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Damage characterization of laminated composites using acoustic emission: A review

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ABSTRACT

Damage characterization of laminated composites has been thoroughly studied in the last decades where researchers developed several damage models, and in combination with experimental evidence, contributed to better understanding of the structural behavior of these structures. Experimental techniques played an essential role on this progress and among the techniques that were utilized, acoustic emission (AE) was extensively used due to its advantages for in-situ damage monitoring with high sensitivity and its capability to inspect continuously a relatively large area. This paper presents a comprehensive review on the use of AE for damage characterization in laminated composites. The review is divided into two sections; the first section discusses the literature for damage diagnostics and it is presented in three subsections: damage initiation detection, damage characterization and damage localization, while the second section is devoted to damage prognostics and it focuses on the remaining useful life (RUL) and residual strength prediction of composite structures using AE data. In every section, efforts have been made to analyze the most relevant literature, discuss in a critical manner the results and conclusions, and identify possibilities for future work.

1. Introduction

Laminated composite structures, driven by advantages in structural efficiency, performance, versatility and cost, have made a significant mark in numerous industries, such as aerospace, wind energy, automotive and naval. However, their full potential is held back by an overall lack of understanding of the damage accumulation process over the lifetime of the structure. It is yet unclear how different damage mechanisms are triggered, which parameters and how they affect their interaction, and what is the precise influence of a particular damage state on the integrity of structural component. As a consequence, large safety factors must be applied in composite design to compensate for this deficiency in understanding. The overdesign due to these large safety factors reduces the potential efficiency of composite structures, particularly in terms of their weight.

In general, the damage mechanisms in laminated composites are categorized into two groups: interlaminar and intralaminar damage mechanisms. Delamination is an interlaminar damage mechanism, which is defined as the initiation and propagation of an interlaminar matrix crack that leads to the separation of two laminae and significantly degrades the out-of-plane and flexural properties and of the composite structure [1–3]. The intralaminar damage mechanisms refer to damages within a lamina, i.e. matrix cracking, fiber breakage, fiber/matrix debonding and fiber pull-out [4–7].

The damage accumulation sequence depends on many variables such as the material properties of the composite’s constituents, the exact layup, the defects induced during manufacturing, the loading profile and the environmental conditions in which the structure operates. Additionally, the inhomogeneous nature of the composite material and the stochastic activation of different damage mechanisms should also be taken into account making the damage process a very complex phenomenon to study.

In the effort to unfold the damage accumulation process, researchers have employed several experimental techniques. Extensive research has been performed the last three decades in the field of damage assessment using experimental techniques and as a result a large amount of sensing technologies exist nowadays [8–17]. These techniques are generally categorized into two main groups: active techniques and passive techniques. In the case of active techniques, the composite structure is excited by a foreign source. Then, according to the response of the excited structure, the damage is identified. The most common active techniques used for damage assessment in the laminated composites are ultrasonic inspection [18,19], active thermography [20–22], modal

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analysis [23,24], radiography [26], guided wave [27, 28], terahertz imaging [29] and shearography [30,31]. The weakness of the active SHM techniques is the fact that they are not capable of online monitoring of the composite structures in operation [32]. In the case of passive techniques, there is not any foreign source to excite the material and the sources are inside the material. These sources may be damage nucleation, damage propagation, plastic deformation, internal friction, etc. The most common passive techniques are acoustic emission (AE) and passive thermography [33]. The superiority of the passive techniques over the active ones is their capability for structural health monitoring (SHM) while the structure is in operation.

This review paper discusses the advantages of AE, which has the potential to be used for SHM. SHM can be described as the process of implementing a real-time damage detection strategy for load bearing structures. This process involves the observation of the mechanical response and the integrity assessment of the structure by using permanently installed sensors. The sensors record data periodically or continuously over the in-service life of the structure. The sensors cannot measure damage but the response of the structure. Thus, the sensitive information is hidden within the data, and feature extraction using advanced data analytics should be performed in order to relate the observations with the damage states. The main target of the feature extraction is to fulfil the four SHM levels; 1) damage detection, 2) damage localization, 3) damage identification and 4) damage severity.

2. AE as an online damage monitoring tool

The literature review shows AE has been widely used for damage assessment in laminated composites. The first papers on this topic, indexed in Scopus, are referred to the two conference papers authored by Hagemaier et al. [34,35] in the 1970s. They used AE to detect material and manufacturing anomalies in graphite composites. As depicted in Fig. 1, since the 1970s, there is an increasing trend to use AE for damage analysis and assessment of composite materials, especially during the last decade. During these five decades, around 700 papers have been published on this topic, including ~450 journal papers and ~250 conference papers. This data was obtained from Scopus (23 October 2019) using the keywords: acoustic emission and composite laminate.

AE is defined as the transmission of an elastic stress wave through the

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**Fig. 1.** The number of indexed papers in Scopus (23 October 2019) using the keywords: acoustic emission and composite laminate.
material which is usually originated from an internal source such as crack initiation and growth [32]. According to Fig. 2, the required apparatus to perform AE monitoring consists of:

- The structure under loading.
- A network of AE sensors to capture the infinitesimal surface vibrations of the test structure and to convert them to the analog signals.
- Pre-amplifiers which magnify the intensity of the analog signals.
- Acquisition and recording section, where the amplified signals are recorded and converted from the analog to digital signals.
- Data processing section, where the recorded digital AE waveforms are analyzed.

The AE analyses are usually performed using AE waveforms or the features extracted from the AE waveforms. Fig. 3 shows a typical AE waveform. The most important features of an AE waveform are the following:

- Threshold: Only the AE signals with the intensity higher than the threshold are recorded by the AE system. It is reported in dB unit.
- Amplitude: The maximum voltage of the signal and it is usually reported in dB unit.
- Duration: The time interval between the first and the last threshold crossings and it is reported in μs unit.
- Rise time: The time interval between the first threshold crossing and the maximum amplitude and it is reported in μs unit.
- Counts: The number that the waveform crosses the threshold in the increasing direction within the waveform’s duration.
- Energy: The area beneath the squared waveform within the waveform’s duration. It is usually reported in attojoule (aJ) unit (1 aJ = 10^{-18} J).
- Peak frequency: The frequency corresponded to the highest magnitude in the frequency distribution obtained from fast Fourier transform (FFT) of the signal. It is reported in kHz unit.

3. Damage diagnostics

The procedure of damage diagnosis using AE consists of three levels; damage initiation detection, damage localization and damage identification. The first level deals with the definition of the damage initiation criteria, irrespective of the damage type. Then, in the second level, the damage is localized using a network of AE sensors and different localization methods. Finally, the damage is identified by analyzing the AE data using unsupervised clustering, supervised classification and signal analysis methods.

3.1. Damage initiation detection

Many researchers used AE to detect the initiation of the damage in laminated composites. The studies cover a variety of loading conditions and specimen configurations; from coupon level tests such as tensile, compression, double cantilever beam (DCB), end-notched flexural (ENF), mixed-mode bending (MMB), 3-point bending (3 PB), 4-point bending (4 PB), buckling, quasi-static transverse indentation, low-velocity impact (LVI) and compression after impact (CAI), to a real composite structure subjected to an arbitrary load. The list of literature of damage initiation detection in laminated composites is reported in Table 1. The studies cover a wide range of the composite materials, including thermoset material; glass/epoxy and carbon/epoxy,
thermoplastic material; glass/polyester and glass/polyamide, sandwich
and hybrid composites.

As presented in Table 1, most of the researchers used either one or
multiple AE features or a combination of AE features with the me-
chanical data for identifying the initiation of damage in the material. AE
events, AE energy, AE counts and also the cumulative values of these
parameters are the main utilized features. In the case where AE events
were used as a criterion, the first identified AE event during the loading
is considered as the moment of the damage initiation [38,39]. On the
other hand, in few papers the first high-energy or high-counts AE signals
were used as the criterion for damage initiation [40–42]. Furthermore,
there are some studies that used the cumulative AE events, cumulative
AE energy, and cumulative AE counts as criterion. The first significant
increase in the gradient of these cumulative curves is considered to be
the moment of damage initiation [5,6,43,44]. The last group of the re-
searchers tried to increase the sensitivity of damage detection by
combining the AE data and the mechanical data by introducing the
sentry function [2,45,46]. The sentry function is defined as the loga-

\[ f(x) = \ln \frac{E_m(x)}{E_{AE}(x)} \]  

where \( E_m(x) \) is the mechanical energy (area under the load-
displacement curve), \( E_{AE}(x) \) is the cumulative AE energy and \( x \) is the
displacement.

Based on the state of the damage in the structure, the sentry function
could show one of the four following trends: 1) Increasing trend: it
shows that the structure is still intact and no damage or some micro
damages occurred in the material. 2) Sharp drop: it reveals that huge
damage occurred in the material. 3) Constant trend: It demonstrates that
there is a balance between the degrading mechanisms, like damages,
and the strengthening mechanisms, like fiber bridging. 4) Gradually
decreasing: It is emphasizing that the load-carrying capability of the
composite structure is losing gradually. Accordingly, the first big drop in
the sentry function curve is considered as the moment of the damage
initiation.

Although different approaches have been proposed for AE-based
detection of damage initiation in laminated composites, this task still
remains open with challenges to be addressed. The limitations of each
proposed method are discussed hereafter. If the first AE event is
considered as the moment of the damage initiation, it may lead to
conservative indication on when the damage initiated. AE is very sen-
sitive to micro damages while most of these micro damages do not
degrade the integrity of the composite structure significantly. For
example, a lot of imperfections might be induced in the laminated
composite structures during the fabrication process, such as the fiber
misalignment, micro voids and impurities [48]. These imperfections
could induce many AE events in the early stage of the loading while the
structure retains its integrity.

In addition, some of these imperfections could induce high-energy
and high-counts AE events. The misalignment of a few numbers of fi-
bers, which frequently happens in the hand layup fabrication process,
results in the breakage of the misaligned fibers in the early stage of the
loading. Thus, observing the first high-energy or high-counts AE event is
not always a reliable indicator of the damage initiation.

Further, the criteria such as “high-energy”, “high-counts”, “the first
significant increase” in the gradient of cumulative curves and “the first
significant drop” in the sentry function curve are qualitative criteria that
can be interpreted in different ways (see Fig. 4).

The possibility of different interpretations of the proposed qualita-
tive criteria to detect the damage initiation in a glass/epoxy DCB test,
performed by the authors, is demonstrated in Fig. 4. According to Fig. 4
(a) and in agreement with the aforementioned explanations, considering
the first recorded AE event as the sign of the damage initiation, leads to
the conservative prediction of damage in the initial loading stages
(displacement = 1.45 mm). As it is clearly seen, no degradation is seen in
the load curve and load increases up to 3.6 times after detecting the first
AE event. In addition, the continuous AE activity initiates at the
displacement of 5.6 mm, which is long after the first captured AE event.
In Fig. 4(b), AE energy is used to detect the damage initiation. The se-
lection of the first high-energy AE event depends on the scale of the AE
energy plot and also the interpretation of the person who is performing
the AE data analysis. If the AE energy is plotted in the scale of the
maximum recorded energy (around 4300 aJ) the first high energy AE
event is detected at the displacement of 43.3 mm which is long after the
first load drop. In addition, if the AE energy curve is shown in a
magnified view (the upper limit of the AE energy axis -the right vertical
axis-is 200 aJ), there are 7 peaks in the AE energy plot with the corre-
sponding displacements of 4.8, 6.6, 8.1, 9.5, 9.9, 10.8 and 13.9 mm,
respectively. Based on the user’s judgment and experience, each one

![Fig. 3. A typical AE waveform and the most important features [36].](image)
### Table 1
Damage initiation detection in laminated composites using AE.

| Materials | Type of the test | Damage modes                                    | The utilized AE parameters | Damage detection approach                                      | Ref. |
|-----------|------------------|-------------------------------------------------|---------------------------|----------------------------------------------------------------|------|
| Aluminum to aluminum adhesively-bonded | Quasi-static and fatigue DCB tests | Micro cracks at adhesive bond | Events | Detecting first micro cracks at the adhesive layer before macroscopic delamination failure by first AE events | [39] |
| Carbon/epoxy | Constant and cyclic internal pressure on the pressure vessel | Fiber breakage | Events | The first AE event | [38] |
| Glass/polyester | DCB | Delamination | Energy | The first high-energy AE event | [42] |
| Glass/epoxy | DCB, ENF and MMB | Delamination | Energy | The first high-energy AE event | [41] |
| Glass/epoxy | 3 PB | Delamination | Counts | The first high-counts AE event | [53] |
| Glass/epoxy | 3 PB | Delamination | Counts | The first high-counts AE event | [40] |
| Glass/epoxy | DCB | Delamination | Counts | The first high-counts AE event | [54] |
| Sandwich composite with glass/epoxy skin and foam core | DCB | Delamination | Counts | The first high-counts AE event | [54] |

#### Damage initiation detection by cumulative curve of AE features

| Glass/epoxy | Quasi-static indentation | Matrix cracking, delamination and fiber breakage | Cumulative energy | Different damage mechanisms were clustered using packet wavelet transform and cumulative energy used to detect the initiation of each damage mode | [55] |
| Carbon/epoxy | DCB | Delamination | Cumulative energy | The first increase in the gradient of cumulative energy curve | [43] |
| Glass/epoxy | ENF | Matrix cracking, fiber/matrix debonding and fiber breakage | Cumulative energy | The signals were clustered using PFM, then the first increase in the gradient of cumulative energy curve for each damage was considered as the initiation of that damage mode | [7] |
| Carbon/epoxy | DCB fatigue | Delamination | Cumulative energy | By fitting a linear equation to the cumulative energy and delamination growth data, crack growth was predicted by AE | [56] |
| Glass/epoxy | Tensile | Layer failure and delamination | Cumulative energy | The first increase in the gradient of cumulative energy curve | [57] |
| Glass/epoxy | DCB | Delamination | Cumulative energy | By fitting a linear equation to the cumulative energy and delamination growth data, crack growth was predicted by AE | [58] |
| Carbon/epoxy | Quasi-static indentation | Matrix cracking, delamination and fiber breakage | Cumulative energy and cumulative events | The signals were clustered by the hierarchical model, then first increase in the gradient of cumulative events and cumulative energy curves showed the damage initiation | [5] |
| Glass/polyamide | Fatigue tensile | Matrix cracking, delamination and fiber breakage | Cumulative events | The signals were clustered according to their amplitude, then the first increase in the gradient of cumulative events curve, for each damage, was considered as the initiation of that damage mode | [6] |
| Glass/epoxy | Quasi-static and fatigue tensile tests | Matrix cracking, fiber/matrix debonding, delamination and fiber breakage | Cumulative events | The signals were clustered using an unsupervised clustering method, then the first increase in the gradient of cumulative energy curve for each damage, was considered as the initiation of that damage mode | [4] |
| Glass/epoxy | DCB | Matrix cracking, fiber/matrix debonding and fiber breakage | Cumulative counts | The signals were clustered by Hilbert transform (HT), then the first increase in the gradient of cumulative counts curve, for each damage, was considered as the initiation of that damage mode | [44] |
| Glass/epoxy | Tensile test of the drilled specimen | Matrix cracking | Cumulative counts | The first increase in the gradient of cumulative counts curve | [59] |
| Glass/epoxy | ENF | Delamination | Cumulative counts | The first increase in the gradient of cumulative energy curve | [60] |
| Sandwich composite with glass/epoxy skin and foam core | DCB | Interfacial debonding, matrix cracking, fiber breakage and core failure | Cumulative counts | Different damage mechanisms were clustered using GKM algorithm and cumulative counts was utilized to detect the initiation of each damage mechanism | [61] |

#### Damage initiation detection by the combination of AE and mechanical data

| Sandwich composite with glass/epoxy skin and foam core | DCB | Delamination | Sentry function | The transition point in the plot of the integration of sentry function against cumulative energy release rate | [62] |
| Glass/epoxy | DCB | Delamination | Sentry function | The first significant drop in the sentry function curve | [63] |
| Glass/polyester | DCB | Delamination | Sentry function | The first significant drop in the sentry function curve | [46] |
| Carbon/epoxy | DCB, ENF and MMB | Delamination | Sentry function | The first significant drop in the sentry function curve | [2] |

**Damage initiation detection by several approaches**

| Hybrid of thin carbon/epoxy and conventional glass/epoxy | Tensile | Fiber fracture and ply fragmentation | Energy and cumulative energy | The first high-energy signal, the first significant increase in the gradient of cumulative energy curve | [64] |
| Carbon/Thermoset resin Carbon/Thermoplastic resin | DCB | Delamination | Events, cumulative energy and cumulative events | The first increase in the gradient of cumulative energy curve, the first increase in the number of AE events, the first increase in the gradient of cumulative events curve | [65] |
| Hemp/epoxy | 3 PB | Global collapse | | | [66] |

(continued on next page)
could be considered as “the first high-energy AE event” and therefore damage initiation. A similar problem exists if AE counts are used for damage indicator. Therefore, the obtained results depend on the plot scale and also the operator’s interpretation. Similar to the previous approaches, in the case of cumulative AE energy, cumulative AE count, and cumulative AE event curves (see Fig. 4(f–k)), choosing the first significant increase in the gradient of the cumulative curves, again completely depends on the scale of the plot (the upper limit of the right vertical axis that corresponds to the cumulative curves). For example, in the real scale plot, the corresponding displacements to the first significant increase in the cumulative AE energy, AE counts, and AE event curves are 7.9, 7.7 and 6.9 mm, while, in the magnified plot, they are 4.7, 4.6 and 5.5 mm, respectively. Therefore, the obtained results from the cumulative curves also depend on the plot scale. The sentry function curve of the DCB specimen is shown in Fig. 4(l). There are two significant drops at the early stage and both drops could be considered as the first “significant” drop. Therefore, one person might choose drop number 1 as the first drop and another person might select drop number 2 as the moment of the damage initiation because of its severity in comparison to the first drop.

In order to avoid the different interpretations of the aforementioned qualitative criteria for damage initiation detection using AE, a quantitative criterion based on the Felicity effect has been proposed in ASTM E2478-11 standard [49], “Determining damage-based design stress for glass fiber reinforced plastic (GFRP) materials using acoustic emission”. Accordingly, the damage initiation is specified by the presence of a “significant AE activity” during the reloading portion of the loading/reloading cycles. The term of “significant AE activity” is determined using a quantitative historic index. In order to obtain the historic index, first, the ultimate strength of the specimen should be determined using a monotonic loading up to the final fracture of the specimen. Then, the similar specimen is subjected to some load/reload cycles. The first load level should be equal to 15% of the ultimate load and it is increased 5% in each subsequent reload cycle. During the reload cycles, the AE signals are recorded until the maximum load of the previous cycle. The historic index is defined as follows [49]:

\[ H(t) = \frac{N}{N - K} \sum_{i=1}^{N} S_{Oi} \]  

(2)

where \( H(t) \) is the historic index at time \( t \), \( N \) is the number of AE hits up to time \( t \), \( S_{Oi} \) is the MARSE value of \( i \)th hit (other parameters such as signal strength or energy can also be used) and \( K \) is a parameter that is depended to the number of hits and it is obtained from Table 2. The damage initiation is indicated when the historic index becomes equal or greater than 1.4 for the first time.

The last challenge that affects the reliability and reproducibility of AE results for the damage evaluation in laminated composites is the fact that most of the AE descriptors such as amplitude, duration, rise time, central frequency, peak frequency and energy are affected by the source/sensor distance, sensor type, coupling quality, damage accumulation and specimen’s geometry (wave mode conversion, dispersion and reflection). For example, Hamstad et al. [50] investigated the propagation of the AE waves during the impact tests of a GFRP pressure vessel. The obtained results showed that some features such as the duration, rise time, amplitude and the spectral content of the signals, originated from the same source, are significantly affected by the source/sensor distance. In addition, the damage state of the structure can affect the AE signals [51]. As the damage accumulates, the medium alters and the recorded AE waveforms, originated from the same damage mechanism but at different damage state of the structure, may have different AE features.

Furthermore, the AE features are also depended on user’s input such as the threshold level, the peak definition time (PDT) and hit definition time (HDT) parameters. To overcome this limit the user’s influence, Chai et al. [52], proposed a new AE parameter, Shannon’s entropy, which is directly extracted from the waveform and its trend is almost similar to counts and energy parameters. The Shannon’s entropy represents the uncertainty of the probability amplitude distribution of the AE waveform. An increase in the Shannon’s entropy indicates the occurrence of an internal change in the material, which can be due to the damage occurrence. The Shannon’s entropy of the AE waveform is obtained in three steps: 1) the voltage per the microsecond values of the waveform should be extracted, 2) the histogram of the discrete probability distribution of the voltage values is plotted with a small bin width, and 3) the Shannon’s entropy of each waveform is calculated using Eq. (3) [52]:

\[ H = \sum_{i=1}^{x} p(x_i) \cdot \log_2(p(x_i)) \]  

(3)

where \( H \) is the Shannon’s entropy, the waveform’s voltage values are given by \( x_1, x_2, \ldots, x_n \) and \( p(x_i) \) is the probability mass associated with \( x_i \). The Shannon’s entropy is a non-negative value and sum of the probabilities should be equal to 1.

3.2. Identification of different damage mechanisms

A composite structure might experience different types of damage in operation, including but not limited to matrix cracking, fiber breakage, fiber/matrix debonding, delamination and fiber pull-out. As already mentioned, the type of damage depends on several factors, such as the loading direction, loading rate, resin and fiber materials, laminate’s
Fig. 4. Damage initiation detection in glass/epoxy DCB specimen using different AE-based approaches.
layup, adhesion quality between the fiber and matrix and environmental conditions like temperature and humidity. The impact of these damages on the integrity of the structure is not equal. For example, micro-matrix cracks usually could not drop the stiffness and the integrity of the structure considerably, while delamination and fiber breakage significantly reduce the out-of-plane and in-plane load-bearing capacity of the structure. Therefore, detecting and distinguishing different damage modes can give a better perspective of the integrity state of the structure. In this case, AE technique has shown an excellent capability to identify different damage mechanisms in composite materials. The literature review reveals that each damage mechanism in composite materials usually generates AE signals with almost unique features. For example, matrix cracking is usually characterized by low amplitude, low frequency and long duration, long rise time and large counts. While, delamination is determined by the intermediate amplitude, low frequency and

**Table 2**

| K | Number of hits, N |
|---|------------------|
| Not applicable | <20 |
| 0 | 20 to 100 |
| 0.8 N | 101 to 500 |
| N-100 | >500 |
very long duration. On the other hand, fiber breakage produces signals with high amplitude, high frequency and short rise time [7,64,66,72]. Among all the AE features such as amplitude, rise time, duration, energy, centroid frequency and peak frequency, two features are treated as the most preferred AE features for damage identification: peak frequency and amplitude. Because the peak frequency is not highly affected by the attenuation phenomenon, it seems to be a better damage distinguishing parameter than the amplitude.

Tables 3 and 4 present the reported peak frequency and amplitude in literature for the AE signals of various damage mechanisms in different composites. The variations in the reported values for each damage mode can be related to the different types of sensors, loading conditions, boundary conditions and the sensors’ position. Irrespective of the variations, one conclusion is that matrix cracking usually has been identified by the lowest amplitude and frequency while the fiber breakage has been characterized by the highest amplitude and frequency. The delamination and interfacial debonding have been also identified by the average frequency and amplitude. However, Öz et al. [73] showed that this conclusion is not always true. They used in-situ digital image correlation (DIC) and AE to identify different damage modes in CFRP composites subjected to tensile loading. They correlated the recorded AE signals to the DIC results and found that the matrix cracking might also produce some high-frequency signals. They also reported that the amplitude of fiber breakage signals depends on the relative position of the damage respect to the specimen’s boundary. Thus, it is highly recommended that other complementary in-situ techniques like DIC, camera, and thermography are employed during the tests to find the sources of the originated AE signals. The results obtained from these techniques can be used in parallel to AE results to correlate the clusters of AE signals to the corresponded damage mechanisms confidently.

Distinguishing the AE signals originated from different damage mechanisms is still a challenging issue. This is because in a real composite structure, subjected to an arbitrary load, several damages usually occur simultaneously and their AE signals arrive at the sensor at the same time. Therefore, correlating each signal to a specific damage mode is not straightforward.

One solution for this problem is designing the specific test coupons with the biased damage modes, in a way that just one damage mode occurs in the coupon or at least one damage mode be the dominant one. Accordingly, the AE features of that damage mode could be captured irrespective of the other damages. By changing the coupon design, layup and loading condition, the AE signals of other damages can also be collected with the minimum interference together. For example, de Groot et al. [74] distinguished the different damage mechanisms, including matrix cracking, fiber/matrix debonding, fiber pullout and fiber breakage in carbon/epoxy laminates based on their frequency. To this aim, they designed and performed a couple of tests, including the tensile test on pure resin, uncured prepregs, $90\degree$, $10\degree$ and $90\degree$ coupons, and the fracture tests on the DCB and single lap joint specimens. The results showed that the AE signals of the pure resin and $90\degree$ coupons tensile tests are only generated by matrix cracking. While, in the case of DCB and single lap shear specimens, in addition to the matrix cracking, debonding also happened in the specimens. In the case of the tensile test of $0\degree$ coupons, besides the two previous damage modes, the fiber breakage and fiber pull-out were also observed. All the damage modes observed in $0\degree$ coupons occurred in $10\degree$ coupons again, except the fiber breakage. Finally, they could identify and distinguish the AE signals of all aforementioned damage modes by comparing the AE frequency of these tests (see Table 5).

Gutkin et al. [75] conducted five different types of test, including

### Table 3

| Reference | Material | Type of the test | Matrix cracking | Fiber/matrix debonding | Delamination | Fiber breakage | Fiber pullout |
|-----------|----------|------------------|-----------------|------------------------|--------------|----------------|---------------|
| [74]      | Carbon/epoxy | Tensile | 90–180          | 240–310                | –            | >300           | 180–240        |
| [75]      | Carbon/epoxy | Tensile, compact tension, compact compression, DCB and 4-ENF | <50 | 200–300          | 50–150       | 400–500        | 500–600        |
| [09]      | Carbon/epoxy | Tensile | <300            | –                       | –            | >500           | >500           |
| [05]      | Carbon/epoxy | Quasi-static indentation | <150 | –              | 150–300        | >400           | –             |
| [100]     | Carbon/epoxy | 3 PB | 60–120          | –                       | 120–210      | 200–350        | –             |
| [08]      | Carbon/epoxy | Tensile | <100            | 200–300                 | –            | 400–450        | –             |
| [102]     | Carbon/epoxy | Tensile | 20–400          | 30–400                  | 120–360      | 50–500         | –             |
| [03]      | Graphite/epoxy | Tensile | <120            | –                       | –            | 120–180        | –             |
| [106]     | 2D woven carbon/epoxy | Tensile | <100            | 150–300                | <100         | 350–600        | –             |
| [105]     | 2D and 3D woven carbon/epoxy | Tensile | <300            | –                       | –            | >300           | –             |
| [63]      | Glass/epoxy | DCB | 140–250         | 250–350                 | –            | 350–450        | –             |
| [77]      | Glass/epoxy | Open-hole tensile (OHT) | 80–250          | 250–375               | –            | 375–480        | –             |
| [106]     | Glass/polypropylene | Tensile | Around 100      | –                       | –            | 150–250        | –             |
| [07]      | GFRP | 45.7-m long wind turbine blade loaded in the flap-wise direction | <30 | 120–250          | 30–120       | –              | –             |
| [108]     | 2D woven glass/epoxy | Tensile | <180            | –                       | >180         | >180           | –             |
| [109]     | 2D and 3D woven glass/epoxy | Tensile | 50–80          | 50–150                  | 150–500      | 150–500        | –             |
| [72]      | Kevlar-woven composites | High strain rate impact | Near 106   | Near 110             | –            | >300           | Near 110       |
| [110]     | Hybrid of carbon & glass/epoxy | Tensile | 200–600         | 200–350                | 100–500      | >1500          | 700–1100       |
| [54]      | Sandwich composite with glass/epoxy skins | DCB | 170–250         | 50–170                  | 350–500      | –              | –             |
| [111]     | carbon/Kevlar hybrid woven composites | High strain rate compressive loading | Near 190 | Near 110            | –            | (Near 400 for carbon) | Near 110       |
| [112]     | Glare, graphite/epoxy and carbon/carbon | Tensile, compact tension, Flexural | Around 140 | Around 300          | –            | Around 405     | –             |
tensile, compact tension, compact compression, DCB and ENF, on CFRP coupons to obtain the AE frequency of the five different damage mechanisms. These damages were matrix cracking, fiber breakage, fiber/matrix debonding, delamination and fiber pull-out. Saeedifar et al. [76] distinguished the AE signals of different damage mechanisms in the adhesively-bonded hybrid double-lap joints using AE. The damages observed in the double lap joints were CFRP skin failure, core steel deformation, adhesive layer failure (which was named cohesive failure) and delamination at the interface of the adhesive layer with CFRP skin or steel core (which was name adhesive failure). In order to characterize the AE signals of the five different damage mechanisms, they conducted four series of tests on the constituent materials: 1) the tensile and shear tests of steel, 2) tensile, in-plane mode I and mode II shear tests of adhesive, 3) tensile test of CFRP and 4) DCB test of CFRP to steel and steel adhesively-bonded coupons. To obtain the AE signals of matrix cracking and fiber breakage, some researchers [54,77] performed tensile tests on pure resin and fiber bundle coupons while the originated AE signals were recorded. This damage identification process requires a large experimental effort and a database with AE characteristics of each individual damage mechanism should be created. As aforementioned, the AE features of each damage mechanism could be obtained by performing the individual constituent tests, but the AE dataset of a damaged composite structure usually contains the AE signals of several damage mechanisms mixed together.

The second level of damage assessment of a composite structure is partitioning the AE signals of different damage mechanisms. This process is usually done according to one of the four following ways: 1) manual discriminating of the AE data, 2) unsupervised clustering, 3) supervised classification and 4) signals processing. The details of the studies devoted to the damage identification and damage clustering using AE are presented in Table 5. Some literature [44,64,74] used one or two AE features, mostly peak frequency and amplitude, to manually group the AE data and to correlate them to the different damage modes. For instance, Nikhbakht et al. [44] manually categorized the AE data recorded during the DCB test into three groups based on their frequency. They correlated these groups to matrix cracking, fiber/matrix debonding and fiber breakage. They also used the in-situ microscopy images to verify the AE results. However, sometimes different damage mechanisms are not completely differentiated using just one AE feature. In this situation, it is better to use multiple AE features simultaneously to identify the damage type with more confidence. In this case, due to the complex relations among the different AE features, the data partitioning process is usually done by the machine learning techniques: unsupervised and supervised techniques. Unsupervised clustering techniques like k-means, genetic k-means (GKM), fuzzy c-means (FCM), Gaussian mixture distribution (GMD), self-organizing map (SOM) and hierarchical models have been frequently used for damage clustering in composite materials. Generally, all unsupervised clustering techniques try to partition a set of AE signals, \((X_1, X_2, ..., X_n)\), into \(k\) clusters (\(k\leq n\), \(C_1, C_2, ..., C_k\)). Among the unsupervised clustering techniques, k-means has been widely used in literature to discriminate different damage mechanisms in laminated composites [4,78–82]. K-means clusters AE data in two steps; it first selects the initial clusters and each cluster randomly and each data point is assigned to the cluster with the nearest cluster’s centroid (Eq. (4)). In the second step, the new centroid of each cluster is updated to the average value of all the data points, which are inside the cluster (Eq. (5)) [83]:

\[
C_{i}^{(t+1)} = \left\{ X_{n} : \|X_{n} - m_{i}^{(t+1)}\|^2 \leq \|X_{n} - m_{i}^{(t)}\|^2 \right\}, 1 \leq j \leq k \quad (4)
\]

\[
m_{i}^{(t+1)} = \frac{1}{\left| C_{i}^{(t+1)} \right|} \sum_{j \in C_{i}^{(t+1)}} X_{j} \quad (5)
\]
## Table 5
Damage distinguishing in laminated composites using AE.

| Material | Type of the test | Types of damage | Utilized method | Utilized AE parameters | The utilized method to validate AE results | Ref. |
|----------|------------------|-----------------|-----------------|------------------------|------------------------------------------|------|
| The manual partitioning of AE data | Carbon/epoxy Tensile | Matrix cracking, fiber/matrix debonding, fiber pull-out and fiber breakage | Manual clustering | Peak frequency | Performing the tensile tests on resin, uncured prepregs, 0° and 90° coupons, and also DCB specimens | [74] |
| | Hybrid of thin carbon/epoxy and conventional glass/epoxy | Tensile | Fiber fracture and ply fragmentation | Manual clustering | Amplitude and AE energy | Visual inspection of the specimens | [64] |
| | Glass/epoxy DCB | Matrix cracking, fiber/matrix debonding and fiber breakage | Manual clustering | Peak frequency | Microscopy images | [44] |
| | Glass/epoxy Tensile and compression tests on dogbone samples and single-lap bonded joints | Matrix micro crack, matrix macro crack and fiber breakage | Manual clustering | Peak frequency | DIC | [125] |
| Damage partitioning using one method | Glass/epoxy Quasi-static and fatigue tensile tests | Matrix cracking, fiber/matrix debonding, delamination, fiber breakage | k-means | Amplitude, energy, rise time, counts and duration | SEM images from the fractured surfaces | [4] |
| Unsupervised and supervised techniques | Carbon/flax fiber hybrid composites | Tensile | Matrix cracking, fiber/matrix debonding, delamination and fiber breakage | k-means | Amplitude, absolute energy, duration, counts to peak and rise-time | SEM images from the fractured surfaces | [79] |
| | Glass/carbon fiber hybrid composites | Pure bending and tensile tests | Matrix cracking, interface failure, fiber breakage and fiber pull out | k-means | Amplitude, Counts, Rise time, Peak frequency, weighted frequency, partial powers | Weighted peak frequency and partial power | [82] |
| | Woven carbon/epoxy | Tensile and flexural tests | Matrix cracking, interface failure and fiber breakage | k-means | Weighted peak frequency and partial power 1 | SEM and DIC | [78] |
| | Flax, glass and hybrid flax-glass fiber woven composites | DCB | Matrix cracking, interface failure, delamination and fiber breakage | k-means | Amplitude, duration, number of counts, energy and rise time | SEM | [81] |
| | Flax fiber reinforced thermoplastic composite | Quasi-static and fatigue tensile tests | Matrix micro-cracking, fiber-matrix debonding, fiber pull-out and fiber breakage | k-means | Amplitude, duration, rise time, energy and numbers of counts to peak | – | [80] |
| | 2D and 3D woven carbon fiber/epoxy | Tensile | Matrix cracking, delamination and fiber breakage | k-means++ | Amplitude, peak frequency and centroid frequency | – | [105] |
| | Glass/epoxy 3 PB | Matrix cracking, fiber/matrix debonding and fiber breakage | FCM | Amplitude, duration and average frequency | SEM images | [7] |
| | Glass/epoxy and carbon/epoxy Tensile test on rod type specimens | Matrix cracking, fiber/matrix debonding and fiber breakage | FCM | Duration, peak amplitude, energy, and the number of counts | SEM images | [36] |
| | Hemp/epoxy and Glass/epoxy 3 PB | Matrix cracking, delamination, Interfacial debonding and fiber breakage | GMD | Peak frequency | – | [66] |
| | Glass/epoxy Buckling | Matrix cracking, delamination and fiber breakage | GMD | Peak frequency and amplitude | Camera images | [71] |
| | Carbon/epoxy Tensile | Matrix cracking, delamination and fiber breakage | SVM | Rite time, counts, duration, amplitude and energy | – | [85] |
| | Carbon/carbon Tensile | Matrix cracking, fiber/matrix debonding, fiber pullout, thermal stress relief, fiber arrangement to the loading direction, matrix friction, fiber push-in and single fibers and fiber bundles failure | Unsupervised clustering | Parametric load, amplitude, rise angle, reverberation frequency | – | [126] |
| Hybrid of flax/epoxy and glass/epoxy Tensile | Matrix cracking, fiber breakage and fiber/matrix debonding | Combining principal component analysis (PCA) and FCM | Amplitude, duration, rise time, counts and energy | SEM images | [86] |
| Glass/epoxy Creep tensile | Matrix cracking, fiber breakage and fiber/matrix debonding | Combining PCA and FCM | Duration, sum and maximum of the square moduli of continues wavelet transform coefficients and maximum of the square discrete wavelet transform detail coefficients | – | [87] |
| Sandwich composite with glass/epoxy skin and foam core DCB | Interfacial debonding, matrix cracking, fiber breakage and core failure | Combining PCA and GKM | Amplitude, peak frequency and energy | Camera and SEM images | [61] |

(continued on next page)
where $C_i^{(t)}$ is cluster $i$ and $m_i^{(t)}$ is the center of cluster $i$ at iteration $t$.

These two steps are repeated until the stop criterion is met, i.e. the maximum number of iterations or a minimum value of changing the cluster centroid’s position between two consequent iterations. Although this technique is simple and has a low computational cost, there is no guarantee that it always converges to the optimum results. In other words, there is a possibility that the algorithm partitions data incorrectly. This is due to the random selection of the initial clusters and hence using FCM is similar to k-means with the difference that in FCM, a membership parameter is defined that allows a data point belongs to more than one cluster at the same time, with different membership values from 0 to 1 (more details about this technique can be found in Ref. [83]). To overcome this limitation, some researchers tried to improve this technique by adding a fuzziness parameter to k-means, which is named fuzzy c-means (FCM), or combining k-means with the genetic algorithm, which is named genetic k-means (GKM) algorithm. The clustering process using FCM is similar to k-means with the difference that in FCM, a membership parameter is defined that allows a data point belongs to more than one cluster at the same time, with different membership values from 0 to 1 (more details about this technique can be found in Ref. [84]). To find the best clustering, FCM tries to minimize objective function $J(X; C)$ (Eq. (6)) [84]:

$$J(X; C) = \sum_{j=1}^{n} \sum_{i=1}^{k} \gamma_{ij}^2 \|X_j - C_i \|^2$$

(6)

where $\gamma_{ij}$ is the membership parameter and $\alpha$ is the fuzzier. The objective function will be minimized if [84]:

$$y_j = \frac{1}{\sum_{m=1}^{n} \left( \gamma_{jm} \right)^{1-\alpha}}; \quad 1 \leq j \leq n$$

(7)

and

$$C_i = \frac{\sum_{j=1}^{n} \left( \gamma_{ij} \right)^{p} X_j}{\sum_{j=1}^{n} \left( \gamma_{ij} \right)^{p}}; \quad 1 \leq i \leq k$$

(8)

In the case of GKM algorithm, the genetic algorithm is used to create better clusters’ centroids in the new iterations by crossover of the previous clusters’ centroids (more details about this technique can be found in Ref. [61]). FCM and GKM have been widely used for damage clustering in composite materials under different loading conditions such as tensile [36, 85, 86], creep tensile [87], 3 PB [7] and fracture mode I [61, 88]. Besides k-means-based methods, other methods like GMD and SOM have been also utilized for damage clustering in composites [5, 66, 71].
GMD assumes that the whole dataset can be expressed as a weighted summation of several Gaussian densities with unknown parameters \( p(x) \) \[89\]:

\[
p(x) = \sum_{k=1}^{K} w_k g \left( \frac{x - \mu_k}{\sigma_k} \right)
\]

where \( g \) is the Gaussian density function with mean vector \( \mu_k \) and covariance matrix \( \Sigma_k \), \( X \) is data and \( w_k \) is the mixture weight function.

\[9\]

The drawback of the hierarchical model is the low rate of the clustering formation can be found in Ref. \[90\]).

The last group of researchers used the signal processing techniques for distinguishing damage modes in composite materials. The frequently used technique in this group is wavelet transform (WT). In WT, a signal is decomposed into low and high frequency subcomponents. Based on the type of WT, both of the low and high frequency parts (packet wavelet transform) or just the low frequency part (discrete wavelet transform) will be decomposed in the other levels till the original signal finally is decomposed into several subcomponents with different frequencies (see Fig. 7). Then, based on the frequency of subcomponents, one or some of them are correlated to the specific damage modes. In the case of AE signals, because most of the times valuable information is placed in the high frequency components (for example, fiber damage signals), packet wavelet transform is usually preferred over discrete wavelet transform.

The frequency range of each subcomponent in the packet wavelet transform tree is calculated using Eq. (14) \[93\]:

\[
\left[ n f_2^{-1}, (n+1) f_2^{-1} \right]
\]

where \( f_2^{-1} \) is the frequency of the coarsest subcomponent and \( n \) is the number of subcomponents. In this study, the frequency range of each subcomponent is calculated using Eq. (14) \[93\]:

\[
\left[ n f_2^{-1}, (n+1) f_2^{-1} \right]
\]
Fig. 5. The performance of k-means, GKM, FCM, SOM, GMD and hierarchical methods to partition the AE signals into three groups (the data belongs to carbon/epoxy laminates subjected to the indentation load) [5].
where $f_s$ is the AE sampling rate, $i$ shows the level of decomposition, and $n$ shows the label of subcomponent, which is equal to $n = 0, 1, \ldots, 2^i - 1$ for decomposition level $i$.

The energy percentage of each subcomponent, respect to the original signal, shows the amount of its corresponding damage mode in the composite structure (more information about WT can be found in Refs. [93,94]):

Fig. 6. The performance of SOM, FCM, GKM and hierarchical methods to partition the artificial AE dataset into four groups at different iterations [3].
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\[ E_n^i = \sum_{t=0}^{T} f_n^i (T)^2 \]  

(15)

\[ P_n^i = \frac{E_n^i}{\sum_{t=0}^{T} E_n^i} \]  

(16)

where \( E_n^i \) is the energy of subcomponent \( n \) located in level \( i \), \( f_n^i \) is the wavelet subcomponent, \( c_n^i \) and \( d_n^i \) show its time period, and \( P_n^i \) represents the energy percentage of the subcomponent respect to the original signal.

WT technique has been used successfully for damage mechanisms identification in FRP composites subjected to tensile [59,95,96], fracture modes I, II, mixed-mode I&II [40,41,54,60] and LVI [55,97] loading conditions. In addition, a good consistency between the quantified damages by this technique and the other unsupervised techniques like FCM [40,41,55] and hierarchical model [97] has been reported in the literature. Beside WT, some other signal processing techniques have been rarely used in literature. For example, Beheshtizadeh et al. [98] compared the performance of Choi–Williams transform with WT for damage characterization in glass/epoxy and carbon/epoxy laminates, subjected to 3 PB loading conditions. They reported that the sensitivity of WT to the low-intensity part of the signals is higher than Choi–Williams. It is due to the fact that the exponential kernel function of the Choi–Williams transform resulted in the missing of some small details. The last signal processing technique used in literature is Hilbert transform (HT). Nazmdar et al. [60] used HT to determine the damage type in glass/epoxy ENF specimens. They used the phase angle parameter of HT as a feature to obtain the frequency of different damage modes.

4. Damage prognostics

Prognostics is a new dynamically rising field where researchers utilize SHM data, machine learning algorithms and probabilistic modeling aiming to provide estimations for the future condition of a composite structure. They focus their efforts on the predictions of remaining useful life (RUL) and residual strength and they design prognostic frameworks with the capability to perform analysis in real-time. In order to succeed that, the availability of online SHM data is essential and AE is good candidate that fulfills this requirement.

Nevertheless, the literature review reveals that there is a limited number of papers published in the prognostics field where the researchers utilize AE data. The papers published in this field can be divided into the three groups, based on the models the authors adopt in order to perform predictions: regression analysis, artificial neural network (ANN) and hidden Markov-based models. The details of the studies focused on the prognostics of laminated composites using AE are presented in Table 6.

The first group of literature used a linear or non-linear regression analysis to find a mathematical correlation between a special AE indicator and a mechanical property of the composite structures, mostly strength and RUL. Then, the mathematical model is used to extrapolate the mechanical properties of the structure in the future using the AE data of the structure. Philippidis and Assimakopoulou [130] used a non-linear data fitting to formulate a regression model between the AE counts and the residual strength of glass/epoxy coupons which were subjected to the constant and variable amplitude fatigue load. Then, they used the model to predict the residual strength of two new specimens: one with a different matrix material but under the same loading conditions as the previous ones and the other one with the same matrix but subjected to a new variable-amplitude fatigue load. The average
error of residual strength prediction for the coupon with the new loading condition and the coupon with new matrix material was 2.89% and 5.46% respectively. Caprino et al. [131] used an exponential regression model to correlate the 4 PB residual strength of pre-fatigued glass/epoxy composites to the total AE counts that had been recorded at the maximum stress level of the pre-fatigue tests.

The second group of researchers used ANN to predict the residual strength of pre-fatigued composite coupons based on their AE activities. The prediction process is usually done in two steps: first, the ANN is trained by the AE data collected from the already tested specimens and then, after the sufficient training, the ANN model is used to predict the degradation of the mechanical properties of a new coupon. Rajendrachopatthy et al. [132] did the tensile test on 18 glass/epoxy specimens. They separated 12 specimens as the training set and used the collected AE data up to 30%, 40%, and 50% of the failure load. Afterward, this AE data and the corresponding maximum strength were used to train the ANN. After the training process, ANN was employed to predict the residual strength of the 6 remained specimens based on their AE activities. The results showed the ANN that was trained with more data (AE data up to 50% of failure load) had a better prediction. Arumugam et al. [133] performed tensile tests on the low-velocity impacted carbon/epoxy laminates. They used the collected AE data up to 50% and 75% of the tensile failure load of the impacted specimens to train an ANN. Then, the trained model was used to predict the residual strength of some new samples with an error range of 0.4%–15%. They claimed that the proposed technique could predict the residual strength of impacted laminates just by loading them up to a percentage of their maximum load without inducing severe damages in them. However, Loutas et al. [134] showed that the nonhomogeneous hidden semi Markov model (NHHSMM) could predict RUL of OHT carbon/epoxy specimens, subjected to the fatigue load, better than ANN, Bayesian neural networks (BNN) (see Fig. 8). They cited three reasons for the superiority of NHHSMM over BNN: 1) BNN works almost as a black box, 2) the oscillation of BNN predictions is much higher than NHHSMM, and 3) despite the claim of the aforementioned literature, the accuracy of BNN prediction is not improved by increasing the numbers of data, while the accuracy of NHHSMM is continually improved as more online AE data come into play. Eleftheroglou et al. [135] used NHHSMM to predict RUL of CFRP specimens using the AE data and DIC results. The results showed that the accuracy of RUL prediction was improved considerably by data fusion in comparison with using the AE data individually.

5. Conclusions

This review addresses the employment of AE technique for damage characterization in laminated composites. The review was structured in two main sections: damage diagnostics and damage prognostics. A comprehensive damage diagnostic is usually done in three levels: damage initiation detection, damage identification and damage localization. Because damage localization was fully addressed in a recently-published review paper, it was not discussed here anymore. In the second section, three main prognostic approaches using the AE data were presented: regression models, ANN and hidden Markov-based models. The main conclusions of the review are listed hereafter:

- Most of AE features such as amplitude, energy, rise time, duration, counts, centroid frequency and peak frequency are highly affected by
the sensor/source distance, sensor type, specimen's geometry and composite lay-up, coupling quality, damage state of the structure and user define parameters, i.e. threshold level, HDT and PDT parameters. These parameters should be taken into account to reach a reliable and robust AE monitoring of composite structures.

- The techniques that directly work with the AE waveform, such as Shannon’s entropy and wavelet transform, can at least minimize the effect of threshold level and HDT and PDT parameters.
- Many researchers proposed the descriptive/qualitative criteria to detect the initiation of damage in laminated composites using AE that could result in different interpretations of damage initiation. Future work should be focused on the definition of some AE-based quantitative criteria for damage initiation detection tailored to the specific composite configurations. The historic index proposed by ASTM E2478-11 standard can be used as the foundation of future work.
- Different unsupervised clustering methods have been widely used for AE signals clustering. The performance of these methods depends on the structure of the AE dataset. For example, for a simple AE dataset, k-means-based techniques, which are simple and fast, may work appropriately. While, for the reliable partitioning of a complicated AE dataset, hierarchical model, which has a higher computational cost, should be used. In addition, the repeatability of the clustering results should be evaluated.
- When a well-labeled training dataset is available, supervised classification techniques should be preferred over unsupervised clustering techniques to distinguish the complicated AE dataset meaningfully. Thus, it is recommended that the researchers create labeled-training dataset although it may requires extensive experimental campaigns.
- Prognostics is a new dynamically rising field, where researchers opt to predict the RUL and the strength of composite structure. In comparison with diagnostics-related literature, there is a limited number of papers where AE is utilized in order to provide the required input.
- The prognostics-related papers are categorized in three groups, based on the type of prediction models: regression models, neural networks-based models and hidden Markov-based models, which by moving from the first one to the last one, the complexity but also the reliability of the models increase.

Declaration of Competing interest

There is no conflict of interest.

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