Feature-Based Analysis of Acoustic Emission Signals for Wear Monitoring in Centerless Through-Feed Grinding

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Abstract. Wear monitoring is a critical aspect of maintaining the health and performance of machinery. During centerless grinding, grinding and regulating wheels as well as work rest blades wear out over time due to contact with workpieces, which impairs the geometrical accuracy and surface quality of the processed parts, and ultimately the productivity of the process. Acoustic emission sensors are a promising source of information for wear monitoring which in turn allows to optimize dressing intervals and prevent rejects. During an experimental series, acoustic emission signals were collected from a centerless through-feed grinding process to identify changes in the signal that could be indicative of wear. The collected acoustic emission signals were preprocessed by digital filtering and extracting a comprehensive set of features. A one-class support vector machine was used to quantify the signal evolution over the span of the experimental series. The resulting resemblance of the signal evolution to the grinding wheel wear effects observed in the geometric properties of the workpieces from the series suggests the validity of this approach.

Keywords: Wear Monitoring · Acoustic Emission Signals · Centerless Grinding

1 Introduction

Wear monitoring plays a critical role in maintaining machinery as it enables timely detection and intervention to prevent expensive breakdowns and ensure optimal performance. To effectively address these challenges, it is essential to carefully choose parameters that can offer real-time insights into internal conditions and mechanical faults of the device [1].

In the context of centerless grinding processes, traditional methods of wear monitoring, such as visual inspection, manual measurements, or fixed grinding wheel dressing intervals, have been commonly used. However, these methods have limitations that hinder their effectiveness in real-time wear monitoring. Visual inspection relies on human judgment and may suffer from subjectivity and inconsistency. Manual measurements,

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although more quantitative, can be time-consuming and impractical for continuous monitoring. Similarly, fixed grinding wheel dressing intervals may not capture wear-related issues in a timely manner, leading to potential quality issues and production delays.

The complex nature of centerless grinding processes, influenced by factors like the grinding wheel, grinding and dressing conditions, and machine setup, further underscores the importance of tool wear monitoring in this field [2]. The condition of machinery can be also monitored using various techniques, including vibration analysis, thermography, and ultrasonic inspection. These techniques can help detect early signs of degradation, thereby allowing for timely intervention. Vibration has been used to pinpoint the potential sources of vibrations and identify the component with faulty behavior [3]. Thermography was also used to locate potential issues using hot or cold spots in a machine [4], while the ultrasonic inspection is a reliable method that gives valuable information about the internal state of the machine through the analysis of sound waves [5].

In the context of grinding processes, acoustic emission (AE) signals have been found to be particularly useful for monitoring wear, which implies a high probability of successful applications in centerless grinding. Especially, detecting grinding wheel wear, loading, chatter analysis, collision detection, grinding burn and cracks, gap elimination, process control, and dressing/truing verification have been deemed feasible [6]. Signal processing methods in both time and frequency domains, such as time direct analysis (TDA), singular spectrum analysis (SSA), Fourier transform, and wavelet transform, have been utilized for online process monitoring. Moreover, different predictive techniques including multivariate regression, artificial neural networks, and support vector machines (SVM) have been applied considering the correlating features of the parameters under study [7].

Previous research has provided evidence of the feasibility of utilizing vibration and acoustic emission signals for monitoring grinding processes. However, the effectiveness and practicality of implementing these approaches for efficient online monitoring in centerless through-feed grinding processes have not yet been thoroughly investigated and validated. Although the feature-based analysis of AE signals appears to be applicable for wear monitoring in centerless through-feed grinding, no thorough investigations and validations have been performed yet. Further research is required to establish the consistency of tool wear detection by these monitoring methods with the measurement of corresponding process conditions and result variables. Therefore, the effectiveness of the method, specifically in the context of centerless through-feed grinding operations, is still to be investigated.

By enhancing wear monitoring in centerless grinding processes, this research makes a distinct contribution by focusing on the development of a one-class support vector machine (SVM) [8] model for evaluating the process state in centerless through-feed grinding using acoustic emission (AE) signals. The one-class SVM is a machine learning algorithm specifically designed for anomaly detection, capable of identifying instances that deviate from the norm. In the context of wear monitoring, the one-class SVM can effectively detect patterns in AE signals, indicating changes in machine behavior possibly relating to wear. To validate the proposed approach, the research will conduct experimental studies in real-world centerless through-feed grinding operations, specifically in an industry-like process setup. This validation will demonstrate the practical applicability, reliability, and effectiveness of the one-class SVM model for wear monitoring.

The paper is structured as follows: Section 2 presents the methodology, including the experimental setup, data acquisition, feature-based process analysis, and the use of the one-class Support Vector Machine (SVM) algorithm for grinding tool condition monitoring. Section 3 provides a summary of the results and includes a discussion of their implications. Section 4 concludes and provides an overview of the entire research, highlighting its contributions and potential directions for future research.

2 Methodology

2.1 Experimental Setup

A partially hardened C53 steel with an initial workpiece diameter of $d_{w,0}$= 15.1 mm was ground with a depth of cut of $a_e = 0.3$ mm. Workpieces with two different lengths were examined in order to investigate any correlation between the grinding wheel width to workpiece length ratio on the process results. The workpiece length for the short workpiece was $l_{w,1}$= 284 mm and for the long workpiece was $l_{w,2}$= 425 mm. The centerless through-feed grinding experiments were carried out on a Mikrosa Kronos S250 grinding machine. The cooling lubricant used was a Hocut 4570 emulsion from Quaker Houghton at a concentration of $c = 6\%$. A vitrified bonded grinding wheel of grit size F90 from Effgen Lapport was used for the tests. The regulating wheel was rubber-bonded with the corundum grit size F120 and from the company Effgen Lapport.

The grinding wheel has been profiled with a run-in zone, grinding zone and spark-out zone. At a total grinding wheel width of $b_{gw,tot} = 250$ mm, the grinding zone took a width of $b_{gw,2}$= 150 mm. Grinding was performed with an elevation of $h = 3.7$ mm over the center and a regulating wheel inclination of $\alpha_r = 3.0°$.

In the grinding investigations, the circular shape deviation f_k, the straightness deviation f_g, the cylindrical shape deviation f_{cyl}, the arithmetic mean roughness R_a and the maximum height of profile R_z were measured. For the form deviations f_k, f_g, f_{cyl}, a form measurement machine of the type MMQ-400 from the company Mahr was used. The roughness values R_a, R_z were measured using an Etamic Nanoscan roughness and countour measurement machine from the manufacturer Hommel. The grinding wheel was dressed in an identical manner before each test point. After the dressing process, the grinding wheel wear behavior was investigated. V_w was continued until a material removal of V_w= 800,000 mm^3 was achieved. At this point, the grinding wheel wear was considered critical due to a diameter deviation of the ground parts in all test points considered. Acoustic emission data were recorded during the process using a measuring chain for acceleration sensors of the type Piezotron/8852A from the company Kistler was used and set to a sampling rate of 1 MHz. During the tests in centerless through-feed grinding, the AE sensor was placed a few millimeters below the workpiece in the run-in zone of the work rest, which lead to well analyzable results. The test setup and the sensor are shown in Fig. 1

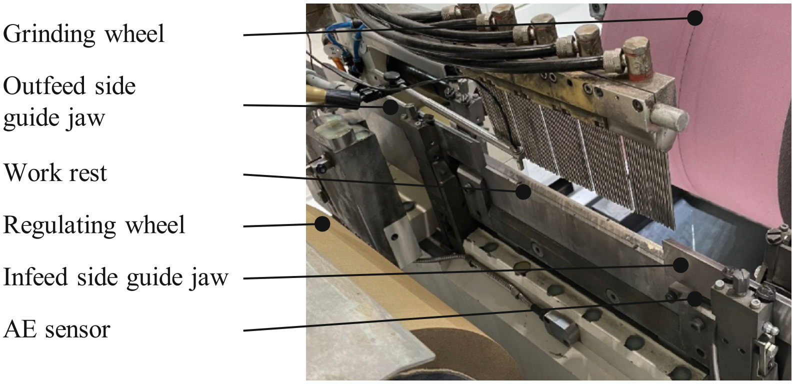

Fig. 1. Experimental configuration and sensor placement.

2.2 Data Acquisition

For the grinding experiments carried out, the grinding wheel radial wear was measured on the basis of the dimensional deviations of the workpieces as a function of the material removal V_w. It was found that increasing dimensional deviations are present starting from a material removal of $V_w = 500{,}000\ \text{mm}^3$ after the previous grinding wheel dressing process. It can be assumed that this is due to a macroscopic grinding wheel wear state in which the entire spark-out zone width has been involved in the material removal process, following a diameter loss of the grinding zone. For the given experimental setup, an increase in the circular shape deviations f_k as well as straightness deviations f_g occurred starting from a material removal of $V_w = 300{,}000$ to $500{,}000\ \text{mm}^3$.

The AE dataset utilized in this research includes four distinct experiments involving two different work rest geometries and two different workpiece lengths. In the first experiment, focusing on the standard support rail geometry, data were recorded for the long workpieces spanning from the 55th to the 270th workpiece ($164{,}000\ \text{mm}^3 < V_w < 803{,}000\ \text{mm}^3$). This range was obtained due to a measurement issue encountered during the experiment. For the short workpieces, the AE signal was captured from the 1st workpiece up to the 270th workpiece ($0\ \text{mm}^3 < V_w < 803{,}000\ \text{mm}^3$). The second experiment involved a non-standard work-rest geometry which was characterized by different workpiece heights on the infeed and outfeed sides of the grinding gap. The exact design of the work rest was not of further importance for the investigations in this study. This experiment merely served to obtain further test data in a divergent process. Herein, the AE signals were recorded for all repetitions of both long and short workpieces (in every case $0\ \text{mm}^3 < V_w < 803{,}000\ \text{mm}^3$). For the long workpieces, data was collected continuously for 270 consecutive workpieces. Similarly, for the short workpieces, the AE signals were recorded for a total of 390 consecutive workpieces. This experimental design allowed for comprehensive data collection across various workpiece ranges, enabling a comprehensive analysis of the AE signals in relation to the different geometries and workpiece sizes.

2.3 Feature-Based Process Analysis

Time series analysis encompasses various techniques, including deep learning approaches such as convolutional neural networks (CNN) or long-short term memory neural networks (LSTM), which can directly process raw or preprocessed time series data without prior feature extraction [9]. Alternatively, the second approach involves transforming the time series into a feature space before further analysis. It entails for instance identifying suitable features from the statistical domain (e.g., mean or median) or the spectral domain (e.g., FFT coefficients). The process of transforming the raw data into a feature space is known as feature extraction. This step is essential to capture relevant patterns and characteristics of the time series [10].

In this paper, the TSFEL (Time Series Feature Extraction Library) [11] was used as a tool for feature extraction in the context of the acoustic emission (AE) signal analysis. The utilization of the TSFEL library allowed for the extraction of a diverse set of features from the AE signal. These features cover various domains, including statistical, spectral, and entropy-based measures [12]. A total of 260 features were extracted for analysis, encompassing various signal characteristics such as FFT mean, Wavelet variance, and absolute energy. These features were selected to provide a comprehensive representation of the data and capture relevant information related to the studied phenomenon. The FFT mean feature quantifies the average frequency content of the signals, while the Wavelet variance feature captures the variability of the signal across different scales. Additionally, the absolute energy feature reflects the overall magnitude of the signals.

2.4 Grinding Tool Condition Monitoring Using the One-Class Support Vector Machine (SVM) Algorithm

Several researchers have explored the application of machine learning algorithms for tool condition monitoring. Sick [13] proposed tool wear monitoring using Artificial Neural Networks (ANN), while Shi and Gindy [14] developed a tool wear prediction model using Least Square Support Vector Machines (SVM). Elangovan et al. [15–17] utilized Bayesian classifiers, decision trees, and SVM for single point tool condition monitoring in turning processes based on vibration signals. Wang et al. [18] studied machine tool conditions using the SVM algorithm. Krishnakumar et al. [19] applied decision trees and ANN for multipoint tool condition monitoring in high-speed machining. Zhang [20] implemented neuro-fuzzy models for tool wear studies using vibration signals. Arun et al. [21] experimentally evaluated grinding wear in cylindrical grinding processes using vibration-based techniques, comparing the performance of various machine learning classifiers [22]. This paper introduces a novel approach for tool wear monitoring based on a one-class support vector machine (SVM) algorithm. Unlike traditional supervised learning methods, our proposed framework operates in an unsupervised manner, focusing on anomaly detection rather than classification. By leveraging the one-class SVM, we aim to address the limitations of existing tool wear monitoring techniques in centerless grinding processes. Our approach utilizes acoustic emission signals as input data, capturing the unique patterns associated with tool wear.

One-class SVM works on the basic idea of minimizing the hypersphere of the single class of examples in training data and considers all the other samples outside the hypersphere to be outliers or out of training data distribution. Figure 2 illustrates the concept of using a one-class SVM to create a hypersphere for classifying out-of-training-distribution data. The process of obtaining the hypersphere, defined by its center c and radius r, involves solving the following constrained optimization problem:

$$\min_{r,c} r^2 \; subject\ to \; ||\Phi(x_i)-c||^2 \leq r^2 \forall i = 1, 2, \ldots, n \tag{1}$$

However, a more flexible formulation that allows for a certain degree of tolerance towards outliers is given by:

$$\min_{r,c,\zeta} r^2 + \frac{1}{\nu n}\sum_{i=1}^{n} \zeta_i \tag{2}$$

$$subject\ to, \; ||\Phi(x_i)-c||^2 \leq r^2 + \zeta_i \forall i = 1, 2, \ldots, n \tag{3}$$

In the given formulation, the function Φ represents a transformation function that maps the original data points x_i into a different space, the mathematical variable ζ_i, represents scalars that describe distances from the hypersphere around c to datapoints outside of the sphere and v is a positive parameter that determines the compromise between the volume of the sphere and the number of outliers [23].

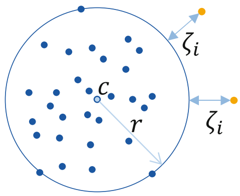

Fig. 2. Hypersphere representation of target data with center c and radius r.

Following the feature extraction process, the extracted features serve as inputs for the algorithm. During the training phase, the algorithm learns to differentiate normal operating conditions from abnormal or worn-out conditions by establishing a boundary in the feature space. Subsequently, the trained one-class SVM is employed to classify new acoustic emission signals based on their similarity to the learned normal behavior. By assessing the proximity of the extracted features from these signals to the established boundary, the algorithm identifies instances that deviate significantly from the norm, indicative of potential wear in the grinding tool.

3 Results and Discussion

To establish a comparison between data analysis and real-world experiments, it is necessary to consider the computational factors relating to the number of short and long workpieces, as well as the value of cutting volume (V_w). The conversion between the number of parts and the V_w value is determined using specific factors, as outlined in the provided Table 1.

Table 1. Conversion factors for establishing comparison between number of workpieces and cutting volume V_w.

Workpiece length l_w [mm]	Cutting volume $= \pi \frac{d_{wA}^2 - d_{wE}^2}{4} \cdot l_w$ [mm^3]
Short (284)	1987.4
Long (425)	2974.1

Based on the measurements obtained from the experiment, it is observed that an increase in the novelty score of the analysis occurs between V_w values of 300,000 mm^3 and 500,000 mm^3. During this range, there is also a significant rise in both the straightness deviation (f_g) and the cylindricity deviation (f_{cyl}) due to grinding wheel wear.

This finding suggests that as the V_w value increases within this specific range, the deviation in straightness and cylindricity becomes more pronounced. This can be attributed to the wear of the grinding wheel, which impacts the accuracy and precision of the workpiece geometry.

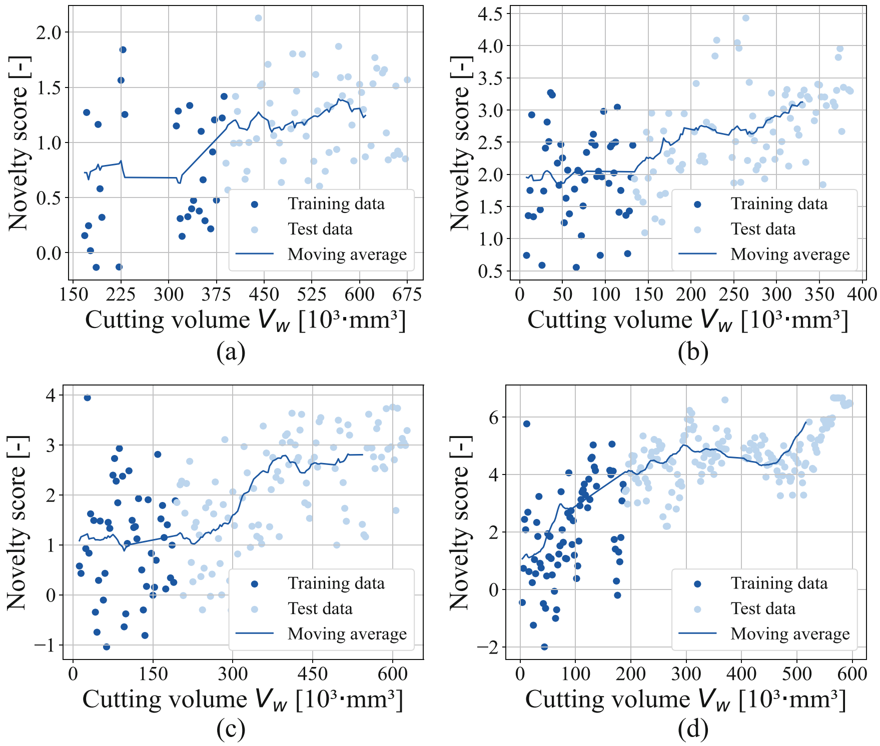

Fig. 3. Figures 3(a) and 3(b) showcase the application of novelty detection on long and short workpieces with a standard work rest geometry, while Figs. 3(c) and 3(d) demonstrate novelty detection on long and short workpieces with a non-standard work rest geometry.

The figures show that there is a comparatively large scatter in the calculated novelty scores. Nevertheless, there was good agreement between the moving average of the novelty scores and the wear-related rise in component shape deviations.

Figures 3(a) and 3(b) depict the application of novelty detection on both long 3(a) and short 3(b) workpieces with a standard work rest geometry. For the short workpieces, 50 training points were used for subsequent prediction, while the long workpieces employed 30 training points. Similarly, Figs. 3(c) and 3(d) demonstrate novelty detection on both long 3(c) and short 3(d) workpieces with a non-standard work rest geometry. In this case, 75 training points were utilized for the short workpieces, and 50 training points were employed for the long workpieces. The variation in the number of training points allows for tailored prediction and analysis based on the specific characteristics of each workpiece.

The presence of bends in the graphs reflects interesting observations regarding tool wear. Specifically, in Figs. 3(b), 3(c) and 3(d), there is a notable change in the trend, indicating a distinct behavior related to tool wear. The bend in the graph signifies a critical point where the tool wear effects become more pronounced, leading to a deviation from the previous trend. This bending point can serve as a reference to identify the threshold at which the tool's condition significantly impacts the machining process. The significance of this observation cannot be reliably confirmed in Fig. 3(a) due to failures in the recording of measurements, which necessitated the use of more than 300,000 mm^3 for training data. Nevertheless, the findings from the first and second experiment series remain compelling and warrant further investigation.

In summary, the key finding of this research is the consistent observation of a significant increase in the novelty score between cutting volume values of 300,000 mm^3 and 500,000 mm^3 in the analyzed data. This trend was observed regardless of the specific workpiece series or geometry under investigation. Consequently, this finding indicates the critical relevance of this cutting volume range in detecting novel or anomalous instances within the grinding process. Furthermore, the presence of bends in the graphs illustrates a distinct behavior related to tool wear, signifying a threshold at which the tool's condition significantly impacts the machining process. These findings highlight the importance of further investigation into the factors influencing tool wear and the relationship between anomalies and grinding process variables.

4 Conclusion and Future Work

This research aimed to improve wear monitoring in centerless grinding processes using acoustic emission (AE) signals by integrating a one-class Support Vector Machine (SVM) algorithm. The combination of feature extraction using TSFEL and SVM algorithm proved to be effective in detecting anomalies during centerless through-feed grinding operations. The analysis of various workpiece geometries and sizes successfully identified wear-related changes in the grinding process, specifically the impact of grinding wheel wear on workpiece geometry accuracy. The observed increase in novelty score and the presence of bending points in the graphs provided evidence of the threshold at which grinding wheel wear significantly affected the machining process, supported by geometry measurements of the workpieces.

The key finding of this research work is the successful detection of deviations associated with grinding wheel wear through AE signal analysis. This finding contributes to the understanding of wear monitoring in centerless grinding operations and highlights the importance of timely intervention and preventive maintenance measures to optimize machine performance and improve product quality.

While this study shows promising results, there are several limitations that need to be addressed in future research. The limited variation in geometry and parameters in the current study calls for further investigation to verify the applicability of the proposed approach in different settings. Additionally, exploring additional features such as vibration and investigating featureless methods that can extract information directly from raw data could provide a more comprehensive understanding of the grinding process and improve wear detection accuracy. Increasing the data sample size and refining the one-class SVM model by fine-tuning parameters, exploring different kernel functions, or considering alternative anomaly detection algorithms is essential to enhance the approach's generalizability and robustness. Future research should also focus on optimizing the model, validating it in larger-scale industrial environments, exploring different grinding processes, and expanding the range of parameters under monitoring. Advancements in these areas will significantly contribute to improving process control and ensuring high-quality results in grinding operations.

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