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On the use of acoustic emission methods for in-situ monitoring in metal additive manufacturing: A review study

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ABSTRACT

Acoustic emission (AE) sensing is emerging as a powerful, non-intrusive tool for in-situ monitoring and in-process defect detection in metal additive manufacturing (AM). Unlike other methods (e.g., optical or thermal), AE enables the real-time detection of mechanical transients directly related to dynamic events such as crack initiation, layer delamination, pore formation, etc. This review provides a systematic overview of AE-based approaches applied to the main classes of AM processes for metals and other materials. For each process, the paper discusses (i) the sensing principles and typical AE sensor configurations; (ii) methodologies for feature extraction and signal interpretation; (iii) the types of defects and anomalies that can be detected; and (iv) the machine learning and artificial intelligence techniques employed for data fusion, classification, and anomaly detection. Attention is also given to how AE data are integrated with other sensing modalities within multimodal monitoring frameworks. The review concludes by identifying open challenges, including calibration and validation issues, data synchronization, model generalization, and deployment in real industrial environments.

1. Introduction

In-situ monitoring methods have attracted continuously growing interest in the additive manufacturing (AM) community due to their potential to transform part qualification and process verification strategies. By enabling near real-time observation of process dynamics, in-situ sensing technologies combined with machine learning and data mining methods may be used to reduce both qualification costs and lead times, which remain major barriers to the widespread industrial adoption of AM [1–5]. In-situ monitoring not only provides data-driven insight into the relationship between process conditions and final part properties; it unlocks new capacities for in-line defect detection, layerwise quality inspection, as well as adaptive and closed-loop control methods.

In recent years, various authors have reviewed the growing body of literature devoted to in-situ sensing and monitoring methods in AM [1–32]. Most review studies have focused on metal AM processes, primarily powder bed fusion (PBF) and directed energy deposition (DED), where the highest level of technological maturity has been achieved so far, driven by the strong industrial demand for improved process stability, quality assurance, and qualification strategies [7–13]. In-situ monitoring approaches for other AM processes, such as material extrusion and polymer-based AM, have also been reviewed, although with a comparatively lower degree of industrial maturity [14,15].

A recurring outcome emerging from this extensive literature is that image-based monitoring and spatially-integrated melt pool monitoring methods currently represent the most technologically mature classes of in-situ sensing techniques for metal AM. In-situ thermography has been intensively investigated, too, although mainly for research or material development applications. Together, these approaches have provided valuable insight into the link between process dynamics and part quality, and have laid the foundation for data-driven process monitoring, in-situ inspection, and qualification. However, despite their technological maturity, optical and thermal sensing approaches exhibit intrinsic limitations. First, their line-of-sight nature constrains the observation to surface phenomena. As a result, these techniques enable the detection of optical and thermal variations occurring on the processed layer or above it (e.g., spatter ejections and plume formations), but do not provide direct information on subsurface events or on phenomena that evolve after subsequent layers are deposited. Similar limitations also apply to melt pool monitoring. Although it focuses on the molten region, the extracted information is inherently related to surface or near-surface features, such as thermal emissions, melt pool dimensions, and morphology. Consequently, critical subsurface phenomena, including pore

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nucleation, crack initiation and propagation, support detachment, and interlayer defects, may remain undetected or only indirectly inferred.

In addition, imaging-based methods are highly sensitive to illumination conditions, surface reflectivity, and perspective distortions, which may introduce variability and reduce robustness across different machines and process conditions. These methods also involve inherent trade-offs between spatial and temporal resolution, which can limit their ability to capture fast transient phenomena while maintaining sufficient spatial detail. Thermal imaging approaches face further practical constraints. Industrially viable solutions are often limited by relatively low spatial and temporal resolution, while their integration typically requires dedicated viewports and modifications to the machine architecture. More advanced thermographic techniques, although capable of higher fidelity measurements, are often too complex and costly to be deployed in real production environments. An additional critical challenge associated with thermal imaging in AM concerns sensor calibration and the reliability of temperature measurements. Accurate thermographic measurements require proper calibration of the camera response with respect to the actual surface temperature, which is particularly difficult in AM environments due to continuously changing emissivity, surface morphology, and material state. The emissivity of the material may vary significantly with temperature, oxidation, phase transformations, and surface roughness, leading to substantial uncertainties in temperature estimation if not properly accounted for. Because of this, the potential of spatially-resolved thermography is only partially exploited in practice.

These limitations have been widely highlighted in review studies focusing on specific defect types, such as porosity and subsurface flaws, as well as in research addressing machine learning (ML) and artificial intelligence (AI) approaches, where several challenges related to the reliable detection of industrially critical defects remain unresolved [1–32].

To address these gaps, alternative and complementary in-situ sensing strategies have been increasingly explored, including approaches inspired by non-destructive testing (NDT) methods adapted for in-process application. In this context, sensing techniques based on acoustic emission (AE) and ultrasonic monitoring have attracted growing interest, owing to their intrinsic sensitivity to dynamic events associated with defect formation, phase transformations, and stress release phenomena [1,2].

AE methods offer the potential to access information that is not directly observable through optical or thermal sensing alone, thereby enabling complementary sensing strategies through fundamentally different physical channels. In particular, AE signals are directly linked to rapid energy-release mechanisms occurring within the material, providing a time-resolved signature of underlying physical phenomena rather than a surface projection of their effects. This enables the detection of transient events such as microcrack initiation, plastic deformation, or abrupt changes at the moment they occur. Moreover, the high temporal resolution of AE sensing, typically in the order of megahertz, allows capturing fast transient phenomena that may not be resolved by alternative sensing methods, which are often limited by sampling rate and bandwidth constraints. This makes AE particularly suitable for identifying short-lived instabilities and abrupt process transitions that are critical for defect formation. In addition, AE signals inherently integrate information over a volumetric region through wave propagation, potentially providing indirect access to spatially distributed phenomena beyond the immediate field of view of conventional sensors. These characteristics make AE a suitable candidate not only as a standalone monitoring tool, but also as a complementary modality within multimodal frameworks, where it can enrich the information content and improve the robustness of defect detection and process characterization [33–36].

However, AE-based monitoring also presents important challenges that must be critically considered. AE signals are highly sensitive to sensor placement, coupling conditions, and propagation path variability, which evolve continuously during the build process. Moreover, acoustic measurements are affected by significant background noise originating from machine components, gas flow, and environmental disturbances, often resulting in lower signal-to-noise ratios compared to other sensing modalities, particularly for airborne configurations. Despite these challenges, the field is currently experiencing rapid progress toward new solutions aimed at mitigating these limitations and enhancing the reliability, robustness, and industrial readiness of AE-based in-situ monitoring. Approaches that until recently were explored mainly in preliminary feasibility studies have now reached a higher level of maturity, demonstrating increasingly competitive performance in realistic operating conditions. These advances include improvements in sensor technologies, signal processing techniques, ML-based inference methods, and multimodal data fusion strategies. Many of these recent developments are not comprehensively covered in the review studies mentioned above, and a unified, structured perspective discussing their capabilities, limitations, performance, and potential applications is still lacking. A brief overview of AE methods was provided by Hossain and Taheri [33], Li et al. [34], and Fatoba and Jen [35], while a more in-depth classification of the literature was presented by Prem et al. [36]. However, since then, significant progress has been achieved in both measurement methodologies and data analysis techniques, substantially expanding the range of feasible applications of AE-based monitoring not only in L-PBF and DED, but also across a broader set of AM processes. This gap has motivated the present work, which aims to provide an up-to-date and critical overview of AE-based in-situ monitoring in AM, with a particular focus on recent advances and their implications for industrial deployment.

In particular, this work (i) consolidates the current state of the art on AE sensing across different AM processes; (ii) provides a structured comparison between different sensing approaches and emerging solutions; (iii) critically discusses the advantages and limitations of AE with respect to other sensing methods; and (iv) reviews recent advances in signal processing, machine learning, and multimodal data fusion for AE-based monitoring. By doing so, the paper seeks to clarify the unique role of AE within the broader landscape of in-situ monitoring technologies and to identify the key challenges that must be addressed for its industrial adoption.

Building upon seminal works and a growing body of literature in this field, the present review addresses real case studies, best practices, successful applications, and achieved results, while uncovering limitations, open issues, industrial gaps, and critical aspects that deserve further studies and technological developments. The scope of this review is limited to metal AM processes, which represent the natural application domain for AE-based monitoring methods, although a few studies have recently begun to explore AE sensing for other materials, such as ceramic AM [33–37].

The paper is organized as follows. Section 2 provides an overview of the fundamental mechanisms and physical aspects at the basis of AE in-situ monitoring in AM. Section 3 reviews the literature on the use of these methods in metal PBF, whereas Section 4 reviews the literature in DED, including wire arc additive manufacturing (WAAM). Section 5 summarizes the critical aspects, open challenges, and future research perspectives to bridge existing industrial gaps. Section 6 finally concludes the paper.

2. AE fundamentals in AM

Understanding the generation mechanism of AE signals during the AM process is fundamental for correctly interpreting AE data and establishing correlations between signals and process-induced defects. In AM, AE signals primarily originate from transient elastic waves excited by the rapid release of energy as the material undergoes phase changes and thermomechanical loadings. When an AE source within the material releases energy, it generates elastic waves that propagate to the material surface and induce vibrations. These vibrations are captured by sensors and converted into electrical signals, which can then be processed to obtain critical state information [38–41].

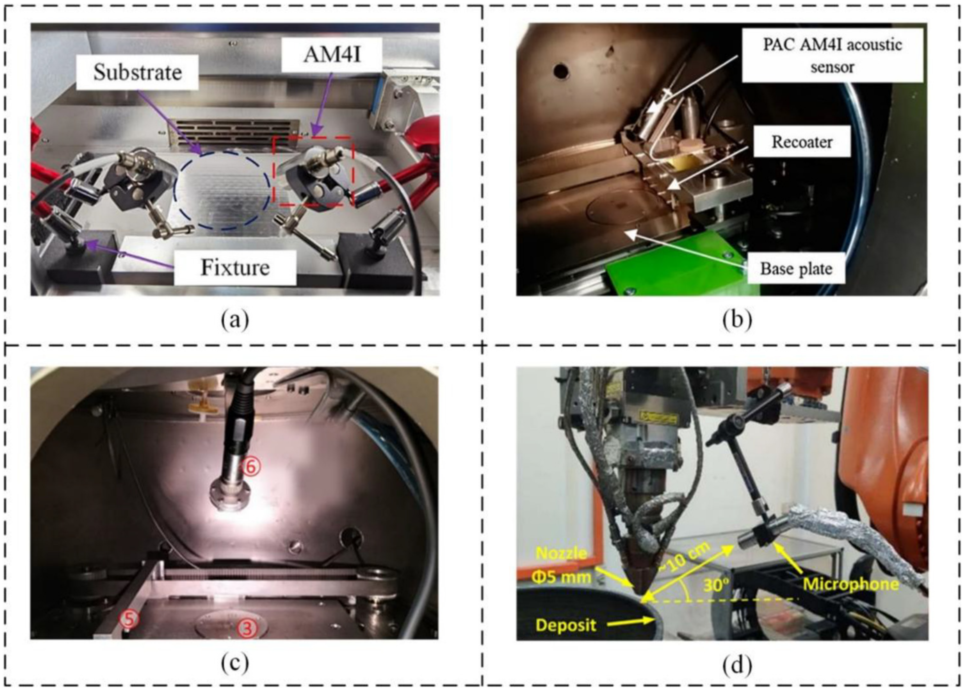

Fig. 1. Monitoring settings for various air-borne acoustic emissions in the laser additive manufacturing process: (a-b) L-PBF process monitoring system equipped with a PAC AM4I acoustic emission sensor [49,50]; (c) L-PBF process monitoring system equipped with a CM16 microphone sensor [51]; (d) Laser directed energy deposition (L-DED) process monitoring system equipped with an Xiris WeldMIC microphone sensor [52].

AE sources are mainly associated with internal structural and microstructural changes, including residual stress accumulation, defect formation, or crack propagation, but also surface phenomena and material ejections from the processed layer [33,42–44]. Therefore, monitoring systems based on AE are potentially suitable to gather real-time knowledge about several underlying AM process mechanisms by capturing acoustic signals that originate from a variety of phenomena affecting the process stability and the product quality [45–48].

Based on the medium through which elastic waves propagate, passive AE monitoring can be classified into two fundamental modes: airborne AE and structure-borne AE. Their core distinction lies in the signal transmission path and coupling medium. Airborne AE sensors are essentially highly sensitive microphones that capture sound pressure waves through the air or gas medium in the environment where the process takes place. These acoustic pressure waves originate from physical phenomena during the process that directly or indirectly cause pressure waves, such as plasma vapor jetting, melt pool surface oscillations, or turbulence of shielding gas. Examples of airborne AE monitoring setups in L-PBF and DED are shown in Fig. 1 [49–52].

The underlying physical mechanism of structure-borne AE, instead, is the transient elastic wave excited by rapid energy release (e.g., elastic strain energy, fracture energy, etc.) within the solid material [53]. Structure-borne AE sensors are typically mounted beneath the baseplate or on machine frames [54–56]. These sensors are directly linked to plastic deformation mechanisms within the solid material, and their signal propagation is modulated by the structural path, making them suitable for monitoring defects such as crack formation and propagation or undesired events like support detachment. Examples of structure-borne AE monitoring setups in L-PBF and DED are shown in Fig. 2 [54–58].

Airborne AE- and structure-borne AE-based techniques are passive monitoring methods, with intrinsic limitations related to sensor coupling stability, limited bandwidth, signal attenuation, and sensitiveness to nuisance factors under harsh processing conditions. These limitations have motivated the interest for an active monitoring approach that can be used in-situ and in process, i.e., laser ultrasonics. In NDT, laser ultrasonics (LU) has emerged as a natural extension of structure-borne AE monitoring, offering non-contact excitation and detection of elastic waves that propagate through the same material pathways as conventional AE signals. By externally generating and optically sensing broadband structure-borne waves, LU retains the fundamental physical basis of AE monitoring, while enabling high signal fidelity, multimodal wave analysis, and flexible spatial deployment [59–61].

The frequency range and characteristics of AE signals directly reflect the physical nature of transient changes within the material, serving as critical evidence for identifying defect types and evaluating forming quality. The frequency range of AE signals is wide, theoretically spanning from sub-audio frequencies to several tens of megahertz. However, in practical AM monitoring, the frequency range of interest primarily depends on several factors, including the physical mechanisms of the AE source, the type of AE sensor, and the attenuation along the signal propagation path. As an example, Hossain et al. [33] showed that the spectral range of AE signals for monitoring purposes spans from macroscopic events, which can be captured at lower frequencies, to microscopic defects, whose detection occurs at frequencies above 50 – 100 kHz (Fig. 3).

Generally speaking, AE signals can be classified into two primary types: continuous signals and burst signals. Continuous AE signals appear in the time domain as a sustained, noise-like fluctuation, which may originate from a multitude of natural sources and typically consists of an overlap of different contributions. Burst signals, instead, appear as one (or more) brief transient pulses distinctly separated from the background noise. The burst waveform features a clear rising edge, peak, and decaying oscillation. In contrast to continuous signals, burst AE signals exhibit pronounced transient characteristics, manifesting as a series of independent pulses, with rapid rise times and exponentially decaying oscillatory waveforms. However, AE sources differentiate not only in terms of their continuous of impulsive patterns, but mainly in their spectral and time-frequency signature. This represents the foundation of most automated anomaly and defect detection methods employing AE signals currently proposed and demonstrated in AM.

LU signals also exhibit broadband frequency characteristics, ranging from hundreds of kilohertz to several tens of megahertz. In the time domain, LU responses can be broadly categorized into stable waveform

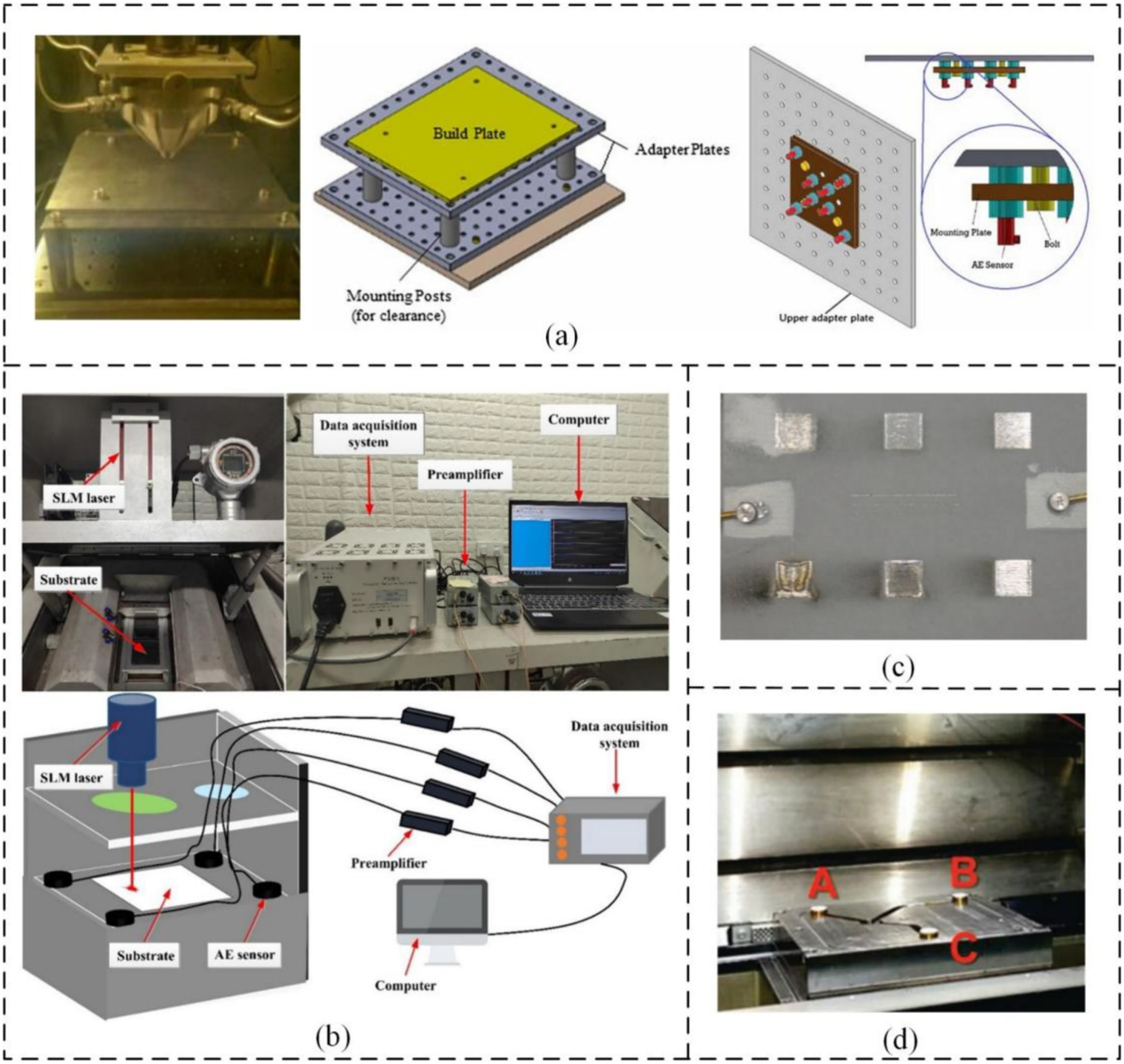

Fig. 2. Monitoring settings for various structure-borne acoustic emissions in laser AM process: (a) L-DED process monitoring system with integrated structure-borne AE sensors [54]; (b) L-PBF process monitoring systems based on structure-borne AE sensors [55,56]; (c) Two sensors are placed on top of the baseplate [57]; (d) Plate modification for the installation of multiple sensors [58].

sequences and transient responses, whereas the spectral distribution depends on the excitation regime and material attenuation. Different ultrasonic wave modes show distinct frequency contents and defect sensitivities: bulk waves are more responsive to internal defects, whereas Rayleigh waves are particularly effective for near-surface and subsurface defect detection [62]. Stable responses reflect variations in microstructure and elastic properties, while transient responses arise from wave reflection or scattering at defect interfaces and are characterized by amplitude changes, phase reversals, or delayed echoes [63].

Fig. 4 shows a classification of AE sensor technologies currently available for in-situ monitoring in AM, which include piezoelectric AE sensors, fiber-optic AE sensors [64] and LU sensors.

The former employs piezoelectric materials as the sensing element, utilizing the piezoelectric effect to convert elastic wave signals into electrical signals. The raw AE signals or transient elastic waves are captured by the sensor and subsequently transmitted, processed, and stored through a series of external devices. It is noteworthy that acoustic sensors exhibit high sensitivity to location and orientation, which can make their readings highly susceptible to process variations [48]. Typical piezoelectric sensors include resonant sensors and broadband sensors. Resonant sensors leverage the mechanical resonance effect of their structure, achieving extremely high sensitivity and signal-to-noise ratio near their natural frequency through resonance amplification. Their relatively narrow operating bandwidth and sharp frequency selectivity make them suitable for high-precision detection of specific frequency components. This class of sensors is typically employed when the mechanism and characteristics of the AE source are relatively well-understood [47]. In contrast, broadband sensors are designed to maintain a flat frequency response and low phase distortion across a wide frequency range. By suppressing structural resonance and optimizing damping de-

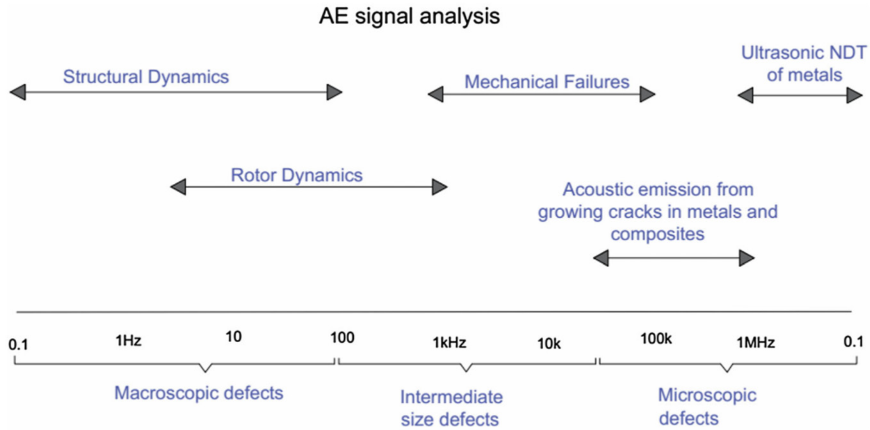

Fig. 3. Range of AE frequency for different types of signal sources and magnitude of typical defects that can be faced in AM [33].

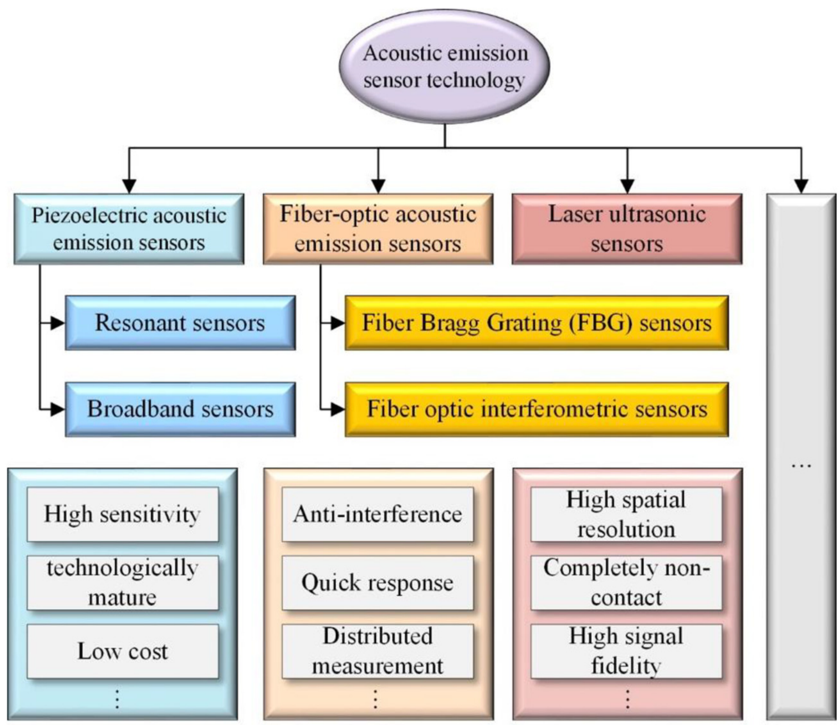

Fig. 4. Acoustic emission sensor technologies and advantages.

sign, they aim to faithfully reproduce the acoustic pressure waveform. Their primary advantage lies in the high-fidelity signal reconstruction capability over a broad frequency band, although a trade-off between sensitivity and bandwidth is often required.

Fiber optic AE sensors are mainly divided into fiber Bragg grating (FBG) sensors and Fiber optic interferometric sensors. Among them, the most widely used in AM are FBG sensors. This type of sensor utilizes an optical fiber to form a modulation zone. When subjected to acoustic wave disturbances, the properties of the light passing through this modulation zone (including amplitude, phase, and wavelength) undergo changes. By demodulating the altered light, the AE signal can be measured. During the AM process, the generated acoustic waves cause periodic expansion or compression of the optical fiber core, leading to corresponding strain in the FBG structure [65]. FBG sensors offer advantages such as high sensitivity, fast response, signal integrity, and insensitivity to radio frequency interference. They are also characterized by thermal sensitivity and an inability to distinguish between wavelength shifts caused by temperature and those induced by strain [66].

LU systems used in AM generally consist of a pulsed laser source for ultrasonic excitation and an optical interferometric or laser doppler vibrometry unit for signal detection. The excitation laser is typically directed onto the solidified track or the substrate surface, where transient thermoelastic expansion or ablation induces broadband elastic waves that propagate within the material [67], as shown in Fig. 5. The detection laser is spatially separated from the excitation point or arranged in a quasi-collinear configuration, allowing the measurement of out-of-plane surface displacement or velocity associated with structure-borne ultrasonic wave propagation. Unlike conventional piezoelectric SBAE sensors that require rigid mechanical coupling to the substrate, laser ultrasonic transducers operate in a fully non-contact manner, which significantly reduces sensitivity to temperature fluctuations, surface roughness, and coupling instability. In practical implementations, the laser ultrasonic excitation and detection heads are commonly positioned either off-axis relative to the processing laser or integrated coaxially through optical beam combining components, enabling flexible monitoring of deposited layers or the underlying substrate.

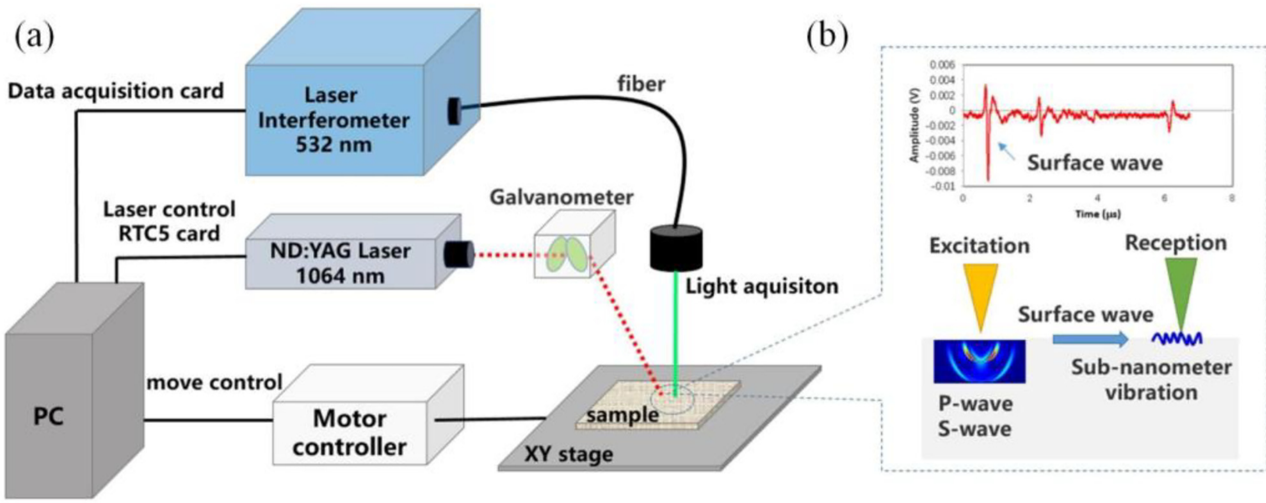

Fig. 5. The composition of the laser vibration meter and the waves generated on the sample surface: (a) This system conducts non-destructive testing in the thermoelastic state by using pulsed laser excitation, It employs a dynamic focused scanning mirror to achieve rapid beam positioning and utilizes a high-bandwidth laser interferometer for non-contact ultrasonic signal acquisition; (b) After the incident wave enters the sample, surface wave, sub-surface wave and p-wave will be generated on the sample surface, These surface waves and longitudinal waves are then received, collected, and detected [67].

LU provides an ultra-broad effective frequency bandwidth, allowing simultaneous acquisition of Rayleigh, longitudinal, and shear wave modes, thereby enriching the information content available for defect detection and material state evaluation. Through scanning-based measurement and synthetic aperture imaging techniques, laser ultrasonics further enables spatial mapping of structural acoustic responses, potentially aiding the localization and quantitative assessment of internal and near-surface defects.

3. AE-based in-situ monitoring in metal PBF

3.1. In-situ sensing methods

The acoustic signals generated in L-PBF are multifaceted, originating from a complex interplay of laser-material interaction, powder-bed dynamics, thermo-mechanical responses, and plastic deformations [35,36].

As in other AM processes, the effectiveness of AE-based monitoring depends on sensor configuration and placement, which influence sensitivity to defect types (e.g., porosity, cracks, delamination), and the ability to distinguish among different process regimes. In L-PBF, both airborne AE and structure-borne AE sensing methods have been proposed.

Concerning airborne AE, its primary focus regards the measurement of process variations deeply connected with the stability of the laser-material interaction. As the high-energy laser beam interacts with the metal powder, the rapid expansion of the vapor plume, plasma formation, keyhole oscillations, and recoil pressure during the laser exposure generate pressure waves. The stability of such waves during the process may be correlated with melt pool morphology and the formation of porosity in the manufactured part, allowing researchers to distinguish between stable conduction mode and unstable regimes.

In addition to melt pool dynamics, powder-bed and surface phenomena contribute significantly to the acoustic profile. The interaction between the laser plume and the surrounding powder particles leads to spattering and denudation. These events, alongside variations of the powder entrainment in the laser-induced vapor flow, produce variations in airborne AE signatures. Other instabilities, such as "balling", where irregular track formation occurs due to modified surface tension, may alter the acoustic emission, too. All these signatures may be used for monitoring the layer-wise quality and stability of the process via in-situ measurement and monitoring of airborne AE. A scheme of the influence of different process regimes and defect formation in L-PBF on airborne AE signal patterns is shown in Fig. 6 [68].

Various authors proposed airborne AE monitoring methods that utilize microphones placed inside the build chamber to detect pressure waves that travel through the chamber atmosphere [50,51,69–71]. Because the gas medium acts as a natural low-pass filter, airborne AE measurement is generally restricted to a lower frequency bandwidth, typically ranging from 20 Hz to 50 kHz [50,51,69–71]. Its non-contact nature offers an industrial advantage, as it does not interfere with the machine's structural integrity or the build plate installation. Nonetheless, airborne AE is susceptible to environmental noise and signal attenuation. It is characterized by a lower signal-to-noise ratio than other sensing methods, and its sensitivity is commonly limited to a narrow range of process phenomena.

While airborne signals allow monitoring events and variations that occur in the exposed layer, thermo-mechanical and plastic deformation under the layer represent the primary sources of structure-borne AE [72,73]. Throughout the heating and cooling cycles, thermal expansion, contraction, and phase transformations generate continuous elastic waves. Specifically, the high-energy, high-frequency waveforms (ranging from 50 kHz to over 1 MHz) are often associated with crack initiation, propagation, and layer-to-layer delamination caused by accumulated residual stresses. For certain alloys, such as Ti-6Al-4V, solid-state phase transformations (e.g., martensitic transformation) provide a rich source of high-frequency acoustic data [72,74]. These internal events often persist even after the laser has ceased scanning, making structure-borne sensors indispensable for detecting sub-surface structural failures [57,73].

The structure-borne nature of these signals makes them complementary to airborne ones and highly sensitive to weak energy releases from various locations of the building. However, as in airborne sensing, attenuation requires proper compensation, and machine- and environment-induced noise must be either filtered or quantitatively characterized as baseline noise. The mechanical motion of the recoater arm, the movement of the build platform, the flow of inert gas, and the operation of cooling pumps and scanner optics all contribute to a background acoustic profile. These signals typically occupy the lower frequency spectrum, and distinguishing these secondary sources from process-relevant signatures is a fundamental requirement for developing robust, high-fidelity monitoring systems capable of real-time defect detection.

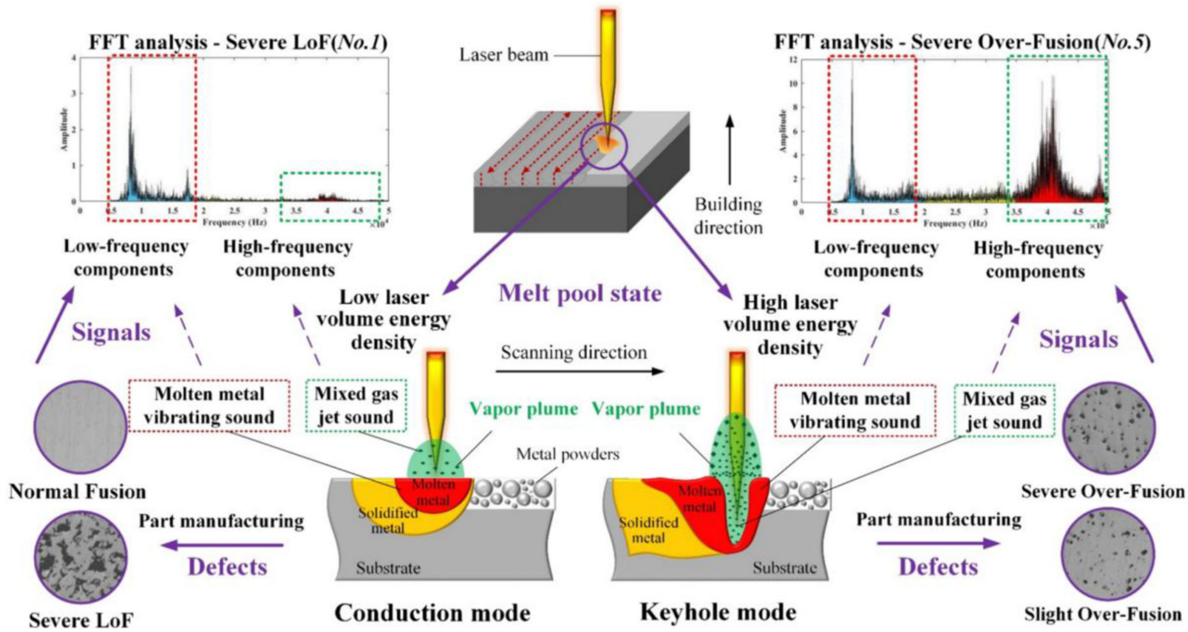

Fig. 6. The correlation mechanism among the melt pool, defects, and signals in the L-PBF process; Lack-of-fusion defects and their signature in the frequency domain originating in conduction mode are depicted on the left, while over-fusion defects and their signature in the frequency domain originating in keyhole mode are depicted on the right [68].

Structure-borne AE systems commonly employ piezoelectric transducers coupled to the build plate or frame to capture high-frequency elastic stress waves that propagate directly through the solid components of the machine [75]. However, the requirement for direct mechanical coupling poses significant integration challenges; sensors must be securely attached to the build plate, often requiring specialized mounting in case pre-heating operations are foreseen.

The trade-off between airborne and structure-borne AE is therefore driven by multiple factors, including the specific phenomenon or defect type of interest, the required sensitivity, possible sensor installation constraints, and other machine-related factors that may detrimentally influence the data quality.

The following three sub-sections review and summarize in-situ monitoring methods employing different sensing techniques, as well as multimodal methods including AE sensing in L-PBF.

3.2. In-situ monitoring and classification of process regimes

First seminal studies of airborne AE sensors for in-line monitoring purposes were carried out in laser welding applications [76] and represented the foundation for successive studies in L-PBF. More recently, several reviews and comparative studies have emphasized that many of the concepts and signal–quality relationships established in laser welding carry over directly to L-PBF, and that acoustic sensing is now regarded as emerging and promising technology for in-situ monitoring alongside optical and thermal methods [11,12].

Wasmer et al. [77] and Shevchik et al. [78] acquired airborne AE signals using an FBG optoacoustic sensor mounted inside the build chamber, approximately 200 mm from the process zone. In both studies, the sensor was implemented on an industrial L-PBF system and sampled at 1 MHz. The fiber was oriented so that its longitudinal axis was perpendicular to the incoming acoustic waves in order to enhance sensitivity. Shevichik et al. [78] proposed a spectral convolutional neural network trained in a supervised manner on data collected in three different porosity conditions, whereas Wasmer et al. [77] proposed a reinforcement learning approach. In both studies, the classifier used as input wavelet spectrograms of AE signals (as shown in Fig. 7). Classification accuracy in the range 83% to 89% and 74% to 82% were achieved, respectively.

In contrast, Ye et al. [79] employed a microphone positioned inside the build chamber at a 30° angle above the build area, with a frequency response spanning 0–100 kHz. Authors varied process parameters to induce different melting states (overheated, slight overheated, normal, slight balling, and balling), and trained a deep belief network to classify these states using either the raw AE signal or its power spectral density. Results showed that classification rates of about 95% could be achieved. Later, Kouprianoff et al. [69] focused on the relationship between airborne acoustic signals and the morphological stability of single tracks and layers. Utilizing a condenser microphone operating within the 2–20 kHz frequency band, their study demonstrated that AE signals are sensitive to variations in powder layer thickness and laser power. They observed a powder thickness (approximately 120 μm) beyond which the melt pool fails to maintain metallurgical contact with the substrate, triggering the "balling effect"[69]. This transition was acoustically identifiable as the sound pressure level (SPL). Time-frequency analysis revealed that the onset of track irregularities and balling was characterized by the appearance of high-amplitude peaks in the 7–10 kHz frequency range [69].

Extending this line of work, Chen et al. [80] examined microphone signal characteristics for single-track and multi-track scans and showed that different scan patterns and process conditions imprint distinct signatures on the acoustic response. Sun et al. [81] further provided a direct mechanistic connection between acoustic signals and melt pool morphology, strengthening the physical basis for using airborne AE as a proxy for melt pool behavior.

Building upon the diagnostic potential of airborne AE, Drissi-Daoudi et al. [50] investigated more complex classification frameworks involving multiple metallic alloys, including 316 L stainless steel, bronze, and Inconel 718. By employing high-frequency AE signals (up to 100 kHz), Drissi-Daoudi et al. [50] proposed a convolutional neural network (CNN) architecture to simultaneously predict both the material type and the process regime (lack-of-fusion, conduction mode, and keyholing), achieving an overall accuracy above 90%, up to 98% in some cases. Authors also showed that different process regimes for different materials affect the signal energy content and its signature in both the time and frequency domains (an example is shown in Fig. 8). In a more recent study [51], the same authors showed that airborne AE signals could

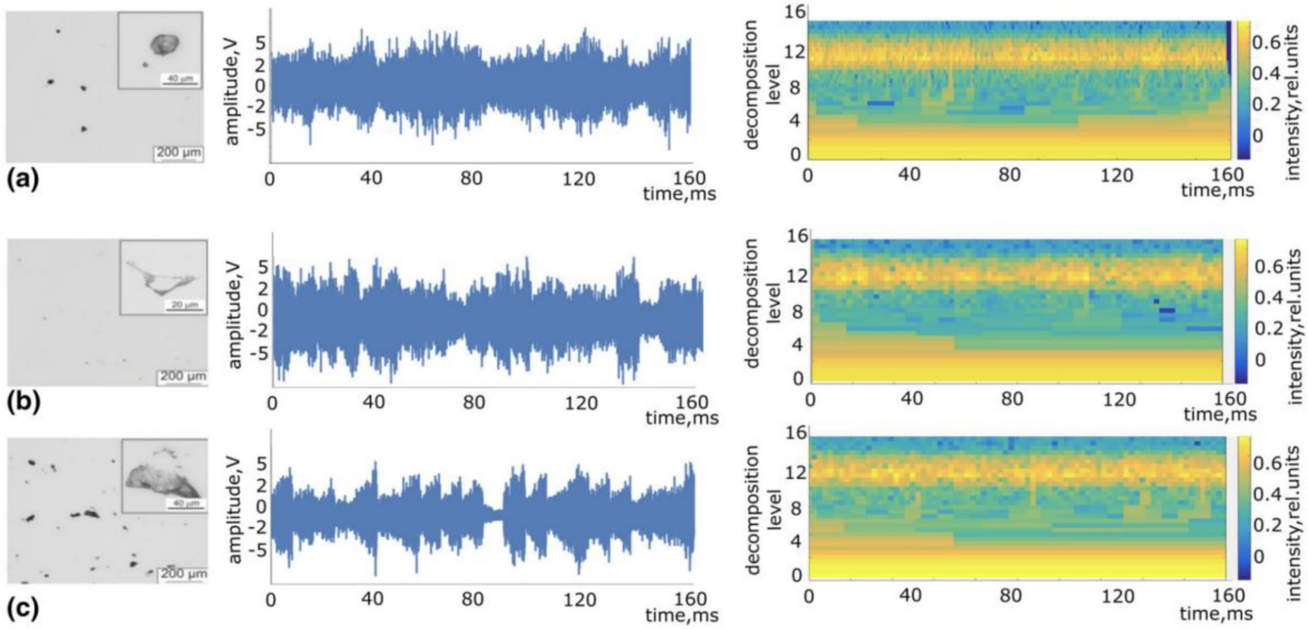

Fig. 7. Left: cross-sectional micrographs of samples manufactured in three different process conditions; Middle: corresponding AE signals in the time domain; Right: corresponding wavelet spectrograms [77].

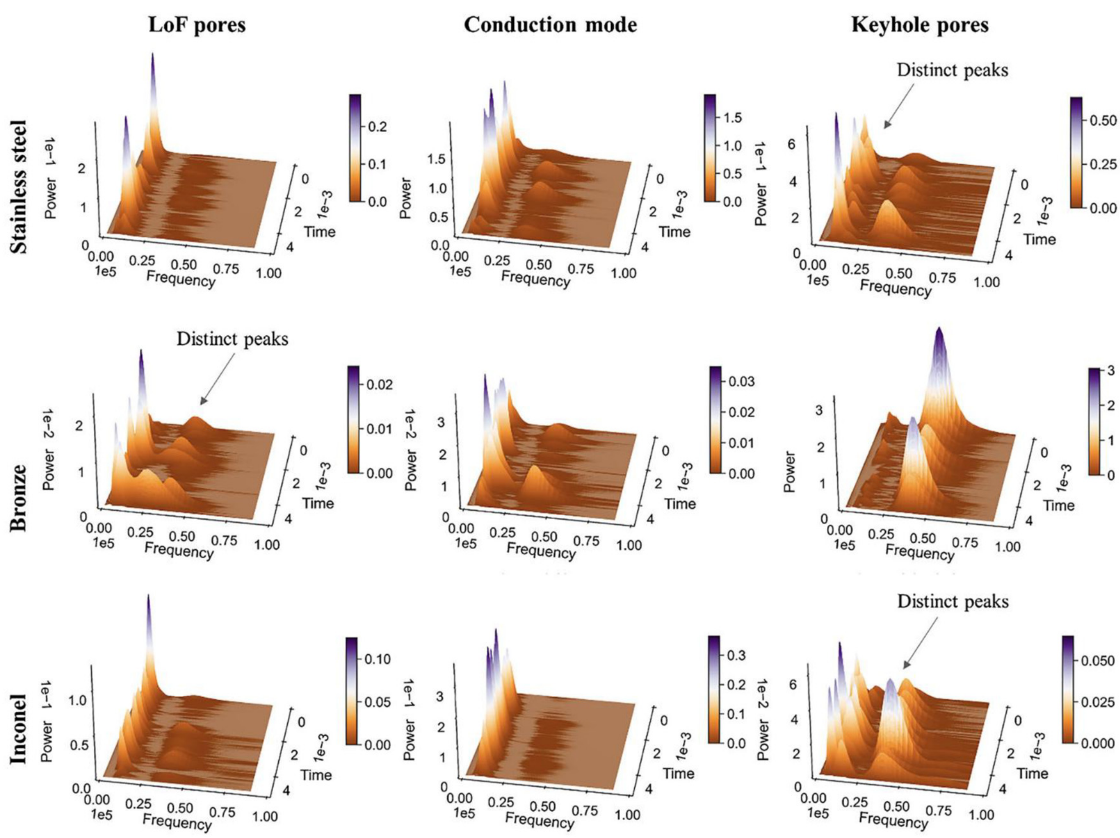

Fig. 8. 3D wavelet representation of the AE signal for three laser regimes occurring in stainless steel, bronze and Inconel depicting the absolute intensities in temporal frequency distribution among the alloy [50].

be used to facilitate the estimation of the processing map, reducing experimental efforts and accelerating the identification of optimal process parameters for a given material. A correlation between process parameters (laser power and scan speed) and synthetic descriptors extracted from intrinsic mode functions of the AE signal was shown and discussed also in [82].

Using the same AE sensing setup of Drissi-Daoudi et al. [50], Pandiyan et al. [83] proposed a semi-supervised approach where the classifier was trained only with the distribution of acoustic signatures corresponding to the defect-free regime. This study presented two generative convolutional neural network architectures based on variational auto-encoder (VAE) and general adversarial network (GAN). For both methods, the anomaly regimes were detected with an accuracy of around 96% - 97%.

In the study of Subasi et al. [84], an optical microphone was used, which uses a laser interferometer to detect the change in the optical path length of light between two mirrors due to acoustic waves. This approach allows a frequency response of 1 MHz, higher than the one of conventional microphones. The optical microphone was placed approximately 24 cm above the base plate. A 10 kHz high-pass filter was applied, and the sampling rate was 2 MHz. Different synthetic features were extracted in frequency and time-frequency domains, and the analysis showed a correlation between such extracted features and the process parameters. The same authors investigated and proposed other machine learning techniques.

In Ref. [70], the authors focused on the interpretation of AE signals and their information content for process regime classification. The study highlighted that frequency information below 40 kHz was the most relevant for classification purposes. Authors also applied empirical mode decomposition (EMD) to examine the natural pattern of AE signals and their constituent modes. In Pandiyan et al. [85], the authors proposed a self-supervised approach that could be used without ground-truth information. The methods employed a Bayesian backbone for learning the manifold representation of different L-PBF process regimes (lack of fusion, conduction mode, and keyhole), which were then clustered within a lower-dimensional space generated via t-distribution stochastic neighbour embedding (t-SNE). Authors also showed the generalization capability of the method, which lends itself to be combined with transfer learning to transfer the learned model across different process conditions. This concept was further developed in the work from Pandiyan et al. [86]. Transfer learning combined with airborne AE was also investigated by Li et al. [49]. Their deep transfer learning method used time-frequency spectrograms of acoustic signals as inputs to the network and was trained to classify different porosity conditions induced by different sets of process parameters. The transfer of knowledge across different scan strategies was discussed, with a classification accuracy of around 98%. Zhang et al. [71] extended airborne AE-based monitoring from process regimes to characterisation of micro (keyhole pores) and macro defects (distortions) by introducing an intra-/inter-layer dynamic analysis of acoustic features and a residual CNN architecture, achieving about 91% accuracy and identifying a proportional relationship between keyhole pores and the 38–42 kHz high-frequency band.

Tempelman et al. [87] investigated the suitability of airborne AE for in-situ detection of keyhole porosity rather than classifying different process regimes. Different kinds of synthetic features were extracted from acoustic signals acquired at 100 kHz during the production of single tracks with different process parameters. Extracted features included statistical moments in the time domain, spectral features and non-stationary features computed via empirical mode decomposition. A support vector machine was used to classify signal data depending on whether keyhole pores were present or not in the track (to this aim, an accurate synchronization of the AE signal to the laser position in the layer was applied). Keyhole pores were detected with an accuracy up to 97%. Most informative features depended on the timescale at which the acoustic data were partitioned, with the high-frequency content (10 – 50 kHz) of the signal that proved to be the most important for detecting pore formations.

More recently, Liu et al. [88] investigated airborne AE signals up to 50 kHz sampled at 100 kHz for the in-situ detection of keyhole-induced porosity. Using AE scalograms and scan speed as inputs to a CNN, they were able to estimate the density of keyhole pores per unit scan length with a statistically significant correlation to the ground truth reference.

In addition to the mainstream literature on airborne AE signals, a few authors explored the use of structure-borne AE signals for in-situ monitoring of melt pool and track formation stability in L-PBF.

Wang et al. [89], instead, used structure-borne AE signals to predict the quality of as-built tracks. AE signals under different laser parameters were collected and processed via wavelet analysis. Self-organizing maps and random forests were combined to predict the quality of tracks, highlighting a good correlation between in-situ gathered data and post-process track characterization. Similarly, Sung et al. [90] correlated features extracted from structure-borne AE signals to the melt pool dimension. Experiments were conducted by varying the laser power and the scan speed. The magnitudes of frequency components extracted via STFT were used as synthetic descriptors, highlighting a high positive correlation with the actual melt pool dimension measured after the process.

Generally speaking, the literature reviewed in this sub-section highlighted the suitability of airborne AE (and in a few cases of structure-borne AE too) to distinguish different process regimes or variations induced by different process parameters. This opens to two different applications: on the one hand, it allows using AE signals to aid the identification of processability windows; on the other hand, it allows developing in-situ monitoring methods to identify transitions from one regime to another. In both cases, airborne AE lends itself to be used as a complementary information source together with other more common sensing techniques, like imaging and infrared thermography methods.

Nonetheless, various open issues and challenges emerge from the current state of the art. Most studies focused on classifying process states induced by different sets of process parameters, but there is a lack of experimental evidence on the suitability of airborne AE signals to detect stochastic anomalies and actual defects. Moreover, the majority of the literature involved sensing setups with microphones inside the build chamber that are appropriate for tests in laboratory conditions, but difficult to implement in real production. Specifically, there is a lack of studies on the influence of microphones on the gas flow, as well as on long-term influences of the harsh process environment on sensor integrity and signal repeatability. These open issues motivate further developments towards more consolidated results targeting a higher technology readiness level in the field of airborne AE for process optimization and monitoring.

So far, LU based on actively generated elastic waves has not been tested for in-situ monitoring in L-PBF. Various authors considered LU as an inspection method applied ex-situ and after the process [91–94], but a first conceptual scheme of a LU architecture for in-situ and layer-wise inspection in L-PBF has been presented in Dai et al. [95] (Fig. 9). In their scheme, one galvanometer is shared by the printing laser and the LU receiver, whereas a second galvanometer is devoted to the excitation laser. The hypothetical method alternates printing and LU scanning of each layer, as a possible way to identify sub-millimeter near-surface cracks. However, the practical application of LU in L-PBF environments remains challenging due to the high surface roughness of as-built parts, which significantly degrades the signal-to-noise ratio, and the inherent complexity of integrating high-precision optical paths into commercial printing chambers. A few seminal studies on the use of LU for in-situ inspection purposes regard the DED process and are discussed in the next section.

A summary of salient sensing and monitoring settings and performance of methods reviewed in this section is provided in Table 1 [49–51,69,71,77–90].

3.3. In-situ crack detection

Moving from monitoring variations in the process regimes during the exposure of this layer to detecting undesired events and defects that occur under the layer, most studies have focused on structure-borne AE.

Only a few authors have investigated the use of airborne AE sensors to this aim. In principle, high-energy pressure waves associated with macro-cracks and delamination events can propagate through the chamber atmosphere and be captured by microphones installed above the build area. As an example, Moore et al. [96] showed that airborne AE may be used to detect macroscopic cracks and delamination events.

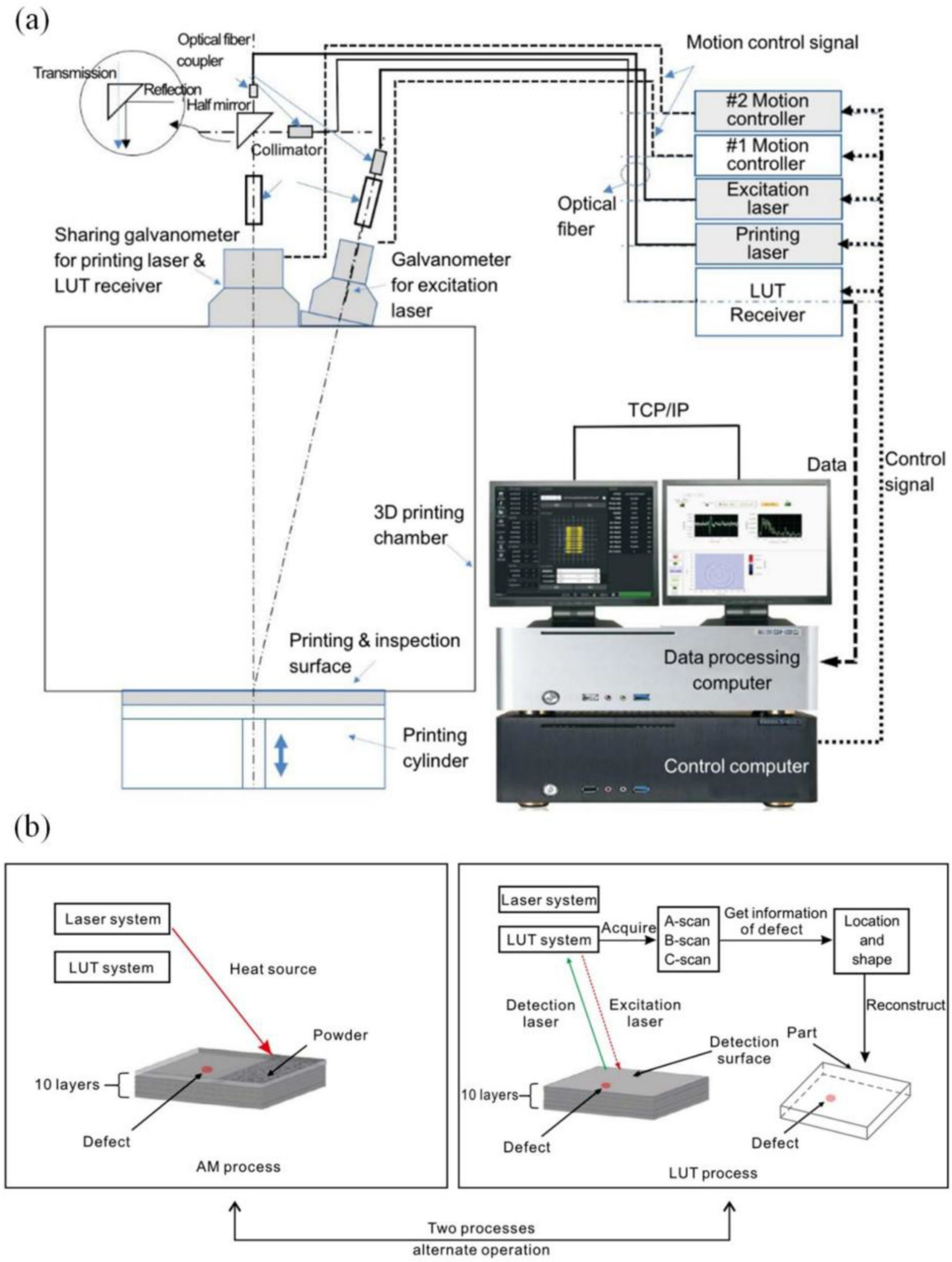

Fig. 9. Conceptual scheme of the in-situ LU monitoring configuration from [95]: (a) In-situ sensing architecture comprising the galvanometer for laser excitation, the LU received, the data processing and control unit; (b) Possible scheme of the LU implementation during the L-PBF process for in-situ defect detection.

In their study, both the amplitude of peaks in the time domain and frequency characteristics were used as synthetic descriptors. In this case, the frequency range was below 20 kHz, while the sampling frequency was 102.4 kHz. However, intrinsic limitations of airborne AE sensing make it poorly suited for reliable crack detection. Richter et al. [97] implemented both airborne and structure-borne AE, aiming to predict both the process state and detect cracking and delamination. The authors showed that the structure-borne signal proved superior in detecting secondary process emissions caused by crack formation and delamination. Indeed, structure-borne AE remains the most effective approach for this class of phenomena, and its adoption has been explored by several groups since the foundational works of Rieder et al. [98,99]. The concept has also been incorporated into patents filed by major L-PBF system manufacturers [100–102].

Rieder et al. [98,99] introduced an ultrasonic monitoring device mounted beneath the baseplate in L-PBF, tracking bottom-plate interface echoes and backwall echo patterns as proxies for material discontinuities as the build height increased. Eschner et al. [42] adopted a similar concept but analyzed the signal's spectrogram to capture the acoustic emission signature of the process rather than the reflected echoes. Plotnikov et al. [58] monitored the root-mean-square (RMS) value of the signal to achieve comparable results.

Table 1
Summary of acoustic-based melting-regime and porosity-state identification in L-PBF.

Ref. No.	Sensor type	Sampling frequency	Sensor bandwidth	Type of defect / application	Accuracy
2019 [77]	FBG	1 MHz	0–200 kHz	Porosity states classification	Up to 82%
2019 [78]	FBG	1 MHz	0–100 kHz	Porosity states classification	Up to 89%
2018 [79]	Condenser mic	200 kHz	0–100 kHz	Melting states classification	95%
2021 [69]	Condenser microphone	102.4 kHz	2–20 kHz	Variations of layer thickness and power	N/A
2023 [80]	Condenser microphone	50 kHz	3.5 Hz–20 kHz	Variation of process parameters and scan pattern	N/A
2024 [81]	Piezoelectric microphone	N/A	4–100 kHz	Melt pool morphology	N/A
2022 [50]	Piezoelectric microphone	1 MHz	0–100 kHz	Material type and process state classification	Up to 98%
2023 [51]	Ultrasound microphone	0.6 MHz	0–200 kHz	Process window estimation	N/A
2021 [83]	Piezoelectric microphone	1 MHz	0–100 kHz	Process state classification	Up to 97%
2024 [84]	Optical microphone	2 MHz	>10 kHz	Process state classification	N/A
2023 [85]	Ultrasonic microphone	400 kHz	0–150 kHz	Process state classification	92%
2024 [86]	Ultrasonic microphone	400 kHz	0–150 kHz	Process state classification	Up to 99.1%
2023 [49]	Piezoelectric microphone	100 kHz	100 kHz	Porosity states classification	98%
2024 [71]	Ultrasonic microphone	100 kHz	38–42 kHz	Classification of micro and macro defect states	91%
2022 [87]	Microphone	100 kHz	N/A	Keyhole pore detection	Up to 97%
2026 [88]	Piezoelectric microphone	100 kHz	up to 50 kHz	Estimation of keyhole pore density	N/A
2024 [89]	Structure-borne AE	2 MHz	Up to 1 MHz	Track quality classification	Up to 98%
2025 [90]	Structure-borne AE	5 MHz	100–200 kHz	Correlation to melt pool dimensions	N/A

Grounding on these seminal works, various recent studies demonstrated the feasibility of in-situ detection of cracks and other sources of sudden energy release in L-PBF.

In Ref. [57], AE monitoring was conducted during single-layer tests with both single-track and multi-track configurations. The occurrence times and locations of AE events were identified and subsequently compared with observations from the specimen cross-sections obtained via X-ray computed tomography (CT). In the initial single-track tests, burst-type AE events were detected during processing, with their origins confirmed to be pores and microcracks within the specimen. Subsequently, in multi-track tests, defects occurring shortly after laser irradiation and those resulting from the laser's return pass were identified. In this case, two piezoelectric AE sensors with high heat resistance were placed on the baseplate. They had a resonance frequency of 250 kHz and exhibited relatively flat and high sensitivity between 150 and 600 kHz, except near the resonant frequency. The output voltages of the two AE sensors were sampled at a sampling frequency of 1.95 MHz.

Seleznev et al. [73] employed a structure-borne AE sensor under the baseplate. The signal passed through a 40 dB pre-amplifier and a 50 – 600 kHz filter. The sampling rate was 2 MHz. Fig. 10 shows a comparison between the time and frequency signature of background noise and noise bursts that are naturally generated during the process, and the signature of a cracking event. Based on the observation that cracks entail a higher energy release than any other acoustic burst due to the natural behaviour of the process, Seleznev et al. [73] proposed a simple thresholding of the AE signal energy to separate and detect crack events from any other natural events. However, other authors pointed out that, due to the highly transient and noisy nature of the L-PBF process and its environment, reliably distinguishing crack events from other short-lived phenomena requires more than simple thresholding [30,51,56]. Indeed, most recent studies adopted multivariate statistics, machine learning or deep learning to enhance in-situ crack detection performances.

Kononenko et al. [56] combined in-situ AE signal acquisition with a machine learning approach for automated classification of AE signal events into noise and cracks. The AE signal was amplified by 40 dB, passed through the 50–600 kHz band-pass filter and recorded with a sampling frequency of 2 MHz. The method proposed by Kononenko et al. [56] involved the extraction of time and frequency synthetic indexes from the AE signals within every acquired time window. Then, principal component analysis (PCA) was applied to reduce the dimensionality of the computed features. Classification of noise and crack events in the lower-dimensional PCA space was finally employed, comparing different classifiers. The authors concluded that spectral features are the most informative, as they allow the highest classification accuracy (in the order of 99%) regardless of the specific classifier adopted.

The use of multiple structure-borne AE sensors was explored by a few authors [75,103]. Bevans et al. [75] adopted four sensors under the baseplate, acquiring signals during the production of AISI 316 L samples under different process parameters and build configurations. Both high and low frequency responses were tested, 150 – 850 kHz and 50 – 400 kHz, respectively, with a sampling frequency of 1 MHz. The experimentation was designed to force localized cracks and support breakages. AE signals were decomposed using wavelet transforms and the resulting spatially localized acoustic emission signatures were correlated to occurred defects and energy release events. Authors showed that spatially localized AE signatures were not only correlated in a statistically significant way to variations of the input energy density, but also to incipient part failures, surface finishing deterioration, and microstructural heterogeneity. The geometry of parts and builds investigated in Bevans et al. [75] together with the fact that the authors tested their method on an industrial EOS M290 machine, paves the way to the potential industrialization of structure-borne AE for localized defect detection in L-PBF.

Grasso et al. [104,105] explored a different application where in-situ AE monitoring represents an enabling capacity for L-PBF of electronic components on multi-material substrates. More specifically, L-PBF was used to fabricate high-performance cooling structures directly on a direct bonded copper (DBC) substrate made of a ceramic core sandwiched between two copper layers. The aim is to enhance the cooling performance while simplifying the production chain, but the new solution also introduces challenges. A major one regards the crack formation in the ceramic layer of the substrate because of significant temperature gradients involved in the L-PBF process, as well as the mismatch in thermal expansion coefficients between copper and Al_2O_3. The study showed that the crack likelihood inflated as a higher number of layers were manufactured and/or larger build areas were exposed by the laser (an example of cracks in the ceramic layer and their signatures in the STFT spectrograms is shown in Fig. 11). To aid a fast in-situ detection of DBC substrate cracking, Grasso et al. [104,105] proposed a monitoring method based on structure-borne AE signals acquired underneath the baseplate. In Grasso et al. [104], a multivariate control charting scheme was applied to key features extracted from the AE signals filtered in the range 65 kHz to 400 kHz, sampled at 1 MHz. The alarm threshold was estimated by using data from crack-free samples, and the method was shown to be effective in detecting larger cracks. To enhance the detection of smaller cracks, Grasso et al. [105] proposed a new approach that combines the envelope of the AE spectrogram with

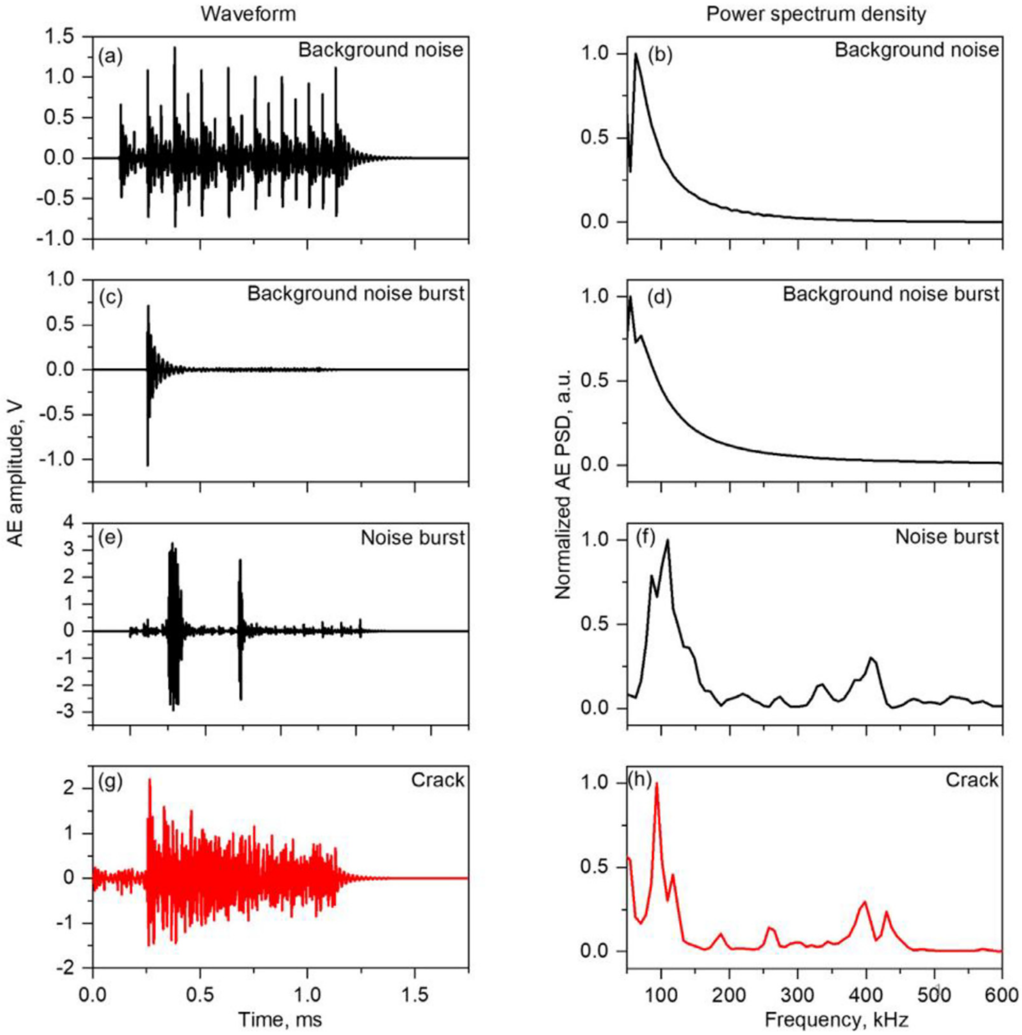

Fig. 10. Different AE signal patterns in the time domain (left) and frequency domain (right) in the presence of either noise (background noise and bursts) and crack events [73].

a one-class support vector machine trained on crack-free signals only. The results highlighted the suitability of the method to detect all types of cracks thanks to an enhanced distinction between actual events and naturally varying time-frequency patterns along the different phases of the process.

Ongoing developments in the field make structure-borne AE monitoring and in-situ crack detection a promising complement to existing in-situ sensing methods, particularly for crack-prone materials and resource-intensive L-PBF applications, where early process interruption can translate into significant savings in material and time. Nonetheless, industrial adoption of the aforementioned methods remains limited and faces various open challenges. Structure-borne AE sensors are intrusive and may require modifications to the machine layout (e.g., cable routing, redesign of the baseplate fixturing system, etc.). In addition, most reported experiments involve simple specimens or even single-track/single-layer tests under controlled laboratory conditions, with limited validations in real industrial scenarios. Other open issues regard the difficulty of defining trustworthy ground truth measurements and reliable validation procedures. These critical aspects are further discussed in Section 6.

A summary of salient sensing and monitoring settings and performance of methods reviewed in this section is provided in Table 2 [42,56,57,73,75,96–99,104–105].

3.4. Multimodal methods

Both airborne and structure-borne AE were pointed out to carry valuable in-situ information complementary to other sensing techniques. This has motivated an increasing research interest for multimodal monitoring and sensor fusion techniques, where AE sensing is used in parallel to other imaging or thermography methods.

Plotnikov et al. [58] integrated a suite of infrared, optical, and AE sensors into a commercial L-PBF system, focusing on the spatial and temporal synchronization of all signals. Data from multiple builds were investigated, and qualitative correlations between data captured with different sensors were highlighted. It represented a preliminary study towards the implementation of multimodal platforms in L-PBF.

Gutknecht et al. [48] compared three monitoring methods, namely a microphone for airborne AE, a co-axial two-colour pyrometer for melt pool temperature, and an off-axis thermal camera. Rather than evaluating defect-detection performance, the study provided a common basis for comparing general sensor characteristics. The microphone exhibited a high sensitivity, but with greater susceptibility due to the strong dependence of signal strength on sensor–melt-pool distance caused by frequency-dependent attenuation. Based on this results, Gutknecht et al. [48] provided several recommendations for sensor implementation and synchronization.

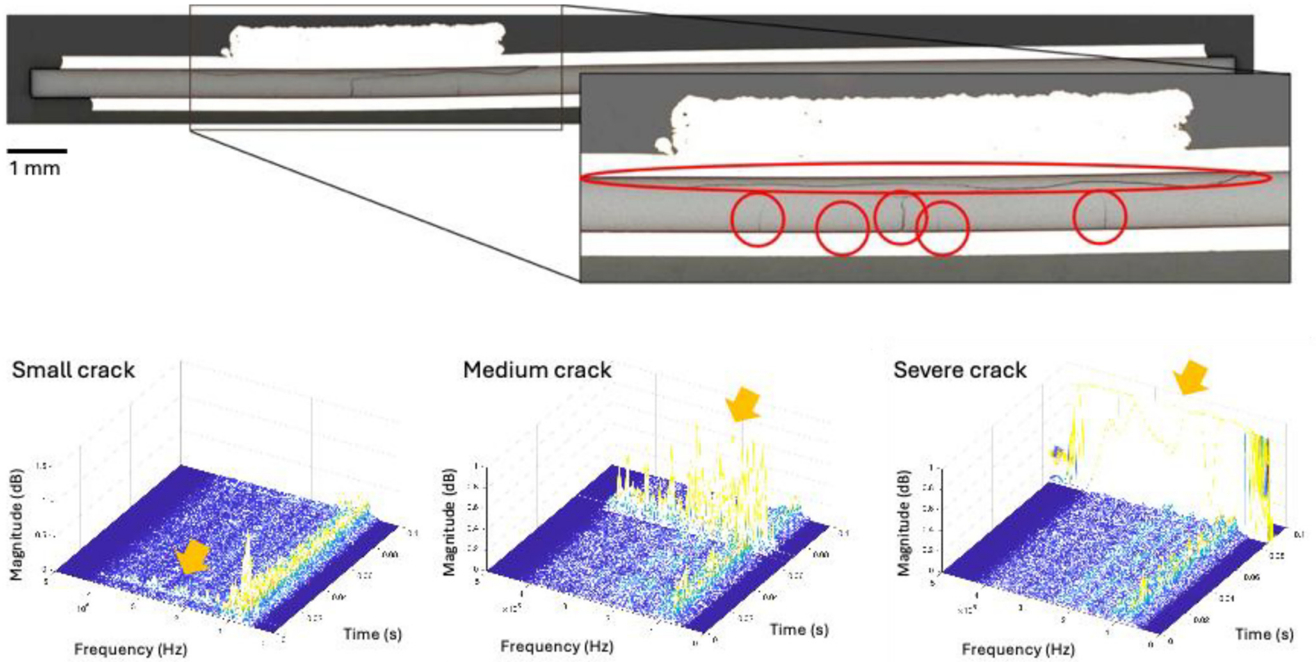

Fig. 11. Top: examples of vertical and horizontal cracks in the ceramic layer of a DBC substrate originated during the L-PBF of a copper sample; Bottom: example of SFTF spectrograms in the presence of small, medium, and large severity cracks [104].

Table 2
Summary of acoustic-based in-situ crack detection in L-PBF.

Ref. No.	Sensor type	Sampling frequency	Sensor bandwidth	Type of defect / application	Accuracy
2023 [96]	Airborne microphone	102.4 kHz	3.75–20 kHz	Detection of cracks and delamination	N/A
2025 [97]	Airborne microphone + structure-borne AE	1.25 MHz	AB: 2–200 kHz; SB: 150–600 kHz	Detection of cracks and delamination	99%
2014 [98]	Structure-borne AE ultrasonic transducer	250 MHz	400 kHz–30 MHz	Detection of material discontinuities	N/A
2016 [99]	Structure-borne AE ultrasonic transducer	250 MHz	400 kHz–30 MHz	Detection of material discontinuities	N/A
2020 [42]	Structure-borne AE piezoceramic	4 MHz	Up to 1 MHz	Detection of material discontinuities	Precision: 86%, recall: 91%, F1: 89%
2021 [57]	Structure-borne AE piezoelectric sensors	1.95 MHz	N/A	Detection of pores and microcracks	N/A
2022 [73]	Structure-borne AE piezo sensor	2 MHz	50–600 kHz	Crack detection	N/A
2023 [56]	Structure-borne AE piezo sensor	2 MHz	50–600 kHz	Crack detection	Up to 99%
2025 [75]	Structure-borne AE	1 MHz	150–850 kHz (high); 50–400 kHz (low)	Crack detection and localization	N/A
2025 [104]	Structure-borne AE	1 MHz	65–400 kHz	Crack detection in ceramic substrate	N/A
2025 [105]	Structure-borne AE	1 MHz	65–400 kHz	Crack detection in ceramic substrate	Up to 100%; false alarm rate up to 0.4%

Other studies that combined microphones with pyrometry and/or imaging methods have demonstrated that acoustic information complements optical signatures and can substantially improve keyhole-pore detection performance [87,106].

In the work of Tempelman et al. [106], airborne AE was combined and synchronized to co-axial pyrometry. Although authors explored data fusion methods combined with classifiers trained on AE spectral features and pyrometry signal amplitudes, they showed that acoustic data alone could be more effective in detecting keyhole porosity. Zhirnov et al. [107] studied the effectiveness of a combination of AE and powder bed imaging in L-PBF monitoring of parts with internal lack-of-fusion defects caused by spatter redeposition and laser attenuation. Using an airborne AE sensor with a frequency range below 51.2 kHz and a sampling rate of 102.4 kHz, they showed a positive correlation between spectral acoustic features and the size and density of the region contaminated by deposited spatters, as well as an inverse correlation with the roughness of manufactured parts. This indicates that airborne AE can be a complementary source of information for monitoring purposes that go beyond the process regime classification and keyhole porosity detection.

Shukla et al. [108] combined a microphone with a co-axial high-speed camera for melt pool monitoring and spatter tracking. The authors showed that AE signal fluctuations were correlated with vapor plume, melt pool asymmetry, and spatter ejection during layer processing. Among other results, the study focused on correlating acoustic signals with the actual physical events, aiding detailed labelling as a prerequisite to advance acoustic monitoring from the layer level to the more local defect level.

In Ref. [109], a multi-sensor monitoring approach was proposed, combining high-speed imaging, photodiodes, and airborne acoustic signals. Converting all signals into 2D representations and using a LeNet-5-based model with Dempster–Shafer fusion, the authors showed that the triple-sensor configuration achieved accuracy between 92% and 100% in classifying different process states induced by different energy densities.

Table 3
Summary of multimodal L-PBF monitoring studies integrating acoustics and other sensing methods.

Ref. No.	Sensor type	Sampling frequency	Sensor bandwidth	Type of defect / application	Accuracy
2019 [58]	Structure-borne AE piezoelectric + infrared camera	1 MHz	N/A	Cross-sensor correlation	N/A
2021 [48]	Airborne AE optical microphone + on-axis two-colour pyrometer + NIR camera	Mic: 2 MHz; Pyrometer: 12.5 kHz; Camera: 5 Hz (per-layer image)	Mic: 10 Hz–1 MHz; Pyrometer: 1450–1800 nm; Camera: ~850 nm bandpass	Cross-sensor correlation	N/A
2022 [106]	Airborne AE microphone + coaxial pyrometry	100 kHz	0–50 kHz	Keyhole porosity detection	Up to 96.75%
2022 [107]	Airborne AE microphone + Structure-borne + powder bed imaging	102.4 kHz	0–51.2 kHz	Lack-of-fusion porosity classification	98%
2024 [81]	Airborne AE ultrasonic microphone + X-ray imaging	Imaging at 20 kfps	Mic: 4–100 kHz	Estimation of vapor depression dynamics	N/A
(2024) [109]	Coaxial photodiode + off-axis high-speed camera + airborne AE	Camera and photodiode: 10 kHz; Mic: 20 kHz	N/A	Process state classification	92.63% – 100%

Another stream of literature regards the combined use of AE sensors and synchrotrons to characterize process dynamics at the melt pool level via in-operando x-ray images augmented by synchronized acoustic signals. Samimi et al. [110] showed that X-ray imaging provides a valuable tool to aid the interpretation of AE signals acquired during the L-PBF process. They also briefly reviewed the state of the art on the combined use of AE and X-ray imaging between 2018 and 2023. Samimi et al. [110] noted that further advances are needed to achieve higher resolution, deeper insight into underlying phenomena, and faster recognition. Accounting for the inherent properties of acoustic signals, such as time-lag effects, would enable more accurate synchronization between AE data and X-ray imaging in future work, improving signal interpretation and supporting machine-learning-based automatic detection. Samimi et al. [110] also emphasized that the use of AE in synchrotron L-PBF experiments provides more comprehensive information on defect formation.

Although this stream of research is mainly focused on interpreting the intimate mechanisms that drive the laser-material interaction, melt pool dynamics, material ejections, and defect formation, it may also be a playground to test new AE-based monitoring techniques using X-ray imaging for in-operando ground truth estimation.

Following this route, Sun et al. [81] used a method commonly used in whistle aeroacoustics, namely nondimensionalized Strouhal number analysis, to correlate AE signals recorded in the keyhole regime to the vapor depression morphology. Results showed that in-situ AE measurement allows estimating vapor depression dynamics related to defect formation. Single-track experiments were performed by varying process parameters. AE signals were processed in the frequency and time-frequency domain, while vapor depression and keyhole formations were directly observed via in-situ x-ray imaging.

A summary of salient sensing and monitoring settings and performance of methods reviewed in this section is provided in Table 3 [48,58,81,106,107,109].

4. AE-based in-situ monitoring in DED/WAAM

With the widespread adoption of DED and WAAM processes in aerospace, energy systems, and other advanced manufacturing sectors, their unique advantages in rapid fabrication, high-performance repair, and remanufacturing of complex metallic components have become increasingly prominent [111]. However, the inherently non-equilibrium thermodynamic nature of both DED and WAAM, characterized by rapid melting–solidification cycles, intense melt-pool convection, and strong multi-physics coupling, renders them highly susceptible to internal defects, including cracks, porosity, and lack-of-fusion regions [112]. These defects not only degrade the mechanical integrity of the fabricated components but also constrain the broader deployment of DED- and WAAM-produced parts in critical service environments [113]. Consequently, achieving real-time process monitoring and early defect identification has become both a central bottleneck and an urgent requirement for advancing DED and WAAM technologies toward robust industrial implementation.

In-situ process monitoring is widely recognized as a critical strategy for improving the performance and reliability of AM processes [114]. Among various approaches, optical and thermal sensing methods have become the dominant techniques. For example, optical sensors are commonly used to capture melt pool geometry in real time, ensuring the stability of melt pool width and height and thereby enhancing the geometric accuracy of fabricated components [115]. Meanwhile, infrared thermography and pyrometry are employed to characterize the temperature field of the melt pool, enabling the estimation of key process parameters such as temperature gradients and solidification rates.

In practical applications, Xiao et al. [116] developed a vision-based monitoring system and proposed a melt pool inter-frame similarity (MPIFS) metric, which improves sensitivity to melt pool fluctuations by approximately three times compared to conventional geometric parameters. To address the challenge of accurate melt pool contour extraction under spatter interference, recent studies have introduced neural network-based image segmentation methods, achieving measurement errors within 0.1 mm [117]. In addition, Li et al. [118] implemented a closed-loop control framework by integrating thermal and visual data, where the melt pool temperature is regulated via an MTC strategy combined with a P-controller, and droplet transfer behavior is adjusted using an image-based intelligent hybrid control method.

Despite their advantages, including non-contact operation and rich information acquisition, optical and thermal monitoring methods exhibit inherent limitations. The presence of plasma radiation, spatter, and shadowing effects during high-energy laser-powder interactions can significantly degrade imaging quality. Moreover, conventional image processing techniques are sensitive to illumination variations, noise, and dynamic melt pool behavior, resulting in limited robustness. More importantly, these methods primarily rely on surface morphology and temperature field measurements, making it difficult to directly access subsurface information. As a result, their capability for early detection of internal defects, such as porosity and cracks, remains limited.

Among various in-situ monitoring techniques, AE sensing has emerged as a research focus for DED and WAAM process monitoring due to its high temporal resolution and sensitivity to various defect-related signatures of the process, such as the initiation and propagation of microcracks, melt-pool vibrations and instabilities, spatter generation, and feedstock–melt pool interactions [119]. These attributes potentially endow AE sensing with a distinct capability for characterizing subsurface quality variations and enabling early-stage defect diagnosis. In recent years, with the advancement of broadband AE sensors, multi-channel array acquisition systems, and sophisticated signal-processing and machine-learning techniques, the application of AE technology in DED and WAAM has expanded considerably. Correspondingly, the research focus has gradually shifted from analyses based solely on single-channel AE signals toward integrated process diagnostics enabled by multi-sensor and multi-physics data fusion [20]. The following subsections review the literature devoted to the different in-situ sensing methods and their applications for process monitoring and defect detection, as well as their possible combination with other monitoring techniques.

4.1. In-situ monitoring methods

In DED and WAAM processes, both structure-borne and airborne AE sensing methods have been explored, each offering distinct advantages and limitations depending on the target phenomena and integration constraints.

Structure-borne AE is currently one of the most mature AE-based monitoring techniques applied in DED processes [120], and has likewise been widely adopted in WAAM [44]. Structure-borne AE sensors are typically surface-mounted or clamped onto the substrate or build platform, and most utilize piezoelectric ceramic elements [44]. Because energy-release phenomena originate within solid structures, structure-borne AE sensing provides a high signal-to-noise ratio, broad bandwidth, and high sensitivity [24]. These advantages render structure-borne AE suitable for both DED and WAAM monitoring under harsh processing conditions, such as intense laser or arc illumination, strong electromagnetic radiation, and high thermal fluctuations. However, the high-temperature environments inherent to these arc- and laser-based deposition processes pose significant challenges to the stable and reliable deployment of structure-borne AE systems. Although the introduction of waveguide-based sensing effectively mitigates the thermal degradation of piezoelectric transducers, such indirect coupling inevitably introduces pronounced frequency attenuation and dispersive wave distortion. As a result, achieving high-fidelity signal transmission and robust decoupling under intense thermal input remains a critical barrier to the industrialization and large-scale application of structure-borne AE monitoring in both DED and WAAM.

In parallel, airborne AE sensing has gained attention owing to its non-contact nature, which eliminates issues associated with thermal shock or unstable mechanical coupling, offering greater flexibility in sensor placement [46]. This makes it particularly suitable for enclosed manufacturing setups and provides an effective complement to structure-borne AE. In DED/WAAM processes, airborne acoustic signals primarily originate from the expansion and contraction of plasma and metal-vapor plumes generated by laser/arc-material interactions, aerodynamic noise from shielding and carrier gas flows, and acoustic disturbances induced by intense melt-pool oscillations and spatter ejection [78]. As a result, airborne AE is suitable to capture macroscopic process stability [121]. When nozzle clogging occurs, powder-feed rates fluctuate, or shielding-gas pressure deviates from normal conditions, the background acoustic spectrum undergoes noticeable frequency shifts [120]. Furthermore, in DED, the interaction between the energy beam and powder stream directly modulates the acoustic pressure field [122], enabling airborne AE to serve as an indicator of melt-pool dynamics. Despite these advantages, airborne AE sensing faces various limitations: significant acoustic attenuation in air, combined with interference from equipment noise and complex acoustic reflections within the processing environment, often results in a signal-to-noise ratio substantially lower than that of structure-borne AE. Therefore, weak signatures associated with internal defect evolution are easily masked, which restricts the technique's ability to provide deep insight into subsurface microcrack activity.

It is also worth noticing that the AE signal characteristics and defect-related responses differ significantly between DED and WAAM. Due to the high energy density and highly localized, transient melt-solidification behavior of the laser heat source, DED generates AE signals that are more sensitive to high-frequency, short-duration events such as thermal cracking, keyhole instability, and micro-pore collapse. In contrast, WAAM employs an arc heat source that produces a larger molten pool and slower thermal cycles, causing its AE signals to more prominently reflect low-frequency to mid-frequency phenomena such as arc fluctuations, droplet transfer events, metal short-circuiting, and the formation of large gas pores. These differences imply that the choice of sensing method and the interpretation of AE features must be tailored to the specific process and defect types of interest.

The following three sub-sections review and summarize in-situ monitoring methods employing different sensing techniques, as well as multimodal methods including AE sensing in DED/WAAM.

4.2. In-situ monitoring and classification of process regimes

A significant body of research has leveraged AE signals to monitor and classify different process regimes in DED and WAAM, aiming to correlate acoustic signatures with process parameters and stability conditions.

Some studies focused on establishing correlations between AE signal characteristics and underlying physical mechanisms. Song et al. [123] analyzed AM-induced defects from both physical-mechanism and signal-feature perspectives, extracting key descriptors such as high/low-frequency spectral ratios, and successfully classified AE signals associated with crack formation, powder–melt interactions, and thermally induced stresses. Similarly, Gaja et al. [124] extracted time-domain statistical features including peak amplitude, duration, and signal energy and used logistic regression models to establish a mapping between AE characteristics and defect formation mechanisms, further demonstrating the significant potential of structure-borne AE for DED monitoring.

With the rapid advancement of deep learning, DED/WAAM quality monitoring has evolved from traditional threshold-based alarms to intelligent pattern-recognition frameworks. Conventional feature-engineering approaches heavily depend on expert knowledge and struggle to capture the complex, nonlinear, and time-varying characteristics inherent in AE signals. Recently, converting one-dimensional AE time-series data into two-dimensional time–frequency representations using wavelet packet decomposition or short-time Fourier transform, followed by convolutional neural network–based automated feature learning, has become a prominent research direction. Zhang et al. [125] introduced spectral convolutional neural networks to analyze and model time–frequency representations of AE signals, enabling successful in-situ monitoring of melt pool depth during the laser welding process. Wang et al. [126] proposed a deep learning framework termed WPD-PWCN, integrating an attention mechanism with wavelet-based convolution. In this approach, wavelet packet decomposition is applied to AE signals to reduce frequency aliasing, followed by feature extraction using a Daubechies-4 wavelet kernel and refinement via an attention module. The method achieves an accuracy of 96.18% in identifying the forming quality of the LDED bonding interface.

In the context of WAAM, Tang et al. [127] proposed a method to identify the arc length by detecting and processing arc acoustic signals based on microphone measurements. This approach employs a wavelet-based signal decomposition technique to extract the trend component of the variable arc acoustic signal and derives a quantitative relationship between the arc length and the acoustic signal. Their results indicate that the arc acoustic signal exhibits regular fluctuations corresponding to the continuous variation of the arc length. Ren et al. [128] microphone-acquired acoustic signals are transformed into two-dimensional time-frequency spectrograms, based on which a time-frequency domain convolutional neural network (TF-CNN) is developed. Logarithmic spectrograms are utilized to characterize raw arc sound signals and serve as input to the optimized CNN model. Experimental results demonstrate that the proposed method can accurately identify four penetration states in the WAAM process, achieving an average accuracy of 98.2%.

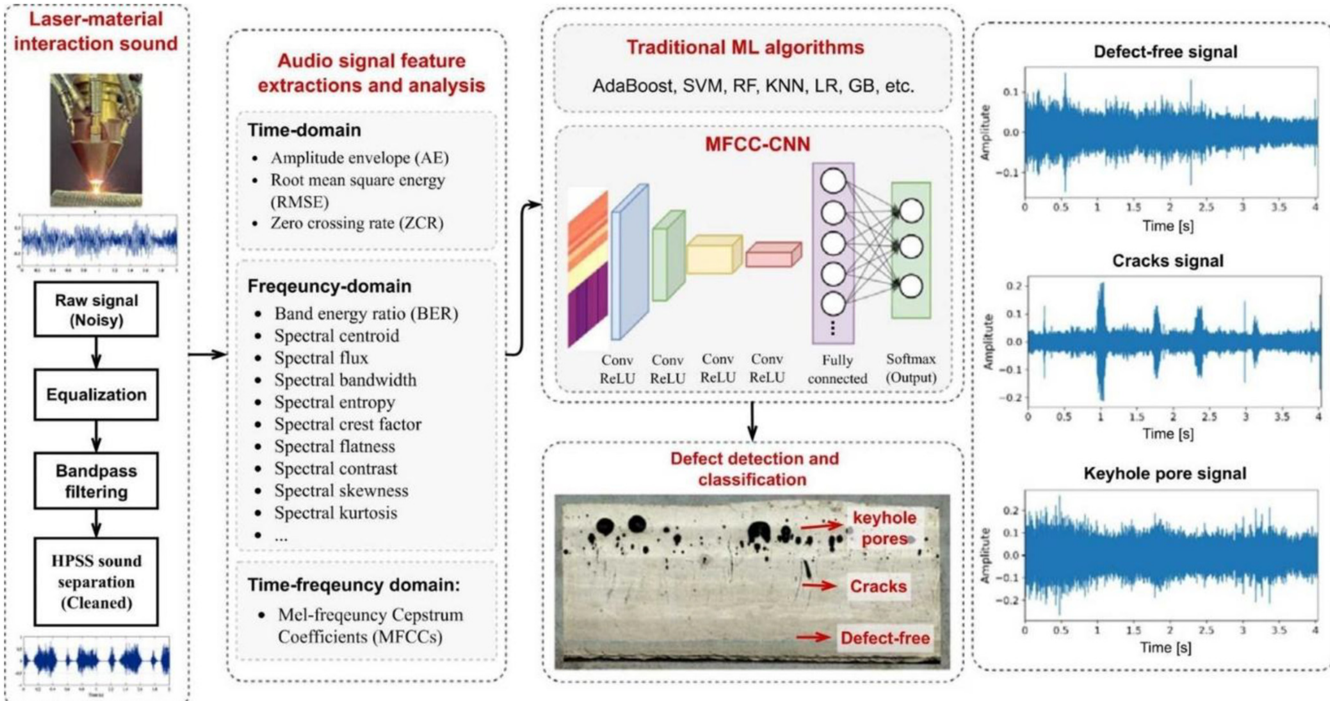

Fig. 12. CNN-based airborne acoustic emission monitoring of porosity defects in DED [52].

4.3. In-situ defect detection

Beyond monitoring process regimes, a major research thrust has been the use of AE for direct detection of defects such as cracks, porosity, and lack-of-fusion, which are critical to part integrity.

Structure-borne AE, thanks to its high sensitivity and ability to detect subsurface micro-damage, has achieved remarkable progress in early crack detection and internal defect identification. Liu et al. [129] incorporated a graph attention network (GAT) into the WAAM process. A one-dimensional convolutional autoencoder is first employed for AE signal dimensionality reduction, followed by GAT-based modeling to capture complex feature relationships. Transfer learning is further utilized to enable online evaluation of fatigue crack propagation in deposited welds. Ansari et al. [130] exploited the exponential attenuation behavior of DED's AE signals and the relative invariance of their second derivatives to environmental noise to construct a robust event-detection framework. This method effectively suppressed equipment-related background noise and significantly enhanced transient acoustic signatures associated with crack initiation and propagation. Kim et al. [131] further explored the use of airborne AE for DED surface-defect inspection, demonstrating through time-frequency analysis that microcrack activity exhibited a highly distinguishable pattern in the 12–16 kHz band, serving as an acoustic fingerprint for early crack identification.

Airborne AE has also been employed for detecting porosity and other process anomalies. Chen et al. [52] highlighted that airborne AE signals generated during laser-material interactions encode not only melt-pool geometric perturbations but also richer physical information related to crack propagation and pore formation. To address the challenges of low signal-to-noise ratio, strong nonlinearity, and multi-source noise coupling in DED, they proposed a multi-feature fusion model based on Mel-frequency cepstral coefficients and convolutional neural networks, as shown in Fig. 12. Specifically, AE signals generated during the LDED process are first processed using mel-frequency cepstral coefficients (MFCC) to produce two-dimensional time-frequency spectrograms. These representations are then fed into a CNN for defect classification. For comparison, conventional machine learning models, including support vector machine (SVM), random forest (RF), and K-nearest neighbor (KNN), are also implemented. The results indicate that the proposed MFCC-CNN framework outperforms traditional machine learning methods, achieving an accuracy exceeding 89% in identifying porosity and crack defects. Meanwhile, airborne acoustic emission is also effective for monitoring contaminants. Ramalho et al. [132] employed a microphone-based acoustic sensing approach to analyze the spectral signatures of different contaminants in the WAAM process, enabling the determination of the spatial locations of arc disturbances caused by these contaminants.

LU has been explored as a complementary technique for defect detection in DED [59–61]. Park et al. [133] proposed a novel approach integrating femtosecond laser ultrasonics with laser polishing to estimate the mechanical properties of metal components during the DED process. As shown in Fig. 13(a), the LU method applied in-situ was combined with a laser polishing step applied along the layer fabrication to enhance the quality of the LU data. Laser polishing allowed reducing the surface roughness of the deposited layer from *Ra* 4.2 μm to 0.31 μm during L-DED of 316 L stainless steel. In this way, authors significantly enhanced the LU's signal-to-noise ratio (SNR), enabling layer-by-layer estimation of Young's modulus and Poisson's ratio with sub-micron spatial resolution. Their work further elucidated how laser energy density influences crystallographic texture and the resulting mechanical performance. Similarly, Cerniglia et al. [63] developed a LU prototype for the in-situ inspection of Inconel alloys during deposition. As shown in Fig. 13(b) and (c), by combining finite element modeling (FEM) with experimental validation, the authors demonstrated that the system could effectively identify near-surface micro-defects with diameters $\geq$ 0.1 mm at depths up to 0.8 mm, proposing a configuration where the LU system is integrated directly onto L-DED robotic arms for fully automated online inspection. Despite these advancements, the industrial implementation of LU in DED faces various challenges, including high surface roughness, thermal-gradient-induced acoustic velocity variations, and complex wave-mode interference, which require further technological developments.

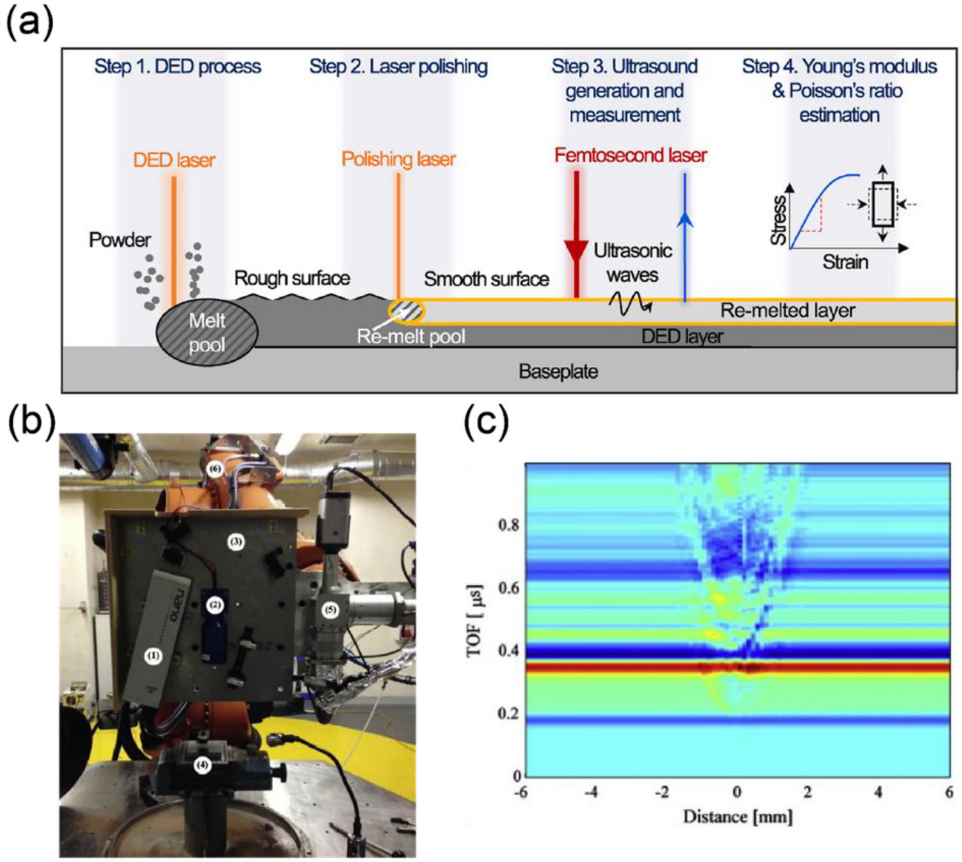

Fig. 13. (a) Integrated system schematic for in-situ mechanical property estimation during the L-DED process [133]; (b) Robotic-integrated laser ultrasonic inspection and typical defect detection results; (c) B-scan image demonstrating the identification of a near-surface micro-defect (≥0.1 mm), characterized by the perturbation of reflected and diffracted wave fronts [63].

4.4. Multimodal methods

Although AE sensing offers advantages such as high temporal resolution, it is inherently limited in its ability to simultaneously capture diverse physical phenomena. More critically, thermal transport plays a central role in DED/WAAM build quality and microstructural evolution [134], yet it lies largely beyond the sensing capabilities of AE systems. Consequently, various authors investigated multimodal sensing configurations that integrate acoustic, optical, and thermal sensing, aiming to enhance the embedded intelligence and autonomy of AM systems.

Xu et al. [135] developed a multimodal monitoring framework integrating structure-borne AE with coaxial vision imaging in DED. By applying a gradient boosting approach for feature fusion and classification, they achieved around 94% accuracy in detecting geometric deviations. Their study demonstrated that acoustic features encode vibrational dynamics of the deposited structure, whereas visual features characterize melt-pool shape and trajectory variations, together forming a highly complementary representation. Chen et al. [136] proposed a multi-sensor fusion-based digital twin method that integrates melt-pool imaging, airborne AE, and short-wave infrared thermography. Through machine-learning-based quality prediction, this framework provided early warnings of pore formation in DED processes.

Beyond traditional feature concatenation approaches, researchers are increasingly designing multimodal deep neural networks capable of adaptive cross-modal feature fusion and hierarchical synergistic learning. For instance, Herberger et al. [137] addressed the challenge of real-time standoff-distance fluctuations in DED by fusing coaxial RGB melt-pool images and microphone data and feeding the combined features into a fully connected neural network. This enabled accurate real-time prediction of standoff distance, ensuring consistency and precision in part fabrication. Moreover, to address the varying contributions of different modalities, attention mechanisms have been incorporated to enable adaptive weighting. Cao et al. [138], for example, employed a combination of AE and photodiode sensors for laser welding monitoring and proposed a cross-attention-based fusion architecture. This approach facilitated deep interactive fusion between photodiode and AE signals, significantly improving the robustness and generalization of weld-quality classification. In addition, Zhang et al. [139] integrated a vision sensor, a spectrometer, and a photodiode to establish a multi-sensor monitoring system for signal acquisition during the laser welding process, and developed a novel convolutional neural network to effectively fuse multi-source information. By exploiting the complementary sensing capabilities of different sensors, this approach enabled a comprehensive representation of the process state. The developed multi-sensor online monitoring system is illustrated in Fig. 14. A recent study by Alcaraz et al. [140] reported that porosity is indeed one of the most prevalent defects in WAAM processes. By integrating multiple sensing modalities, including current sensors, a capacitive microphone, structural acoustic-emission sensors, a spectrometer, and a flow meter, the authors established a comprehensive in-situ monitoring framework for WAAM. Furthermore, they developed a long short-term memory (LSTM) network, which achieved a porosity-detection accuracy of about 90%. Zhang et al. [141] developed a monitoring system comprising a microphone and two vision-based sensors to enable precise and real-time observation of the deposited geometry during the WAAM process. Their study highlighted that the acoustic signals carry distinctive features intrinsic to the manufacturing process, while images of the melt pool width reveal the lateral spreading of the molten material, and height im-

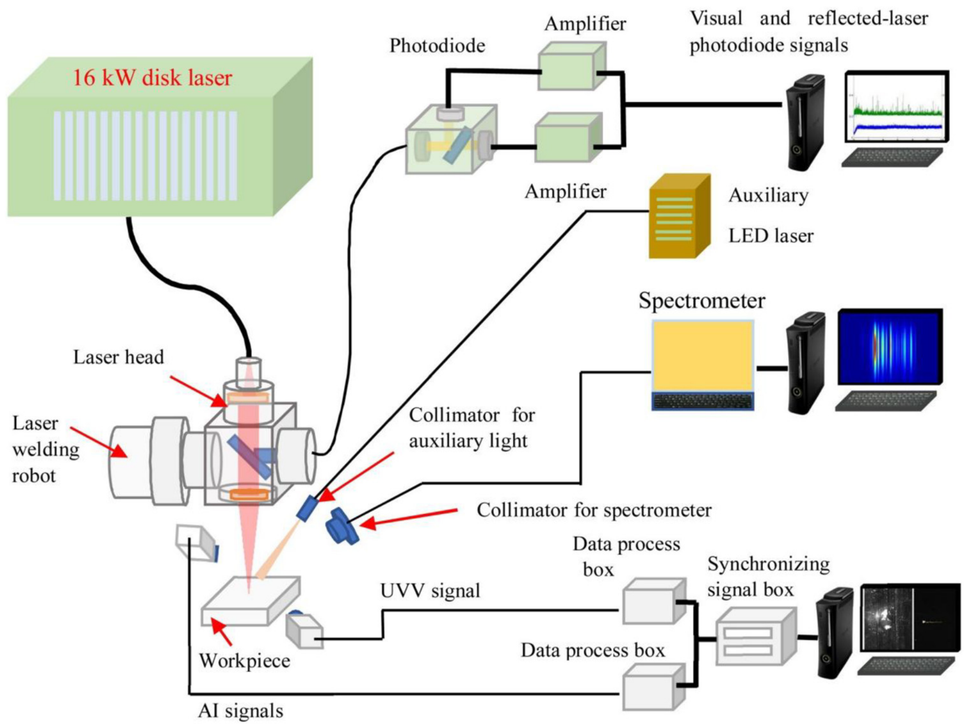

Fig. 14. Laser welding quality monitoring based on multi-sensor signal fusion [139].

ages capture the vertical dimension and dynamic evolution of the melt pool.

Despite its potential in laboratory environments, multimodal AE fusion still faces major challenges in industrial deployment. Some of them are analogous to the ones faced in other AM processes, while others are specific to the DED/WAAM process. The first concerns data heterogeneity: AE produces MHz-level high-frequency waveforms, whereas optical and thermal imaging outputs consist of frame sequences typically below 100 Hz, resulting in substantial discrepancies in sampling rate, temporal resolution, and data structure. The second is spatiotemporal synchronization: aligning heterogeneous signals and mapping AE signatures accurately to melt-pool spatial coordinates remains a fundamental bottleneck. The third challenge lies in computational demand: multimodal data streams combined with deep learning models impose heavy computational loads, placing stringent requirements on edge-computing hardware and efficient fusion algorithms. The fourth challenge arises from complex deposition paths and multi-layer stacking, which continuously alter the propagation distance and direction of acoustic emission waves, leading to pronounced path-dependent signal variations. Moreover, as the number of deposited layers increases, cumulative attenuation and instability of AE signals become increasingly significant, further complicating reliable feature extraction and interpretation. Looking ahead, by enabling real-time fusion of acoustic–optical–thermal data, high-fidelity virtual process models can be constructed to support defect identification, quality prediction, and closed-loop process control, ultimately steering DED technology from experience-driven production toward fully data-driven and intelligence-driven manufacturing.

A summary of salient sensing and monitoring settings and performance of methods reviewed in this section is provided in Table 4 [45,52,63,126,133,135,136,142–148].

5. Discussion

The wide and quickly growing literature reviewed in this study highlights the potential of AE techniques for both in-situ monitoring and in-situ inspection in AM processes. In-situ monitoring refers to the continuous observation of the process dynamics, capturing either transient events or sustained shifts associated with anomalies and defects, ranging from melt-pool instability to crack initiation, delamination, and porosity formation. Because AE is sensitive to the release of elastic strain energy at the microscale and possesses high temporal resolution, it can detect changes in process state in real time, enabling early anomaly detection. In contrast, in-situ inspection is aimed at assessing the integrity of the part itself, rather than the dynamics of the process, by interpreting AE features as signatures of defect type, severity, and spatial localization within the build volume. To this aim, AE can function as a non-destructive subsurface diagnostic tool, complementing other sensing methods that primarily target surface or near-surface features. While monitoring leverages AE as a process sensor, inspection leverages AE for quality and integrity assessment while the part is being built. The dual role is particularly advantageous in AM, where many defects originate during transient thermal–mechanical events but manifest as structural discontinuities that may influence the final performance. Consequently, AE methods are particularly interesting as they can contribute to unified process–structure characterization and first-time-right AM production.

As pointed out in Ref. [2], in-situ methods based on AE and ultrasounds are currently characterized by a relatively low TRL compared to other approaches. According to Ref. [2], microphones have been studied for in-situ monitoring of welding for decades, but so far they have achieved a limited industrial adoption both in welding and in AM, mainly due to data quality issues and high risk for false positives. Nevertheless, most recent studies have shown relevant and promising progress, in terms of both data processing techniques and sensing methods (e.g., optical microphones with frequency response up to 1 MHz or more, embedded structure-borne AE sensors, and laser ultrasound exciting units). Acoustic features have been successfully correlated to machine states, process regimes, anomalies, and defects, using different AE sensor types and covering different frequency ranges. Moreover, reviewed studies highlighted that fluctuations in AE signals can be caused by unstable process conditions, while keyhole and lack-of-fusion regimes exhibit separable time-frequency spectral features. Cracks, sup-

Table 4
Summary of in-situ monitoring studies in DED and WAAM applications.

Ref. No.	Sensor type	Sampling frequency	Sensor Bandwidth	Process type	Type of defect / application	Accuracy
2024 [142]	Airborne AE microphone	40 kHz	20 Hz–20 kHz	WAAM	Porosity conditions	Up to 98.31%
2023 [52]	Airborne AE microphone	44.1 kHz	50 Hz–20 kHz	DED	Crack + keyhole pores	89%
2022 [45]	Airborne AE microphone + welding camera	44.1 kHz	50 Hz–20 kHz	WAAM	Geometric process stability	N/A
2023 [143]	Airborne AE microphone	25.6 kHz	40 Hz–15 kHz	WAAM	Pore + geometric integrity	False alarm rate < 2%
2019 [144]	Structure-borne AE	N/A	N/A	WAAM	Process stability	N/A
2024 [145]	Structure-borne AE	1 MHz	50–1300 kHz	DED	Forming quality	Up to 94%
2025 [126]	Structure-borne AE	1 MHz	200–1300 kHz	DED	Bonding quality	96.18%
2021 [146]	Structure-borne AE	5 MHz	1–1000 kHz	DED	Cladding state + crack defect	99.76%
2021 [133]	Laser ultrasonics	50 GHz	N/A	DED	Mechanical properties	N/A
2015 [63]	laser ultrasonics	N/A	N/A	DED	Surface flaws	N/A
2023 [136]	Airborne AE microphone + CCD	44.1 kHz/10 Hz	50 Hz–20 kHz	DED	Cracks + keyhole pores	98.5%
2025 [135]	AE + CCD	500 kHz/30 Hz	35–65 kHz	DED	Geometric + porosity	94.4%
2023 [147]	Airborne AE microphone + CCD + IR camera	44.1 kHz/30 Hz/30 Hz	50 Hz–20 kHz	DED	Cracks and keyhole	96%
2022 [148]	CCD + IR camera	N/A	N/A	WAAM	Geometric anomaly	N/A

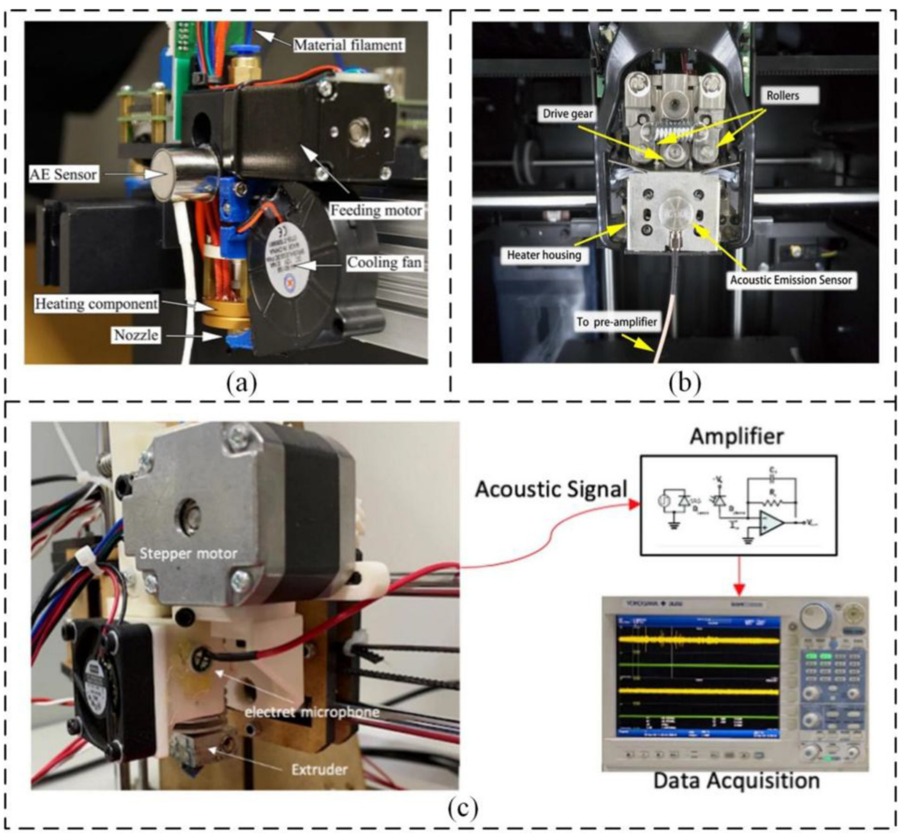

Fig. 15. Application of acoustic emission monitoring technology in the FDM process: (a-b) FDM equipment with SBAE sensors configured [149,150]; (c) FDM equipment with ABAE sensors configured [151].

port detachment, and delamination also exhibit specific signatures in the time and frequency domains that make them detectable in different application scenarios.

Beyond the commonly studied L-PBF and DED/WAAM processes, AE technology also demonstrates unique application potential in other AM processes, such as fused deposition modeling (FDM) and VAT photopolymerization. As illustrated in Fig. 15, structure-borne AE sensors mounted on the extruder and platform have been successfully used in FDM for real-time fault diagnosis and filament breakage detection [149,150]. Low-cost microphones have also been explored as alternatives to traditional AE sensors, achieving nearly 100% classification accuracy for distinguishing normal, clogged, and material-deficient states using multi-domain signal analysis and machine learning [151]. In VAT photopolymerization (Fig. 16), AE sensors (e.g., PVDF) have been employed to monitor the curing process and resin–film separation, where AE energy levels serve as effective indicators for early defect detection [152]. These examples suggest that AE-based monitoring is not limited to high-energy beam-based AM processes but can be adapted to a wider range of additive manufacturing technologies, often with cost-effective and non-intrusive implementations. Furthermore, AE monitoring has been applied in many other industrial fields, including machining, quality assessment of laser shock peening (LSP), arc welding monitoring, and leakage detection [153–155]. Although these processes differ from AM in various aspects, the accumulated knowledge on AE acquisition, signal

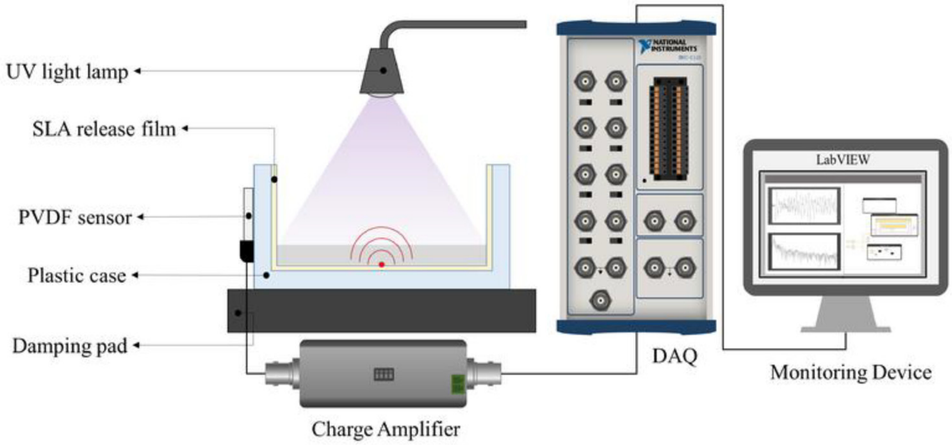

Fig. 16. Application of acoustic emission monitoring technology in SLA process [152].

conditioning, analysis, and interpretation provides a substantial foundation for extending AE-based monitoring strategies to AM.

Nonetheless, several open issues and challenges remain before AE can be deployed as a reliable in-situ monitoring or in-situ inspection approach in real AM production. Most of them are related to the intrinsic properties of AE measurements. AM processes are affected by complex noise environments, including recoater motion, gas flow, pumps, and scanner dynamics, often concentrated in overlapping frequency bands (from a few kHz up to hundreds of kHz), which complicate signal separation and reduce signal-to-noise ratio. In addition, the heterogeneous and evolving material state during a build introduces non-stationary propagation paths, frequency filtering effects, and signal attenuation issues that inflate the natural variability of the signals, possibly masking the onset of real anomalies and defects. Undesired variations in salient features, coupled with high sensitivity to nuisance factors and naturally occurring stochastic fluctuations, make defect-to-signature mapping difficult to generalize across processes, materials, and geometries.

The deployment of AE sensors in industrial AM environments presents several challenges, some of which still represent open issues. In processes such as electron beam powder bed fusion (EB-PBF), the build chamber operates under high vacuum and at elevated temperatures, often exceeding 600–800 °C at the build plate for the entire duration of the process. Under these conditions, direct sensor mounting on the build plate or surrounding structures becomes extremely challenging or infeasible. Conventional piezoelectric AE sensors exhibit significant degradation of piezoelectric properties above 200–300 °C, while coupling media may fail or lose mechanical integrity at much lower temperatures. In addition, the vacuum environment prevents the use of airborne sensing and complicates thermal management and signal transmission. As a result, no studies to date have demonstrated reliable AE monitoring directly integrated within EB-PBF systems.

The high-temperature environments inherent to arc- and laser-based DED processes pose similar, although less extreme, challenges. Local temperatures in the melt pool exceed 1500–2000 °C, while substrate and fixture temperatures can still reach several hundred degrees Celsius. These conditions induce strong thermal gradients and cyclic thermo-mechanical loading, which can degrade sensor coupling and introduce variability in signal transmission. Moreover, wave propagation characteristics (e.g., velocity, attenuation, and dispersion) are temperature-dependent, further complicating the interpretation and repeatability of AE measurements. Although AE monitoring has been successfully demonstrated in controlled experimental setups, these factors still represent a significant barrier to robust and scalable industrial deployment.

In L-PBF, although baseplate and chamber temperatures are typically lower, AE sensor integration still faces practical constraints. Structure-borne sensors must be mechanically coupled to the build platform or machine frame, often requiring modifications to the machine architecture and careful routing of cables in confined and harsh environments. AE wave propagation is strongly influenced by the evolving geometry of the part and the build plate, leading to time-varying attenuation, scattering, and mode conversion effects. These factors can alter the frequency content and amplitude of the signals, reducing the stability and transferability of extracted features.

Although the reviewed literature highlights substantial progress in addressing these challenges, with promising defect detection performance demonstrated in representative environments, some issues remain open and may still represent barriers to the widespread adoption of AE-based solutions in real production. One specific aspect that remains nontrivial and is addressed by few authors in the literature consists of localizing and spatially attributing AE events. Uncertain wave velocity in the melt/solid transition zone, and multimodal propagation (i.e., the fact that elastic waves do not travel through the material as a single simple wave type, but rather as a superposition of different propagation modes) inflate the localization uncertainty. Promising results have been achieved employing multiple structure-borne sensors, but spatially resolved monitoring and inspection still deserve further developments and extended validation.

Aiming to overcome some limitations of AE methods, active ultrasonic methods such as LU have been investigated in a few seminal works. They offer a promising pathway for high-resolution in-situ inspection by enabling controlled excitation and detection of elastic waves, rather than relying solely on spontaneous emission as in AE. Because LU can interrogate the evolving build with tunable frequency content and well-defined input energy, they provide potentially rich information on material consolidation, porosity, crack formation, elastic modulus evolution, and interlayer bonding, and can potentially support layerwise defect screening and localization. Furthermore, their non-contact nature facilitates integration and offers compatibility with high-temperature and reactive environments. However, significant challenges remain for practical deployment in AM: the surface condition and optical properties of the partially consolidated material can introduce variability in excitation and detection efficiency; the time budget per layer may be incompatible with the relatively slow scanning requirements of high-resolution ultrasonic interrogation; and the changing thermomechanical state and geometry of the part complicate the interpretation of ultrasonic signatures and inversion procedures. Additionally, the integration of LU in AM systems demands careful co-design of optics, scanning strategies, synchronization with exposure, and safety constraints, alongside the development of fast data-processing and defect-classification algorithms to avoid production bottlenecks.

In addition to sensor-specific and measurement-related issues, other bottlenecks and challenges regard the way in which sensor data shall be handled, processed, and used to develop trustworthy and efficient monitoring methodologies. From a data perspective, AE systems generate high-rate, high-dimensional, and time–frequency features that translate into massive data volumes that may be difficult to handle in industrial environments. Signals acquired at megahertz during every layer of processes lasting for hours or days require careful dimensionality reduction as well as computationally efficient real-time processing and inference. Opportunities may arise from recent advances in time-series foundation models, which may enable self-supervised learning from large volumes of unlabeled acoustic data and improve generalization across different process conditions, materials, and machine configurations [156].

Similarly to what is commonly done for machine vision and other in-situ monitoring tools, the literature reviewed in this study mainly consists of methods tested and verified off-line. Although off-line testing represents a necessary step in the development stage, the lack of actual real-time implementations limits the demonstration of practical feasibility and hinders the transition toward deployable edge-based solutions.

Some of these issues become even more critical in the presence of multimodal methods combining AE with other sensors. Multimodal monitoring has attracted increasing interest in recent years, with examples and case studies in several AM processes. However, in the presence of multimodal methods that include AE measurements, accurate triggering and synchronization are of critical importance to avoid signal misinterpretation and reduce false alarm rates. In this context, even small timing offsets between sensing channels can lead to incorrect association of events to process states or defect signatures, obscure causality relationships, and compromise downstream data fusion and machine learning algorithms.

Two other issues are particularly critical and specific to in-situ AE monitoring. One regards the lack of standardized AE databases and calibration protocols. Another one regards the difficulty or impossibility of defining trustworthy ground truth for anomaly detection and machine learning validation. While post-process inspection (e.g., microscopy, X-ray computer tomography, or dye penetrant analysis) can confirm the presence of defects such as cracks, keyhole porosity, or lack-of-fusion, these methods provide static information that lacks temporal resolution, making it impossible to determine the exact moment or process state at which the defect originated. Consequently, associating AE events to specific sources of strain energy release during the build remains highly uncertain, as defects may nucleate, propagate, or become detectable at different times than when AE transient signals are emitted. This gap between transient acoustic activity and static post-build evidence complicates causal attribution, prevents reliable event labeling, and undermines supervised learning approaches that require accurate defect–time correspondence. Without temporally resolved ground truth, benchmarking and validating AE-based detection becomes inherently ambiguous, and the risk of both false positives and false negatives increases.

In some cases, authors manually labelled events based on the human expert's evaluation of observed time-frequency signatures. In many other cases, authors proposed process state classification methods, where rather than detecting individual events or defects, machine learning and deep learning classifiers were trained to distinguish data patterns under different process conditions. In this latter scenario, no accurate labelling and ground truth definition were needed, as different states or regimes are directly controlled by varying process parameters. However, classification performances obtained under such controlled conditions are not necessarily representative of the performance that would be achieved under realistic operating conditions, where natural process variability is present, and where parameter variations are not deliberately introduced to generate separable classes. As a result, models can appear highly accurate in distinguishing distinct parameter regimes, yet struggle to generalize to more subtle and naturally occurring deviations associated with defect formation or process instability. This raises an important distinction between state classification and defect or anomaly detection, and highlights the need for validation strategies that better reflect the stochastic, complex, and highly dynamic nature of real AM processes.

The lack of standardized AE databases and calibration protocols also represents a barrier to industrial development as it prevents benchmarking, comparability, and reproducibility across machines, materials, sensors, and monitoring scenarios. Without shared reference datasets and calibration procedures, it is difficult to determine whether observed AE signatures are intrinsic to the process and defect mechanisms, or are instead artifacts of sensor placement, coupling, frequency response, or other machine-related settings. This variability undermines the transferability of detection algorithms and machine learning models, which require consistent feature distributions and well-characterized sensor behavior to generalize beyond the specific testbed on which they were trained. In industrial environments, especially in highly regulated sectors, the adoption of in-situ monitoring technologies demands demonstrable reliability, repeatability, and traceability, all of which rely on consistent calibration and standardized performance metrics. Furthermore, the absence of common datasets slows down technology qualification and prevents regulatory bodies and certification agencies from establishing acceptance criteria. Ultimately, standardization is required not only for scientific comparability but also to enable supply chain interoperability, quality assurance, and integration of AE-based monitoring into production workflows.

In summary, additional research and development efforts are needed in the following fields:

(1) Data quality enhancement and mitigation of nuisance factors;
(2) Defect-to-signature mapping and generalization across different machines, materials, geometries;
(3) Localization and spatial attribution of AE events;
(4) Efficient handling of real-time data flows and massive data volumes;
(5) Trustworthy validation of methods in the absence of temporally-resolved ground truth references;
(6) Accurate multimodal synchronization;
(7) Standardization of signal databases and calibration protocols.

Looking ahead, several promising research directions remain largely unexplored and could significantly advance the role of AE in AM. One direction regards the use of in-situ AE monitoring not only for defect detection, but as a feedback signal for closed-loop control, enabling real-time corrective actions to mitigate instabilities and improve process robustness. Another emerging route is the combined use of real AE data with process modeling and simulation, where physics-based models could help interpret acoustic signatures, reduce data requirements for machine learning, and support virtual process optimization. Moreover, the adoption of in-situ AE for anticipated qualification of critical components offers the potential to reduce reliance on time-consuming and costly post-process inspection, accelerating certification workflows in safety-critical sectors. Collectively, these directions suggest a transition from AE as a diagnostic and research tool toward AE among enabling technologies for first-time-right manufacturing and digital qualification, unlocking substantial gains in throughput, cost efficiency, and quality assurance.

6. Conclusions

In-situ monitoring techniques are widely recognized for their potential to reshape qualification and process verification strategies in AM. Such capabilities are essential to reduce the cost, time, and uncertainty associated with conventional post-process inspection and qualification workflows, which remain major barriers to large-scale industrial adoption. The literature reviewed in this study highlights that AE-based sensing approaches provide a complementary perspective within this landscape. Their intrinsic sensitivity to subsurface and volumetric events, together with their dual applicability for process monitoring and layerwise inspection, enables access to failure mechanisms that may escape detection through mainstream optical or thermal sensing. Recent developments demonstrate significant progress in sensor technologies, signal processing, and anomaly detection, and illustrate how AE can aid a deeper understanding of the link between process conditions, defect formation, and final part properties. At the same time, several scientific and technological challenges remain, particularly regarding noise mitigation, defect-to-signature mapping, localization of AE events, lack of actual ground truth, multimodal synchronization, database standardization, and real-time implementation. Addressing these gaps will be essential to advance AE from a diagnostic research tool toward a robust and certifiable in-situ monitoring solution. Future progress in this field will likely emerge at the intersection of sensing, modeling, and data analytics. Thanks to continuous research and development effort AE methods may reach higher maturity in different AM processes and applications, contributing to unlock first-time-right manufacturing and more efficient solutions for industrial qualification.

Declaration of competing interests

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

CRediT authorship contribution statement

Zhiwen Li: Writing – review & editing, Writing – original draft. **Hang Zheng:** Writing – review & editing, Writing – original draft. **Zhifen Zhang:** Writing – review & editing, Visualization, Supervision, Conceptualization. **Jie Wang:** Writing – original draft. **Guangrui Wen:** Writing – review & editing, Supervision, Conceptualization. **Marco Grasso:** Writing – review & editing, Writing – original draft, Conceptualization. **Bianca Maria Colosimo:** Writing – review & editing, Supervision, Conceptualization.

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