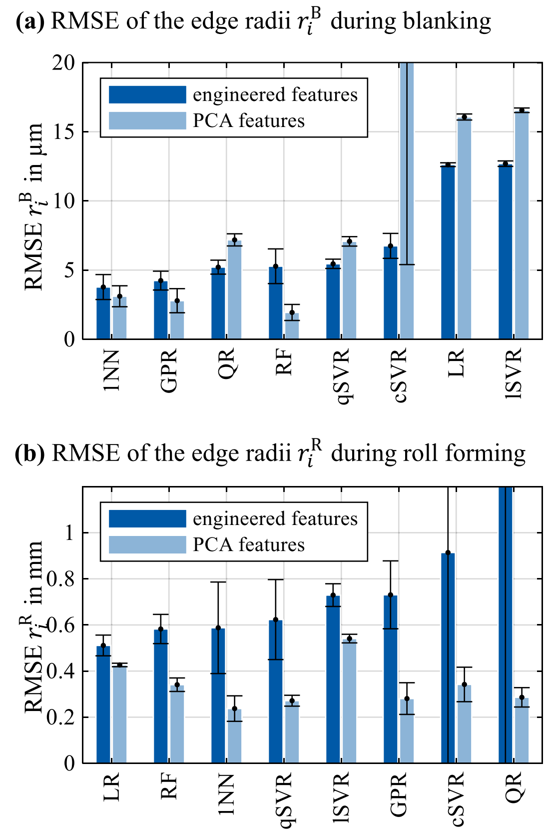

Fig. 12 Model performance quantified by the RMSE for estimating the edge radii based on an initial parameter configuration for blanking (**a**) and the roll forming (**b**) using engineered features as well as PCA features as input data

characteristic in the force signal, the torque signal slightly varies around a constant mean (see Fig. 7). In this context, model-based extraction algorithms like PCA are able to detect even slight changes in a given signal and using them for modelling. Similar to the blanking process the one-layer neural network (NN1) delivers the best results on average.

After the selection of the ANN as suitable regressive ML model type, its hyperparameter are optimized. Therefore, a Bayesian optimization with 30 iterations is conducted. Using the structure of ANN, the number of layers of the network and the number of neurons per layer are varied. To avoid the problem of overfitting during the training procedure of the ANN the regularization strength λ is optimized. It prevents the network to memorize the training data and helps to generalize the ANN to unseen test data. A constant activation function of the network (rectified linear unit activation function) is determined. The structure of the ANN, the hyperparameter to be varied as well as their range and the achievable performance of the optimized ANN is shown in Table 3. By optimizing the ANN, estimation of the cutting edge radii r_i^B during blanking is improved by 1.426 µm using the PCA features and by 1.784 µm using the engineered features. In roll forming, estimation of the roll edge radii r_i^R is improved by 0.585 mm using the PCA features and by 0.013 mm using the engineered features.

5.2 Results for predicting the wear state based on PCA features and engineered features

After the ANN is optimized its final performance to estimate the edge radii for both process is quantified by the RMSE. To confirm the certainty of these statistical parameters within a confidence interval of 99%, the ANN is trained 30 times. The resulting confidence interval is calculated based on a one-sample *t* test and a Student's *t*-distribution.

Consequently, the estimated edge radii are located within an interval around the mean estimated value of the model with a probability of 99%. Table 4 summarizes the results of the estimated edge radii for the the blanking and roll forming process using engineered and model-based features as input for the ANN.

For roll forming it is obvious, that the PCA features provide better results than the engineered features. This is mainly due to the fact that the engineered features react sensitively to small variations of the algorithmically determined characteristic points in the torque signal. Thereby, the cyclostationary torque signal shows hardly any characteristic variation and fluctuates around a quasi-stationary mean. A change in the physical state of the roll forming process causes only a minimal change in the torque signal. In contrast, PCA features are able to detect even small fluctuations in the cyclostationary torque signal when the process state changes. Besides removing redundant data and ignoring small changes in the background of the data (e. g noise), the PCA maximizes the variance of the signal. This means that even these small fluctuations resulting from physical changes in the process are detected and amplified, while noise or a bias is automatically removed. Since the engineered features are redundant using multiple of them would not provide any further information for the ANN model. In this context, the model performance of the ANN for the roll forming process using engineered features reaches a RSME of 271.313 ± 14.929 µm, but the best estimation quality is provided by the PCA features with 22.901 ± 1.825 µm. In contrast, the characteristic profile of the blanking force enables the determination of features in different phases, which correlate directly with the physical properties of the process. Thus, the engineered features combined with the optimized ANN are able to estimate the cutting edge radii of the punch with an 1.696 ± 0.247 µm and the PCA features combined with this model only provide an estimation quality of 2.141 ± 0.601 µm.

Table 3 Results of the hyperparameter optimization for the ANN

Model parameter	Blanking	Roll forming
Number of layers	3	3
Neurons layer 1	102	99
Neurons layer 2	5	222
Neurons layer 3	238	298
Regularization strength λ	6.162 • 10–5	1.483 • 10–5
Engineered features—improvement to initial configuration Δ RMSE [µm]	1.784	12.951
PCA features – improvement to initial configuration Δ RMSE [µm]	1.426	585.044

5.3 Results for predicting the wear state based on combined features

Since both features types are suitable for an inline estimation of abrasive wear states in forming processes, their combination can improve the ML model performance. For this purpose, it is necessary to perform a feature selection. Therefore, in this study a wrapper method in feedforward selection mode is used. Wrapper methods analyses the performance of the ML model when a certain subset of features is chosen [70]. Afterwards, the feature subset that leads to the highest performance of the ML model is selected. The application of wrapper methods is an iterative process in which different compositions of features are fed to model. The wrapper algorithm in this study selects a subset of features from the combined feature matrix $\boldsymbol{f}_{\mathrm{COM}} \in \mathbb{R}^{m \times 24}$ where the number of 24 feature is composed of 12 model-based features from the PCA and 12 engineered features. The procedure starts with a zero model which selects a single feature that minimize the loss of the ANN. Afterwards, a second feature is added while the first feature is fixed. Again, the algorithm tries to minimize the loss of the ANN. This procedure will be repeated until 12 feature are selected. Table 5 show the results for the optimized feature subset and the improvement while using a single feature type. It is shown that for both processes an improvement of the model quality is achieved.

Table 4 Model performance quantified by the RMSE to estimate the wear states using engineered feature as well as PCA features

Features process	Blanking		Roll forming	
	PCA	Engineered	PCA	Engineered
RMSE [µm]	2.141 ± 0.601	1.696 ± 0.147	22.901 ± 1.825	217.313 ± 14.629

Table 5 Model performance quantified by the statistical parameter to predict the wear states using a combination of engineered feature as well as features extracted by a PCA

combined features	Blanking f_1, f_3, f_{11}, f_5, W_{punch}, $F_{\text{punch,max}}$, $F_{\text{push,mean}}$, $F_{\text{push,std}}$, $F_{\text{push,max}}$, $F_{\text{with,mean}}$, $F_{\text{with,std}}$, $F_{\text{with,max}}$,	Roll forming f_2,f_3, f_4,f_5,f_6,f_7,f_9 ,f_{10},f_{11}, kurtosis and variance
RMSE [µm]	0.832 ± 0.258	22.214 ± 1.765
Improvement to optimized model [µm]	0.864	0.691

The RMSE reduced by 0.864 µm during blanking and by 0.691 µm during roll forming.

6 Conclusions and future work

The results in this study show that a regressive ML model is able to inline estimate abrasive wear states on sheet metal forming tools. Two sheet metal forming processes, blanking and roll forming, are investigated. Although the time series characteristics of the two processes are substantially different, good results are obtained in estimating the cutting edge radii and the roll edge radii on the forming tools taking into account the systematic procedure of the KDT-EA. Based on this procedure model, the acquired time series (blanking-force and roll forming-torque) are preprocessed and two different feature types are extracted. Thereby, from each time series 12 model-based PCA features and 12 engineered features are extracted. Whereas the PCA features combined with the optimized ANN are able to estimate the wear state with a RMSE of 2.141 ± 0.601 µm for blanking and 22.901 ± 1.825 µm for roll forming, the engineered features estimate the wear state with a RMSE of 1.696 ± 0.147 µm during blanking and 217.313 ± 14.629 µm during roll forming. Next to the optimization procedure of the ANN as well as artificially expending the data set by data augmentation techniques (SMOTE), an optimal selected feature subset out of combined feature matrix $\boldsymbol{f}_{\text{COM}}$ improves the estimation quality for blanking up to 0.832 ± 0.258 µm for roll forming up to 22.214 ± 1.765 µm for roll forming. In addition to good quality of estimation the study shows that the KDT-EA is suitable for inline detecting abrasive wear states on sheet metal forming tools. This offers a systematic procedure to implement and transfer ML models to industrial condition monitoring applications regardless of the sensorial acquired data characteristics but considering technical boundary conditions of manufacturing processes. Especially the step of an automatically transformation (feature extraction and feature selection) combined with the model optimization increase the overall ML model performance and supports companies who are inexperienced in the field of ML with the selection and implementation via the systematic procedure.

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Declarations

Conflict of interest The authors report no declarations of interest.

References

1. Ingarao G, Di Lorenzo R, Micari F (2011) Sustainability issues in sheet metal forming processes: an overview. J Clean Prod 4:337–347. https://doi.org/10.1016/j.jclepro.2010.10.005
2. Yoon H-S et al (2014) A comparison of energy consumption in bulk forming, subtractive, and additive processes: review and case study. Int J Precis Eng 3:261–279. https://doi.org/10.1007/s40684-014-0033-0
3. Hou L, Bergmann NW (2012) Novel industrial wireless sensor networks for machine condition monitoring and fault diagnosis. IEEE Trans Instrum Meas 61(10):2787–2798. https://doi.org/10.1109/TIM.2012.2200817
4. Xing Z et al (2018) Simulated analysis and experimental investigation on edge qualities of high strength steels hot blanking parts. Procedia Manuf 15:619–626. https://doi.org/10.1016/j.promfg.2018.07.286
5. Pereira MP, Yan W, Bf R (2012) Wear at the die radius in sheet metal stamping. Wear. https://doi.org/10.1016/j.wear.2011.10.006
6. Dilda V, Mori L, Noterdaeme O, Schmitz C (2021) Manufacturing: analytics unleashes productivity and profitability, report. McKinsey & Company
7. Hambli R (2001) Blanking tool wear modeling using the finite element method. Int J Mach Tools Manuf 41(12):1815–1829. https://doi.org/10.1016/S0890-6955(01)00024-4
8. Galakhar AS, Gates JD, Daniel WJT, Meehan PA (2011) Adhesive tool wear in the cold roll forming process. Wear 271(11–12):2728–2745. https://doi.org/10.1016/j.wear.2011.05.047
9. Wuest T, Weimer D, Irgens C, Thoben K-D (2016) Machine learning in manufacturing: advantages, challenges, and applications. Prod Manuf Res 4(1):23–45. https://doi.org/10.1080/21693277.2016.1192517
10. Fayyad U, Piatetsky-Shapiro G, Smyth P (1996) From data mining to knowledge discovery in databases. AI Mag 17:37–54. https://doi.org/10.1609/aimag.v17i3.1230
11. Chapman P, et al (2000) CRISP-DM 1.0. Step-by-step data mining guide. SPSS Inc. 9 (13)
12. Huber S, Wiemer H, Schneider D, Ihlenfeldt S (2019) DMME: Data mining methodology for engineering applications—a holistic extension to the CRISP-DM model. Procedia CIRP 79:403–408. https://doi.org/10.1016/j.procir.2019.02.106
13. Kubik C, Molitor DA, Becker M, Groche P (2022) Knowledge discovery from time series in engineering applications using machine learning techniques. J Manuf Sci Eng. DOI 10(1115/1):4054158
14. Lange K (1985) Handbook of metal forming. McGraw-Hill, New York
15. Kubik C, Knauer SM, Groche P (2021) Smart sheet metal forming: importance of data acquisition, preprocessing and transformation on the performance of a multiclass support vector machine for predicting wear states during blanking. J Intell Manuf 23:1489. https://doi.org/10.1007/s10845-021-01789-w
16. Galakhar AS, Daniel WJT, Meehan PA (2009) Prediction of roll profile wear in the cold roll forming process. KEM 410–411:643–660. https://doi.org/10.4028/www.scientific.net/KEM.410-411.643
17. Hoffmann H, Nürnberg G, Ersoy-Nürnberg K, Herrmann G (2007) A new approach to determine the wear coefficient for wear prediction of sheet metal forming tools. Prod Eng 1(4):357–363. https://doi.org/10.1007/s11740-007-0065-1
18. Kataoka S, Murakawa M, Aizawa T, Ike H (2004) Tribology of dry deep-drawing of various metal sheets with use of ceramics tools. Surf Coat 177(1):582–590. https://doi.org/10.1016/S0257-8972(03)00930-7
19. Hohmann J, Schatz T, Groche P (2017) Intelligent wear identification based on sensory inline information for a stamping process. In: Proceedings of 5th International Conference on Advanced Manufacturing Engineering and Technologies, 2017, pp 285–295
20. Kubik C, Hohmann J, Groche P (2021) Exploitation of force displacement curves in blanking—feature engineering beyond defect detection. Int J Adv Manuf Syst 19(6):403. https://doi.org/10.1007/s00170-020-06450-z
21. Archard JF, Hirst W (1956) The wear of metals under unlubricated conditions. Proc of the R Soc of Lond 236(1206):397–410. https://doi.org/10.1098/rspa.1956.0144
22. Galakhar AS, Meehan PA, Daniel WJT, Ding SC (2007) A method of approximate tool wear analysis in cold roll forming. In: 5th Australasian Congress on Applied Mechanics, ACAM 2007, 10–12 December 2007, Brisbane, Australia
23. Mucha J (2010) An experimental analysis of effects of various material tool's wear on burr during generator sheets blanking. Int J Adv Manuf Technol 50(5–8):495–507. https://doi.org/10.1007/s00170-010-2554-1
24. Cheon S, Kim H (2016) Prediction of tool wear in the blanking process using updated geometry. Wear 352–353:160–170. https://doi.org/10.1016/j.wear.2016.01.024
25. Hambli R (2002) Design of experiment based analysis for sheet metal blanking processes optimisation. Int J Adv Manuf Syst 19(6):403–410. https://doi.org/10.1007/s001700200041
26. Hernández JJ, Franco P, Estrems M, Faura F (2006) Modelling and experimental analysis of the effects of tool wear on form errors in stainless steel blanking. J Mater Process Technol 180(1–3):143–150. https://doi.org/10.1016/j.jmatprotec.2006.05.015
27. Hambli R, Soulat D, Chamekh A (2009) Finite element prediction of blanking tool cost caused by wear. Int J Adv Manuf Syst 44(7–8):648–656. https://doi.org/10.1007/s00170-008-1859-9
28. Faura F, López J, Sanes J (1997) Criterion for tool wear limitation on blanking 18–8 stainless steel strips. Rev Metal 33(5):304–310. https://doi.org/10.3989/revmetalm.1997.v33.i5.842
29. Jardine AKS, Lin D, Banjevic D (2006) A review on machinery diagnostics and prognostics implementing condition-based maintenance. MSSP 20(7):1483–1510. https://doi.org/10.1016/j.ymssp.2005.09.012
30. Jemielniak K (1999) Commercial tool condition monitoring systems. Int J Adv Manuf Technol 15(10):711–721. https://doi.org/10.1007/s001700050123
31. Isermann R (2011) Fault-diagnosis applications. Springer, Berlin, Heidelberg
32. Qiu J et al (2016) A survey of machine learning for big data processing. EURASIP J Adv Signal Process 1:80. https://doi.org/10.1186/s13634-016-0355-x
33. Schwabacher M, Goebel K (2007) Survey of artificial intelligence for aritficial intelligence for prognostics. The AAAI Press Menlo Park 2007:108–115
34. Klingenberg W, de Boer TW (2008) Condition-based maintenance in punching/blanking of sheet metal. Int J Mach Tools Manuf 48(5):589–598. https://doi.org/10.1016/j.ijmachtools.2007.08.013
35. Hoppe F et al (2019) Feature-based supervision of shear cutting processes on the basis of force measurements: evaluation of feature engineering and feature extraction. Procedia Manuf 34:847–856. https://doi.org/10.1016/j.promfg.2019.06.164
36. Becker M, Groche P (2019) Towards nonstop availability in roll forming through digitalization. In: Wulfsberg JP, Hintze W und Behrens B-A (ed) Production at the leading edge of technology. In: Proceedings of the 9th Congress of the German Academic Association for Production Technology. Springer Vieweg, Berlin, pp 219–228

37. Lee CW (2020) On-line model identification for the machining process based on multirate process data. J Manuf Syst 56:622–630. https://doi.org/10.1016/j.jmsy.2020.04.006
38. Quatrini E, Costantino F, Di Gravio G, Patriarca R (2020) Machine learning for anomaly detection and process phase classification to improve safety and maintenance activities. J Manuf Syst 56:117–132. https://doi.org/10.1016/j.jmsy.2020.05.013
39. Choudhury SK, Kishore KK (2000) Tool wear measurement in turning using force ratio. Int J Mach Tools Manuf 40(6):899–909. https://doi.org/10.1016/S0890-6955(99)00088-7
40. Al-Momani ES, Mayyas AT, Rawabdeh I, Alqudah R (2012) Modeling blanking process using multiple regression analysis and artificial neural networks. J Mater Eng Perform 21(8):1611–1619. https://doi.org/10.1007/s11665-011-0079-x
41. Kirchen I, et al (2017) Data-driven model development for quality prediction in forming technology. IEEE 15th International Conference on Industrial Informatics. In: IEEE 15th International Conference on Industrial Informatics. Emden, Germany, pp 775–780
42. Hao L, Bian L, Gebraeel N, Shi J (2017) Residual life prediction of multistage manufacturing processes with interaction between tool wear and product quality degradation. IEEE Trans Automat Sci Eng 14(2):1211–1224. https://doi.org/10.1109/TASE.2015.2513208
43. Breiman L (2001) Random forests. Mach Learn 45(1):5–32. https://doi.org/10.1023/A:1010933404324
44. Patill V, Patil P, Ingale N, Date H (2021-2021) Methodology for identification of quality of clean-cut surface for IS2062HR sheet metal blanking using Random Forest 2021 5th Conference on Information and Communication Technology (CICT). In: 2021 5th Conference on Information and Communication Technology (CICT). Kurnool, India, 10.12.2021-12.12.2021. IEEE, pp 1–5
45. Ge M, Du R, Zhang G, Xu Y (2002) Fault diagnosis using support vector machine with an application in sheet metal stamping operations. MSSP 18(1):143–159. https://doi.org/10.1016/S0888-3270(03)00071-2
46. Liu W et al (2007) Springback prediction for sheet metal forming based on GA-ANN technology. J Mater Process Technol 187–188:227–231. https://doi.org/10.1016/j.jmatprotec.2006.11.087
47. Qiu T, Lai X, Ni J (2020) Machine learning based novelty detection methods for progressive stamping process health monitoring. In: 15th International Manufacturing Science and Engineering Conference. ASME
48. Bozdemir M, Gölcü M (2008) Artificial neural network analysis of Springback in V bending. J Appl Sci 17(8):3038–3043
49. Cheng Y et al (2018) Data and knowledge mining with big data towards smart production. J Ind Inf Integr 9:1–13. https://doi.org/10.1016/j.jii.2017.08.001
50. Fu Z, Mo J, Chen L, Chen W (2010) Using genetic algorithm-back propagation neural network prediction and finite-element model simulation to optimize the process of multiple-step incremental air-bending forming of sheet metal. Mater Des 31(1):267–277. https://doi.org/10.1016/j.matdes.2009.06.019
51. Alsamhan A et al (2019) Prediction of formation force during single-point incremental sheet metal forming using artificial intelligence techniques. PLoS One 14(8):e0221341. https://doi.org/10.1371/journal.pone.0221341
52. Chamekh A, BelHadjSalah H, Hambli R, Gahbiche A (2006) Inverse identification using the bulge test and artificial neural networks. J Mater Process Technol 177(1–3):307–310. https://doi.org/10.1016/j.jmatprotec.2006.03.214
53. Derogar A, Djavanroodi F (2011) Artificial neural network modeling of forming limit diagram. Mater Manuf Process 26(11):1415–1422. https://doi.org/10.1080/10426914.2010.544818
54. Unterberg M et al (2019) In-situ material classification in sheet-metal blanking using deep convolutional neural networks. Prod Eng 13(6):743–749. https://doi.org/10.1007/s11740-019-00928-w
55. Hambli R (2002) Prediction of burr height formation in blanking processes using neural network. Int J Mech Sci 44(10):2089–2102. https://doi.org/10.1016/S0020-7403(02)00168-6
56. Stanke J et al (2018) A predictive model for die roll height in fine blanking using machine learning methods. Procedia Manuf 15:570–577. https://doi.org/10.1016/j.promfg.2018.07.279
57. Lemu HG, Trzepieciński T (2014) Multiple regression and neural network based characterization of friction in sheet metal forming. AMR 1051:204–210. https://doi.org/10.4028/www.scientific.net/AMR.1051.204
58. MATLAB (2022) version 9.11.0 (R2010a). The MathWorks Inc., Natick, Massachusetts
59. Becker M, Traub T, Groche P (2022) Intelligente Rollformanlagen - Hinter den Prozess blicken. Bleche Rohre Profile (2), pp 42–44
60. Traub T, Groche P (2018) Energy efficient roll forming processes through numerical simulations. J Phys Conf Ser 1063:12182. https://doi.org/10.1088/1742-6596/1063/1/012182
61. Feistle M et al (2017) Reduction of burr formation for conventional shear cutting of boron-alloyed sheets through focused heat treatment. Procedia CIRP 63:493–498. https://doi.org/10.1016/j.procir.2017.03.161
62. Guyon I, Elisseeff A, Kaelbling LP (2003) An introduction to variable and feature selection. J Mach Learn Res 3(7–8):1157–1182. https://doi.org/10.1162/153244303322753616
63. Domingos P (2012) A few useful things to know about machine learning. Commun ACM 55(10):78. https://doi.org/10.1145/2347736.2347755
64. Li CJ (2006) Signal processing in manufacturing monitoring. In: Wang L und Gao RX (ed) Condition monitoring and control for intelligent manufacturing, Bd. 21. Springer, London (Springer Series in Advanced Manufacturing), pp 245–265
65. Schorr S, Möller M, Heib J, Bähre D (2020) Quality prediction of drilled and reamed bores based on torque measurements and the machine learning method of random forest. Procedia Manuf 48:894–901. https://doi.org/10.1016/j.promfg.2020.05.127
66. Addison DJF, Wermter S, Arevian GZ (2003) A comparison of feature extraction and selection techniques. Proc Int Conf Artif Neural Netw 2003:212–215
67. Wu F-C, Chyu C-C (2004) Optimization of correlated multiple quality characteristics robust design using principal component analysis. J Manuf Syst 23(2):134–143. https://doi.org/10.1016/S0278-6125(05)00005-1
68. Rato TJ, Reis MS (2020) An integrated multiresolution framework for quality prediction and process monitoring in batch processes. J Manuf Syst 57:198–216. https://doi.org/10.1016/j.jmsy.2020.09.007
69. Lewin DR (1995) Predictive maintenance using PCA. Control Eng Pract 3(3):415–421. https://doi.org/10.1016/0967-0661(95)00015-M
70. Kohavi R, John GH (1997) Wrappers for feature subset selection. Artif Intell 97(1–2):273–324. https://doi.org/10.1016/S0004-3702(97)00043-X