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*turning, cutting tool wear,
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ALGORITHM FOR PARAMETERIZATION OF AN ACOUSTIC EMISSION MEASUREMENT SYSTEM IN THE TURNING PROCESS

This study investigates the use of Acoustic Emission (AE) for monitoring cutting tool wear during turning. Experiments were carried out using a Vallen AMSY-6 system and a VS370-A2 sensor. The work focuses on optimizing AE system settings, including filter bandwidth, detection threshold, and impulsive signal acquisition under varying cutting conditions. A systematic procedure for configuring the AE measurement process was established. Results show that employing a 20 kHz–800 kHz band-pass filter and a detection threshold of ~90 dB effectively isolates AE events associated with cutting and reveals a pronounced increase in AE activity when the tool is worn. These findings confirm AE as a sensitive technique for detecting cutting edge wear and underline its potential for real-time tool condition monitoring.

1. INTRODUCTION

The quality and efficiency of machining depend strongly on the condition of the cutting tool. Progressive edge wear degrades dimensional accuracy and surface finish, while sudden tool failure can halt production, damage parts, or even cause machine collisions. Tool failures account for up to 22% of unplanned CNC downtime [1], highlighting the need for effective monitoring. Industry practice often relies on conservative replacement schedules based on fixed time or cycle counts. Such strategies are inefficient: early replacement wastes tool life, while late replacement risks failure, unplanned stops, and costly scrap [2]. With increasing automation and the advent of Industry 4.0, demand is rising for intelligent monitoring systems that maximize tool utilization and minimize unplanned downtime [2]. Consequently, the integration of Cyber-Physical Systems (CPS) that combine advanced sensing with process control has emerged as a critical research direction [3].

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To meet these demands, Tool Condition Monitoring (TCM) methods have been extensively developed over recent decades. These include direct techniques, such as laser-based wear measurements, as well as indirect approaches that analyse process-generated signals. The most widely studied signals include cutting forces, vibrations, noise (including acoustic emission), and spindle or drive motor currents. Each method has inherent strengths and limitations. Force measurement, for instance, offers high sensitivity and strong correlation with process dynamics but requires rigid dynamometer integration with the machine tool. In contrast, vibration and acoustic emission sensors provide broad frequency coverage and high sensitivity, though their effectiveness depends on proper placement on the machine [4]. Previous studies have demonstrated that analysing cutting forces can optimize process parameters and reliably predict tool life, particularly during complex operations such as drilling in hard-to-machine alloys like Inconel 718 [5].

In recent years, diagnostic programs for tool wear have increasingly incorporated the analysis of noise levels and frequency spectra. For instance, Salm et al. [6] demonstrated a real-time acoustic measurement system tailored for cutting-tool analysis during the machining of stainless steel, emphasizing the value of acoustic signals in industrial settings. Furthermore, comprehensive reviews by Li et al. [4] highlight that while audible sound is highly sensitive to tool degradation, its effectiveness depends on robust frequency-domain processing to mitigate environmental factory noise. Integrating these vibroacoustic features with advanced classification algorithms, as seen in hybrid turning diagnostics, provides a more holistic view of the tool's condition

In recent years, acoustic emission (AE) measurement and analysis have gained increasing attention as a non-destructive approach for tool diagnostics. AE refers to elastic stress waves generated within a material due to localized deformations or fractures. In machining, these manifest as high-frequency bursts caused by phenomena such as microcracking of the cutting edge, detachment of tool particles, or friction within the tool–chip contact zone [7]. The level and characteristics of the emitted triboemission during cutting are fundamentally influenced by a complex interplay of various factors. These include tool geometry, the material properties of both the cutting tool and the workpiece, and the machine tool's dynamic parameters. Furthermore, environmental parameters—specifically ambient temperature and humidity—can significantly affect the triboemission levels and the stability of signal transmission. Understanding these influences is essential for developing robust monitoring systems, as variations in these parameters can alter the acoustic response even under constant wear conditions. AE techniques enable highly sensitive, real-time detection of such events without interfering with the machining process. Unlike dynamometers, AE measurements do not affect the stiffness of the machine–tool–workpiece system, allowing monitoring under unaltered cutting conditions [7]. These advantages have made AE a promising source of information for tool condition assessment and its application has expanded across various machining processes. Literature surveys report the successful use of AE signals for detecting tool wear, chip breakage, chatter, and built-up edge formation during turning, milling, drilling, and other operations [8].

Numerous studies have demonstrated the effectiveness of acoustic emission (AE) for tool wear diagnostics across diverse machining operations. In turning, AE signals have been shown to correlate strongly with cutting edge wear, enabling the early detection of tool

degradation with accuracy comparable to conventional cutting force measurements [9]. In milling, promising results have been achieved by combining AE analysis with artificial intelligence. Ahmed et al. [10] employed spectrogram representations of AE signals from milling processes and a deep ResNet neural network to automatically classify tool states (new, partially worn, fully worn), emphasizing the practical benefits of such monitoring in reducing costs and material waste. AE has also proven valuable in drilling applications. Hase [7] reported that frequency-domain analysis of AE signals during micro-drilling (<1 mm diameter) can detect process disturbances such as chip entanglement and material adhesion to the drill, while capturing high-frequency bursts preceding catastrophic drill failure, enabling predictive maintenance. AE-based monitoring has further extended to non-conventional processes. Soleymani and Hadad [11] applied acoustic signal analysis to track tool condition in Electrical Discharge Turning (EDT), a hybrid process combining conventional turning with electrical discharge machining (EDM). Their study utilized a neural network classifier trained on process sound features, with particular attention to acquisition and processing parameters (sampling rate, FFT window length, feature extraction) to maximize classification accuracy. Collectively, these studies highlight AE as a versatile diagnostic tool applicable to conventional (turning, milling, drilling) as well as advanced and hybrid machining operations.

A key challenge in applying AE for tool condition monitoring lies in the complexity of the acquired signal and the difficulty of its direct interpretation. AE signals are highly transient, consisting of low-energy bursts with broad frequency spectra, which necessitates advanced processing to extract meaningful features. Current research highlights the effectiveness of time–frequency analysis and machine learning in identifying AE patterns associated with tool wear. Short-Time Fourier Transform (STFT) and wavelet transforms are widely used for AE signal analysis. For example, Fourier-based spectral analysis of AE during turning has enabled the identification of characteristic frequency bands linked to specific wear mechanisms (e.g., abrasive wear producing signals in the 200–1000 kHz range), allowing for precise wear type classification [12]. Wavelet analysis, in turn, offers adaptive processing of signals with non-stationary time and frequency characteristics. Recent studies confirm the utility of wavelet decomposition for extracting wear features from close-to-process signals [13]. Xu et al. [1] employed wavelet decomposition to isolate optimal frequency bands in AE and vibration signals containing tool state information, then fused these features and used them to train a back-propagation (BP) neural network, achieving intelligent recognition of wear progression in turning. Increasingly, machine learning-based solutions are reported, where algorithms learn wear-related patterns directly from large sensor datasets, bypassing the need for complex physical models of cutting phenomena. For instance, Ferrando et al. [14] proposed a tool wear prediction framework based on multi-threshold AE signal analysis (using wavelet transforms) combined with random forest models, outperforming traditional regression-based approaches. Similarly, neural network-based classifiers have demonstrated high accuracy in tool state classification using processed AE signals [10], while comparative studies highlight the potential of various architectures like LSTM and GRU for robust wear prediction [15].

Despite intensive research and numerous promising results, several challenges still hinder the widespread adoption of AE-based monitoring systems in industrial practice. Literature reviews indicate that, despite the abundance of studies, Tool Condition Monitoring

(TCM) methods remain rarely implemented on the shop floor [4]. A primary barrier is the lack of systematic parameterization of AE measurement systems—specifically, the selection of sensor configurations and acquisition settings optimized for a given process. AE signals are highly sensitive to sensor mounting conditions and measurement system setup, meaning that poorly designed monitoring systems can yield misleading or inconsistent results. Experimental findings also highlight the influence of tool coatings, which not only affect tool life but also alter the acoustic emission characteristics generated during cutting [2]. Among the most common AE-based wear indicators is the count of recorded bursts (the so-called hit count). However, this metric is strongly dependent on the selected detection threshold; inappropriate threshold settings can lead to significant variability in results, complicating reliable wear prediction [15]. Likewise, the broadband nature of AE signals creates the challenge of isolating frequency components most correlated with wear progression. Numerous studies have emphasized that selecting an appropriate frequency band is both critical and non-trivial for ensuring robust monitoring performance [15].

Most existing studies have focused on analyzing recorded AE signals and developing indicators or classification algorithms, typically assuming a predefined measurement system configuration [6,16]. In contrast, the selection of the hardware and acquisition parameters—such as the AE sensor type and mounting location, sampling frequency, filtering, and amplification—remains comparatively underexplored [17]. This gap represents a critical barrier to the advancement of reliable tool condition monitoring. In turning, where AE signals exhibit a predominantly continuous nature, similar to grinding processes [18] and are often superimposed with other phenomena such as machine vibrations and structural noise, proper parameterization of the AE measurement system is essential to achieve high sensitivity and selectivity in detecting cutting edge wear [19]. Therefore, research aimed at determining optimal AE system settings for tool wear diagnostics in turning is necessary. Establishing such guidelines will improve the accuracy and reliability of tool wear monitoring and, consequently, enhance the efficiency and safety of machining operations [20].

2. MATERIALS AND METHODS

The experiments were conducted on a turning setup equipped with a lathe, where machining was performed using a replaceable carbide insert. A schematic of the experimental setup is presented in Fig. 1 [Fig. 1].

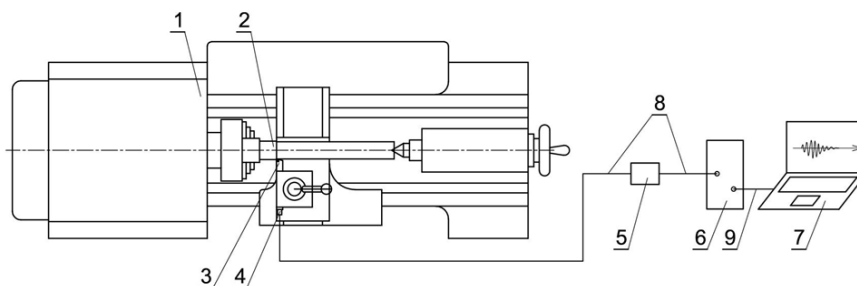


Fig. 1. Schematic of the experimental setup. 1) Lathe, 2) Workpiece, 3) Turning tool, 4) AE sensor mounted on the tool holder, 5) Pre-amplifier, 6) AMSY-6 measurement system, 7) Data acquisition computer, 8) Signal cables

The experimental setup is shown in Fig. 2. The experimental trials were conducted in a laboratory environment under controlled conditions, with a stabilized ambient temperature of $20 \pm 2^\circ\text{C}$ and a relative humidity of $45 \pm 5\%$. Maintaining these parameters was crucial for ensuring the stability of the acoustic coupling and the consistency of signal transmission throughout the tests.

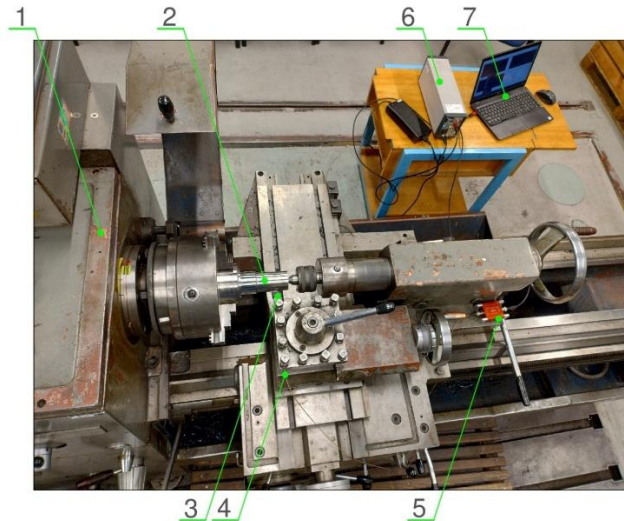


Fig. 2. Top view of the lathe with the connected measurement equipment. 1) lathe, 2) workpiece, 3) turning tool, 4) AE sensor (mounted on the tool holder), 5) pre-amplifier, 6) AMSY-6 measurement system, 7) data acquisition computer

Acoustic emission was measured using a Vallen AMSY-6 system (Vallen Systeme GmbH) paired with a piezoelectric AE sensor (VS370-A2) and an AEP5 preamplifier. The AE sensor was mounted on the shank tool for turning near the cutting insert, ensuring rigid coupling and good acoustic contact by applying a thin layer of petroleum jelly as a coupling medium. The sensor signal (SMC) was transmitted via cable to the AEP5 preamplifier, which provided 34 dB gain and broadband signal transmission (approximately 2.5 kHz to 2400 kHz). The preamplifier was powered by a 28 V supply from the AMSY-6 system, and the amplified AE signal was delivered through a coaxial connection to the AMSY-6 acquisition module. The VS370-A2 is a passive sensor without an integrated preamplifier, featuring compact dimensions ($\text{Ø}8.5 \times 13$ mm) and a mass of 3.5 g. It offers a frequency response from 170 to 590 kHz, with a resonance frequency near 370 kHz, making it particularly sensitive to high-frequency AE bursts associated with microcracking and friction in the cutting zone.

After assembling and connecting the experimental setup, the measurement parameters were configured. As a first step, the characteristics of the workpiece material—in this case, steel machined on the lathe—were specified. The configuration of the measurement system was performed using Vallen VisualAE (AE-Suite) software. Initially, the factory default parameter set “Metallic Structures” (Fig. 3), provided by the system manufacturer, was loaded. The default settings for this configuration included a total gain of 34 dB, a detection threshold of 40 dB, a rearm time of 3200 μs , and a duration discrimination time of 400 μs . The associated band-pass filter covered the 95–850 kHz range, matching the typical AE frequency spectrum for metallic materials. These defaults served as the starting point for further adjustments to suit the experimental conditions.

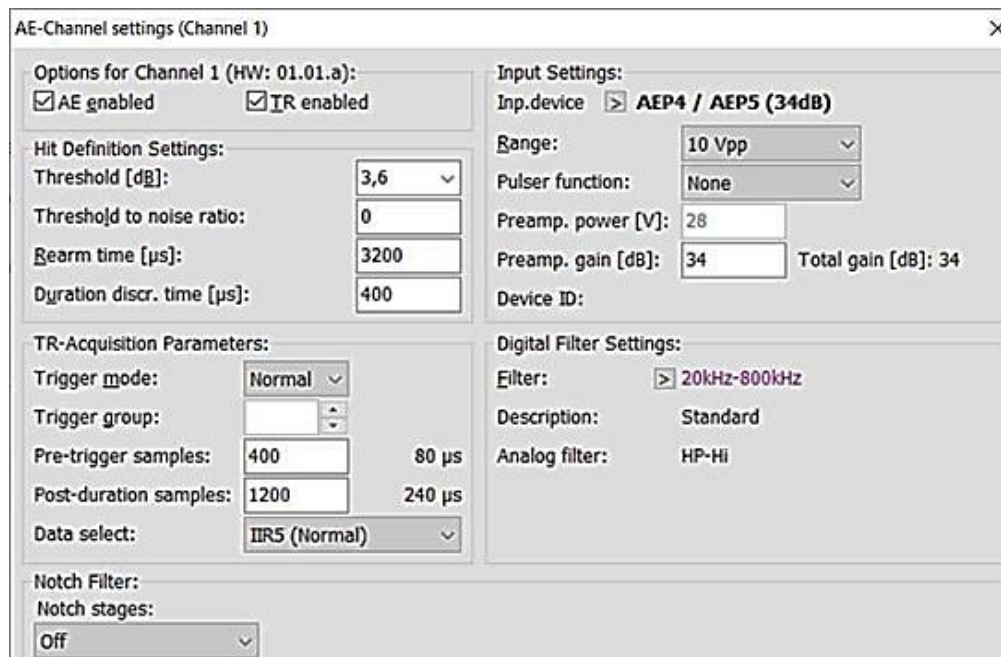


Fig. 3. Configuration window of the AE acquisition channel (Channel 1). The initial settings include a 3.6 dB threshold, a 20–800 kHz band-pass filter, and default RT/DDT values under the ‘Metallic Structures’ profile

In the subsequent stage, the system settings were fine-tuned based on preliminary measurements. The AE detection threshold was increased to 90 dB, a value selected based on preliminary noise floor measurements. With the machine-tool system in an idle state, the recorded background noise level remained below 55 dB. Setting the threshold at 90 dB provided a sufficient safety margin to effectively isolate genuine triboemission signals from environmental and machine-induced electrical or mechanical disturbances. Default hit definition times were retained: RT (Rearm Time) = 3.2 ms and DDT (Duration Discrimination Time) = 400 μ s, consistent with recommendations for metallic structures. A broadband band-pass filter of 20–800 kHz was applied, slightly wider than the sensor’s nominal range, to capture potential frequency components outside its primary resonance. Additionally, a high-pass filter (HP 20 kHz) was enabled in the analogy path to suppress low-frequency components outside the usable range. Full waveform acquisition of AE transients was performed at a sampling rate of 5 MHz per channel, following the default settings of the Metallic Structures profile. All data were recorded on a single channel (Channel 1) assigned to the VS370-A2 sensor. The key AE system configuration parameters used in the experiment are summarized in Table 1.

Table 1. Key AE acquisition parameters used in the experiments

Parameter	Setting
AE filter bandwidth	20–800 kHz
Preamplifier gain	34 dB (AEP5)
Detection threshold (Threshold)	90 dB
Rearm time (RT)	3.2 ms
Duration discrimination time (DDT)	0.4 ms (400 μ s)
Sampling rate	5 MHz
Number of AE channels	1 (VS370-A2 sensor)

3. RESULTS

The measurement procedure began with the acquisition of background noise (Fig. 4).

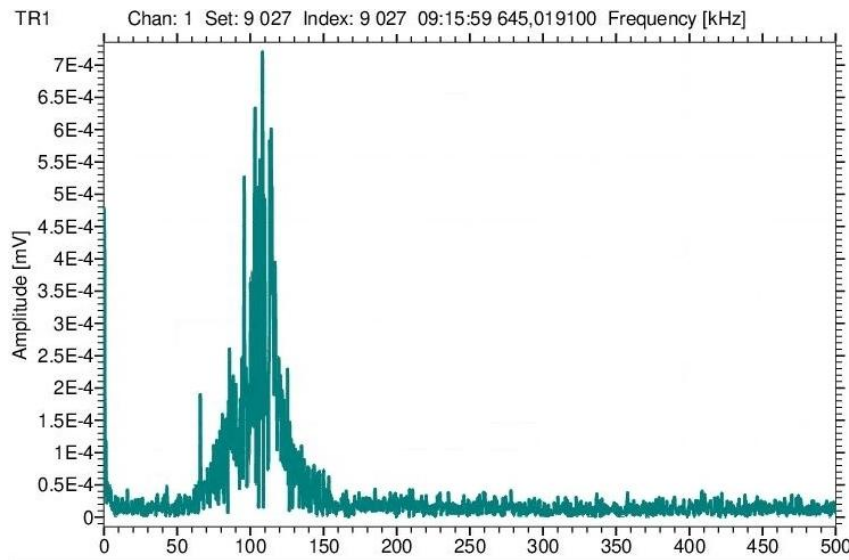


Fig. 4. FFT spectrum of the recorded AE signal with the machine turned off

With the machine turned off, no significant frequency components above several tens of kilohertz were observed. Subsequently, AE measurements were performed during spindle motor operation. The lathe was started (spindle motor engaged), and a trial ‘cutting’ pass was conducted on the workpiece without tool–material contact. The AE sensor captured signals generated solely by the machine operation. Due to the previously configured filters, the system remained sensitive to high-frequency bursts while suppressing low-frequency mechanical vibrations outside the band of interest. An FFT analysis of the AE signal from this process was also performed (Fig. 5).

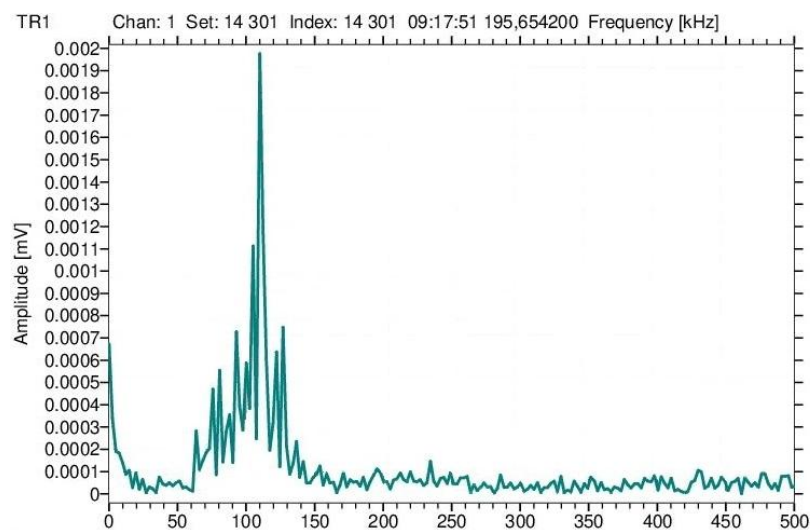


Fig. 5. FFT spectrum of the AE signal during lathe operation (spindle rotation and cutting)

The next step involved fine-tuning the detection sensitivity based on these observations. Spectral analysis indicated that most of the useful AE signals were concentrated within the sensor's operational frequency band (on the order of several hundred kilohertz). Therefore, a wide band-pass filter of 20–800 kHz was retained to capture as much emission information as possible without attenuating critical components. A detection threshold of 85 dB was found to be appropriate: AE events generated during cutting clearly exceeded this level, triggering hit registration, while background noise and lower-level disturbances did not result in false detections. Consequently, the acquisition parameters adopted for the subsequent tests (Table 1) ensured selective detection of genuine acoustic emissions associated with the cutting process. The AE spectrum recorded during cutting revealed a distinct increase in frequency content within the 140–350 kHz range, with a dominant peak near ~270 kHz, consistent with the sensor's frequency response. The emergence of these components indicates the detection of emissions typical for machining, such as microcracking and material detachment along the cutting edge, which generate high-frequency elastic waves. By contrast, in the lower frequency range (<100 kHz), no significant signals above background were observed, suggesting that background components were effectively filtered or had negligible influence on AE detection.

After defining the system parameters, a measurement trial was conducted using a new cutting tool. During the trial, the AE system recorded both the number of detected AE hits—defined as acoustic emission events exceeding the 85 dB threshold—and the characteristics of the captured signals. The hit count was automatically logged by the AE-Suite software for each tool pass over the workpiece. Additionally, selected AE waveforms were stored for subsequent qualitative analysis. The recorded results indicated that the selected threshold was too low for this process. The acoustic emission exhibited an excessive number of detections (hits), which obscured the ability to clearly distinguish between the responses of new and worn inserts. The primary objective of this study is to parameterize the AE measurement system to achieve minimal or negligible AE activity for a new insert, while capturing a pronounced increase in emission for a worn insert. Such configuration will enable a reliable correlation between acoustic emission levels and the degree of tool wear.

A critical step in optimizing the AE monitoring system is narrowing the filter bandwidth and precisely tuning the frequency range to match the emissions generated by insert wear. This approach enables the suppression of disturbances unrelated to tool condition, thereby improving measurement accuracy and analysis reliability. Due to the excessive AE activity observed at the current stage of testing, the detection threshold was raised to 95 dB. This value was experimentally validated, allowing effective differentiation of acoustic emission levels corresponding to varying degrees of insert wear. With the threshold properly set, AE measurements are expected to provide accurate tracking of emission growth as tool wear progresses (Fig. 6).

After setting the TRH threshold, cutting is performed with a new insert, which serves as the reference condition. The next step involves machining with a worn insert. During this stage, the operator monitors whether the acoustic emission level increases. If a noticeable increase is observed, the parameterization procedure is considered complete. If no clear increase is detected, it must first be verified whether the number of recorded acoustic events exceeds that observed with the new insert. If the event count is higher, the operator must

adjust the RT and DDT parameters, shift the band-pass filter range, and repeat the cutting test until satisfactory results are obtained. If the event count does not exceed the baseline, the band-pass filter must be adjusted directly, and the measurement procedure repeated. This iterative process continues until the desired acoustic emission measurement performance is achieved. The procedure described in the section can be represented as the block diagram shown in Fig. 7.

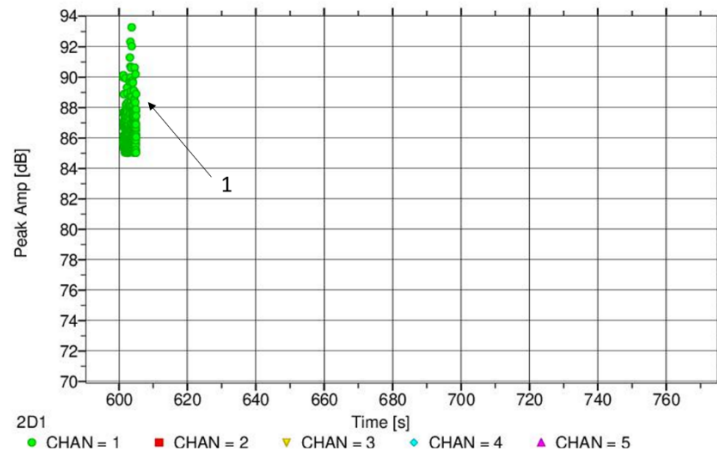


Fig. 6. Recorded acoustic emission during cutting with a new insert (Threshold = 85 dB, filter bandwidth = 226–305 kHz). 1- Recorded emission for cutting with a new insert

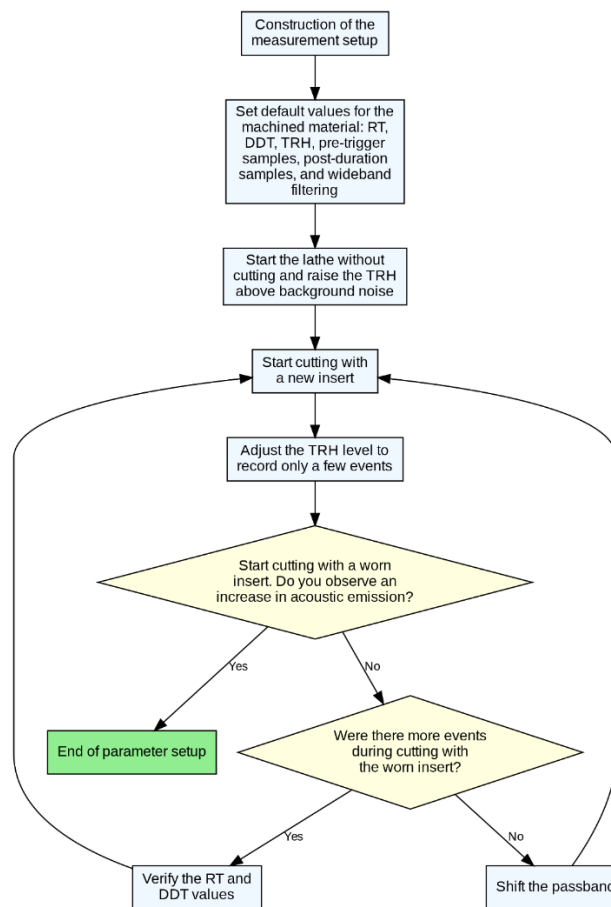


Fig. 7. Block diagram of the acoustic emission measurement procedure in the turning process

The effectiveness of the developed procedure was validated by comparing results obtained for a new and a worn tool. A clear difference was observed in the number of recorded AE hits, with the worn tool generating significantly more acoustic emission events than the new tool (Fig. 8). These findings indicate that acoustic emission activity increases with cutting edge wear, as expected: progressive degradation leads to more frequent microcracking and frictional events along the edge, which generate AE bursts. This difference confirmed that the adopted settings (filtering and threshold) enable effective differentiation of tool condition based on AE signals. Additionally, time-domain waveforms of selected AE hits were analysed. For the worn insert, more frequent and stronger AE bursts with short durations (on the order of tens of microseconds) were observed. Their characteristic shape—marked by a rapid amplitude rise followed by a fast decay of oscillations—matches typical emissions associated with the fracturing of microfragments from the tool material. In contrast, the AE signal from the new insert exhibited fewer high-amplitude events, producing a relatively calmer profile. This qualitative analysis of AE waveforms confirmed that the recorded events were genuine emissions generated during cutting, rather than random noise. Therefore, the implemented measurement procedure, which combines high-frequency filtering with threshold-based detection, proved effective for detecting tool wear phenomena.

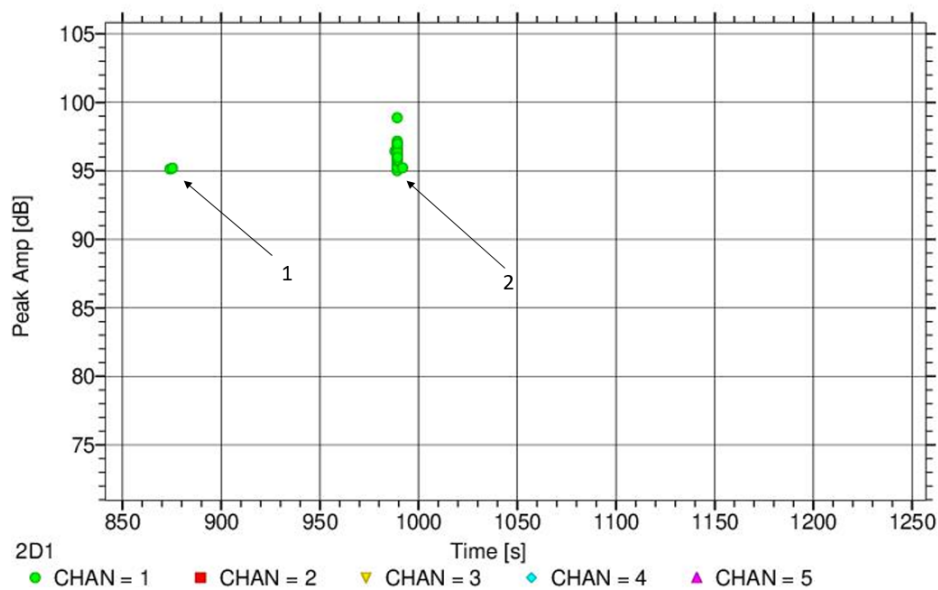


Fig. 8. Acoustic emission signals recorded for a new and a worn insert under identical cutting conditions. The measurement parameters were configured to highlight the increase in AE activity with tool wear, enabling non-invasive tracking of insert degradation. 1 – Emission for the new insert, 2 – Emission for the worn insert

The experimental findings are in high agreement with contemporary research in the field of tool condition monitoring. The observed increase in AE activity (hit count and amplitude) as tool wear progresses aligns with the results reported by Hoang et al. (2023), who demonstrated that acoustic emission signals are highly sensitive indicators of the cutting edge state during the turning process, especially when integrated with vibration analysis. Furthermore, the focus on identifying wear-related patterns through spectral and noise level

analysis follows the diagnostic trends discussed by Li et al. (2024), emphasizing the importance of monitoring audio-based frequency shifts in intelligent machining systems. The effectiveness of the developed AE-based procedure in capturing machining states aligns with broader trends in advanced diagnostics; for instance, the study by Dado et al. (2025) highlights the robustness of acoustic emission for adaptive process control and real-time monitoring even in highly heterogeneous materials like wood, underscoring the cross-domain versatility of AE-based monitoring systems. These comparisons validate that the established system configuration effectively captures the physical phenomena of tool degradation documented in recent scientific literature.

4. CONCLUSION

The conducted experiments confirmed that acoustic emission can serve as an effective source of information on cutting tool condition, provided that the measurement system is properly parameterized. The broadband filter set to 226–305 kHz and the detection threshold of 95 dB, as determined in the experiment, enabled the suppression of background noise and the selective detection of AE bursts generated by tool wear phenomena. As a result, the AE system recorded significantly increased acoustic emission activity for the worn tool, manifested by a greater number and amplitude of detected AE events compared to the new insert. These results confirm that a properly configured AE setup allows for early detection of tool wear indicators during machining.

From an industrial perspective, the obtained results are particularly significant as they address a key research gap related to the parameterization of acoustic emission systems. Previous studies have predominantly focused on AE data analysis and tool state classification methods, often overlooking the critical stage of acquisition parameter selection. The approach presented in this work demonstrates that, even during system configuration, through careful adjustment of filtering, detection thresholds, and evaluation of system response to both background noise and cutting conditions, it is possible to achieve highly sensitive and selective monitoring of cutting edge condition. This methodology provides a foundation for developing reliable diagnostic systems for industrial environments. By enabling real-time, non-intrusive AE measurements, the method allows a shift away from conservative, schedule-based tool replacement strategies toward condition-based utilization. Furthermore, the proposed parameterization approach serves as a practical baseline for advancing intelligent Tool Condition Monitoring (TCM) systems aligned with the Industry 4.0 paradigm, integrating AE sensors with digital infrastructure, data analytics, and machine learning techniques.

Future research in this area should focus on the automation of the proposed parameterization procedure using adaptive algorithms to minimize human intervention during system setup. Additionally, integrating the established AE features with machine learning models for real-time tool wear classification and predictive maintenance represents a promising direction for further industrial application. Future research will also involve a more in-depth statistical analysis of the time-domain signals, including parameters such as skewness and kurtosis, to extract additional wear-related features.

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