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ORIGINAL ARTICLE

Application of acoustic emissions in machining processes: analysis and critical review

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Abstract
Monitoring and controlling of metal cutting processes is an essential task in any modern precision machining setup. The implementation of proper monitoring process leads to promising results in terms of cutting tool life, machining costs, and production rates. Several techniques have been used to detect, monitor, and analyze different parameters associated with the cutting processes such as cutting tool wear, chip breakage and fracture, chatter vibrations, and formation of built-up edge (BUE). In this work, a review study is presented to discuss the research activities using the acoustic emission (AE) signals to monitor and control various machining processes. The discussed work does not only present an investigation of the AE signals, measured variables, and AE sensor setup during machining processes, but also shows several methods used for analyzing and processing the AE signals. The work focuses on studies, which employed AE in monitoring, and analyzing some specific characteristics such as chip formation and morphology, surface quality, and tool wear evolution for different machining operations and materials.

Keywords Acoustic emission (AE) · Machining processes · Chip formation · Tool monitoring · Surface quality

Nomenclature

AE	Acoustic emission
BUE	Built-up edge
RMS	Root mean square
H-P filter	Hodrick-Prescott filter
L-P filter	Low-pass filter
FFT	Fast Fourier transform
WT	Wavelet transfer
DCT	Discrete cosine transform
DFT	Discrete Fourier transform
STFT	Short-time Fourier transform
CWT	Continuous wavelet transform
HHHT	Hilbert and Hilbert-Huang transform
$AE_{r.m.s}$	The root mean square value of AE signals
R_a	Average surface roughness
A/D	Analog to digital
AE_{MARSE}	Acoustic emission energy counts
DSP	Digital signal processing
ANN	Artificial neural network
MAMP-MVMP	The mean average and mean variance of mean power
LPCC	Linear predictive cepstrum coefficient
MVD	Mean value deviance
MERSE	Measured area under the rectified signal envelope
β	Beta distribution
CFRP	Carbon fiber reinforced polymer

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1 Machining monitoring technique background

During machining processes, cutting tools encounter some challenging phenomena such as chipping, breakage, chatter, and built-up edge (BUE). Therefore, monitoring these phenomena is crucial as it can provide a good process characterization to maximize the production output by selecting optimal cutting conditions. Besides, applying monitoring techniques has an effective role in improving the work safety conditions and the quality of product/process. Lauro et al. [1] discussed many monitoring techniques for cutting processes through different literature studies which focused on studying cutting forces, tool life, cutting temperature, and chip formation mechanisms. They investigated the machining monitoring processes and found that monitoring techniques can be divided into two main categories: direct approach and indirect approach. On the one hand, the direct approach (off-line) is mainly focused on the actual values of the measured cutting characteristics, and it gives a high degree of accuracy. However, it has a limited practical access, which makes it a non-effective tool for detecting machining phenomena. On the other hand, the indirect approach (on-line) depends on using empirical correlations to obtain the actual values of machining characteristics by processing and analyzing measured signals. However, it offers less accuracy than the direct approach; it has an advantage of on-line detection for the cutting phenomena especially for the cutting tool monitoring as was presented and discussed by Teti et al. and Zhu et al. [2, 3]. The indirect approach usage can offer promising results in improving product/process quality as it focuses on high-quality control inspection. Nevertheless, Garcia et al. [4] claimed that for applying an optimization chain between sensor selections, characterization and processing of measured signal predictive correlation models need to be established. Some examples of the indirect approach are as follows:

- Cutting forces: on-line prediction of the cutting forces can clarify several machining phenomena such as chip formation mechanism, estimation of tool wear evolution, resultant cutting temperature, and energy consumption as has been discussed by Deng et al. [5]. The cutting forces can be measured using the two main methods: direct and indirect measurements. The direct measurements can be obtained by mounting the tool/workpiece on a dynamometer, and it gives highly accurate values for both direction and magnitude. The indirect methods offer less accurate predictions of generated cutting forces than direct methods; however, specific cases just need some force predictions deduced from the workpiece/tool interaction as has been presented by Childs [6].
- Vibrations: on-line monitoring for the induced vibration during the cutting processes is an important factor as it affects the surface quality, machining component performance, and tool conditions as presented by Devillez and Dudzinski [7]. Also, the vibration signatures can be used for the tool wear mode prediction using a correlation between vibration frequency domain and the tool wear evolution as presented and discussed by Dimla [8]. Accelerometers are mainly used to measure the induced vibrations as they can be mounted on spindle and tool holders; however, they have limitations to measure the vibration frequency and amplitude as previously discussed by Devillez and Dudzinski in a previous work [7].
- Temperature: the heat generated near the cutting edge causes several problems such as tool wear, high surface roughness, and difficult chip formation. Several attempts [9–11] have been introduced in the open literature to reduce the amount of heat generated using sustainable cooling approaches; however, measuring the cutting temperature to evaluate these approaches is still a challenge. There are two basic variables while monitoring the cutting temperature: measuring the temperature distribution along cutting region (especially above 700 °C) and the average temperature of chip/tool contact area [6]. Moreover, the cutting temperature has a significant role in chip formation process through specific characteristics such as plastic deformation, the degree of corrosion and diffusion, fatigue properties, workpiece microstructure, and tool wear as presented by Byrne [12]. Thermocouples are commonly used sensors for the cutting temperature measurement since they can be mounted in either workpiece or cutting tool, and their working range is considered wide enough to analyze the machining performance. Furthermore, they can be easily used and are not considered as expensive sensors as mentioned by Sivasakthivel and Sudhakaran [13]. Other measurement methods for cutting temperature distributions used are infrared radiation pyrometer during grinding of AISI 1055 annealed and hardness [14], infrared thermal camera during cutting of AISI 4140 [15], and milling of Al 7050 aluminum alloy [16].
- Lauro et al. [1] presented a literature survey that introduced more advanced monitoring methods such as using optical surface measurement methods, charge-coupled device camera, inductive sensor, and ultrasonic waves in order to monitor and predict several machining quality characteristics such as surface roughness, tool wear, and cutting forces.

Another indirect monitoring technique is using acoustic signals, which is the focus of this paper. This research reviewed several literature review studies related to various applications using acoustic emission (AE) methods during cutting processes. Besides introducing several methods for analyzing and processing the measured signals, this work analyzed numerous studies that used AE signals in monitoring and predicting some machining characteristics such as cutting tool conditions, chip-tool interaction, chip formation mechanism, and surface quality. In the next section, an introduction to AE signals, measured variables, and AE sensor setup during machining processes is given and discussed.

2 Acoustic emissions

Acoustic emissions (AE) are defined as a directly transient elastic energy generated from mechanical deformation stress waves induced into different materials. Stress waves are considered the main sources of AE. Thus, analysis and detection of these stress waves at material structure surface can be investigated using AE monitoring systems. Hence, the damage and fracture mechanisms can be located, identified, quantified, and detected through AE techniques as has been presented and discussed by Holford [17]. They analyzed the AE signal sources and found that they can be divided into two main categories: primary and secondary AE sources. Primary AE sources include the fracture mechanics parameters and the growth of fatigue cracks while other sources whether they include cracks or not are categorized as secondary AE signals. Examples of primary AE sources are ductile tearing, inclusions, cleavage, and micro-fracture. On the other hand, secondary AE sources are the crack closure processes and crack developments (e.g., crack detection, leakage, loose parts identification, fretting). The recorded AE signals can be expressed using several basic parameters, namely average frequency, peak signal amplitude, rise time, and ring-down count. These parameters are function of the sensor frequency response, propagation medium, sensor damping characteristics, structure frequency response, gain of the amplifier, voltage threshold, and sensitivity of the sensor [17]. Analysis and processing of recorded AE signals can be established using time and/or frequency domains. Crouse [18] mentioned that AE signals are used to inspect and monitor the functional performance of several applications such as pressure vessels, aircraft, pipelines, bucket trucks, welding processes control, storage tanks, and characterization of ceramic and composite components.

Grosse and Ohtsu [19] identified the advantages of AE signal usage as follows:

- Highly effective in preservice testing, leakage detection, on-line monitoring of systems and components, and characterization and testing of mechanical properties
- Good material anisotropy
- Less geometrical sensitivity and intrusiveness
- Remote scanning and real-time evaluation
- Higher performance/price ratio

While, on the other side, the AE disadvantages are as follows:

- Lower repeatability as AE is stress unique and it has different loading effects
- Acoustic stress wave attenuation
- AE signals are very sensitive to the extraneous noise

During tests, one should note that acoustic emission sensors work at much higher frequency than microphones and their physical structures are different than microphones. Also, they should be strategically located around the workpiece/tool zone to monitor anomalies, and accordingly detect cracks, leaks, or any other phenomena. Although the microphones are limited in frequency response to about 20 kHz, they would provide some qualitative measure of anomalies for such cases where AE sensor cannot be physically attached. Furthermore, some phenomenon would produce acoustic emission within the same frequency range of a microphone (i.e., within 20 kHz), and therefore, it is not economically wise to use AE sensors as they are much more expensive than microphones.

3 Technology of acoustic emission measurements in cutting processes

This section discusses the AE signals, the measured variables, and the AE sensor setup during machining processes. As mentioned before that the AE is defined as a directly transient elastic energy induced from material due to deformation or fracture, this AE energy depends mainly on material deformation rate, material volume, and applied stresses [20–22]. AE is considered as one of the significant and advanced nondestructive tools in the applications of real-time process monitoring. A sensor/transducer acoustically attached to a sample can detect the emitted elastic energy and undergo dynamic changes as reported by Raj and Jayakumar [23]. AE signals during machining processes have been classified into two main categories: continuous and burst. Continuous AE can be noticed during cutting ductile materials at the plastic deformation zone while burst waves can be observed during the crack growth of material like cutting edge and chip breakage, chatter vibration, and chip tangling [24–26]. Karimi et al. [27] concluded that the use of AE sensors to monitor the machining processes is an effective on-line detection/monitoring technique as its sensitivity and reliability provide significant results in investigating and analyzing several machining characteristics and malfunctions. Several measured AE variables are used to investigate and monitor the cutting process. The pressure sound can be obtained through three different measurements: peak, average, and root mean square (RMS). Basically, RMS signals are obtained by squaring the input signals, average of filtered low-pass frequency, and outputs a square root conversion. Root mean square values are commonly used since it provides a direct relationship to the energy content of the signal. However, the frequency character of the raw signal may effectively express the frequency response of the used sensor better than RMS signals as mentioned in a previous work by

Webster et al. [28]. It should be stated that the operations involved in determining the RMS signals could negatively affect its potential to use, especially for detecting events such as cracks and burn on the part as mentioned and discussed by Aguiar et al. [29]. Another variable is energy density, and it obtains the amount of energy per unit volume of a sound wave. Energy density depends on density, speed of sound, and root mean square of sound pressure. Furthermore, intensity is another AE variable since it represents the acoustic energy mean value, which crosses a unit area perpendicular to the direction of propagation in a unit time. This has been discussed and confirmed by Egan and Kinsler et al. [30, 31].

Rogers [32] investigated the piezoelectric sensor technology and they showed promising capabilities in measuring AE during various machining processes. Most of machining process phenomena can be monitored and detected using these sensors, which have dynamic bandwidth within the range of 100 to 900 kHz. AE signal processing are performed using effective data acquisition systems; Fig. 1 shows schematic of AE signal processing. As shown in Fig. 1, a pre-amplifier/buffer amplifier is used to process the recorded AE signals since it has a high input impedance and low output impedance. Regarding analog signal processing, H-P and L-P filters and RMS converter are used for filtering and segmentation, then the analog-digital converter can be applied. Also, frequency domain analysis needs to be obtained as it can provide more information related to the feature extraction and selections especially for the cutting processes [2, 33, 34]. Researchers did not stop on that but they continued to develop many techniques for transformation digital time domain signals into frequency domain signals such as fast Fourier transform (FFT) and wavelet transfer (WT).

Regarding AE sensor location, Woulfe [35] found that the mounting of AE sensor needs a coupling element between the workpiece surface and sensor itself and this element should be free of any inclusions since it may affect the acoustical coupling efficiency. Hutton and Hu [36] and Li et al. [37] used a non-intrusive coupling fluid in their investigations to couple the AE sensor with the spindle drive shaft, and they observed good results in AE signal processing. In addition, Inasaki [24] and Karpuschewski et al. [38] implemented radio frequency transmission, slip rings, and inductive coupling to transmit AE signals from sensors to AE coupling. Another study by Jemielniak [39] showed that mounting the AE sensor on the cutting tool inner structure surface can lead to longer duration of signal recording. Woulfe [35] focused on mounting the AE sensor of the workpiece side; however, it can be noticed that varying the distance between the AE sensor and source should be taken into account as it can affect the AE processing of the signals. Thus, the current study concludes that many difficulties can be observed in mounting AE sensors. Therefore, the use of AE coupling elements is very necessary to avoid any problems and barriers in AE signal processing.

Finally, it is well known that the acoustic emission sensors work at much higher frequency than microphones and their physical structures are different than microphones. Also, they would be strategically located around the workpiece/tool zone to monitor anomalies, and accordingly detect cracks, leaks, or any other phenomena. Although the microphones are limited in frequency response to about 20 kHz, they would provide some qualitative measure of anomalies for parts where you can not physically attach an AE sensor. Furthermore, some phenomenon would produce acoustic emission within the same frequency range of a microphone (i.e., within 20 kHz), and therefore, it is not economically wise to use AE sensors as they are much more expensive than microphones.

4 Processing and analysis of the measured signals during machining processes

Selecting the suitable processing technique of AE signals is a crucial factor to address the acquired signals, which can detect, analyze, and investigate the desired machining phenomena. Various techniques have been obtained through literature [40–42]: the frequency domain analysis using FFT or power spectral density, time domain analysis using once per revolution sampling, and WT technique which provides time-frequency domain analysis. Besides, this research presents several studies, which focused on implementing these techniques for analyzing and monitoring the recorded signals during various cutting processes.

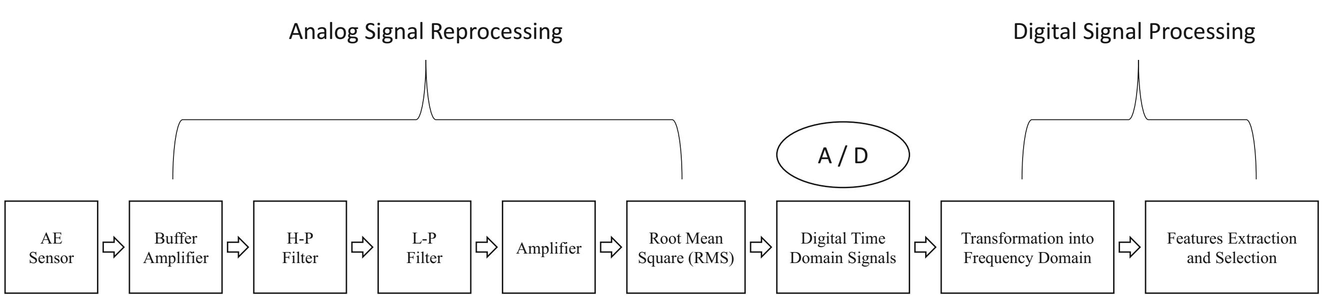

Fig. 1 Schematic of AE signal processing

4.1 Fast Fourier transform

Kang et al. [43] applied FFT technique in monitoring spindle vibration during high-speed machining process through analyzing the tooth and rotation frequencies of the recorded acceleration signals. Liao et al. [44] showed that, in terms of the tool condition monitoring, the discrete cosine transform (DCT) and the discrete Fourier transform (DFT) have shown promising results in extracting the fundamental frequency component which can express and analyze the tool wear evolution. Another study by Liu et al. [45] has demonstrated a high potential in using FFT to filter and avoid the undesired frequency components and high-noise vibration signals during machining process. Short-time Fourier transform (STFT) is another FFT method that is being employed in analyzing the AE signals. It provided good results in detecting and analyzing the patterns with a well-defined frequency and non-overlapping events as discussed by Teti and Baciu [46]. In spite of previous superior applications of FFT, Zhu et al. [3] highlighted some specific theoretical disadvantages using FFT especially in the analysis of machining processes signals.

4.2 Wavelet transform

Wavelet transform technique is being applied in different platforms (e.g., applied physics, applied mathematics, engineering applications) as it can offer time-frequency domain analysis. Throughout the manufacturing applications, it showed a promising trend in monitoring and diagnosing of machinery faults and detecting the tool wear characteristics as discussed by Zhu et al. and Lauro et al. [1, 3]. Liao et al. [44] presented various advantages stating that WT has more potential in analyzing and processing the recorded signals than FFT:

- Local time-dependent properties are easily captured using WT while FFT can only obtain global properties
- More fine tuning can be applied
- Providing infinite possible basis functions

Furthermore, this study investigated the other advantages for using WT rather than FFT during machining processes. Exploring a descriptive natural shape rather than the sine wave is one of these advantages. Also, several features for analyzing the recorded signals have been noticed in WT by Scheffer and Heyns [47] such as higher derivative discontinuities, breakdown points, and self-similarity. The continuous wavelet transform (CWT) has a high potential in analyzing the stationary and non-stationary signals especially in the application of tool condition monitoring; however, it takes long computational time since more data are observed to be redundant. Thus, the discrete wavelet transform (DWT) has been used for faster computational time as previously presented by Zhu et al. [3]. Grzesik and Brol [48] implemented the CWT during the hard turning process in order to study the properties of multifractal roughness profile to investigate the cutting tool effects (standard wiper ceramic). Another study by Kasashima et al. [49] focused on using DWT for analyzing the induced cutting forces during milling process of stainless steel 304. Moreover, Xu et al. [50] used wavelet packet analysis in building a practical on-line fault diagnosis for tool condition monitoring and vibration analysis during cutting processes, and it has shown promising results regarding extracting features and model robustness.

4.3 Other signal processing and analysis techniques

Hilbert and Hilbert-Huang transform (HHT) is considered an integral transform like Laplace and Fourier transformations, and it is being used to solve inverse problems and give information about instantaneous phase, amplitude, and frequency of vibration systems [51]. Cao et al. [52] used the HHT spectrum (standard deviations and means) over a sampling frequency of 6.4 kHz to obtain the chatter indices to study the vibration signals resulting from milling of aluminum 7050. Furthermore, Kalvod and Hwang [41] have used HHT during milling of aluminum to investigate and characterize the induced cutting forces and vibrations and their effects on tool wear state. The significant variations happened in the frequency peaks using resultant HHT that shows a good correlation to monitor the cutter wear evolution. Moreover, this study explored another combined signal processing technique for AE application using Choi-Williams distribution (CWD), Zhao-Atlas-Marks distribution (ZAMD), and formant analysis methods. This method provides better time-frequency domain resolution which can overcome the non-stationary signal capturing and small spectral peak problems found in a previous study by Marinescu and Axinte [53]. Also, another processing technique called principal component analysis (PCA) is being used for reducing signal data high dimensionality as it can eliminate the interrelated variables into the recorded signals. Thus, the significant feature can be extracted easily as demonstrated by Simeone et al. [54]. Table 1 shows different applications of WT and HHT techniques in processing and analysis of various recorded signals during machining processes.

Also, the time domain analysis is one of the important and commonly used techniques to process the AE signals. The measured AE parameters for the time domain analysis are the amplitude, energy, RMS amplitude, kurtosis, counts, rise time, and peak amplitude. Statistical and time series approaches are usually employed to address the acquired signals, which can detect, and investigate the desired machining phenomena. For example, Li and He [63] used the time domain analysis to monitor the induced surface roughness when end-milling of Inconel 718. In addition, Liang and Dornfeld [64] employed the time series analysis to monitor the tool wear behavior. Also, Mukhopadhyay et al. employed the statistical

Table 1 WT and HHT applications in machining process monitoring

Type of recorded signal	Machining process	Material	Signal processing technique	Authors
Vibration signals	Turning	AISI4140	WT	[55]
Cutting forces	Grinding	Ceramic	WT	[44]
Acoustic emission	Drilling	Laminated composite	WT	[56]
Acoustic emission vibration signals	Grinding	AISI 1045	HHT	[57]
Electrical signals	Drilling	S45C steel	WT	[58]
Vibration signals	Milling	Al 7050-T7451 aluminum alloy	WT	[59]
Acoustic emission	Turning	AISI-D3	WT	[60]
Current forces	Milling	AISI 1018	WT	[61]
Current signals	Milling	SAE 1045	HHT	[62]

analysis techniques to monitor the tool wear when turning metal matrix composite [65].

Also, artificial intelligent techniques have shown promising results in processing AE signals with offering a strong correlation between the measured signals and the machining phenomena. For example, the fuzzy models were developed to find a correlation between the measured AE signals and the grinding wheel surface regularity as presented and discussed by Alexandre et al. [66]. In addition, artificial neural network-based models were developed to find a correlation between the spindle current, spindle vibrations, cutting forces, sound pressure, and measured flank wear as discussed by Ghosh et al. [67]. Also, Kwak and Ha [68] achieved an intelligent diagnosis using AE signals and artificial neural network to predict the burning and chatter vibration phenomena.

In the next sections of this study, few studies related to AE applications in monitoring and detection of the cutting processes are presented and discussed. Three main cutting quality aspects are reviewed: the chip formation and morphology, surface quality, and cutting tool wear evolution.

5 Chip formation and morphology

This section presents various studies that use AE signals to monitor and predict chip formation mechanism and chip morphology during different cutting processes.

Uehara and Kanda [69] used the AE signals in measuring the propagations of workpiece and tool sides and showed promising results in monitoring the occurrence of BUE. Also, AE energy levels showed good results in monitoring saw-toothed chip during cutting of stainless steel and titanium alloy and discontinuous chip during cutting of brass alloy. In the case of micro-grinding of brittle materials, AE energy is higher in the plastic deformation zone than in fracture zone. Bifano and Yi [70] found that the relation between AE energy and material removal rate has the similar trend between material removal rate and specific cutting energy. Another work by Kakade et al. [71] focused on using AE signal parameters to monitor and assess the chip formation processes during face milling of mild steel. This work illustrated that the continuous chip formation can be observed at higher AE rise time while the broken chips were noticed at smaller event duration. Furthermore, AE signals were used to monitor the rubbing and deformation of work material, so this study showed that AE can be a useful tool for chip formation monitoring. Barry and Byrne [72] analyzed the chip formation processes during machining of hardened steel. The study showed that the root mean square value of AE signals ($AE_{r.m.s}$) was two times its value compared with the machining of softer steels. The reason behind that was the induced chip morphology as saw-tooth chips were formed due to the rapid release of elastic strain energy. Therefore, high AE energy can be noticed. Another study by Barry et al. [73] used the AE signal parameters to study the chip formation mechanism of Ti-6Al-4V. In addition, welding between tool and chip was noticed due to the occurrence of the thermoplastic instability. The weld fracture represented the main source of AE signals at cutting speed higher than 0.5 m/s. Also, Barry and Byrne [74] analyzed the machining of hardened steel and it showed that no standard correlation can be observed between $AE_{r.m.s}$ and the depth of cut as $AE_{r.m.s}$ might decrease or increase or remain the same with increasing the depth of cut. However, it was concluded that $AE_{r.m.s}$ is correlated with plastic deformation work rate and sliding friction.

Furthermore, Mian et al. [75] proposed an indirect method to analyze the AE signals, so that they can investigate the minimum chip thickness during micro-milling of various materials such as aluminum, copper, single and multi-phase steel, titanium, and Inconel. The main objective was finding a correlation between AE signals during tool engagement below the minimum chip thickness and cutting at the shear zone. $AE_{r.m.s}$ was used as an effective indicator to predict the processing mechanism. In addition, experimental values were compared with literature review results, and a good agreement was provided. The proposed approach has an advantage since it offers an experimental monitoring technique to predict the minimum chip thickness; however, all literature techniques were proposed depending on numerical models, which cannot be useful in terms of the process monitoring. Thus, a real-time process monitoring based on AE signals could help in micro-structure change prediction, which is mainly required with difficult-to-cut materials because of its higher tendency of adhesion. In addition, AE signals were used to explore the energy levels for several deformation mechanisms during micro-milling processes. Non-ferrous, ferrous, and difficult-to-cut materials were under examination and they were tested. The characterization of chip formation and morphology were correlated with AE energies. Therefore, the size effects of micro-cutting processes can be easily controlled using this monitoring technique, which can detect the micro-machining, shearing, and micro-fracture mechanisms. Moreover, the AE energy increase is associated with the increase of the undeformed chip thickness to width of cut ratio. Microstructure phase is an important factor in controlling the chip segmentation for ferrous materials since pearlite phase has a significant effect on the micro-machining mechanism. However, other several factors are responsible for the chip segmentation control for non-ferrous and difficult-to-cut materials. For example, stick-slip zone formation on the flank face has an effective factor for shearing mechanism through micro-milling of titanium [76].

Bhuiyan et al. [77] focused on monitoring the effect of chip formation on the tool life using AE signal analysis during turning of ASSAB-705 medium carbon steel. The study reported that the chip formation frequency range was between 68.3 and 634.83 kHz. Furthermore, higher RMS values of AE signals, which increased the tool wear, were associated with the increase in feed rate, cutting speed, and depth of cut at stable chip formation zones. However, tool wear was decreased with chip breakage zones even at higher levels of feed rate and cutting speed. The proposed setup showed several advantages of predicting plastic deformation and tool wear, which cannot be done using the conventional techniques.

Also, Hase et al. [78] and Dhale [79] listed several AE sources during chip formation process as the follows:

- Shearing process
- Cutting tool/chips/workpiece rubbing
- Cutting tool wear
- Chip breakages and collisions
- Built-up edge formation
- Cutting tool damage
- Entanglement of chips onto the workpiece or cutting tool
- Cutting tool vibrations

Figure 2 shows a schematic of previously mentioned AE sources during cutting processes.

AE signals were used to study both chip formation and morphology during micro-end-milling of aluminum alloy (AA 1100) by Prakash et al. [80]. The discrete wavelet transformation (DWT) and fast Fourier transformation (FFT) were applied to analyze the AE signals in time and frequency domains. The study found that the built-up edge (BUE) formation can be easily monitored through $AE_{r.m.s}$ while the micro-fracture and shearing mechanisms were associated with the higher order of AE-specific energies. Regarding the chip morphology, low AE amplitude and frequency were effective indicators for tight curl chip formation, while elemental chips were formed at high AE amplitude and frequency as shown in Fig. 3.

Similar observations were made by Hase et al. [78] during turning of SKS3 with cermet tools at different hardness values. In general, the amplitude of AE signals for serrated type chips is larger than flow type chips showing that nature of AE signal is closely related to the type of chips formed. A recent work presented by Filippov et al. [81] studied the stability of the peak-less tool turning using AE signals processed

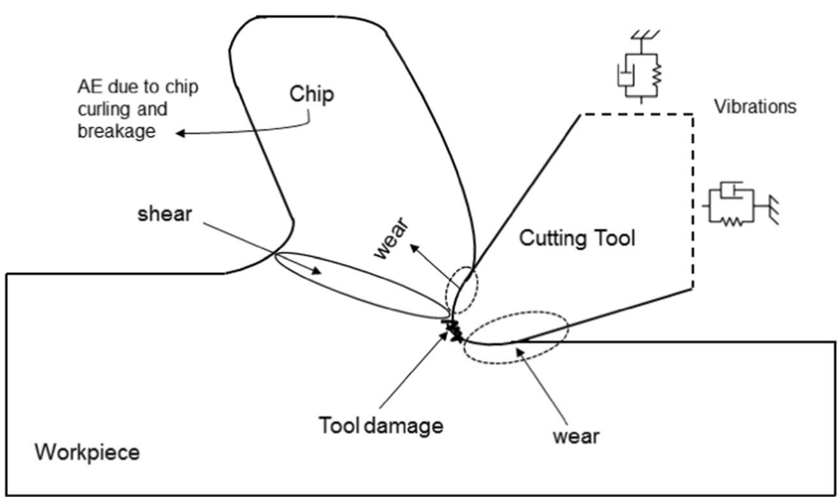

Fig. 2 Sources of AE during machining processes

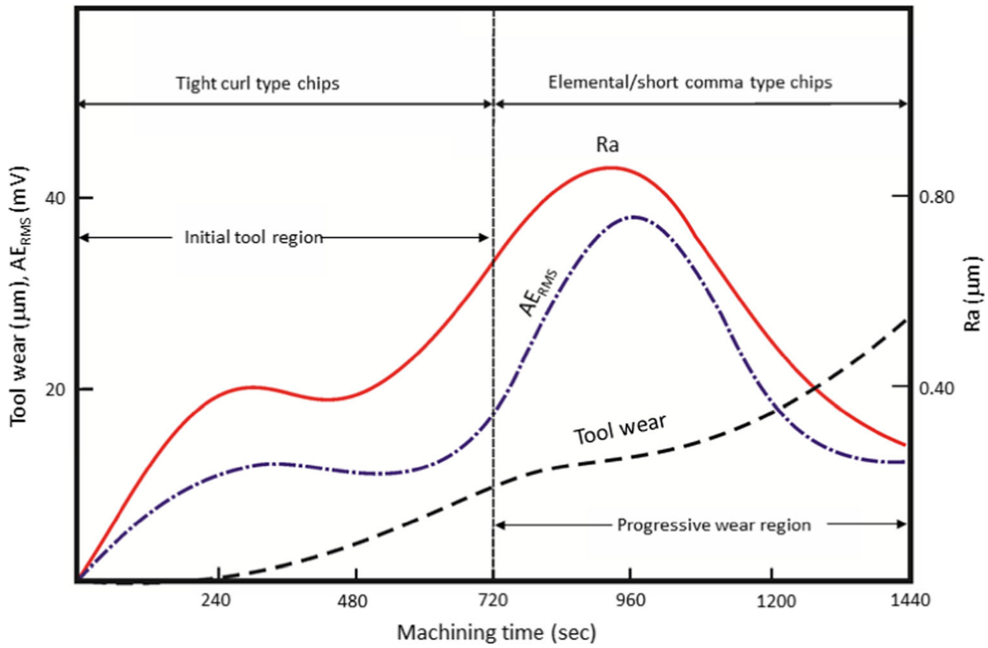

Fig. 3 Response graph between AE, machining parameters vs machining time [80]

by short-time Fourier transformation (STFT). Wertheim et al. [82] proposed an algorithm to detect the drill position by processing of measured AE signals during drilling of carbon fiber-reinforced plastic (CFRP). Detecting the drill position precisely would help in fixing different problems when drilling CFRP.

6 Surface quality

In this section, we are presenting a review of many studies related to the surface quality detection/monitoring for several types of machining processes using AE signals.

Using different cutting conditions during finish turning of AISI 1045, the acoustic emission variations were used to predict the growth of induced surface roughness. Several AE parameters showed effective results for predicting surface roughness depending on its frequency band range. For example, Diniz et al. [83] found that at frequency band from 50 to 500 kHz, $AE_{r.m.s}$ standard deviations and zero crossing rate in the raw signal are the most important parameter, while $AE_{r.m.s}$ and its standard deviation values are suitable in case of 200 to 300 kHz.

Beggan et al. [84] used AE signals to monitor the surface quality during turning of EN1APb steel. Implementing AE signals has revealed an effective correlation between average surface roughness (R_a) and root mean square values of acoustic emissions ($AE_{r.m.s}$). In addition, a comparison between the modeled and measured values for both average surface roughness (R_a) and $AE_{r.m.s}$ has shown similar trends at medium and high cutting feed rates and speeds. The study analysis led to the development of a real-time PC-based as a surface quality monitoring system (surface quality sensor).

Susič and Grabec [85] proposed a new system to predict the surface roughness during grinding processes. They applied an artificial neural network technique to estimate the correlations between surface and AE characteristics using empirically developed model. They compared the model and experimental values in order to validate the developed model; however, a high residual error was obtained at the beginning of the process. This error was adjusted after the wheel started removing material continuously and the model accuracy was 80%. The research concluded that the proposed system and the developed model can effectively describe the surface characteristics during grinding process as long as the grinding wheel is not newly dressed and there is no a significant wear that can lead to unstable process.

A new method was proposed for grinding wheel condition monitoring using $AE_{r.m.s}$ signals by Gomes de Oliveira and Dornfeld [86]. The acoustic emission signals resulting from the contact between diamond tool and grinding wheel are acquired by the AE sensor and transformed into RMS level using A/D conversion system and finally read by the computer. The system can be used for a plunge grinding operation by plotting the average acoustic energy over the whole wheel length vs grinding time.

Guo and Ammula [87] developed a monitoring system based on real-time acoustic emission to investigate and monitor the white layer phenomenon which takes place during hard turning processes. The study presented a promising technique for the surface integrity estimation. $AE_{r.m.s}$ variations with cutting time have been observed during hard turning AISI 52100 using CBN inserts. $AE_{r.m.s}$ value decreases with increasing flank wear until the appearance of the white layer. Then, it starts increasing up to a certain limit where a thick white layer has been formed. In addition, frequency and AE count rate also showed good correlation with the formation of the white layer. Hence, these AE parameters can be used as effective indicators to express this critical phenomenon.

Pittner et al. [88] exploited statistical and AE signal analysis to monitor and control several surface roughness parameters. A good correlation between the cutting speed, cutting feed, $AE_{r.m.s}$, and surface roughness indicators was detected. $AE_{r.m.s}$ showed good results in classifying surface roughness parameters rather than cutting speed; however, feed rate still has the highest significant effect.

Monitoring of ultra-precision diamond turning of OFHC polycrystalline copper was carried out by Dornfeld et al. [89]. The AE polar map and the chemically etched workpiece showed a good correlation. Due to digital-to-analog (DA) converter limitations, grains smaller than 100 μm cannot be resolved in AE map; however, larger grains can be quite clearly observed in both AE polar map and chemically etched workpiece. These large grains have severe effect on surface finish and homogeneity of the workpiece. Thus, in addition to act as a tool-workpiece contact sensor, the AE polar map can be quite satisfactorily used for detecting problem areas and defective zones on the workpiece surface.

Bourne et al. [90] proposed a tool and workpiece surface detection system based on AE signals using two different algorithms: single touch-off and three touch-off operations. Algorithm based on three touch-off operations can be easily used in cases of the unknown orientation of workpiece surface. The study used micro-level surface damage using approach seeds up to 50–100 μs to evaluate the system capabilities. Furthermore, they developed a model to predict the touch-off undershoot/overshoot as a function of surface roughness and orientation. The experimental and model values were compared and the model validation revealed a promising accuracy within a micron or less.

Min et al. [91] illustrated that the workpiece coordination setup and accurate measurements of tool length are two challenges in ultra-precision machining to minimize the workpiece surface damage. In this work, they used AE sensors to achieve both two mentioned requirements at the same time as these sensors have high-precision detection of tool/workpiece contact. Besides, the study applied two different approaches: continuous and incremental. They found that a smaller surface damage was obtained using the incremental method while reducing setup time was obtained using the continuous approach. Furthermore, this research used the digital signal processing (DSP) as an improvement step to simplify the contact detection setup and reducing the signal processing time.

Pawade and Joshi [92] discussed the surface integrity results in Inconel 718 machining using AE signals. The experimental setup of this work is shown in Fig. 4. The deformation

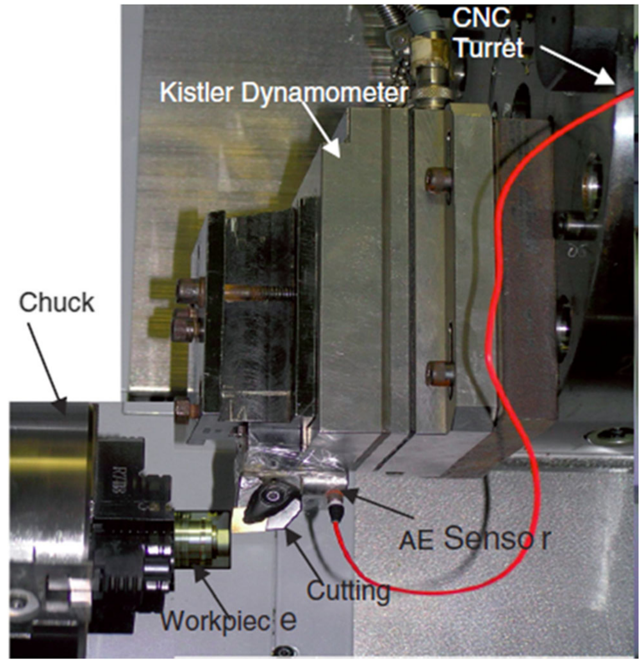

Fig. 4 Experimental setup of Inconel 718 machining using AE signals [92]

zone activities during the cutting processes can be captured using AE signals as it could help in investigating or controlling the induced surface quality. They correlated several machining parameters (e.g., cutting speed, feed rate, and tool edge geometry) with AE characteristics. The study realized that the cutting speed is the only significant parameter, which affects the AE signal frequency and amplitude. Also, a better surface quality was obtained at the lower level of perturbations of energy and count profiles. They concluded that the surface anomalies and chip formation mechanism during cutting processes of Inconel 718 can be easily detected by studying the AE signal variations.

Marinescu and Axinte [93] proposed a new method based on AE energy counts (AE_{MARSE}) and area under the resultant cutting force to find out region for damaged-free workpiece surface while machining Inconel 718 using PVD coated and solid carbide ineserts in an end-milling operation. It can be seen that during the initial number of cuts, AE values do not fluctuate too much and with increasing number of cuts, scattering also increases showing too much variations in AE values.

Gok et al. [94] used many cutting tools with different coatings (TiAlN, TiN, and TiC) during the up- and down-milling process strategies for EN X40CrMoV5-1 workpiece. Their work studied the relationship between the generated surface roughness and cutting sound pressure level for creating concave and convex surfaces. Acoustic sound pressure levels have obtained higher values in the case of convex than concave surfaces because of the larger contact area between the tool cutting edge and workpiece in the inner concave surface.

Higher R_a and acoustic pressure values were observed in the concave surfaces using up-milling strategy due to the occurring of the chatter mechanism; however, higher R_a and acoustic pressure values were observed in the convex surfaces using down-milling strategy than up-milling due to the overlap of cutting tool edges on the workpiece. Furthermore, the acoustic pressure levels were decreased with increasing the milling position angle during contouring milling operation; however, no significant changes were noticed in the case of ramping operation. Also, in order to control the dimensional inaccuracy, Gaja and Liou proposed a depth-of-cut monitoring system to predict the real depth of cut in real time by employing AE signals and regression techniques [95].

Moreover, several studies [79, 96] confirmed the effective relationship between the machined surface quality and AE signal parameters, especially for RMS values. Thus, this technique offers an on-line monitoring system to control and characterize the quality of machined surfaces.

7 Cutting tool wear

Different attempts [97–101] were made in the open literature related to the tool design development in order to improve the tool life and provide self-cooling feature. Also, the tool condition monitoring systems provide a good process characterization to maximize the production output by selecting optimal cutting conditions. Throughout this section, several studies are analyzed to study the implementation of AE to monitor and identify the cutting tool wear evolution of the machining processes.

Diei and Dornfeld [102, 103] investigated the relationship between sensivity of AE signals to chip formation mechanism in face milling. They noticed significant increase in AE signals upon chip formation initiation and exit of the tool from the workpiece.

Diniz et al. [83] studied the tool wear effects on the resultant surface quality during finish turning of 1045 steel. The most significant frequency range was found between 200 and 300 kHz as it provides good capabilities of tool wear and surface roughness monitoring. Also, the increase in both flank wear and surface roughness increased the scatter of $AE_{r.m.s}$. Kakade et al. [83] used AE sensor based on piezoelectric materials to monitor the flank wear during face milling of mild steel using carbide TiN-coated cutter. In this study, rise time and some events were used to evaluate and monitor the progressive tool wear. After initiating a flank wear of 0.22 mm, there was a rapid increase in AE parameter values which can be easily noticed, so this experimental approach offered a promising on-line wear detection technique. Heiple et al. [104] studied the sliding friction between the tool flank and the workpiece. Furthermore, they concluded that changes in the tool wear and AE signals are mainly dependent on material properties. Ravindra et al. [105] investigated AE signal implementation to monitor the tool wear evolution during machining of C-60 steel. The study used many AE parameters, such as RMS voltage, rise time, and energy; however, RMS values obtained the highest correlation with the flank wear values.

An additional work by Cho and Komvopoulos [106] focused on using AE signals to investigate the tool life, and the results were highly correlated with the tool life determined using maximum wear land width. They investigated that changes take place for the interfacial friction coefficient, wear in tool/workpiece contact area, and cutting tool material properties have significant effect on $AE_{r.m.s}$. Hence, AE signals can be utilized as effectively as a monitoring system for tool wear behavior. Another study by Dolinšek and Kopač [107] focused on tool wear identification using AE signals during cutting of C45 E4 steel by coated carbide tool with TiN and coated cermet tool. The energy of AE signals was varied in the frequency range of 100–610 kHz. The power spectrum of AE signals for cermet tool showed higher effect than carbide tool due to its higher damping characteristics. Furthermore, useful information from the power spectrum of AE signals were correlated with the flank wear results for both types and it showed a promising practical technique to monitor the progressive tool wear.

Also, Kopač and Šali [108] used a condenser microphone to record the sound pressure at 0.5 m from the cutting zone during turning of CK15 (DIN) using cermet cutting tool without any coating. They applied different levels of cutting speed and feed rate to find a correlation between the sound pressure level and flank tool wear. The study noticed that an increase in the sound pressure amplitude was observed with increasing the flank tool wear at a frequency between 6 and 20 kHz. Also, a clear increase in sound intensity was observed with increasing the feed rate values between 2 and 19 kHz. Another research by Pai and Rao [109] employed AE signals in face milling of En-8 steel using uncoated carbide inserts to monitor the tool condition changes. They performed experimental trials using different numbers of inserts inside the cutter under several cutting conditions. The root mean square voltage and ring-down counts related to AE parameters were used to investigate the tool wear state. The increase of root mean square voltage value resulted in increasing the flank wear. However, accumulative ring-down counts showed promising correlation results than root mean square voltage in terms of monitoring the progressive tool wear.

In another work by Ansenk and Broens (2004), face milling monitoring was done using a three-axis CNC milling center with an AE sensor directly attached to the workpiece. They collected the $AE_{r.m.s}$ signal in a continuous manner similar to the technique used in grinding operation by De oliveira [86]. In $AE_{r.m.s}$ plot, each data point corresponds to one spindle rotation showing a clear spike due to entrance of tool into the workpiece. The AE intensity mapping for a total of around

200 successive spindle rotations is developed. $AE_{r.m.s}$ signals can be seen in the plot for each cutting insert (numbered 1 to 6) with a gap of 60° between inserts. During the cutting progress, AE signals due to rubbing of cutting inserts have been recorded. Thus, the tool monitoring could be accomplished using this mapping technique to investigate the tool contact, tool failure, and inserts' positional accuracy in the tool holder.

The high-speed machining offers promising advantages regarding productivity, surface roughness, and accuracy. However, the rapid rate of tool wear is still the main associated problem with this process. Giriraj et al. [110] applied AE signals during high-speed machining of aluminum LM-6 using titanium aluminum nitride-coated solid carbide end-milling tool to investigate the evolution of flank wear over cutting time. They implemented the design of experiments to plan the experimental trials for measuring both of AE signals (millivolt) and flank tool wear (μm). Artificial neural network (ANN) analysis was conducted for AE and flank wear and a good correlation was found with a maximum deviation of 4%. This is indicative of an effective on-line tool wear monitoring approach. Minimizing the cutting process defects is a significant factor to achieve high workpiece quality and process stability; therefore, developing new proposed monitoring techniques is highly required. Thus, AE sensors were used to find a correlation between its signals and flank wear as a proposed method for on-line detection of tool conditions. Arul et al. [111] conducted several trials during drilling of woven glass fabric/epoxy with high-speed steel (HSS) drills. $AE_{r.m.s}$ showed good results to obtain the flank wear evolution as it increased progressively during the first ten holes. A steady state was detected during the second set of trials (11–20), and finally, a rapid increase was noticed for both flank wear and $AE_{r.m.s}$ during the third set of trials (21–30). Furthermore, the study noticed a dominant peak at 70 kHz after drilling of 30 holes and found that more than 30 holes using the same tool setup and conditions can lead to tolerance defects.

Also, Jemielniak and Arrazola [112] presented an integration technique for tool monitoring condition during micro-milling of cold work tool steel. They used two sensors: AE and cutting force sensors. The proposed technique showed strong abilities in detecting the tool-workpiece interaction effects and monitoring the cutting process integrity using the measured AE parameters and dynamometer resonance vibrations. Another study by Sundaram et al. [113] used AE signals to monitor the cutting tool conditions during turning of C45 steel (250 HB) using polycrystalline diamond (PCD) insert. Average and root mean square values were used to explore the flank wear progress and significant effects were detected in the flank wear progress after 200 kHz. Also, tool breakage was predicted using AE peak-to-peak amplitude. Studying wear stages for drill bits is an important research topic to achieve stable cutting process. Therefore, it is required to identify a newly developed technique to detect and monitor the induced torque and tool wear. During drilling of SAE 1040 steel using HSS tool by Gómez et al. [114], AE signals and torque were measured and a good correlation was found between the mean power of AE signals and measured torque values. The mean average and mean variance of mean power (MAMP-MVMP) were utilized to monitor the drill bit wear at different cutting conditions. They showed promising results to study the effects of cutting parameters on the tool wear evolution, and it can also be used to detect the chip fracture. High-quality signal processing and data acquisition systems are necessary for AE monitoring systems to detect several machining phenomena like tool wear, surface integrity, and chip morphology as has been mentioned and discussed by Teti et al. [2].

Patra [115] implemented the AE sensors and wavelet packet transform to explore the drilling tool wear mechanism. ANN-based data gathered from wavelet packet transform obtained a good correlation to predict the tool wear using acoustic signals. Hence, the monitoring of tool wear for automated drilling process can be accomplished using the proposed scheme. Prakash and Kanthababu [116] found that during micro-end-milling of different materials (i.e., copper, steel, aluminum), the low-order $AE_{r.m.s}$ values can be observed during formation of BUE on the flank face of micro-end-mill due to the occurrence of progressive wear at this region. Bhaskaran et al. [60] employed the $AE_{r.m.s}$ to monitor the tool wear behavior during turning hard steel of 60 HRC. Negative skew values of $AE_{r.m.s}$ were noticed, and they indicated that the wear land value has passed its threshold, while increasing kurtosis values of $AE_{r.m.s}$ show high rubbing between the tool and workpiece. Thus, both of the previous features of $AE_{r.m.s}$ offered a promising approach to monitor and detect tool wear behavior.

Also, Mukhopadhyay et al. [65] recorded the AE energy during turning of aluminum reinforced with silicon carbide to estimate the cutting tool wear using statistical analysis techniques. AE energy results over cutting period showed significant changes. Coefficients of variation, variance, and β-distribution were calculated to determine the relationship between AE energy and the flank wear. Skewness and kurtosis variations of β-distribution showed good results, especially in monitoring flank tool wear at later stages. These variations have high correlations to detect different wear mechanisms, such as abrasion, and removal/scratching of tool material. Also, the peak amplitude distribution of AE signal has a strong correlation in early stages of the flank tool wear up to 0.4 mm. Ai et al. [117] exploited linear predictive cepstrum coefficient (LPCC) orders to monitor the cutting tool wear during the milling process. This technique obtained good results regarding wear evolution characterization especially at the sixth-, seventh-, and eighth-order components. Also, Bhuiyan et al. [118] utilized the $AE_{r.m.s}$ values to explore the effects of feed rate and depth of cut on the vibration components in x, y, and z

directions during turning process. The study identified that tool wear evolution can be represented using *x* vibration component (V_x) results since its magnitude increases with the increase of feed rate and depth of cut levels.

Kosaraju et al. [119] used AE signals to monitor the flank wear evolution at a different time interval during machining of titanium (grade 5) using PVD/TiAlN-coated carbide tools. The study determined that $AE_{r.m.s}$ was significantly increased with increasing the flank tool wear values in a frequency range about 30–60 kHz. They proposed a regression model for AE signals and its maximum residual error was around 2.33%. Thus, this study offered a promising technique for on-line tool wear monitoring using AE signal analysis and modeling. Tamizharasan et al. [120] applied AE signals and design of experiment technique to study the flank wear during the turning process. Signal-to-noise ratio analysis for both of AE signals and flank wear showed a good linear correlation. Figure 5 shows nature of AE signals during turning process at several cutting conditions which can help in monitoring and predicting the tool wear behavior as presented and discussed by Siddhpura and Paurobally [20].

Moia et al. [121] used AE signals to monitor the aluminum oxide grinding wheel state (sharp or worn). The study exploited statistical analysis and neural network to analyze the acoustically recorded data. RMS, mean value deviance (MDV), and measured area under the rectified signal envelope (MARSE) of AE signals were used as AE indicators, and they revealed that the material removal dressing threshold was about 100 μm. This indication has high importance as it can prevent workpiece to be ground under unstable conditions of grinding wheel. However, the study results are still limited to the previously mentioned case under specific grinding wheel type and dressing condition, so developing a generalized monitoring approach for dressing process is still required. The tool life monitoring and prediction were essential keys to improve the cutting performance quality. Olufayo and Abou-El-Hossein [122] used the AE parameters to monitor and assess the tool life during the high-speed end-milling process of the H13 tool with coated carbide inserts. The main purpose of this work was finding a correlation between the tool life and AE features. Wavelet transform, statistical analysis, and neural network were used to analyze the data created from the proposed multi-sensor approach. Several AE parameters were implemented such as AE_{mean}, $AE_{r.m.s}$, AE energy, and wavelet sum and its corresponding coefficients. AE_{mean} and $AE_{r.m.s}$ revealed high correlation in terms of tool life monitoring as shown in Fig. 6.

Seemuang et al. [123] explored the noise magnitudes from power spectrum and found significant changes using different levels of cutting speed and feed rate. Also, the flank wear results provided a good correlation with AE energy using same settings of cutting parameters. Hence, AE can be effectively used to monitor and detect the flank wear behavior using a low-cost system for tool wear assessment and monitoring. Also, an effective system for tool condition monitoring was proposed by Uekita and Takaya [124] using a multi-sensor fusion strategy which includes acoustic emissions and spindle current. In addition, another work presented by Yiming et al. [125] employed (AE) signals to identify a correlation between AE features and attrition wear. The AE energy results using time-frequency domain showed that the cutting tool is worn when the AE energy deteriorates rapidly. Another recent work done by Badge et al. [126] focused on the applications of AE signals on dressing of grinding wheels, by finding a correlation between the measured AE signal and dressing energy through a new term called "the specific acoustic-emission dressing energy". An additional work by Boaron and Weingaertner [127] proposed effective AE-based quick test method in order to obtain the status of grinding wheel topography at different cutting speeds. The proposed technique is a useful tool for wear assessment using both time and frequency domain analysis.

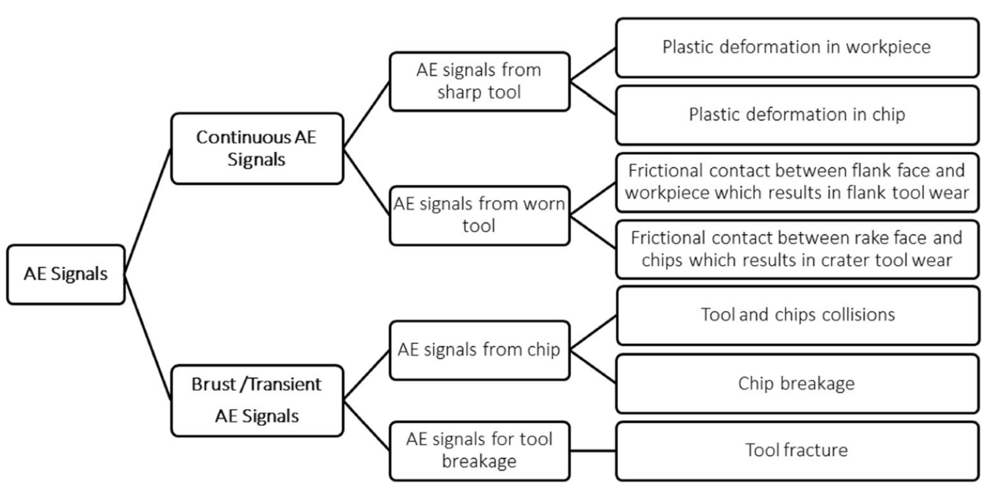

Fig. 5 AE singles at different cutting tool conditions during turning process [20]

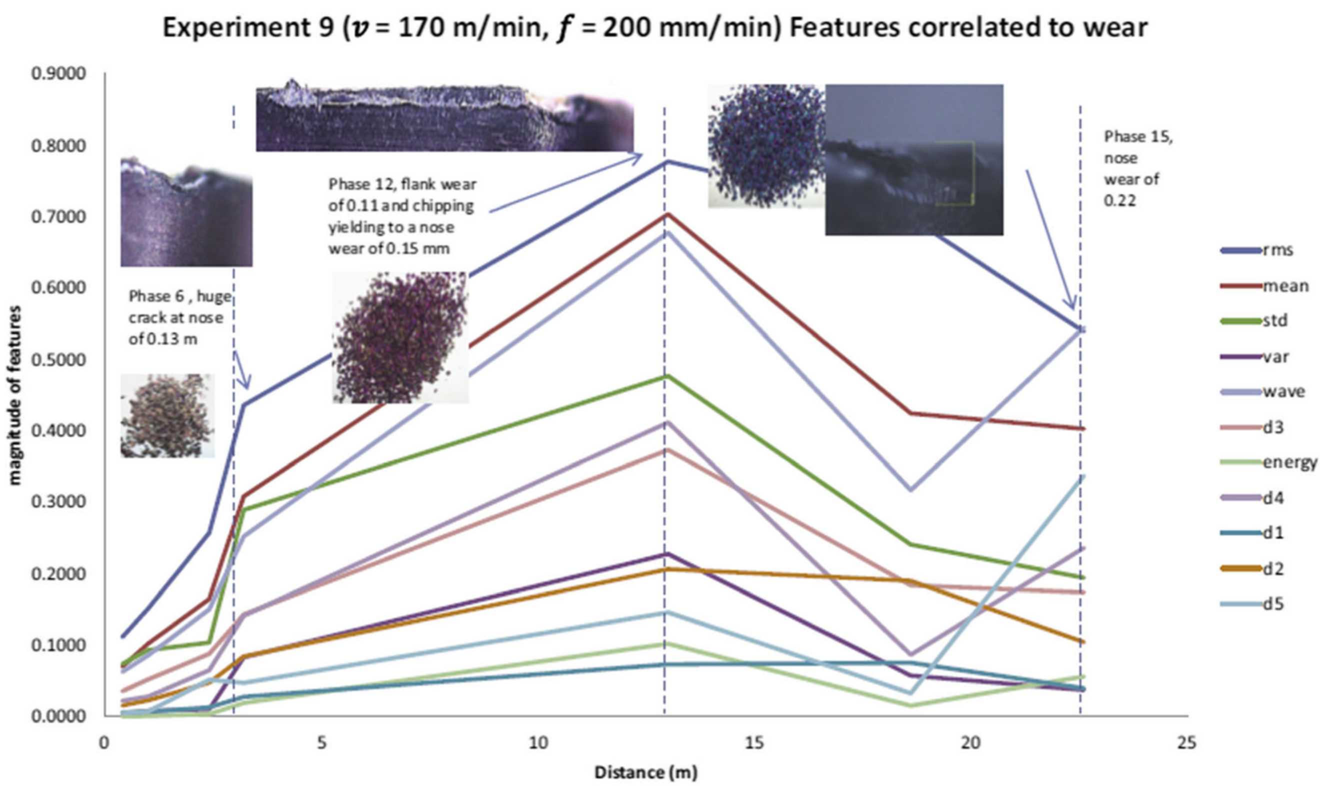

Fig. 6 Correlation between tool wear behavior and AE features along specific distance [122]

8 Current research gap and future trends

Monitoring the chip formation, induced surface quality, and tool wear using AE signals could show effective results during machining processes as its proper implementation leads to longer cutting tool life, lower machining costs, and higher production rates. Despite of the previous advantages, there are several limitations of employing AE signals to monitor the machining process characteristics. After reviewing several literature studies as has been previously discussed, these limitations can be summarized as follows:

- Complex algorithms and feasibility issues in real time
- Signal filtering from noise and signal detection at low cutting speeds
- Accurate placement and alignment of acoustic sensor due to limited footprint of tool
- Unfamiliarity with AE technology and interpretation of its signals

Also, some future trends have been summarized upon investigating the previous limitations. These future trends are:

- Developing a smart and standardized industrial AE sensor which can be fit and robust for different applications
- Implementing an integrated artificial intelligent system (e.g., artificial neuro-fuzzy interface system) which could effectively handle the noise and signal processing at low cutting speeds
- Proposing a general guideline for AE sensor setup and location for different machining operations to avoid any obstacles in processing and analyzing the measured signals

Developing and employing these future techniques could lead to enhance the effectiveness of using AE signals in machining processes and consequently better results would be achieved in terms of improving the cutting tool performance, minimizing the machining costs and increasing the production rates.

9 Conclusions

Machining process monitoring is an integral part of process automation and control which is essential part of any modern manufacturing enterprise. A successful implementation of the process monitoring process is the first set to ensure the product quality and maximize production output. One of the effective techniques used to monitor the machining processes is analyzing the induced acoustic emissions. Studying and understating its mechanisms and finding a correlation between its online measured values and the cutting quality characteristics is still a challenge. In this work, a state-of-the art review is presented to provide a solid background about the applications of AE signals in monitoring and controlling various machining phenomena. Also, it presents the measurement technology of acoustic signals. The research to date proved that AE signals offer an effective on-line monitoring technique for the characterization of the chip formation and its morphology, surface quality, and the progression of tool wear. AE sources during cutting processes were identified and discussed, namely breakage and collisions of chips, cutting tool wear, and formation of built-up edge. Fast Fourier transformation (FFT), wavelet transformation, and Hilbert and Hilbert-Huang transformation (HHT) techniques show a high potential for application of AE signal processing and analysis in different machining applications. Also, research investigations showed that the frequency domain spectrum analysis is better than the time domain for finding an adequate correlation between AE signals and various machining characteristics. Despite high usage of AE signals as an effective signal to monitor machining process, AE sensor setup and location are very influencing factors that affect the successful application of the monitoring technique.

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