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Review

Acoustic emission monitoring of wood materials and timber structures: A critical review

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ABSTRACT

The growing interest in timber construction and using more wood for civil engineering applications has given highlighted importance of developing non-destructive evaluation (NDE) methods for structural health monitoring and quality control of wooden construction. This study, critically reviews the acoustic emission (AE) method and its applications in the wood and timber industry. Various other NDE methods for wood monitoring such as infrared spectroscopy, stress wave, guided wave propagation, X-ray computed tomography and thermography are also included. The concept and experimentation of AE are explained, and the impact of wood properties on AE signal velocity and energy attenuation is discussed. The state-of-the-art AE monitoring of wood and timber structures is organized into six applications: (1) wood machining monitoring; (2) wood drying; (3) wood fracture; (4) timber structural health monitoring; (5) termite infestation monitoring; and (6) quality control. For each application, the opportunities that the AE method offers for in-situ monitoring or smart assessment of wood-based materials are discussed, and the challenges and direction for future research are critically outlined. Overall, compared with structural health monitoring of other materials, less attention has been paid to data-driven methods and machine learning applied to AE monitoring of wood and timber. In addition, most studies have focused on extracting simple time-domain features, whereas there is a gap in using sophisticated signal processing and feature engineering techniques. Future research should explore the sensor fusion for monitoring full-scale timber buildings and structures and focus on applying AE to large-size structures containing defects. Moreover, the effectiveness of AE methods used for wood composites and mass timber structures should be further studied.

1. Introduction

The growing interest in green construction has emphasized the use of renewable materials to fabricate environmentally friendly and sustainable structures. This has highlighted the importance of using wood as a renewable material for building and construction. Efficient wood manufacturing and innovative construction and inspection of wood structures require rigorous monitoring and quality control protocols. In the past few decades, different non-destructive evaluation (NDE) methods have been used for wood and timber monitoring, among which acoustic emission (AE) has been widely practiced. AE has been applied to different engineering applications while it is one of the commonly used methods for structural health monitoring [1–4]. It is also used for equipment condition monitoring [5] and manufacturing processes [6–7]. In materials, civil, and structural engineering, AE has been widely practiced for damage detection [8] and characterization [9] of composite materials. Also, it has been applied to monitoring the concrete structures [10–11]. AE has also been used to monitor the wood-based materials and timber structures; however, the literature lacks a comprehensive review of its recent applications. This review aims to discuss the opportunities and challenges of AE applied to wood materials and timber structures. Accordingly, there are five objectives to be

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covered in this study:

- introducing the different NDE methods applied to wood and timber structures (section 2),
- addressing the concept of AE, its experimentation and data acquisition, and signal processing (section 3),
- explaining the main features of AE signals such as wave velocity and attenuation, and discussing the impact of wood properties on AE characteristics (section 4),
- discussing the main applications of AE for monitoring wood materials and timber structures (section 5). This includes using AE for wood machining, drying, damage detection, health monitoring, termite infestation monitoring, and quality control.
- Discussing the main challenges associated with AE monitoring of wood and timber structures and outlining the direction for future research (section 6).

2. Non-destructive evaluation (NDE) methods of wood

Different NDE methods including color measurement, X-ray computed tomography (X-ray CT), thermography, near-infrared spectroscopy (NIRS), and wave propagation methods were used, as reported in the literature, to assess the physical and mechanical properties of wood. The color measurement method uses the variation in wood color caused by different processes such as the thermal treatment or aging to predict the physical and mechanical properties of wood, such as the moisture content (MC), density, porosity, water absorption, swelling coefficient, and dynamic modulus of elasticity (MOE) [12–13]. The thermal treatment of wood makes the pale wood color darker [14]. During such processes the color change in wood is usually due to the degradation and chemical changes of hemicelluloses and lignin. The CIE color measurement system, which includes three color parameters of L^* (lightness), a^* (red/green coordinates), and b^* (blue/yellow coordinates), is usually used in the color measurement method. However, the inhomogeneous surface color of the timber and its variation may restrict its applications [15]. In the tomography method, maps of the internal structure of the materials are produced using the images of the distribution of the dielectric properties inside them. These maps are called tomograms. The X-ray CT is used to assess different wood properties, including its density and MC, and identify internal log features, including pith, sapwood, heartwood, knots, and defects [16]. However, the application of tomography for the evaluation of wood is limited due to its high operation cost. The ultrasonic timber tomography was also performed, in which the mortises were identified using the obtained tomograms considering the wood anisotropy [17].

The thermography method is based on thermal radiation measurement. In this method, an infrared camera is used to detect the surface radiation of the electromagnetic spectrum in the long-infrared range, using which, an image called a thermogram is produced. The thermal conductivity of materials changes due to the variations in their physical and mechanical properties or the presence of defects and damage. The thermography method is usually used to detect defects and damage in wood structures by observing anomalous hot spots in the thermograms [18]. Although the thermography method has been mainly used for defect detection in wood, wood density estimation has also been performed using this method [19].

The NIRS is a spectroscopic NDE method that works based on the absorption or emission at the NIR range. The molecules in organic materials such as wood absorb the NIR light and vibrate. Therefore, the molecular structure of wood can be identified using NIRS. The NIRS may require frequent calibration and may be challenging when used to evaluate thick wood structures [20]. The NIRS has been extensively used for the classification and characterization of wood [21]. For example, the NIRS is effective in the evaluation of the physical and mechanical properties of wood, including its density, MOE, and modulus of rupture (MOR) [22]. It has also been used to examine wood's chemical properties, such as estimating its lignin and extractives content [23–24].

The NDE methods for wood assessment based on wave propagation include stress wave, ultrasonic wave, guided wave, and AE techniques. The stress and ultrasonic wave methods are used to predict the dynamic MOE of wood-based materials using the measured wave velocity [25–28]. It has also been used to detect check formation in weathered timber [29]. The propagating wave is induced in the material using a mechanical impact in the stress wave method. In contrast, a piezoelectric actuator is used to generate the wave in the ultrasonic wave method. The wave characteristics depends on various parameters including the wood species and its anatomy, MC, RH, etc. [30]. The relationship between the dynamic MOE and static MOE depended on the MC and wood species [31–32]. Therefore, the stress and ultrasonic wave methods may not offer a robust tool for estimating the static MOE in different conditions. Guided wave propagation methods have been widely used to assess the mechanical properties of materials and damage detection purposes [33–36]. The characteristics of guided Lamb waves, such as the wave velocity and amplitude, are linked to the elastic and viscoelastic properties of the material in which they are propagating, including the MOE and the storage and loss moduli [37,38]. Furthermore, the Lamb waves offer a vital tool for evaluating large wood structures and detecting damage in them, as they can propagate over long distances due to their low attenuation nature. The Lamb wave propagation method has been recently used to estimate the moisture-dependent mechanical properties of wood [39,40] and to assess the effect of artificial weathering on wood properties [41]. In addition, artificial intelligence methods can predict the MOR of wood using the measured Lamb wave characteristics [42,43]. Among the mentioned NDE methods, the AE technique has been broadly used to monitor wood materials' structural integrity and mechanical behavior and damage detection in them. The advantages of the AE technique include the capability for non-destructive and in-situ evaluation of wood structures, assessing the position of the developing crack or damage, and monitoring the dynamic behavior of wood materials under loading. For instance, the AE has been used to assess the surface checks formation and water movement in wood during the drying process [44]. The crack tip propagation during wood machining has also been monitored using the cluster analysis of AE data [45].

3. Background on acoustic emission

3.1. Concepts

When the stored strain energy is rapidly released in a material due to irreversible microstructural changes in its internal structure an elastic wave is radiated within the material, called acoustic emission [46,47]. The stress field causing the strain energy release may be generated due to mechanical, thermal, and chemical stress [48]. The release of the strain energy and generation of the elastic (acoustic) wave occur, for example, in wood under mechanical loading and deformation, during the wood machining processes, or due to crack growth and fracture mechanisms. Several factors affect the elastic wave generated by the AE source, including the wave propagation velocity within the material in different directions, geometry and discontinuities of the material, and the attenuation, reflection, and refraction of the wave. Moreover, the wave propagation velocity is impacted by the material properties of the propagation medium and the wave type and frequency.

Besides the advantages of the AE technique for NDE of structures mentioned in the previous section, it has limitations that need to be accounted when assessing wood and wood-based materials. For example, wood is an anisotropic and heterogeneous natural material for which the longitudinal acoustic wave propagates with different velocities in the longitudinal, radial, and tangential directions [49]. Consequently, identifying the AE source location may not be achievable using the conventional AE signal processing techniques. It is usually challenging to distinguish the AE signal from noise. In addition, the dissipation of the acoustic wave energy and the resulting decay in wave amplitude is higher in viscoelastic and porous materials such as wood [50]. It results in a lower AE signal-to-noise ratio, which emphasizes the need for more advanced signal processing algorithms to monitor the integrity of wood structures accurately and characterize them. Monitoring the signal waveform and the acquired signal's frequency spectrum may help to distinguish the AE signal from the background noise.

3.2. Experimentation

The experimental setup used in AE includes transducers, preamplifiers, filters, amplifiers, and data acquisition and storage instruments. A schematic of the experimental setup used in the AE technique is shown in Fig. 1. The emitted elastic wave in AE measurements is usually in the frequency range from a few kHz to several MHz, acquired using piezoelectric transducers that convert the mechanical vibration of the material surface to an electrical signal. Typically, the generated AE signals in wood materials range from a few kHz to ~ 200 kHz [51]. The properties of the material's surface and the contact quality between the transducer and the material's surface impact how the vibration is transferred to the transducer [52]. Therefore, the preparation of the wood surface, applying adequate pressure between the transducer and the wood surface, and using a proper coupling agent should be considered. An illustration of a piezoelectric transducer (PZT) used to acquire the AE signal and convert it to an electrical signal is shown in Fig. 2. The proper selection of the AE transducer plays a vital role in the AE measurements. For instance, the sensitivity and the frequency response of the selected transducer should be suitable concerning the material properties of the specimen under investigation and the purpose of the measurements. When monitoring wood structures, for example, it may be better to use low frequency and high sensitivity transducers to overcome their inherent high wave attenuation.

The distance between the piezoelectric transducers and the AE source significantly affects the AE signal-to-noise ratio and consequently the obtained results, especially in dissipative materials like wood. Therefore, the positioning of the transducers becomes very important when monitoring wood structures using the AE technique. Furthermore, the dissipation of the acoustic wave energy is different in the longitudinal, radial, and tangential directions of wood. Thus, the position and properties of the transducers, background noise, and material properties of the specimens should be considered before processing and interpreting the acquired signals.

3.3. Signal processing

The acquired AE signals are processed in time and frequency domains to obtain various AE parameters using which the structural monitoring or damage detection in wood is performed. These AE parameters include but are not limited to the event, burst, amplitude, threshold, count, root mean square (RMS) voltage, duration, energy, rise time, frequency, and spectrum [54]. As mentioned before, it is usually challenging to obtain helpful information from the AE signals. A commonly used technique is to identify the transient waves in the AE signal and attain the AE parameters from them. The transient waves isolated from the AE signals are called AE hits. To detect the AE hits, a threshold voltage level is selected, and the acquired AE signals are compared with it. The threshold level is typically adjusted to be higher than the background noise, and the AE signals with amplitude higher than this level are identified as an AE hit. A brief description of the AE parameters used for monitoring purposes is given in Table 1. Some of the introduced AE parameters are also illustrated in Fig. 3.

4. Impact of wood properties on AE wave characteristics

The characteristics of the AE signals detected from wood-based materials and timber structures depend on different parameters. These include but are not limited to the following factors [56]:

- Wood species, geometry, orientation,
- Wood MC,
- Wood temperature,
- Transducer frequency and location,
- Transducer orientation.

When the source of energy release is not available, the AE signals are artificially generated using the pencil lead break method, as shown in Fig. 4. While it is discussed in section 2.3 that different features can be extracted from the detected signals in time, frequency, or time–frequency domains, two of the most studied signals parameters in the literature are the AE signal velocity and its energy attenuation in the time domain.

The two-point time difference location and signal correlation analysis can be used to calculate the signal velocity using the following formula:

$$v = \Delta x / \Delta t$$

where Δx is the distance between the two sensors and Δt corresponds to the time needed for the AE signal to propagate from one sensor to the next, calculated using the cross-correlation analysis. The cross-correlation function $R_{xy}(\tau)$ between two random signals $x(t)$ and y(t) is calculated as below:

$$R_{xy}(\tau) = lim_{T\to\infty}\frac{1}{T}\int_0^T x(t)y(t+\tau)dt \tag{2}$$

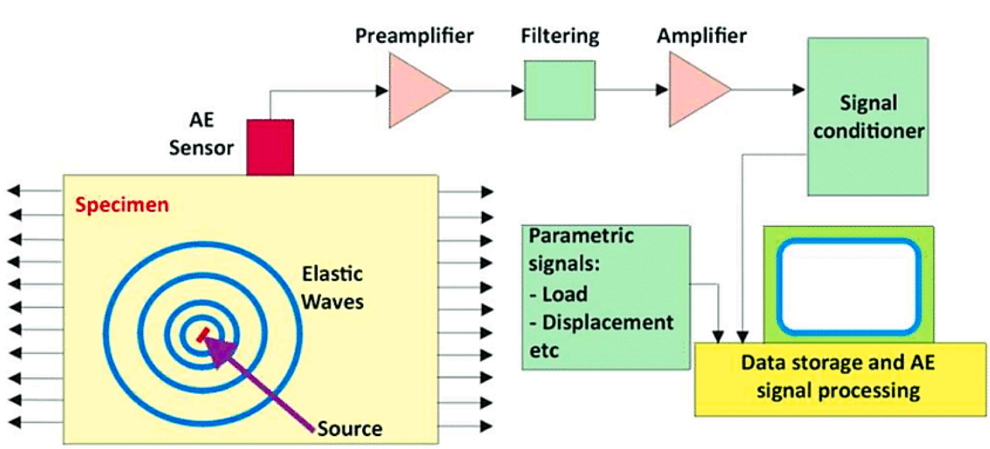

Fig. 1. A schematic of the experimental setup used in the AE technique [53].

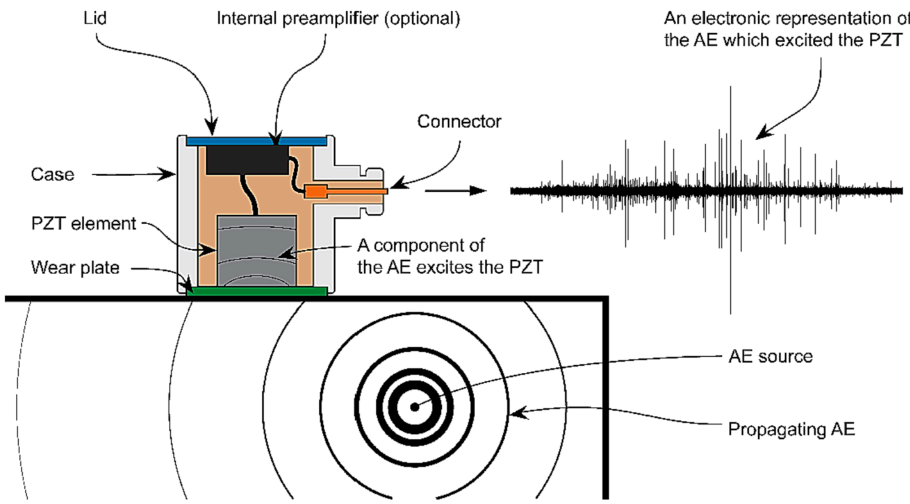

Fig. 2. An illustration of a piezoelectric transducer (PZT) used to acquire the AE signal and convert it to an electrical signal [48].

Table 1
Description of different AE parameters.

AE parameter	Parameter description
Event	The emission of an acoustic wave due to changes in the material
Burst	The individual event occurred in brittle materials such as dry wood
Amplitude	The maximum (peak) of the AE signal
Threshold	The threshold voltage level that the AE signals with an amplitude higher than this level are identified as an AE hit
Counts	The number of times that an AE signal exceeds the threshold voltage level
RMS	The root mean square of the voltage shows the rectified time-averaged AE signal
Duration	The time interval in which the AE signal exceeds the defined threshold level
Energy	The energy of the AE signal that equals the area under the rectified signal envelope
Rise time	The time between the first time an AE signal exceeds the threshold level and the peak amplitude
Frequency	The ratio of the counts to the duration

The signal velocity has been used in many investigations to assess the impact of wood characteristics on the generated AE signal. The signal attenuation in the propagation direction is also defined as follows:

$$\eta = \frac{P_1}{P_2} \tag{3}$$

Where P_1 and P_2 correspond to the AE signal energy detected by the two sensors. Having a random signal $x(t)$ with n components, the signal energy is calculated as below:

$$P = \sum_{i=1}^{n} (x_i)^2 \tag{4}$$

The energy attenuation is sensitive to wood micro-structure, the

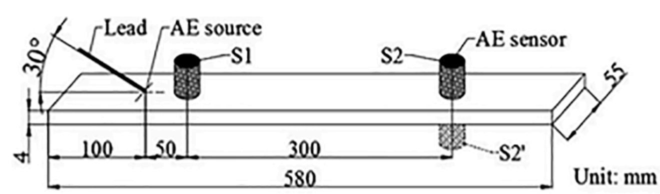

Fig. 4. Pencil lead break method for generation of AE signal. The generated signals can be detected at two locations using a pair of AE sensors using which the velocity and attenuation of the signal can be calculated [57].

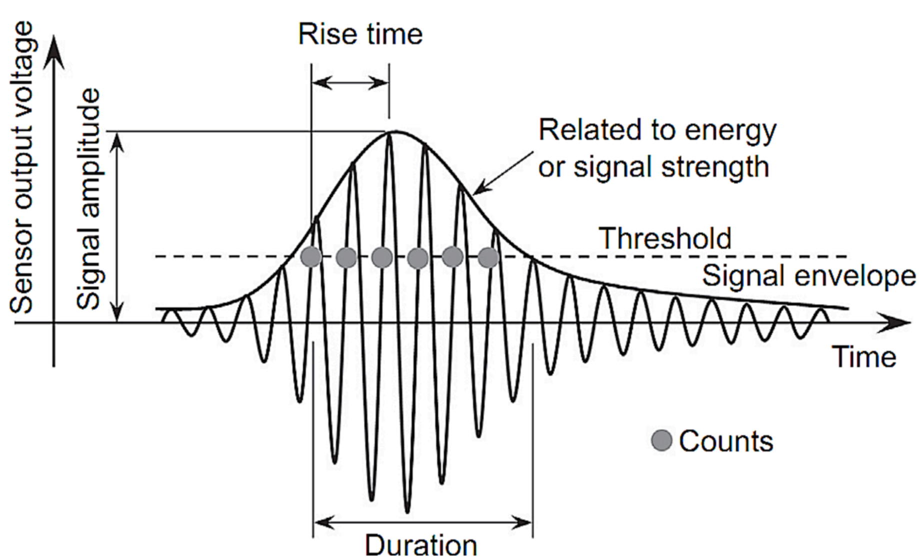

Fig. 3. An illustration of an acquired AE signal and the corresponding AE parameters [55].

wave propagation direction, the transducer orientation. It is a factor to study the damping behavior of wood, which can be linked to the viscoelasticity of the material. Yang et al. [58] outlined the attenuation mechanism impacted by wood MC:

1- Wave scatter at or around the cell wall in which the scattering is governed by the water content,
2- Wave scattering in cell wall containing free water in which, the energy loss is linked to the particle vibration due to ultrasonic energy.

It should be noted that the presence of cavities and micro-discontinuous interfaces inside the wood can also result in wave scattering [57]. Yang et al. [58] showed a significant variation in acoustic energy attenuation with MC. Others have also studied the role of wood MC and temperature on the acoustic wave velocity and energy attenuation [59–61]. Gao et al. [62] reported that the acoustic wave velocity is higher in wood with a sub-zero temperature. Kang and Booker [59] discussed that the MC has a more highlighted influence on the acoustic wave velocity than wood temperature. The impacts of wood MC on the AE signal velocity and its energy attenuation are shown in Fig. 5. It can be seen that while the velocity of the AE signal is decreased with increasing the MC, the higher water content in wood results in more energy loss and worsens the transmission quality of the AE signal [63].

Apart from the impact of wood temperature and MC, the AE sensor placement and the wave propagation direction with regard to the sensor orientation and the wood grain orientation hugely impact the AE wave characteristics. It is known that the energy attenuation is higher in the tangential and radial direction; thus, higher signal amplitude can be achieved when AE signals are propagated in the longitudinal direction [56]. The transducer orientation can also propagate the acoustic wave parallel or perpendicular to the transducer face. Li et al. [51] studied the impact of these two transducer orientations on the acoustic wave velocity and attenuation (Fig. 6). The transducers only capture the wave signal whose induced displacement field (particle motion) is perpendicular to the transducer surface. Therefore, the transducer orientation may affect the wave type and component acquired by it. As a result, the type of the wave acquired by the sensors S1 and S2 should be different than that acquired by the S3 and S4 sensors. Knowing that different wave types (longitudinal, shear, and guided waves) exhibit different wave attenuation in a certain material, the energy attenuation of the acquired wave signal may depend on the transducer orientation. Li et al. [51] showed that the wave velocity using sensors S3 and S4 is 4.6 times larger than that detected by sensors S1 and S2. It was also demonstrated that the signals detected by sensors S1 and S2 had a higher frequency nature (100 ~ 150 kHz) that better correlated with the damping behavior and viscoelastic properties of wood. This is consistent with the general statement that higher signal frequency is usually correlated with a higher attenuation rate [64]. On the other hand, the signals detected from sensors S3 and S4 have a lower frequency nature (30 ~ 50 kHz) and

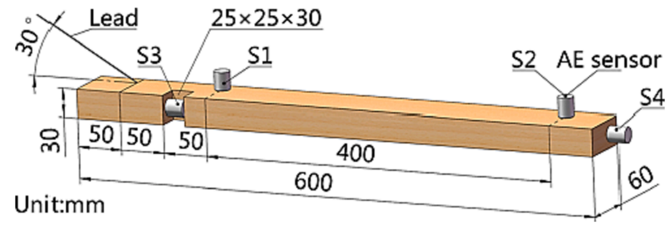

Fig. 6. Two types of sensor placement for AE signal acquisition showing two different transducer orientations. The propagated wave can be perpendicular to the transducer face (sensors S1 and S2) or parallel to the transducer face (sensors S3 and S4) [51].

were less sensitive to the viscous properties of wood. Li et al. [51] suggested that such an AE signal can be used for monitoring structural defects in wood; however, further research is needed to assess its effectiveness.

The above discussion illustrates the significance of wood characteristics such as micro-structure or physical properties on the propagated AE signal. The energy attenuation and the role of wood and transducer parameters on wave energy attenuation should also be well understood. The sensitivity of AE signals to different wood characteristics can be used for monitoring wood materials and timber structures. The applications of AE in wood and timber structures are discussed in the following section.

5. Applications

5.1. *Wood machining monitoring*

AE is widely applicable in monitoring the wood processing and manufacturing processes. Among the many applications in which AE can be employed for process monitoring, wood machining monitoring by AE has been frequently studied in the literature. Kyshawi et al. [7] discussed that the sources of AE during the machining processes are as follow:

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

Fig. 7 shows the wear, shear, and chip breakage during the machining process, AE can detect. Thus, AE can help monitor the workpiece, cutting tool, and process stability during the machining

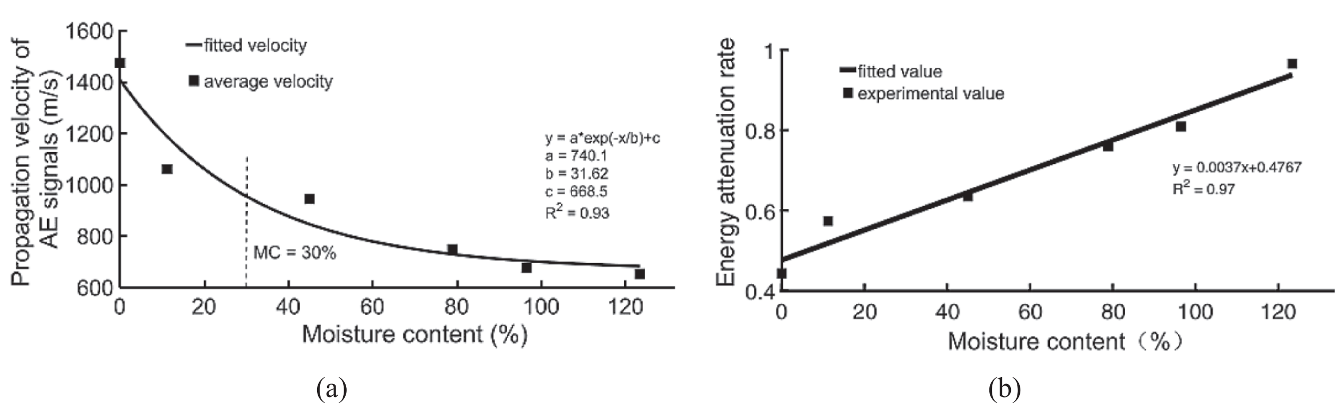

Fig. 5. The impact of wood MC on the propagation velocity of AE signals (a) and energy attenuation rate (b) [63].

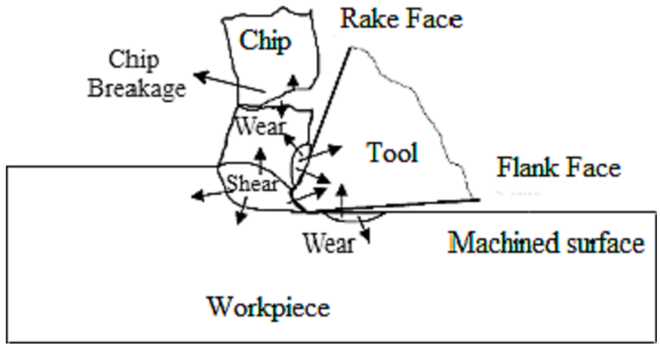

Fig. 7. Different sources of AE during the machining processes [65].

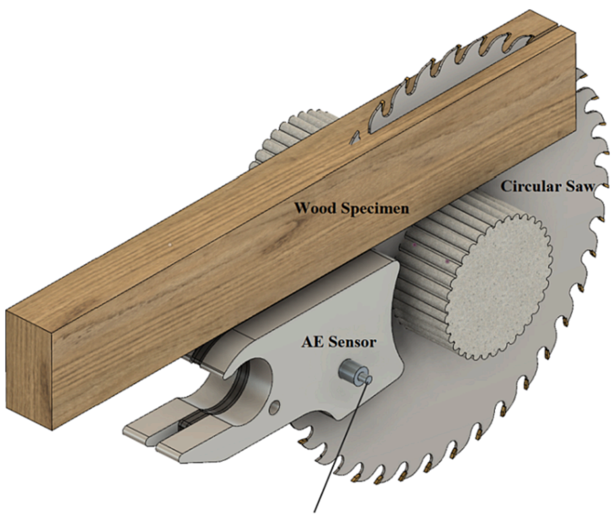

Fig. 8. Schematic of AE sensor for monitoring the circular sawing process of wood. The interaction between the blade and the wood specimen and its impact on the blade vibration is sensed through the sensor placed on the saw guide.

processes [65]. Wood machining is practiced during lumber manufacturing and secondary wood processing applications the saw-milling context. Within the sawmilling context, the main objectives to monitor are:

- Quality of the sawn lumber by monitoring the sawing deviation or waviness,
- Tool wear,
- Tool temperature,
- Dust emission

The focus of the literature on AE monitoring of wood machining in sawmilling applications was on the circular sawing process. Nasir et al. [66] showed that AE could be placed on the saw guided (Fig. 8) during the circular sawing process, where it can easily detect the interaction between the tool and wood and the tool vibration. Their study showed that AE could successfully monitor and predict the cutting power and waviness during the circular sawing process of Douglas fir. AE was also shown to successfully monitor the waviness of sawn lumber during the circular sawing of wood [66].

Wood machining is accompanied by dust emissions, resulting in occupational health and safety concerns. Not only is very fine and dried sawdust a source of fire hazard, but exposure to airborne dust may lead to lung and other respiratory diseases [67]. It has been shown that AE placed on a saw guide could monitor the airborne dust generated during the circular sawing process of hem-fir wood [68]. Features extracted from the AE signals in the time domain could train an artificial neural network (ANN) for predicting airborne dust. While a dust detector monitors the overall airborne dust level, it fails to spot the machine contributing more to dust emission in a production unit with more than one cutting machine working simultaneously. While an AE sensor placed on the saw guide can monitor the waviness and airborne dust, some other aspects of wood machining, such as tool temperature, are more challenging to be monitored with a single sensor. Nasir et al. [69] showed that while the tool temperature in the sawing process of hem-fir can be monitored with an R^2 of 0.76, combining the AE with an accel-erometer (also placed on the saw guide) would lead to an $R^2 = 0.86$. Sensor fusion has also been practiced for classifying the green and frozen wood in the sawmilling context [70]. AE combined with power, acous-tic, and vibration signals were used for monitoring. Table 2 summarizes the research on AE applied to wood machining monitoring.

Few studies have also been done on employing AE for monitoring the machining of wood-based materials in secondary processing applica-tions [71–73]. Unlike the wood primary processing applications, in which waviness is desired to be monitored, secondary processing application of wood is more concerned with the surface roughness of the machined surface. AE was shown to correlate with the surface roughness during the wood milling [71] and the circular sawing [72]. These studies used linear and polynomial regression [71,72] and extracted simple features such as signal root mean square (RMS). However, research on

Table 2
Summary of research on using AE in wood machining monitoring.

Process	Specimen	Sensor[1]	Sensor placement	Decision Making	Objective	Reference
Circular sawing	Douglas-fir wood	AE	Saw guided	ANN	airborne dust	[68]
Circular sawing	Douglas-fir wood	AE	Saw guided	ANFIS[2]	power, waviness	[66]
Circular sawing	hem-fir wood	AE, ACC, MIC, P	Saw guided	random-forest	wood condition (green, frozen)	[70]
Circular sawing	hem-fir wood	AE, ACC, MIC, P	Saw guided	random-forest	tool temperature	[69]
Circular sawing	hem-fir wood	AE, ACC, MIC, P	Saw guided	random forest, SVM[3]	tool wear	[74]
Peripheral milling	radiata pine wood	AE	*	linear and polynomial regression	surface roughness and grain angel	[71]
Milling	solid wood, MDF and particleboard	AE	side face of the tool and workpiece	**	cutting resistance	[73]
Circular sawing	Medium-density fiberboard	AE	*	linear regression	surface roughness	[72]

* Not available.
** Not Applicable.
1- P = power, AE = acoustic emission, MIC = microphone, ACC = accelerometer.
2- ANFIS = adaptive neuro-fuzzy inference system.
3- SVM = support vector machine.

wood monitoring in the sawmilling context has focused on extracting different sensory features from the time and time–frequency domains and put more emphasis on feature selection for optimal monitoring [68–70,74]. The natural complexity of the wood, due to its anatomy and high variation requires big data acquisition and performing an in-depth signal processing and feature extraction/selection combined with expert decision-making models. Currently, previous research lacks employing deep learning for AE monitoring of wood machining processes; however, machine learning methods such as fully-connected ANNs [68] or ensemble-learning methods such as random forest [69,70,74] have been utilized. Another issue is the possibility of sensor failure and the necessity to employ the sensor fusion approach. The harsh conditions during the wood machining processes, especially in the sawmilling context, increase the chance of sensor failure. Thus, sensor fusion can be a solution to enhance the monitoring performance while addressing the sensor failure challenge. Vibration or sound signals have been successfully used for waviness monitoring [75,76]. Yet, the literature lacks a systematic analysis of sensor fusion for waviness or surface roughness monitoring during wood machining. It should be mentioned that sensor fusion should not be due to poor signal processing and feature engineering and cause sensor redundancy. The literature also lacks employing deep learning methods for wood machining monitoring. A comparative study on using machine learning versus deep learning taking into accounts the opportunities and challenges of both approaches [77] should be done in the future.

5.2. Wood drying monitoring

Stress-related defects during the drying process can lead to fracture and check formation, which is a source of AE. Thus, AE could be used for monitoring the wood drying process. The AE monitoring of the wood drying process started in the early 1980s [78–80], where features such as AE count rate [81] or the cumulative AE energy [82] was reported to have been effective in controlling the kiln drying conditions.

The main challenge is that there are many sources of AE during the wood drying other than checks formation and wood fracture. These include moisture transport, friction between fibers, and thermal deformations [82]. Kowalski and Smoczkiewicz [82] discussed that these AE sources are more dominant during the first stages of wood drying, in which the MC is above the fiber saturation point (FSP), and the corresponding AE signals have low energy. A similar trend is reported by other researchers [83,84]. Further drying and moisture drop below the FSP results in wood shrinkage that generates another group of AE signal. The moisture gradient between the dried surface and wet core of wood causes tensile and compressive stress near the surface and in the core of wood, respectively. Less numerous AE signals are generated in this stage but with higher energy levels [82,85]. Drying at higher temperatures or lower humidity can contribute to the formation of AE activities during this stage [85]. During the drying of the wet core, the shrinkage stress is reversed, putting the core under tension that generates the third group of AE signals. Kowalski and Smoczkiewicz [82] stated that wood destruction occurs with the shrinkage of the wood surface, and crack formation initiates in regions with maximum tensile stress. The tensile stress perpendicular to the grain during the drying process may cause intermittent slips in the crystalline cellulose within the cell wall [86]. Identifying the AE threshold beyond which further increment in the localized strain energy results in checks formation is of critical importance. Having such a threshold can provide AE monitoring of wood drying and develop a control system to practice kiln drying without (or with minimal) checks formation.

Booker [86] stated that the literature lacks a direct correlation between the check formation and a specific AE features, and most studies failed to monitor the checks initiation and relate specific AE features to surface check development [87,88], whereas it can lead to large size macroscopic cracks. Booker [86] observed that surface checking happened at an almost constant AE rate at 20 °C; however, higher temperatures resulted in surface checking at a noticeably lower AE rate due to the collapse shrinkage. The temperature and humidity make the correlation between the check formation and AE parameters more complex. Lower AE activity at higher humidity is reported in the literature [79,89], but Booker [86] stated that the AE activity is not simply linked to either the temperature or humidity during the drying but through a complex interaction between these parameters. They discussed that the board surface behaves within the nonlinear range of the stress–strain diagram during the process before surface checking formation. Thus, the elastic or viscoelastic modeling of the wood drying process may not accurately describe the stress–strain behavior when surface checking is likely to occur during the drying process. However, if well-extracted and studied, AE parameters may be able to identify the development of the check during the drying. Booker [86] reported higher AE activities once the instantaneous strain reached its proportional limit. Despite the effectiveness of AE for monitoring the surface checking during the drying process, there is a lack of knowledge on AE applied to internal check monitoring. Quarles [83] reported that AE failed to detect the internal checks due to insufficient AE activities. They suggested using wave guides or embedded transducers to study internal checks during the wood drying process.

Some parameters further complicate the AE monitoring of the wood drying process. The generated AE signals during wood drying may significantly vary between different wood species. For example, the drying of pinewood with many visible annual rings corresponded to more AE activities. In contrast, lower AE activity was observed during the drying of birch, characterized by a more uniform structure [82]. The process can become more complex when considering the role of natural defects in wood structure in the AE activities generated during wood drying. For example, Čunderlik et al. [90] showed that AE activities during the drying of tension and opposite beech wood are significantly different. This is due to the difference between the wood structures in the tension and opposite wood, resulting in other fracture behavior during the drying. Also, the AE activities can be different between the heartwood and sapwood [91].

As explained above, the AE events during the wood drying are mainly due to the water transport and check formation. It was discussed that while some studies failed to monitor the check formation during wood drying by the AE method, some could successfully employ the technique. This is mainly because AE event could be different among wood species. Also, wood's geometry and natural defects can impact the generated AE activities. Moreover, the interaction between wood MC and temperature and humidity during the drying can make the AE monitoring even more challenging. Apart from these factors, some parameters of the AE transducer can impact the quality of AE monitoring during wood drying. Some of these factors include:

- The type and frequency range of the AE transducer
- Sensor placement (location and direction) and wave attenuation challenges
- Type of signal processing and feature extraction

Due to wave attenuation, it is very important to place the transducer at locations with a higher probability of large check occurrence [56]. Kawomoto [92–94] proposed an acousto-ultrasonic technique to find the potential locations for large checks during the drying. It is generally known that acoustic signal attenuation is more prominent in the radial and tangential directions, so an AE signal with a larger amplitude can be obtained in the longitudinal direction [56]. Also, larger wave attenuation was reported when the AE wave propagation direction is parallel to the transducer face [51]. The wave attenuation further emphasizes the importance of sensor placement for accurate monitoring of the drying process.

Another critical factor is the signal processing method and feature extraction. Most research on AE monitoring of the wood drying process has focused on the signal in the time domain, and data-driven approaches such as machine learning have rarely been employed in wood drying monitoring. Kim et al. [44] combined principal component analysis (PCA) and ANN for pattern classification of acoustic emission signals during wood drying. They could successfully differentiate the AE signals from those related to check formation due to moisture movement. Most studies on AE monitoring of the wood drying process were performed during the 1980s, 1990s, and early 2000s without incorporating advanced signal processing and feature engineering. The recent advancements in machine learning and deep learning can facilitate finding the hidden patterns in AE signals to monitor the drying process. The time-series signals can be analyzed by recurrent neural networks (RNNs), or check formation threshold can be identified by employing autoencoders for anomaly detection. This may positively contribute to the development of smart kiln drying processes. Some promising results in using AE in controlling the drying process were reported by Beall et al. [95]. They reported that having a closed-loop control system can reduce the drying time while resulting in dried lumber with equal or higher quality compared to lumber dried with the conventional drying method. The literature currently lacks studies on AE that monitor other drying defects such as warping or uneven MC distribution (i.e. water pockets). A detailed review of wood drying defects is provided by Ward and Simpson [96].

5.3. Wood fracture and damage detection

AE has become one of the standard NDE tools used in monitoring the failure processes in wood, wood-based products, and other composite materials [97,98]. Some AE parameters used in understanding the material's failure, including the AE amplitude, AE count, and AE hits, have been reported in the literature [99]. Several approaches have been implemented in investigating the likelihood of failure monitoring using AE. One of them includes relating the AE events to specific stages of material failure. To illustrate, Lamy et al. [98] reported the correlation between AE hits and the mechanical behavior of wooden material; increased AE events as a result of micro-crack formation were observed before fiber breakage in wood. Some researchers also noted the use of AE to distinguish fracture modes in wood, where AE parameters (such as peak amplitude and signal duration) were successfully correlated to wood fracture [100]. They observed high AE amplitude at the fracture stage of the specimens, demonstrating the feasibility of using AE for such purposes. Similarly, identifying the failure mechanism of wood-based materials using the AE technique is also possible [45]. Additional experimental works supporting these approaches are well documented in the literature. For instance, the location and detection of cracks in double cantilever beam (DCB) specimens using the AE technique were established [45]. They found a correlation between AE observations and standard methods for determining failure location during the fracture test. Fig. 9 shows the experimental setup for failure monitoring in the DCB specimens under mechanical loadings. Reiterer et al. [101] and Lamy et al. [98] also utilized AE to identify and monitor the fracture in wood. The fracture intensity in wood due to MC changes via climatic variations has also been studied using AE [102]. The authors found a positive correlation between high AE frequency events and numerical modeling of fracture intensity in wood specimens at varying relative humidity (RH) conditions. High AE frequency events indicated the occurrence of fracture, which could be associated with mechanical damage in wood, thus, demonstrating the possibility of using AE in detecting and tracing damage development in wood specimens.

Ando et al. [103] examined the shearing fracture process of old (in use for > 200 years) and new wood (within three years of use) using AE. They reported that the cumulative AE events caused by the fracture of wood structures at the microscopic level were higher in old wood compared to the low AE events observed in the case of new wood. This indicates the possibility of distinguishing the shearing fracture modes between woods structures at different service conditions. The AE technique has also found applications in the adhesive industry by evaluating fracture behavior contributing to the bonding strength and durability (delamination resistance) of glued wood elements. This was demonstrated in Clerc et al. [104], where the correlation between AE signals and the fracture mechanism of bond-line in adhesively bonded wood was established. Further, the natural clusters in the AE signals were identified using unsupervised pattern recognition and used to explain the fracture process in the bonded wood, where wood failure and failure in the wood-adhesive interface could successfully be grouped into different clusters.

The application of AE to monitor the failure mechanism of wood-based composites has also been reported (Fig. 10). For instance, Niemz et al. [105] applied the AE technique in monitoring the crack location in wood composites such as medium-density fiberboard (MDF), oriented strand board (OSB), and plywood. Several AE parameters such as signal energy, signal amplitude, and the average number of AE signals were used to study wood-based composites' fracture behavior.

In the same way, the AE technique was found suitable to evaluate the fracture toughness in wood-plastic composites (WPCs). Some authors [106] detected the crack initiation point of WPC under bending conditions through a sharp increase in cumulative AE counts (Fig. 11). They concluded that AE could be an effective and reliable method in characterizing the fracture toughness in these materials compared to standard techniques, such as stress intensity factor analysis. Ritschel et al. [107] also utilized AE in monitoring the damage evolution in 3- and 5-layered commercial plywood panels. They found an increase in AE activity rate with additional plies in plywood, which demonstrates that the layered structure of plywood contributes to further fracture mechanisms at the microscopic and mesoscopic levels. The authors also attributed

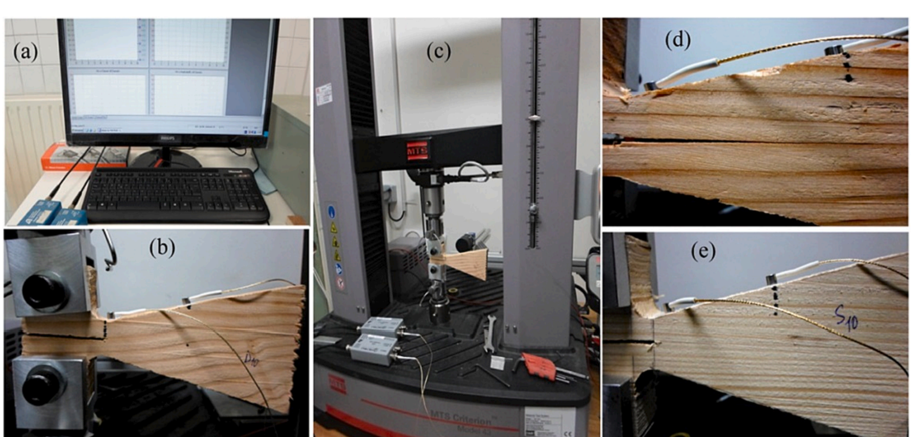

Fig. 9. The experimental setup for fracture monitoring under mechanical loading using the AE technique. The setup was designed for the mode I fracture test to study the crack tip propagation in the double cantilever beam (DCB) specimen while the sample geometry provided stability of energy release rate during the crack growth process (a) AE equipment (b) DCB specimen (Douglas fir) (c) mechanical testing machine (d) crack tip propagation (e) DCB specimen (white fir) [45].

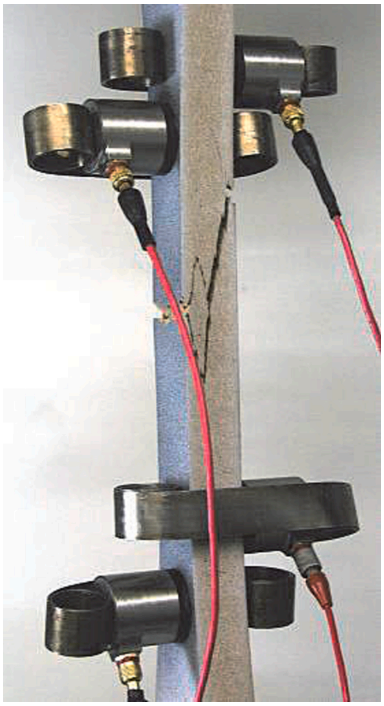

Fig. 10. AE sensors for detecting crack location during mechanical (tensile) loading of wood-based composite. The experimental setup with four AE sensors was designed to allow for a simplified linear location between AE sensors placed on each panel plane [105].

the multiple AE energy classes observed during the tensile loading to the cracks induced by the layers of plywood. A summary of studies on using AE for fracture and damage detection in wood materials is shown in Table 3.

There are different factors impacting the response of AE to wood failure and fracture, among which the mode of fracture (i.e. mode-I, II, III and mixed-mode fracture) is of great importance [109,110]. Schniewind et al. [111] compared the cumulative AE events for mode I and mixed-mode fracture for oak and pine wood and observed a significantly higher AE activity in mixed-mode compared to mode I fracture. They suggested that mixed-mode AE events could be more suitable for pattern recognition analysis.

Other than the fracture mode, the AE signals can be noticeably influenced by the type of wood (i.e. softwood and hardwood). The fracture pattern and the consequent AE signals acquired from the wood of coniferous and deciduous trees exhibit some differences. Reiterer et al. [101] investigated the mode I fracture behavior of certain softwood and hardwood species and observed higher AE counts (until reaching the maximum force) in softwoods compared to hardwoods. This could be linked to the ductility behavior in softwood species resulting in build-up of a process zone with more micro-cracks. However, the hardwood species were found to be fractured in a more brittle way. Chen et al. [112] also reported different AE activities when monitoring the failure mechanism of hardwood (red lauan) and softwood (Sitka spruce) under static and fatigue torsional loading. The AE activity under static loading and prior to the maximum load indicates microcracks initiation before the visible cracking in both wood species. They reported higher AE counts for red lauan during the torsional loading and observed that AE events were largely impacted by the grain angle of wood.

Additionally, the direction of crack propagation with regard to the loading direction can affect the fracture behavior of wood and the acquired AE signal. Ohuchi et al. [113] compared the fracture toughness of sugi in different planes (RL, TL, LT, RT, LR, and TR specimens, in which T, L, and R denote to tangential, longitudinal, and radial direction). They showed a significant impact of wood plane on the fracture toughness and the acquired AE signals, and concluded that AE could be used for detection of the fracture process of the latewood in the TR specimens (where load is applied in the tangential direction and the crack is progressed in the radial direction).

While the use of AE in fracture and damage detection looks promising, specific challenges should be addressed. For instance, several parameters such as wood species (due to different anatomical features) and sample geometry could lead to the disparity of results. Likewise, the coupling technique and number of AE sensors placed on the test piece might affect the acquisition of AE signals and needs to be documented. The limitations of AE signal acquisition and processing for fracture analysis may necessitate combining AE technique with other NDE methods such as the digital image correlation (DIC) technique. The wood microcrack initiation, propagation behavior and acoustic emission parameters and surface strain could be correlated providing opportunities for in-situ monitoring of wood fracture using the combined AE and DIC methods [114]. Wood is a complex material with variations in

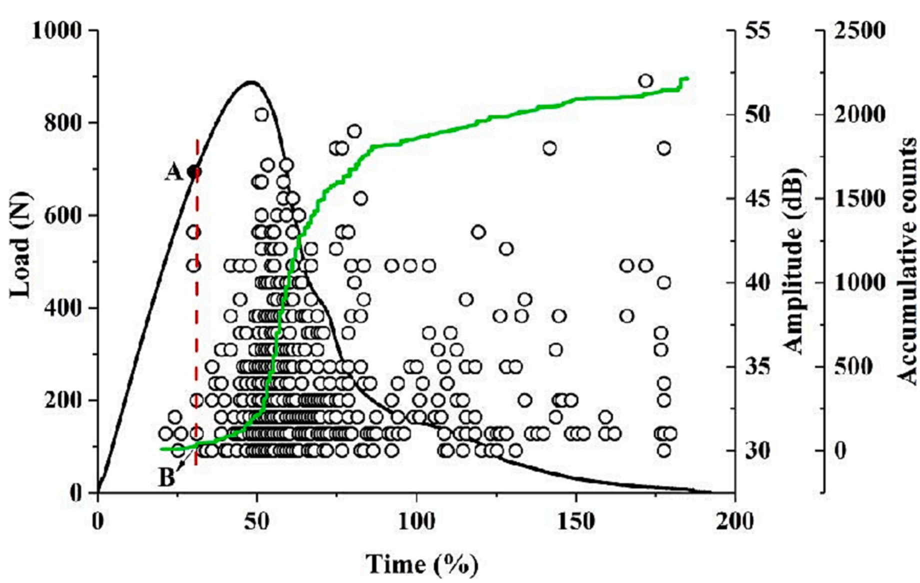

Fig. 11. A graph showing the relationship between AE events and load-time during the bending test of 50%, 60%, and 70% wood fiber/recycled high-density polyethylene composites. The slope of the accumulative counts increased with the crack initiation and propagation in the WPC specimens [106].

Table 3
Summary of research on using AE for fracture and damage detection in wood materials.

Wood Type	AE Parameter	Loading/Testing Approach	Damage Mode	Application	Reference
Double cantilever beam	AE hits and AE events	Monotonic loading	Fiber breakage	Crack tip detection	[98]
Small clear and notched specimens	AE amplitude	Three-point bending in a tangential direction	Microcrack formation	Fracture and damage mode detection	[100]
Double cantilever beam	AE amplitude and Frequency	Mode I fracture test	Crack tip growth	Crack tip propagation monitoring	[45]
Solid wood (shearing specimen)	Cumulative AE events	Shearing in the Longitudinal-radial surface	Microscopic fracturing	Shearing fracture detection	[103]
Wood-based composites (Oriented strand board, Plywood…)	AE amplitude and energy	Tensile loading	Macroscopic fracturing	Crack detection	[105]
Plywood	AE energy and events	Tensile loading parallel to the grain of face veneers	Microscopic and mesoscopic fracturing/damage	Damage evolution in plywood structures	[107]
Wood-plastic composite (high-density polyethylene)	AE cumulative counts	Three-point bending	Fiber breakage and debonding	Fracture toughness determination	[106]
Small clear specimens	AE amplitude and frequency	Monotonic loading parallel to the grain	Cell wall buckling	Crack and damage detection	[108]

properties (due to anisotropy, MC, etc.) that affect the acoustic wave propagation velocity. Future studies should focus on understanding the underlying mechanisms contributing to the varying acoustic wave velocity at different wood conditions. Also, the change in the AE energy system near the crack zone used in detecting damage should be subjected to further scrutiny since the complexity of wood could contribute to several deformations in the same zone. The wood MC influences the material's ductility and energy release rate, and thus, the MC gradient in the sample and fracture zone needs to be considered.

Further, the current literature focused mainly on the fracture and damage detection of small clear specimens (defect-free) that does not necessarily reflect the material properties of full-size lumber used in structural applications. Studies should be conducted to understand the relationship between the AE signal generated by small clear specimens and full-size lumber. The application of AE on mass timber (such as cross-laminated timber and glulam) used in load-bearing applications might be explored to determine the similarity of results with other wood-based composites. Similarly, the influence of different material properties (for instance, wood-based composites) on the AE signal amplitudes and source clusters should be studied. To illustrate, the role of adhesive properties (strength) on the ability to absorb damage needs to be understood for glued wood elements.

5.4. AE for structural health monitoring

The monitoring of timber-based structures in structural applications is crucial, and this is due to the influence of wood's anisotropy, MC, and response to load on their behavior and service conditions [115–118]. Several techniques have been tested for this purpose; however, structural health monitoring (SHM) gained the most acceptance in the past decade. SHM, which ensures the longevity of structures by minimizing the risk of failure, has been deemed appropriate for in-situ assessment of timber-based structures [98,117]. Several studies could be located in the literature on the application of SHM to such structures. For instance, Omenzetter et al. [115] monitored the shear wall deformation and seismic and wind response of timber buildings. Amongst the standard SHM techniques (ultrasonic guided waves, magnetic flux inspection, etc.), AE has shown excellent potential for in-situ monitoring of timber-based structures [116,119,120].

The application of AE in monitoring small-clear wood and large-sized timber elements has been reported [121–123]. A common agreement in the literature is that the sources of AE signals in timber-based structures are related to damage identification and help determine such structures' in-situ conditions [118]. For instance, several studies found a direct correlation between AE signals and cracking (initiation and propagation) in timber structures [98,122,124]. Similarly, timber's properties, such as bending stress, deformation, and material cracking which are pointers of fiber damage, were successfully monitored using the AE technique [99,122,125]. Some authors also revealed the likelihood of detecting the location of damage in wooden boards by AE monitoring [126]. Monitoring these properties becomes essential due to their contribution to failure in timber structures. The graphical representations of small specimens and large-sized timber elements monitored by the AE technique are shown in Figs. 12 & 13.

Wood-based composites, a group of products made with different wood materials, including plywood, particleboard, fiber-board, glued-laminated timber, and laminated veneer lumber (LVL), have also been monitored using the AE technique [119,127]. The growing interest in these materials is due to the technological advancement in wood joinery and their improved strength properties, making them desirable in structural applications [128]. For AE monitoring in large-sized timber panels (wood composites) and structures, some authors placed sensors at several locations to capture the complete sample/structure in acquiring AE signals [117,128]. A diagrammatic representation of such an approach is shown (Fig. 14). To illustrate, past studies [127] utilized AE in monitoring damage initiation and accumulation in wood-based composites such as plywood and LVL. They found more AE events for plywood than LVL; the difference was attributed to microscopic features, adhesive bonds, and lay-up pattern of the laminated materials, which could have affected the AE signals [127]. In contrast, another study on wood composites, including cross-ply wood and plywood, found no direct correlation between AE events and damage/crack growth propagation in such materials [128]. The authors concluded that the AE technique might be unreliable for structural failure predictions in these materials. Thus, there is no unanimous agreement regarding the relationship between AE activities and damage detection in wood-based composites, and further research is required.

Like wood-based composites, several materials, such as fiber-reinforced polymers, have been combined with wood to repair and reinforce timber structures [130–132]. Notably among them are carbon-fiber pultruded laminates (CFRP) and glass-fiber-reinforced polymer (GFRP), due to their strength and light-weight compared to other materials [53,133]. The condition monitoring of fiber-reinforced structures such as CFRP and GFRP is important in determining the need for repair or replacement in such structures [134,135]. For instance, Rescalvo et al. [53] reported the application of AE in assessing the mechanical behavior of CFRP and GFRP composites. They observed a good correlation between AE events and mechanical failure patterns in fiber-reinforced composites. Some limitations observed by the authors include moisture variation and heterogeneity of wood which could impact the composites' properties and, in turn, their mechanical behavior. Other researchers [129] also revealed the feasibility of assessing the mechanical damage of some fiber-reinforced beams, including basalt fabric, carbon fabric, and carbon pultruded laminate

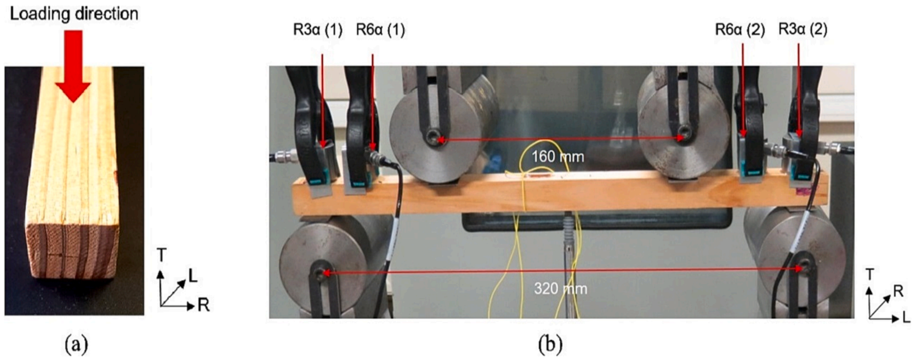

Fig. 12. **AE monitoring of small clear specimen under bending, the vertical arrows pointing downward indicates the position of sensors used in AE signal acquisition** [125].

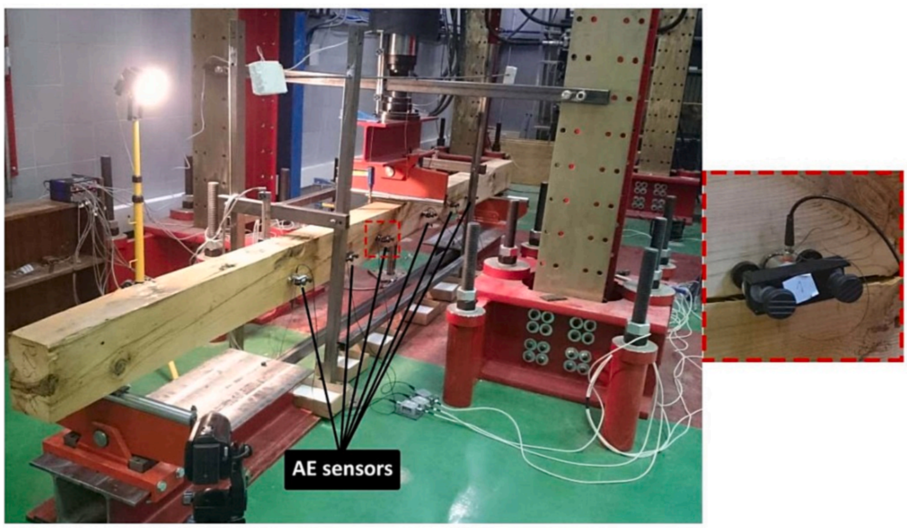

Fig. 13. **AE Monitoring of large-sized timber beam under bending test; the 6 multi-resonant sensors (marked using black lines) were placed on the beam to monitor its mechanical behavior** [53].

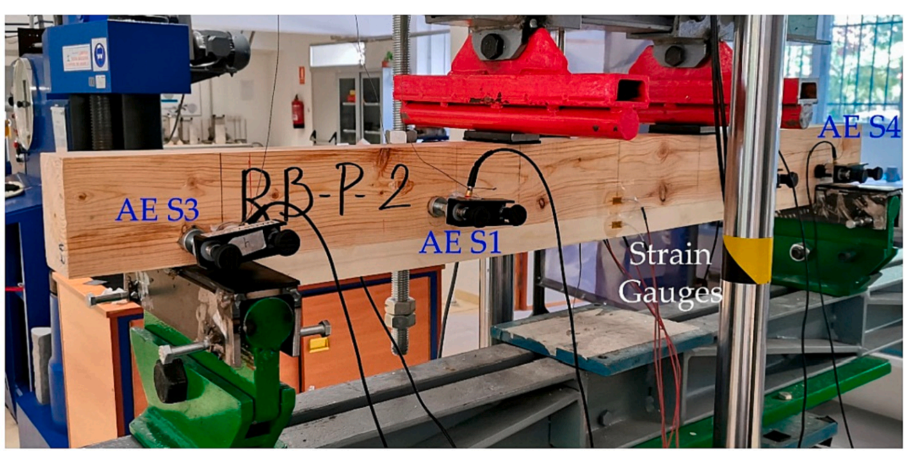

Fig. 14. **Delamination and damage monitoring of pine beam reinforced with poplar using AE technique** [129].

using the AE technique.

AE was also used to monitor failure mechanisms contributing to adhesive bond performance in fiber-reinforced polymers. A positive relationship was observed between the AE hits and failure mode when CFRPs were placed under the pull-off test in evaluating the quality of wood-CFRP laminates [133]. A description of the pull-off test is shown (Fig. 15). The authors concluded that high frequencies signals could indicate damage initiation in these materials. This indicates the suitability of AE in evaluating the quality of fiber-reinforced polymers.

Overall, the studies reported a clear relationship between AE events and failure prediction in timber-based structures. Even though some challenges associated with timber's properties (MC variability,

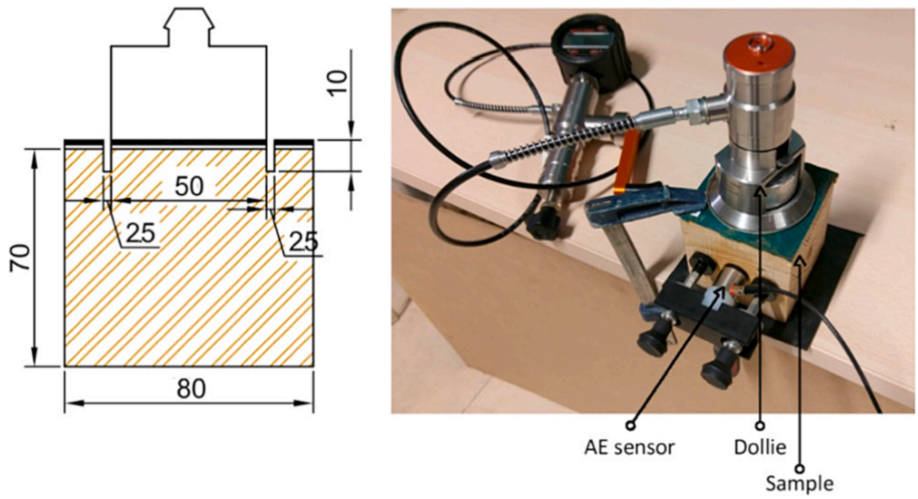

Fig. 15. **A description of the pull-off test for evaluating CFRP quality. AE sensor is placed and its signal activities were correlated with the failure mode when CFRPs were placed under the pull-off test** [133].

heterogeneity, anatomy, etc.) and layup patterns for laminated composites have been observed in AE monitoring of timber structures, the strict control of these factors could help improve AE results, and thus, encourages the use of AE in the monitoring of timber-based structures.

5.5. AE monitoring of termite infestation in timber structures

Termites, a group of eusocial insects in the family of *Termitidae*, have been recognized as the most damaging insect pests for wood-based structures [136–137]. The damage caused by termites could result in substantial financial loss in replacement or repair costs. While several termite detection systems have been tested for wooden structures, they have drawbacks, including inaccessibility of the entire structure and subjectivity of the personnel during the inspection. This could be tackled by a non-destructive technique such as AE that gives acoustic signals upon spotting termite activities in wood [138,139]. Using AE for monitoring termite infestations in these structures relies on generating AE signals when termites give off vibratory signals by drumming their heads or through their movement in wood [140].

Several authors have reported the feasibility of monitoring termite infestations in wooden structures using AE. For instance, some researchers [141] used AE to monitor the activity rhythm of *Reticulitermes speratus,* a dangerous termite in the United States. Also, Fuchikawa et al. [136] investigated the influence of temperature on the activity rhythm in subterranean termite colonies using AE, where a strong peak of activity was observed between 23 °C and 25 °C. The temperature and RH influence the feeding activities and thus the survival of termites. This led to the exploration of AE in monitoring the feeding activities of dry-wood termites capable of infesting wood even with low MC [142]. Fig. 16 shows the testing setup for AE monitoring of termite activity in wood. An increase in the AE events with an increase in temperature irrespective of the RH conditions was also reported, in line with other works [143]. It was concluded that AE is a suitable approach to monitor termite feeding in wood because the micro-fracturing occurs when the wood is attacked by termites that give off AE signals [142].

A preliminary investigation on monitoring termite infestation in wood was found in the literature [144]. They found a higher AE magnitude for the infested areas than for non-infested areas, indicating the possibility of using AE to distinguish areas of termite infestation in wood (Fig. 17). Further, Nanda et al. [137] developed a novel system that detects termite infestation and its population in damaged building structures using AE coupled with machine learning techniques (such as SVM and ANN). They fed some input parameters such as acoustic signals, temperature signals, and a combination of both signals into the machine learning models to compare their performance. The highest accuracy for termite detection was achieved when AE signals were combined with the temperature (93.83 %). In comparison, the model fed only with the AE signals detected the termite activity with an accuracy of 92.67 %. Models based on ANN performed better than SVM in estimating the termite population in the damaged structures. Similar accuracy (91.88 %) was reported in detecting subterranean termite (C. *curvignathus*) activities in wood using the AE method in which the energy and entropy of the AE signals were used to train an SVM (Fig. 18) [145].

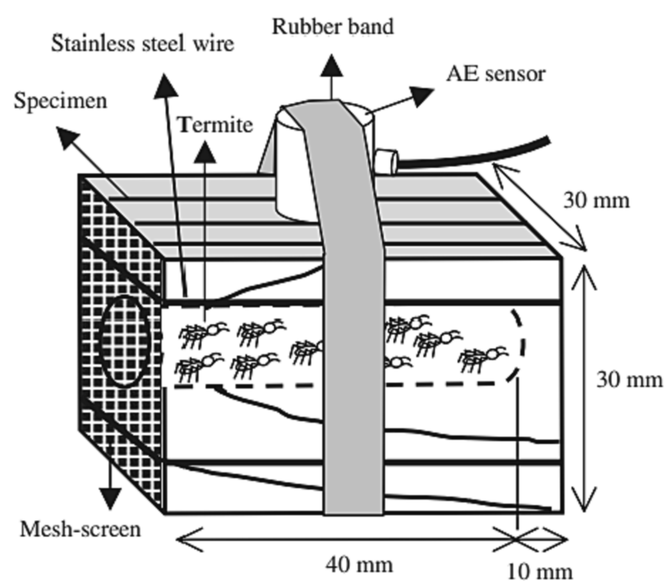

Fig. 16. **AE monitoring of the feeding activity of *Incisitermes minor*** [143].

AE has been established as a practical and effective non-destructive approach to monitoring several wood quality parameters such as fracture and damage evolution, wood drying, and machining. However, its application in detecting fungal decay and termite activities in wood and wood-based structures is quite limited. Therefore, more research should be conducted to understand the influence of several parameters (temperature, MC, relative humidity, etc.) on termite activity rhythm and how they correlate to AE signals. The role of the termite population in the AE signals generated during termite infestation in wood should also be elucidated.

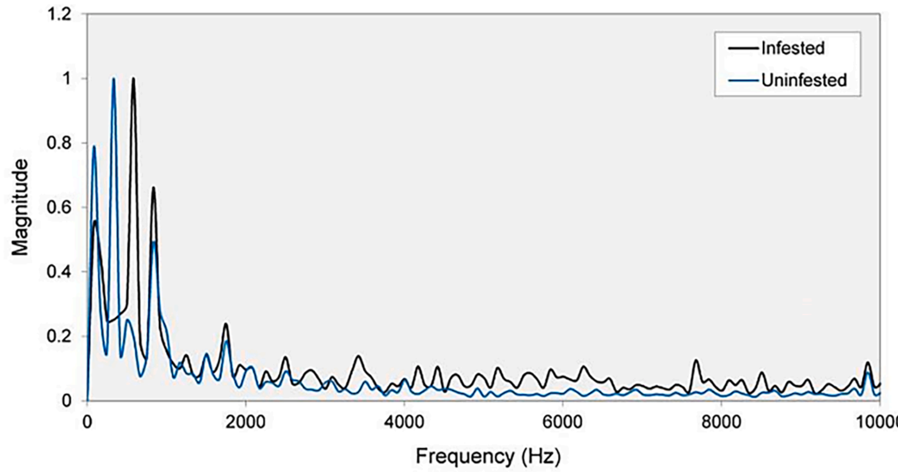

Fig. 17. Acoustic emission signal on infested and non-infested wood [144].

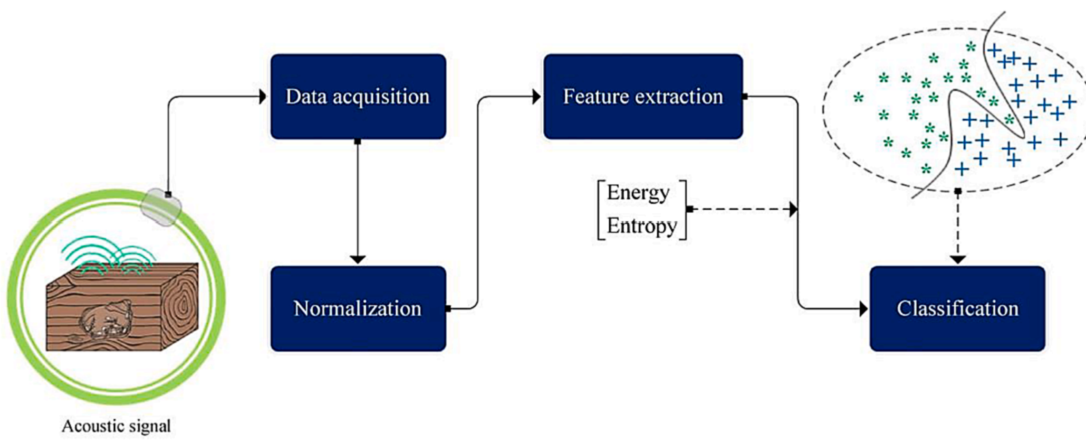

Fig. 18. Schematic of the signal processing in termite detection system using the energy and entropy of the acquired AE signals [145].

5.6. Other applications

The most common applications of AE monitoring were already discussed; however, AE has also been practiced in some other applications, mainly for the quality control of wood products. Examples include using AE to classify thermally modified wood [47,146]. Wood treated at different temperatures exhibits varying mechanical and physical properties. Classification of thermally modified wood is a crucial quality control task. Other NDE-based methods include color measurement [147–149] or NIR-spectroscopy [150–151], have been used in the literature for classification of wood treated at different temperatures. Nasir et al. [47,146] used AE combined with ML modeling to classify and characterize the thermally modified wood. Thermal treatment changes the MC and microstructure of wood. It was discussed in section 4 that the AE signal is sensitive to the variation in wood MC and its microstructure. The growing interest in using thermally modified wood [152,153] requires more attention to developing intelligent NDE-based models for quality control of these products. Also, the growing attention in timber building monitoring [154,155] may provide a potential application for AE technique that combined with other sensing technologies are used for SHM of timber buildings.

In other applications, the AE method was used to detect the fines in wood composite manufacturing. The presence of fines (small particles) in the wood panels is not desired as it requires more resin utilization resulting in increased weight. Campbell et al. [156] and Edwards et al. [157] showed that the AE system could monitor the presence and percentage of fines in the flakes furnish during the wood composite fabrication.

6. Conclusions, limitations, and outlook

It is evident from the published findings that AE could be incorporated in evaluating the structural integrity of wood and wood-based materials by understanding their mechanical behavior under various loading conditions and degradation scenarios. It is believed that considering the discussed factors in AE experimentation and analysis would increase the confidence in the technique and lead to its adoption in industrial applications, especially when the high structural performance of wood-based products is desired. Despite the discussed advantages, some challenges should be solved for the full implementation of this technique in the wood industry, as explained below:

1- The AE parameters such as wave attenuation and velocity highly depend on the type of wood species. This, combined with the anatomical complexities of wood, makes the AE signal acquisition and processing more challenging. The variation between the wave attenuation and velocity in different directions (i.e. longitudinal, radial, and tangential) further complicates the AE monitoring of wood structures. Apart from the factors related to wood species and their microstructures, the AE technique is greatly affected by sensor location (its proximity to the source of generated AE) and the transducer direction. Future research should further explore the number and positioning of AE sensors for monitoring wood-based materials and timber structures under different loading scenarios and degradation conditions.

2- The role of wood moisture content and relative humidity can further complicate the in-situ monitoring of wood structures. While the general impact of these factors on the characteristics of AE signals is understood, there is a knowledge gap in developing standard monitoring protocols for in-service structures considering the variation of moisture content and relative humidity. The combined effect of moisture content and humidity with the natural defects and anatomical complexity of wood requires further investigation to enable robust online monitoring procedures.

3- A crucial factor to consider is the challenges in the AE monitoring of large-size timber structures. Currently, there has been more focus on standard laboratory-size wood specimens, while it eventually needs to be used for in-situ monitoring of large-size structures. Assessing large size wood structures containing natural defects can impact the generated AE activities; thus, a deeper understanding of the role of size and defects in timber structures when assessed by AE techniques is required.

4- Compared to solid wood, there are minimal studies on applying the AE technique to monitor the performance of wood composites and engineered wood products. Specifically, the literature lacks a comprehensive investigation on monitoring the performance of mass timber structures such as cross-laminated timber (CLT) and glued-laminated timber. The growing interest in mass timber building construction necessitates developing robust monitoring strategies for quality control and inspection of these structures.

5- An additional factor adding challenge to AE monitoring of wood and timber structures is the complex sources of AE that may be due to a variety of factors. While the literature has focused on the role of each factor on the generated AE signals, the combined effect of some parameters should be investigated in future research. There should be more research to provide protocols for structural timber under a combination of mechanical, environmental, and biological degradation.

6- While multi-sensory systems and sensor fusion approaches have been practiced in different fields for developing reliable monitoring frameworks, there are few studies on employing such an approach to monitor the performance of wood materials. Examples are limited to wood machining monitoring, in which the AE was combined with other sensors to improve the monitoring performance of wood machining. The above-explained challenges due to wood complexities combined with many factors (e.g. MC, RH, loading conditions, defects, etc.) may require using a multi-sensory framework to account for the system complexity. However, there is a knowledge gap in this regard. Specifically, employing AE combined with a sensor fusion approach for timber building monitoring should be studied in the future.

7- Despite the importance of feature engineering and data processing in developing an accurate monitoring system, there is a significant gap in the literature on employing data-driven techniques when AE monitoring wood materials. Most published works have shown a correlation between some AE parameters and the wood condition (damage, crack, properties, etc.). In contrast fewer studies have built a predictive model using data-driven methods such as machine learning. Among the discussed applications, machine learning was mainly applied to AE monitoring during the wood machining process. Without sophisticated signal processing, feature engineering, and suitable data-driven methods, it is hard to judge the effectiveness of AE monitoring in a specific application. Therefore, future research should focus on developing data-driven monitoring models rather than just describing the general trends in the acquired signals or simply performing correlation analysis. AE applied to structural health monitoring has a vast potential to embrace a data-driven approach among the discussed application. Also, mass-scale data acquisition from timber buildings and wood structures can result in big data, which requires data analysis methods such as deep learning for better analysis.

Declaration of Competing Interest

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.

Data availability

No data was used for the research described in the article.

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