Acoustic emission-driven anomaly detection in machining

Praveen Jai Bharath Nadkarni, Dhanalekshmi Prasad Yedurkar, Matthias Merzkirch, Markus G. R. Sause

Angaben zur Veröffentlichung / Publication details:

Nadkarni, Praveen Jai Bharath, Dhanalekshmi Prasad Yedurkar, Matthias Merzkirch, and Markus G. R. Sause. 2025. "Acoustic emission-driven anomaly detection in machining." In DGZfP AE-2025 - SCHALL 25 – Schallemissionsanalyse und Zustandsüberwachung mit geführten Wellen, 27.–28. März 2025, Dresden, Germany, 1–10. Mayen: NDT.net. https://doi.org/10.58286/31631.

Acoustic Emission-Driven Anomaly Detection in Machining

Praveen Jai Bharath NADKARNI [1], Dhanalekshmi YEDURKAR [1], Matthias MERZKIRCH [1], Markus G. R. SAUSE [1]
[1] University of Augsburg, 86159, Augsburg, Germany
Contact E-Mail: praveen.nadkarni@uni-a.de

Abstract. In manufacturing, maintaining process stability and reducing machine downtime are critical for achieving high productivity and reliable product quality. This study aims to develop a robust anomaly detection framework integrated within condition monitoring for computer numerical control (CNC) turning centres for processes such as turning, drilling and reaming. The systematic approach begins with sensor selection, followed by the integration of acoustic emission (AE) sensors onto the machine. These sensors capture data at a high acquisition frequency that reveal subtle changes in tool conditions, workpiece interactions, and machine performance due to tool wear, material inconsistencies, and variations in machine data. The initial focus is on single-spindle machines as a proof of concept, with the goal of extending the sensor integration, data acquisition and machine learning models to multi-spindle configurations. The framework effectively distinguishes between normal operations and deviations by processing the AE signals and extracting key features in the time, frequency and time-frequency domains. Additionally, the system aims for real-time identification and aids in removal of faulty components, ensuring that only high-quality parts proceed through the production line. The investigations on the single-spindle machine provide a solid foundation for algorithm development, facilitating precise adjustments to the detection framework. These algorithms may be adapted to the more complex multi-spindle scenario, which involves concurrent operations and increased signal interference, utilizing transfer learning to leverage the knowledge gained from the single-spindle setup for efficient adaptation in the multi-spindle context. By integrating acoustic emission sensor technology, condition monitoring, and artificial intelligence (AI)-supported data-driven analysis, this approach ensures a reliable solution for process monitoring, significantly improving productivity and operational reliability in manufacturing environment.

Keywords: Condition Monitoring, Digital Signal Processing, Ultrasonic Sensors, CNC Machining, Quality Assurance

Media and Publishing Partner

https://doi.org/10.58286/31631

Introduction

Tool condition monitoring (TCM) plays a crucial role in manufacturing for quality assurance (QA) by ensuring the tools consistently produce high quality components. TCM aids in extending tool life and reducing the need for frequent tool replacements. As a result, it reduces defective components and machine downtimes, streamline production processes, and ultimately saves time and money.

The state-of-the-art methods in TCM are discussed in detail based on measured signals, sensors used, and signal processing techniques incorporated [1]. It is noteworthy to consider previous research works on TCM by statistical methods, as well as machine learning and deep learning algorithms applied to machining and tool monitoring [2]. Additionally, extensive research is carried out focussing on tool wear monitoring on milling machines in previous projects [3]. There has also been in-depth analysis on TCM for single-spindle turning machines [4] and condition monitoring for a multi-spindle drilling process. These studies have identified key trends, highlighted the potential of deep learning techniques and validated real-time monitoring approaches using sensor data including acoustic emission, contributing to enhanced machining efficiency and reliability. However, little work has been identified so far on the condition monitoring of a multi-spindle turning machine. The objectives include investigating a sensor data-based process monitoring system, using machine learning algorithms-based methods to detect, classify and quantify anomalies related to machining deviations and use of transfer models for data analysis of a single-spindle machine to the complex case of a multi-spindle machine. This study focuses on employing acoustic emission sensors which have already been proven highly effective in various applications within the manufacturing sector including the domains like sheet metal stamping [5], additive manufacturing [6] apart from machining.

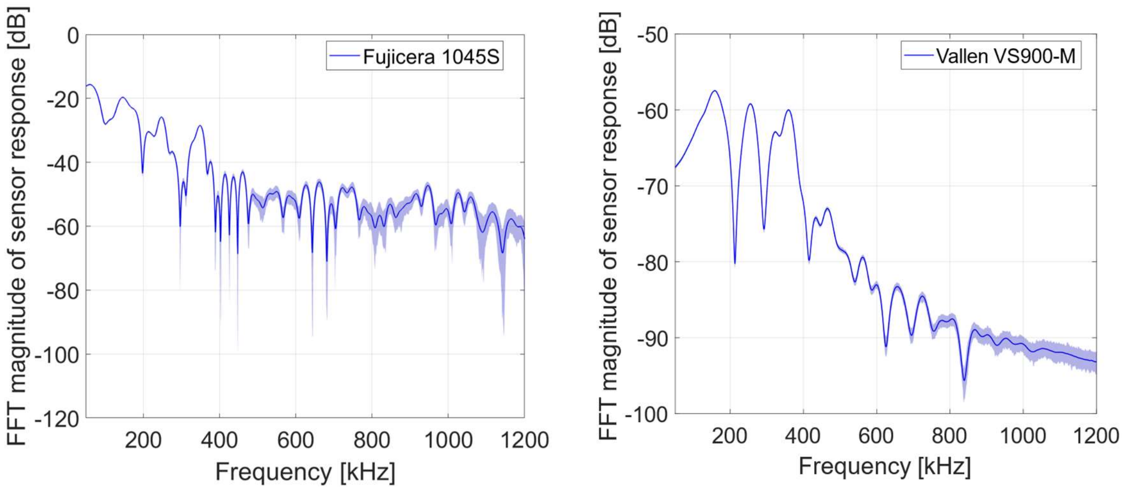
1. Material and Method

The trials were conducted using a ferritic stainless steel 1.4003, provided by Berger Holding GmbH & Co. KG (Berger), ensuring material consistency throughout the study. The primary focus is monitoring the turning and reaming processes, which are kept identical to Berger's standard procedures, except for adjustments needed by machine limitations. The reamer is an inhouse manufactured tool from Berger, while the turning insert is TCS27 from Tungaloy Corporation.

Signals were recorded while using different tool conditions: new tools, used tools (which have reached the end of their designated lifespan) and the worn-out tools (which are used to machine with different parameters such that significant changes are seen in recorded signals). The signals from the acoustic emission sensors need to be synchronised with the machine data such as spindle rotational speed, current etc., along with the quality inspection data facilitating labels for the machined parts. At Berger, the quality inspection process is done by a robotic inspection cell. For the trials at University of Augsburg, the labels are determined by the type of the tool used. Data analysis, signal processing and development of prediction models for multiple sensor data are done using the MATLAB-based software framework— sensor data transformation, reduction, extraction, analysis and management (STREAM), formerly known as ultra-high-ultrasonics (UHU) framework [7,8].

2. Sensor Selection and Placement

The data acquisition utilizes primarily the ultrasonic, acoustic emission sensors 1045S from Fujicera alongside VS900-M from Vallen Systeme GmbH, which are both wide band frequency sensors known for their flat response across a broad range of frequencies as seen in Figure 1. Due to their ability to capture signals across a wide spectrum and their robust casing, these sensors are suited for the trials. The sensors are spring-loaded and mounted with Korasilon coupling agent to ensure stable signal transmission. Before mounting on the machines, the sensors are first tested in a mobile sensor verification setup [9]. In this setup, sensors are subjected to pulse signals to record their signature responses. Furthermore, at any point, the sensors can be verified to ensure proper functioning and accurate data acquisition.



a) b)

Figure 1. Sensor sensitivity curves of acoustic emission sensors in the frequency domain a) Fujicera 1045S b) Vallen VS900-M

The measurement system PROfile from BCMtec GmbH is utilised for data acquisition, which connects to a network switch via a power over ethernet (PoE) cable and includes a dedicated software for streamlined data recording. The responses are recorded at 1 MHz sampling rate for ± 50 mV and ± 5 V inputs, with a selectable range of 100 kHz to 2 MHz.

Initially, a sensor was mounted at a generic location on the turret to evaluate its effectiveness in process monitoring. Subsequently, the sensors were also placed directly on the tool holders, as close to the tool as possible, to enhance monitoring accuracy, see Figures 2 to 4.

The adapters for sensor mounting were installed without modifying the machine. This was achieved by utilising a false tool holder on the turret and retrofitting adapters using of existing holes on the tool holders. To fabricate the adapters, acrylonitrile styrene acrylate (ASA), a weather resistant material was used which is also stable in the environments with cutting fluids. It is suggested to avoid materials like polylactic acid (PLA), polycarbonate (PC) and polyamide-based ONYX filaments for such environments as they are hygroscopic, making them unsuitable for such conditions [10]. The 3D-printed adapters from PLA, ONYX and ASA were also tested in a climate chamber under varying conditions, with temperatures ranging from 5 °C to 70 °C, and relative humidity levels between 0 % and 70 %. These tests were conducted across different cycles, ensuring exposure to a range of temperatures and humidity variations. Only the adapters made from ASA remained stable, while those made from PLA deformed. ONYX did not show visible deformation but appeared to absorb moisture. The use of 3D-printed adapters allowed rapid prototyping, cost-effectiveness, and design flexibility.

Figure 2 illustrates the experimental setup at University of Augsburg, featuring a single-spindle machine DMG MORI CTX Alpha 500 with two data acquisition boxes along with the sensor integration where four sensors are placed at different location on the turret. One Vallen VS900-M sensor is positioned at generic location as shown in Figure 3 while the remaining three Fujicera 1045S sensors are mounted directly on the tool holders. Figure 4 provides a closer view of some of these sensor arrangements, namely reamer tool holder on position 5 and turning insert tool holder on position 12.

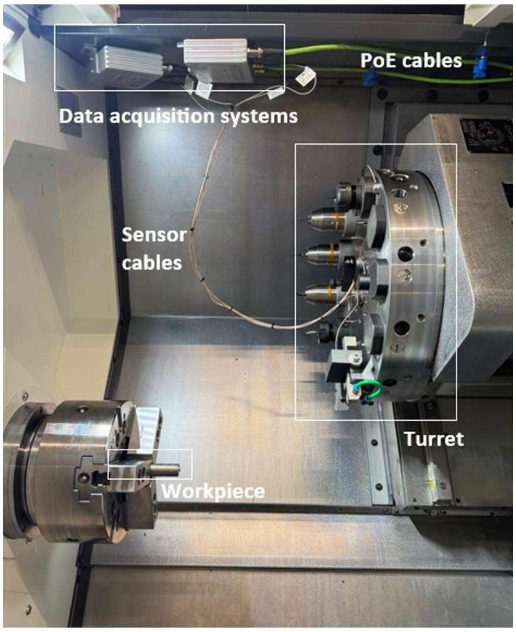


Figure 2. Setup on single-spindle turning machine DMG MORI CTX Alpha 500 at University of Augsburg

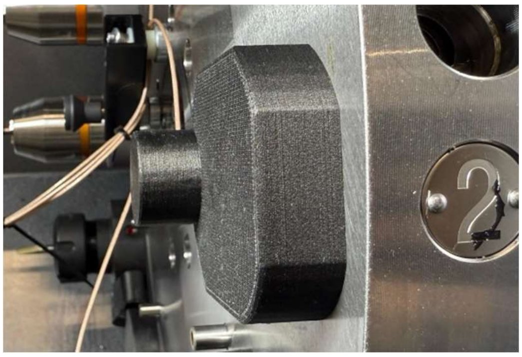
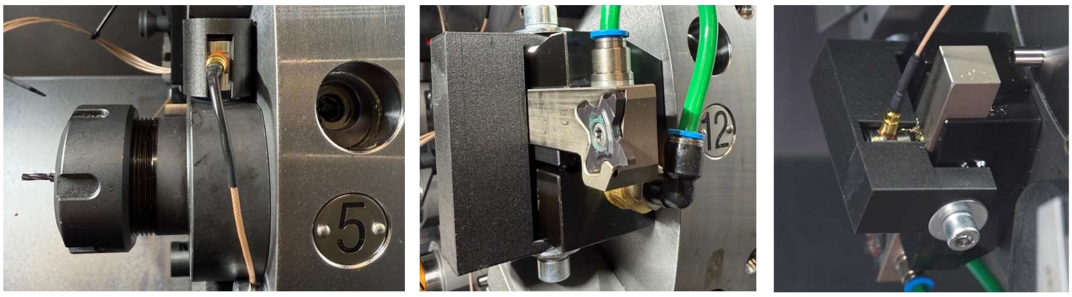


Figure 3. Sensor mounted using an adapter at a generic location on turret (Position 2)



a) b) c)

Figure 4. Sensor integration on tool holders a) Reamer tool holder (Position 5) b) Turning insert tool holder (Position 12) – front view with insert c) Turning insert tool holder (Position 12) – back view with sensor

At the company Berger, the setup follows a similar approach, where the adapters are used to mount the sensors directly onto the tools being monitored. Figure 5 illustrates the machining chamber of a multi-spindle turning machine by TORNOS Multi Swiss 8 x 26, where the adapters in cyan are placed on position 3 where the workpiece is turned and at position 6 where the reaming occurs. These adapters are strategically placed to monitor the turning and reaming process respectively. A closer view of the sensor integration at Berger is depicted in Figure 6.

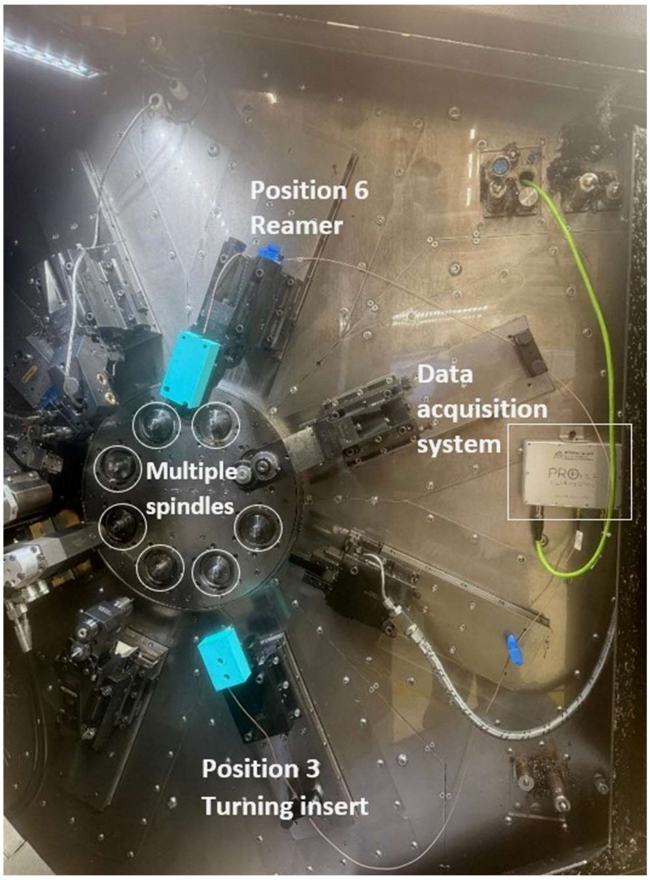


Figure 5. Setup on multi spindle turning machine TORNOS Multi Swiss 8 x 26 with sensor integration on Position 3 and Position 6 tool holders at Berger Holding GmbH & Co. KG

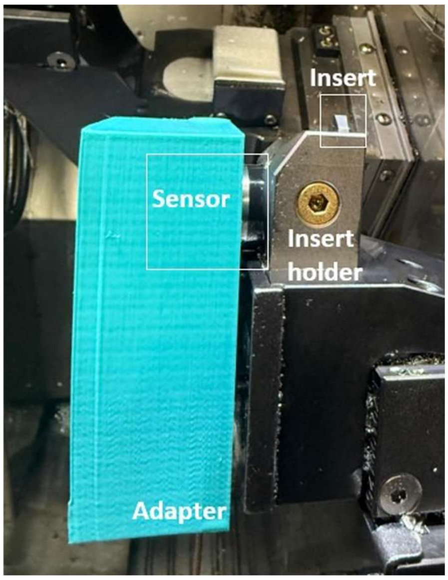


Figure 6. Sensor mounted using an adapter on the turning insert tool holder (Position 3)

3. Results and Discussion

Initial AE signals were recorded during machining at University of Augsburg and are analysed to detect any notable changes. Figure 7 depicts the acoustic emission sensor data using good tools for one sequence of machining operations on single-spindle machine comprising of facing, roughing, turning, pilot drilling, pre-drilling, reaming, pre-drilling (distinct from the earlier step), drilling and finally slotting. The sensor is placed at a generic location on turret as shown in Figure 3.

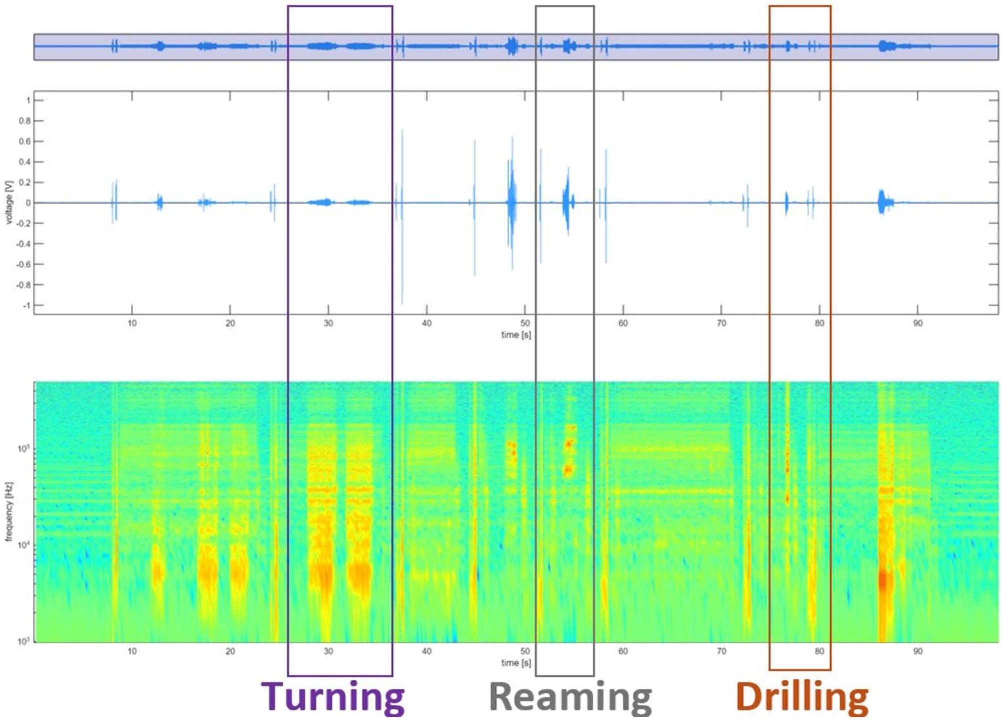


Figure 7. Acoustic emission sensor data (top: amplitude-time plot, bottom: spectrogram) using a good tool for one sequence of machining operations, on single-spindle machine

3.1 Effect of sensor placement

The amplitudes of the signals captured simultaneously during the turning exhibit significant variations depending on sensor placement. Figure 8 presents a comparison of signals recorded at different sensor locations during the turning process, section marked in Figure 7. These locations include the generic location as shown in Figure 3, as well as the sensor integrated directly on the tool holder of the insert as shown in Figure 4 b) and Figure 4 c). Notably, the magnitude of responses from the generic location, see Figure 8 a), are approximately 10 % of the readings obtained from the sensor mounted directly on the turning insert tool holder, see Figure 8 b).

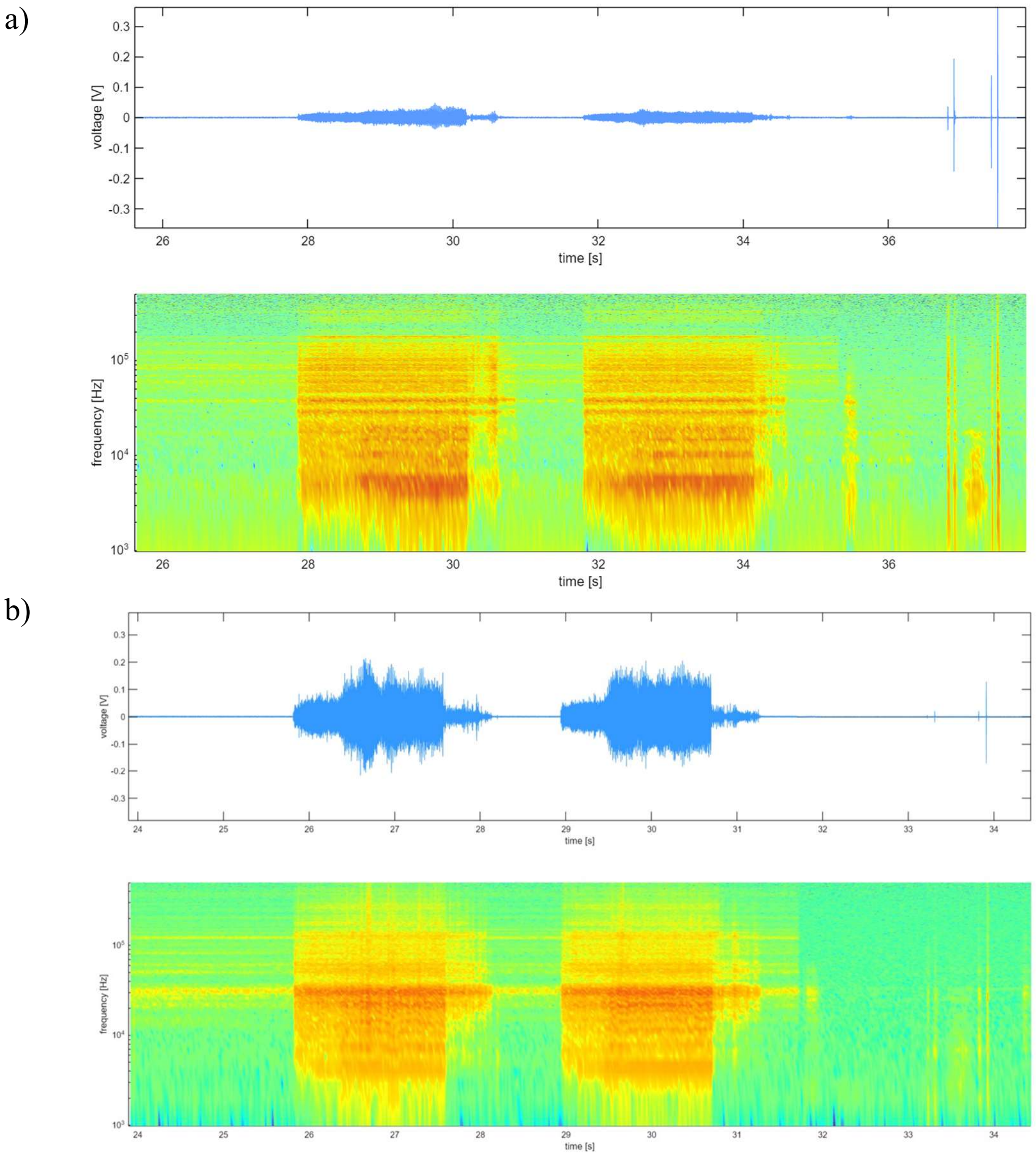


Figure 8. Acoustic emission sensor data comparison (top: amplitude-time plot, bottom: spectrogram) for turning and location of sensor placement a) Generic location on turret on single-spindle machine as shown in Figure 3. b) At turning insert tool holder as shown in Figure 4 c)

3.2 Effect of various tool conditions

The integration of the sensors directly on the tool holders demonstrated improved sensitivity. Based on this, further analysis considers the impact of different tool conditions. In Figure 9, the sensor data comparison between different types of tools is shown for the turning process, section marked in Figure 7 with the sensor mounted on the turning tool insert holder. Figure 9 a) shows the signals recorded during turning with good tools, while Figure 9 b) corresponds to used tools and the Figure 9 c) is with worn-out tools. A clear difference in observed in, e.g. the maximum amplitudes, with the signals from good tools exhibiting lower values compared to others. Further detailed analysis and feature extraction are required, including extraction of additional features such as root mean square (RMS) values, spectral power density or partial powers to gain deeper insights into signal variations [3].

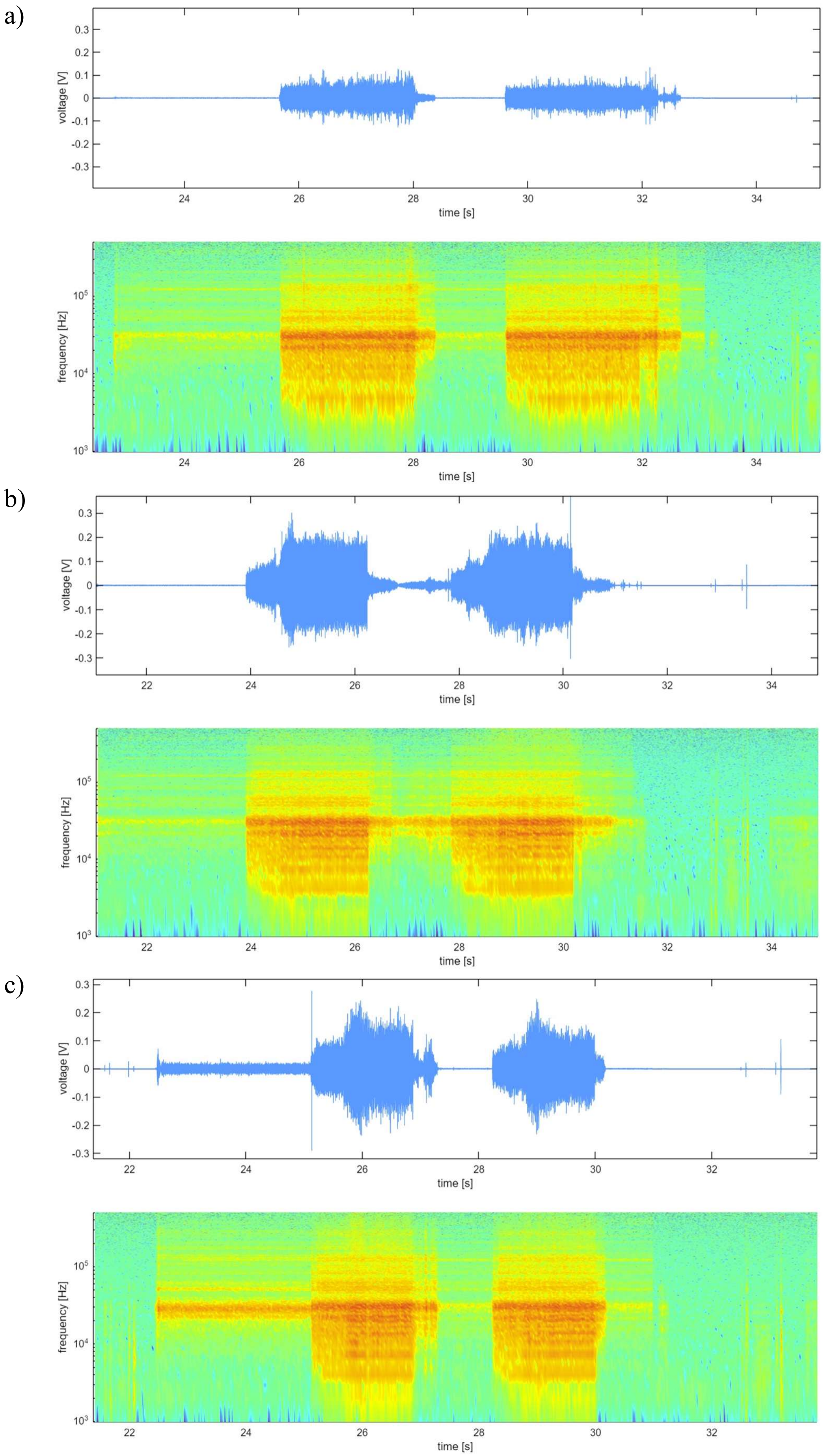


Figure 9. Acoustic emission sensor data comparison (top: amplitude-time plot, bottom: spectrogram) for turning with different types of tools used a) Good tool b) Used tool c) Worn-out tool, on single-spindle machine

5. Summary and Outlook

Real-time, inline process monitoring is essential for improving accuracy and efficiency. This work lays the foundation for developing data driven models that leverage anomaly detection in the acoustic emission data to identify defective parts. For industrial sensor integration with enhanced durability during extensive data collection and real-time monitoring, the 3D-printed adapters are suggested to be replaced with more robust adapters. A further analysis is necessary once extensive data is gathered from both the acoustic emission sensors and machine data. Digital signal processing (DSP) using digital filtering techniques is required to gain a clearer understanding of these variations. In-depth feature extraction, data pre-processing, and model refinement shall be crucial to enhance the accuracy and robustness of the anomaly detection system. Such robust system then aids in segregating the defective parts, thereby ensuring only quality products reach the consumer. Additionally, frequent anomaly detection can serve as an indicator for timely tool replacement. The machine learning models trained on the data from the single-spindle aim to also aid in the detection of anomalies in the multi-spindle machines. This comprehensive approach will ultimately facilitate better decision-making and more precise tool management.
Further, for data fusion within a data infrastructure, the ultrasonic data needs to be synchronised with the machine data and the signals for individual machining process shall be trimmed and labelled for good and bad parts. This shall enable further analysis using time series data classifications. The developed models aim to be robust enough to identify the anomalies with minimal training on the newer use cases. Extracted features can be further evaluated using supervised learning techniques such as support vector machine (SVM) and decision tree (DT). Additionally, this work seeks to lay the groundwork for building time series-based foundation models focussed on acoustic emission signals.

Acknowledgements

We would like to thank VDI/VDE Innovation + Technik GmbH for the funding as part of the "TurnKI" project. We would also like to thank all the project partners involved in the project. Special thanks to Berger Holding GmbH & Co. KG for providing the workpiece material, tools required, as well as the expert advice in production. We also thank BCMtec GmbH for their advice and support in the field of sensor technology and in providing the measurement software.

References

[1] Rehorn, A., Jiang, J. & Orban, P. State-of-the-art methods and results in tool condition monitoring: a review. *Int J Adv Manuf Technol* 26, 693–710 (2005). https://doi.org/10.1007/s00170-004-2038-2.

[2] Serin, G., Sener, B., Ozbayoglu, A.M. *et al.* Review of tool condition monitoring in machining and opportunities for deep learning. *Int J Adv Manuf Technol* 109, 953–974 (2020). https://doi.org/10.1007/s00170-020-05449-

[3] Baumeister, C., Achzet , M., Luong, Q.R., Linscheid, F.F., Brück, B., Schlech, T., Sause, M.G.R. Akustische Überwachung des Werkzeugverschleißes bei der zerspanenden Bearbeitung, SCHALL 2023, März 2023, Wetzlar

[4] Turšič, N.; Klančnik, S. Tool Condition Monitoring Using Machine Tool Spindle Current and Long Short-Term Memory Neural Network Model Analysis. *Sensors* 2024, *24*, 2490. https://doi.org/10.3390/s24082490

[5] Saidoun, A., Vu, Q., & Zhang, F. (2023). Online monitoring of manufacturing processes by acoustic emission. EWGAE35 & ICAE10 Conference on Acoustic Emission Testing, Ljubljana, Slovenia, September 2022. *e-Journal of Non-destructive Testing* Vol. 28(1). https://doi.org/10.58286/27607

[6] Muktadir, M., Hasan, M. N., & Alam, M. (2023). Additive manufacturing and acoustic Emission: a brief review. *Journal of Additive Manufacturing Technologies*, *2*(1), 632. https://doi.org/10.18416/

[7] Linscheid, F. F., Sause, M. G. R. "Hard- und Softwarefusion von mehreren akustischen Messmethoden zur Zustandsüberwachung." in DGZfP Jahrestagung 2021 (virtuell): Materialcharakterisierung, 10. - 11. Mai 2021. Deutsche Gesellschaft für Zerstörungsfreie Prüfung (DGZfP), Berlin, 1-8

[8] Linscheid, F. F, Entwicklung eines Zustandsüberwachungssystems durch Kombination von akustischen Überwachungsverfahren. Dissertation, 2022, Universität Augsburg

[9] Fernandes de Oliveira Junior, A., Schlech, T., Sause, M., Studies on a Mobile Acoustic Emission Sensor Verification Device. e-Journal of Nondestructive Testing (2024). 29. 10.58286/30240.

[10] Ramírez-Revilla, S., Camacho-Valencia, D., Gonzales-Condori, E.G. *et al.* Evaluation and comparison of the degradability and compressive and tensile properties of 3D printing polymeric materials: PLA, PETG, PC, and ASA. *MRS Communications* 13**,** 55–62 (2023). https://doi.org/10.1557/s43579-022-00311-4