Autoencoder based Wear Assessment in Sheet Metal Forming

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Corrigendum: Autoencoder based Wear Assessment in Sheet Metal Forming (2020 IOP Conf. Ser.: Mater. Sci. Eng. 1157 012082)

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Page 6:
In Section 4.1 the following table appears:

Table 2
CNN-Structure

| No. layer | Layer type | Architecture Parameter |
|-----------|------------|------------------------|
|           |            | Filter | Kernel | Strides | Act. |
| 1         | Input      | 32     | 7      | 2       | relu |
| 2         | Conv       | 32     | 7      | 2       | relu |
| 3         | Dropout    | 0.2    |        |         |      |
| 4         | Conv       | 16     | 7      | 2       | relu |
| 5         | Conv-T     | 16     | 7      | 2       | relu |
| 6         | Dropout    | 0.2    |        |         |      |
| 7         | Conv-T     | 32     | 7      | 2       | tanh |

This should be:

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| 6         | Dropout    | 0.2    |        |         |      |
| 7         | Conv-T     | 32     | 7      | 2       | tanh |
| 8         | Conv-T     | 1      | 7      | 1       |      |
Autoencoder based Wear Assessment in Sheet Metal Forming

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Abstract. The amount of information contained in process signals such as acoustic emission and force signals has proven vital for the detection of changes in physical conditions or quality feature prediction in sheet metal forming applications. Both signal types have also been researched in the context of wear detection, yet systems that reliably identify the wear state at a given time in sheet metal forming processes based on these signals do not exist. This paper proposes an architecture to assess the wear increase within a given time frame in an experiment based on an autoencoder. The ability of autoencoders to encode and decode signals has been widely studied and this approach leverages the fact that autoencoders are more likely to learn representative encodings on stable and homogeneous signals than on heterogeneous signals with high fluctuations. This approach utilizes the circumstance that high tool wear leads to changes in the signal and signal fluctuation. In consequence, autoencoders can be utilized to track tool wear progression without the need for labelled data. The findings show a strong similarity to physical models for the wear progression of tool components, indicating the validity of this approach. Additionally, an analysis of the signals yields characteristic effects of the considered force signals that could specifically represent wear resistance.

1. Introduction

The digitalization in manufacturing is accompanied by massive amounts of data acquired on site, imposing constraints of the physical infrastructure and is often lacking critical context information, complicating its analysis. The challenges arising with amount and quality of data, as well as its transmission processing and the development of value-added applications based on production data is tackled by the framework of an Internet of Production [1]. Sheet metal forming is a class of manufacturing technologies often used in mass production for components in the automotive and aerospace industry. Various factors, such as unexpected high tool wear or even a broken tool deteriorate the quality of products or interrupt the production in sheet metal forming, leading to cost intensive production stops. Yet, workpiece quantities paired with high resolution sensor systems for force, strain or acoustic emission signals impair special challenges to reveal important information regarding tool conditions and quality predictions. Therefore, a tool condition monitoring (TCM) is vital, because it allows to maintain the desired part quality and to increase productivity [2]. A McKinsey & Company study estimated that the appropriate use of online TCM techniques by manufacturers typically reduces machine downtime by 30 to 50 percent and increases machine life by 20 to 40 percent [3].

TCM in sheet metal forming focuses on identifying wear states, process conditions and changes in process’ underlying physical mechanisms. It was demonstrated that using machine learning approaches,
force [4], acoustic emission [5] and acceleration signals [6] are promising candidates in understanding different aspects of wear progression and providing a robust foundation of wear control regimens.

The tool state is investigated based on the deviation of the recorded stamping force from the normal stamping force shape (or force signature) recorded using an unworn tool. VOSS et al. determined and correlated the type and stage of wear and lubrication state with the change in force signature features by analyzing semi-industrial press data using the principal component analysis (PCA). Observed effects were linked to the increase of friction between tool and workpiece caused by the adhesive wear while the change in the lubrication regimen was found to affect the progression of the force signature slope. The change in the force signature magnitude due to wear progression was earlier reported by Skare and coupled with distinct acoustic emissions when the stick-slip phenomenon between part and tooling began occurring [7]. Additionally, the automated extraction of meaningful features has been studied in [8], concluding that redundancies between features used for further analysis can be minimized by PCA.

Acoustic emission is the one of the most frequently used process signal in online wear monitoring due to its ability to detect the early stages of wear and friction occurrence. Different concepts were investigated by establishing quantitative indices or extracting the most wear-relevant features. For example, the relative cumulative spectral power index (RC SPI), which is the cumulative frequency domain magnitude of the signal corresponding to each part divided by that of the first part, was employed to obtain a single quantitative measure representing the complete spectrum that corresponds to each part [9]. This result was confirmed by Shanbhag et al., where RMS and maximum absolute peak amplitude were used to distinguish worn and unworn tools. The band power feature of the acoustic emission burst is used to distinguish the galling and non-galling wear condition in combination with the acoustic emission mean frequency to determine the onset of the galling wear condition [10].

From previous research, it is evident that determining the galling and non-galling condition, the onset of the galling wear in addition to the lubrication state is possible utilizing a manual feature extraction approach. However, the aforementioned approaches have neither proven to be generalizable nor are they applicable in industrial contexts since they require wear state information for training that is not available or only in tedious manual measurements in an industrial setting. To enable a reliable TCM, a flexible approach that provides insight into the wear progression without the need of labeled data, while at the same time being quickly applicable in an industrial setting, is needed. Such an approach would enable a TCM for industrial applications and significantly reduce scrap and machine downtimes.

Neural networks can be trained to extract complex features from time series data, requiring high processing resources for training but low effort to apply the learned model. Autoencoder (AE) belong to the class of unsupervised learning algorithms. An input is propagated through a neural network and through a bottleneck, thus effectively encoding the input to a low dimensional representation. This encoding is then decoded to reconstruct the input as accurately as possible. Following recent research, the reconstruction error (RE) that serves as a measure for the performance of an AE can be correlated to the tool wear state [11], marking it viable as an unsupervised tool to monitor the wear state [12].

In this contribution, the focus is set on the fine blanking process as a representative for sheet metal forming processes. After a short introduction to fine blanking in Section 2 and AE in Section 3, the experimental data sets consisting of about 30,000 strokes in total that are used to examine the validity of the proposed approach are introduced in Section 4. Eventually, the derived indicator for wear increase using both signal types is matched to the theoretical wear progression of tool components, accompanied by a qualitative evaluation of signal features that may cause the instability of the signal in specific process stages, see Section 5. Lastly, a conclusion and a roadmap for future work is given in Section 6.

2. Problem Statement
The study presented in this paper focuses on fine blanking due to its high industrial relevance. However, the results are likely to be applicable to other sheet metal forming processes due to their similarities.
2.1. The Fine Blanking Process
Fine blanking is often used in automotive, aerospace and medical industries for the production of safety-critical components [13]. Despite the constant high quality in general, qualitative defects of the fine blanked components can impair their functionality. Standard measures of sheet metal coils processed in fine blanking range from 1 – 20 mm in thickness and 50 – 250 mm in width. The main benefits of fine blanking are a high geometrical accuracy of the produced workpieces and up to 100 % smooth cut on the shearing surface, making a secondary finishing process for the shearing surface unnecessary [13]. The force data, which will be used as a basis in the following chapters, has been generated and collected during research projects. In the experiments, a servo-mechanical Feintool XFT 2500 speed fine blanking press is used. The acoustic emission data set has been acquired at the local site of an industry partner that voluntarily contributes the data to this research project.

![Wear stages](image)

**Figure 1**: Three wear stages in fine blanking: a) shows a high wear increase during run-in time, b) is shows a stable wear plateau, whereas c) indicates the end of the tool lifecycle.

2.2. Wear in Fine Blanking
In the sheet metal stamping industry, an understanding of tool wear has become increasingly important due to the implementation of higher strength sheet steels, the reduced use of lubricants in the press shop, and the desire to lower the cost of tool failure and quality defects. During fine blanking and depending on the process parameters, wear occurs simultaneously in the form of adhesion, abrasion, fatigue, and chipping. The usually dominant wear mechanism adhesion (galling) [14]. Wear level increases with time as more parts are produced, more friction and fatigue cycles are passed, and accordingly, greater adhesion and abrasion cause the surface to stick and chip. However, the wear progression does not increase linearly with the number of punches. The non-linear wear progression is related to the stick-slip phenomena and the surface degradation rate causing uneven a wear progression rate, see Figure 1. In the beginning, when the two surfaces (punch and workpiece) are in contact, applying high pressure causes the roughness profiles (peaks and asperities) to interfere. When the sliding motion is initiated, all the interfered surfaces break, leading to loose particles between the two surfaces. During the first phase of the wear, these particles trigger accelerated abrasive but mostly accelerated adhesive, representing the run-in phase. In the succeeding punches, the wear progression rate tends to remain constant, causing a plateau phase. This is caused by the change of the punch tribology from containing peaks and asperities to an almost smooth surface. Additionally, as the number of strokes increase, the temperature increases as well, causing the sliding motion to be easier. However, while the wear is almost constant in this phase, the heat and residual stresses accumulate while reaching the fatigue limit of the punch, leading to the start of the third wear stage. In this stage, the punch bulk may breakdown into loose particles or even crack causing punch failure [15] where the fatigue wear is most dominant [16].

3. Autoencoder
An AE is a self-supervised learning technique that is leveraged in many machine learning applications with the purpose of reconstructing its inputs instead of predicting a target value [17]. Figure 2 shows the common structure of an AE. A vanilla AE consists of three types of layers, namely, the input layer, the
hidden layer and the output layer. In the simplest case, given one hidden layer, the encoder stage of an AE takes an $n$-dimensional input $x$ and maps it to $z$, an $m$-dimensional vector with $m \ll n$. Following, the decoder stage of the AE maps $z$ to the $n$-dimensional reconstruction $\hat{x}$ of $x$. AE are trained to minimize the RE (such as squared errors), often referred to as the loss. Similar to traditional neural networks, AE utilizes error back-propagation to minimize the loss, continuously updating the weight matrix $W$ and biases $b$ that are initially selected at random for each layer $l$ and apply non-linearity through activation functions. In this work, the mean squared error (MSE) is used as the loss function. After training, the optimized weight matrices $W$ and bias matrix $b$ of the model are obtained. Further information about the carried out methodology for this work is described in section 4.

3.1. Convolutional Autoencoder

The performance of convolutional neural networks (CNN) in the tasks of image and time series classification suggest the usage of convolutional autoencoders (CAE) for signal processing purposes. Strictly speaking, CAE are special cases of traditional AE, which use convolutional layers and pooling layers instead of or in addition to fully connected layers. Convolutions are commonly used in digital signal processing, e. g. for image processing. Contrary to convolutions in traditional signal processing approaches, e. g. blurring of an image, CNN have no fixed filter weights but rather learn the optimal weights by minimizing the RE through optimization algorithms such as gradient descent. Besides convolutions to encode the input $x$, CAE leverage transposed convolutional layers to upsample (deconvolute) the encoding and to reconstruct the input. Mathematically speaking, a convolution is an operation on two functions $f$ (input) and $g$ (kernel) that yields a third function $h$ (output) with $f \ast g = h$. A deconvolution is the inverse operation to a convolution with the objective of reconstructing the input from the output and the kernel.

4. Data Sets and Methodology

The goal of the methodology is to derive an indicator for wear increase in an unsupervised fashion that relates to the theoretical wear increase curve presented in Section 2.2. To do so, the focus is set on the RE of CAE that represents the differences of the decoded CAE output compared to the input signal. The hypothesis is that during a punch series the force and acoustic emission signal changes which correlate to the wear state of the fine blanking tool. An AE in general learns to encode the properties of rather homogeneous and stable data well, but if the underlying distribution of the data changes or anomalies and fluctuations occur, significant errors occur during encoding and decoding, leading to a large RE.

4.1. Data and Preprocessing

The force data set consists of four experiments executed on stainless steel with varying punch coating and used lubricant with the same geometry. For all experiments, previously unused punch have been used. The acoustic emission data set of 17,147 strokes has been collected in a cooperation with an industry partner, thus, details of the tool geometry as well as other process parameters cannot be published. Nevertheless, the recording starts with a new punch and ends when the tool has reached a wear state which cannot produce parts of sufficient quality. Due to the low number of strokes for the
force signals, they can only represent the run-in phase of wear development, which is complemented by the one large acoustic emission data set that should include all three wear phases. The exact number of strokes for each experiment is given in Table 1.

The force data is acquired stroke-wise, where each stroke is represented by 10,500 force data points acquired with piezo electronic force sensors working on 10 kHz sampling rate. The experiments are referred to with $E_1, E_2, E_3, E_4$, respectively. For data-cleaning, a sensor-drift within the signals has been removed, so that each stroke starts and ends with zero forces applied. In experiment $E_1$ a malfunction of the lubricator has been reported, resulting in anomalies in the experiment that have to be taken into account during evaluation. Furthermore, $E_3$ only consists of about 2,000 strokes, because data of about 1,000 strokes after the 600th stroke are missing. From the raw force data, the interval that refers to the process phase where the sheet metal is stripped from the punch as described in [18] is extracted. The reason for investigating the stripping phase individually is that the signal period of one stroke is dominated by the blanking force used to blank the sheet metal. By only taking the stripping phase into account, the friction related forces have a higher impact on the signal.

The acoustic emission data is acquired by using a 400 kHz mechanical vibration sensor on the tool plate of the industrial partner. Similar to the force measurements, the data is acquired stroke-wise and has been processed with a 50 kHz high-pass filter to reduce low-frequency noise in the signal. Each stroke thus is represented by 140,000 data points. Every data set is scaled to have mean 0 and unit variance with the StandardScaler module from sklearn. Hereby, the $z$-score of every time series value $x_i$ is calculated with $z_i = \frac{x_i-\mu}{s}$, where $\mu$ denotes the mean and $s$ the standard deviation of the time series.

The programming work done for this contribution has been carried out on python 3.8.7 and the libraries keras, numpy, sklearn, pandas, scipy and matplotlib. For training and reconstruction a Tesla P100 (force data) and a V100 (acoustic emission data) GPU have been used.

| Exp. | #Strokes | Lubricant |
|------|----------|-----------|
| $E_1$ | 3,344 | Chloride |
| $E_2$ | 3,204 | No-Chloride |
| $E_3$ | 2,056 | Chloride |
| $E_4$ | 3,340 | No-Chloride |
| $E_5$ | 17,147 | Confidential |

Table 1

4.2. Reconstruction Error Evaluation

The RE is investigated as a measure for tool wear increase. Both signals have been trained using the same architecture presented in Table 2, using four layers for both decoding and encoding the signal. For the force data, the CAE is trained on the first 200 strokes of an experiment and it is subsequently investigated at which stroke a significant increase of the RE can be identified. For the acoustic emission data, the CAE is trained on the first 1,000 strokes of the stroke series. The trained CAE is then utilized to reconstruct each of the following strokes without retraining the CAE. The reconstruction errors for each subsequent stroke are then saved for further analysis. The training and evaluation are performed on the blanking and stripping process phase of the force data of all four experiments, as well as the combined signal of both blanking and stripping for the acoustic emission data set.

5. Results

The results are grouped by the type of signal considered. First, the force sensor signal is analysed to identify patterns in the RE of CAE of the stripping segment, since at this stage the frictional forces that are best represented in the stripping segment are of interests. Furthermore, a qualitative evaluation of
the signal characteristic possibly causing the higher or lower RE in specific intervals is given. Second, the acoustic emission data experiment is evaluated representing a complete lifecycle of the punch.

5.1. Run-in Phase Monitoring with Stamping Force

Note that the goal is not to have the highest possible reconstruction error, but rather to use the properties of AE to generate high RE when significant changes in the underlying signal occur. Also recall, that the first experiment came with significant anomalies caused by a malfunction in the lubricator, while the third experiment is missing a critical amount of stroke data. Nevertheless, the result of both segments show similar characteristics to the cleaner data sets from experiments two and four. All experiments show a considerable higher RE in the first half of the experiment, while a comparably low RE at the end of the experiment. Interestingly, the strokes that has been used for training the CAE do not show lower REs than the rest of the data.

**Figure 4:** Left are the (cumulated) RE is presented. Right are selected strokes of the second experiment are presented that are representative for the change in the force signal of the stripping segments.

The cumulated RE shows high similarities to logarithmic growth functions, with the second and fourth experiment showing more similarities than the first and third. Representative for all experiments, the force signal of the 100th, 1000th, 2000th and 3000th stroke of experiment \( E_2 \) are presented in Figure 4. The 100th and 1000th stroke show similar characteristics of a higher pulling force in the beginning, followed by a slow and steady increase to about 0. In both signals, especially at the beginning and end of the signal, higher fluctuations can be observed, while this phenomenon as well as the higher pulling force at the beginning is flattened at the 2000th stroke and is not observable in the 3000th signal. This effect is observable in experiments \( E_1, E_2, E_3, E_4 \).

5.2. Monitoring with Acoustic Emission

Figure 5 shows the RE of the CAE trained on the first 1.000 strokes on the complete data set and the reconstruction of the following 16.147 strokes. Most strikingly, the CAE shows a very low RE between the 5.500th and the 11.500th stroke. On the contrary, between the 1.500th and 5.500th and between the 11.500th and 17.147th stroke the RE is significantly higher, resulting from a poor reconstruction of the CAE. Cumulated over the complete course of the experiment results in a strong increase until stroke 5.500, with a plateau of 6.000 strokes followed by a high gradient phase until the end of the stroke series.

5.3. Discussion

The force signal’s effect of fluctuations during the stripping phase can be caused by stick-slip effects during the strip off. This can be particularly observed in the beginning of the experiment and disappears towards the end of the experiment. The worse performance of the CAE in the beginning of the experiment is a result of the smoothing functionality of CAE, because the stick-slip effect is smoothed by the prediction procedure, increasing the reconstruction error of signals with such an effect. This
observation together with the findings presented in [7], stating that the stick-slip effect directly corresponds to wear increase, support the hypothesis that CAE can serve well for online monitoring of wear using the above described mechanisms. Additionally, after the sheet metal is stripped of, minor vibrations can be observed in the signal of the first strokes. This vibration flattens with the number of executed strokes to a large extend causing a reduction of the reconstruction error at the end of the experiments. The high RE for the acoustic emission signals at the beginning and end of the experiment corresponds well onto the theoretical model of wear increase. Furthermore, the cumulative plots of the force sensor related experiments also tend to flatten later about 3.000 strokes, indicating that the signal is getting more stable towards the end of the experiment.

The fact that for all force signal experiments the same pattern of higher errors at the beginning together with the same qualitative change over time can be observed, underlines the assumption that the run-in phase of wear progression might be completed after the experiment execution and not enough strokes had been performed to definitely display the second phase, which was reached in the acoustic emission dataset after about 5.500 strokes. The results are promising but yet cannot give immediate proof that the methodology works on heterogeneous data and if it is generalizable to various scenarios.

Figure 5: On the left side the (cumulated) RE of the acoustic emission data set is presented. On the right side selected strokes of the second experiment are presented that are representative for the change in the acoustic emission signal.

6. Conclusion and Future Work
In the ongoing digitization of manufacturing processes, the amount of data available for each operation steadily increases, while appropriate methods to analyze the data with just little context information given are missing. Thus, unsupervised methods to explore the inner structure and hierarchy of data are needed, so that changes of data over time can be tracked. In manufacturing, capturing this change can relate to various changes in the physical conditions of manufacturing processes. This work proposes an unsupervised method to analyze force and acoustic emission data for an exemplary sheet metal forming process by using CAE and the RE as a metric to indicate changes and artefacts in the signal.

The study reveals that time intervals in which most of the artefacts occur overlap with the wear progression in theory. For the force data, specifically stick-slip phenomena can be quantified by the usage of CAE since the properties of CAE to smooth time series data result in a higher reconstruction error for signals with more vibrations and fluctuations. For the acoustic emission data set an observation of the full lifecycle of a punch reveals that the same method is suitable to detect instable phases during the process execution that maps well to the theory of wear progression. Although the presented findings are promising, further research needs to be conducted with accurate punch wear measurements in short intervals for the complete tool lifecycle to further validate the methodology. Additionally, experiments where both acoustic emission and force signal are recorded are needed to provide information whether both signals represent the same kind of outliers with high RE, or whether they represent different
phenomena. Nevertheless, the yet presented results indicate that the proposed method can provide an indicator for instable process phases while only utilizing minimal (200 respective 1000 strokes) unlabelled data and thus, is applicable in an online fashion in industrial scenarios.

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