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Review

The Damage identification based guided waves in composite structures with AI schemes: A review

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Abstract: Lamb waves (LWs) are guided waves (GWs) with unique properties that make them ideal for Non-Destructive Testing (NDT) and Structural Health Monitoring (SHM). Over the last two decades, LW-based techniques have gained significant traction in academic and industrial research. A primary advantage of LWs is their ability to propagate over long distances in plate or shell structures, navigating curves and reaching hidden or buried areas, capabilities essential for detecting interlaminar damage in composites. As LW wave structures are frequency and phase-velocity-dependent, they are now suitable for various engineering applications, offering a promising, cost-effective solution for automated, real-time structural integrity monitoring. This paper provides a comprehensive overview of LW behavior, modeling, applications, and limitations in detecting fatigue damage within composite structures. Furthermore, the study explores the integration of Artificial Intelligence (AI) algorithms, including Artificial Neural Networks (ANNs), Machine Learning (ML), and Deep Learning (DL), which have emerged as powerful tools for predicting fatigue damage. By leveraging historical data from LW sensing systems, these AI models can accurately forecast structural conditions without the need for complex analytical modeling, significantly reducing processing time.

Keywords: Lamb waves technique; piezoelectric transducers (PZTs); fatigue damage detection; composite structures; artificial neural networks (ANNs); machine learning (ML); deep learning (DL)

1. Introduction

Composite materials have become widely used in engineering across a variety of fields. It's particularly important in industries like aviation, aerospace, and automotive, and is also utilized in constructing ships, submarines, and nuclear and chemical facilities. These materials offer impressive stiffness and strength relative to their weight, as well as enhanced resistance to fatigue and damage.

The expanding use of composite materials in increasingly ambitious projects, such as taller buildings, longer bridges, and larger aircraft, is driving a critical need for advanced structural health monitoring and damage detection.

Common issues that can arise include things like fiber breakage, matrix cracking, debonding between fibers and the matrix, and delaminations or interlayer cracks. These types of damage can seriously impact the strength and overall structural integrity. So, catching these problems early is crucial to avoid catastrophic failures, especially since these structures are often expected to perform well near their limits.

A solid monitoring system can keep tabs on the development of structural damage, allowing for timely maintenance or repairs to maintain safety and integrity.

One effective way to achieve this is through SHM systems. By adding extra safety measures, SHM systems help maximize the lifespan of structures and can also lower the overall costs related to maintaining them.

SHM is an expanding field with applications across rotating machinery, offshore platforms, aerospace, and civil infrastructure [1,2]. Implementing SHM is critical for assets where failure poses a risk to human life, particularly in composite structures. Early detection of damage allows for timely intervention, such as restricting usage or performing essential repairs, to prevent catastrophic failure.

SHM aims to assess a structure's health by using a set of sensors that are permanently installed on it, keeping tabs over time. It starts with a check-up on the structure's safety and general condition, then looks at how much life it has left. There are two ways to do SHM: passively and actively. With passive SHM, the sensors just 'listen' to the structure to catch any changes in the components. On the other hand, active SHM involves a network of sensors that actively probe the structure’s health, helping to figure out if there’s any damage or not. In recent years, a variety of quantitative methods have been researched and put into practice for detecting damage in both metal and composite structures. Most of these methods depend on non-destructive (ND) techniques.

LWs techniques offer significant potential for damage detection in composite structures across diverse engineering sectors. Compared to traditional NDT methods, LW-based approaches provide faster, more cost-effective assessments of various damage types. While monitoring complex geometries requires specialized expertise, a primary advantage of LWs is the ability to inspect large areas using a minimal number of transducers. However, optimizing transducer placement remains a significant challenge. The integration of piezoelectric transducers (PZTs) with guided LWs has gained considerable traction due to their superior weight, cost, and functional benefits [3,4].

The piezoelectric effect can be thought of as a connection between mechanical and electrical aspects of a material, like mechanical stress, strain, and electric field or charge. Basically, when mechanical stress is put on a piezoelectric material, it generates an electrical charge, which we refer to as piezoelectricity. This means that the one-dimensional movement can be used to deform the piezoelectric in various ways (just look at **Figure 1**). Plus, this process works both ways; an electric field or charge can be applied to create mechanical strain or stress. **Figure 2** illustrates both the direct and reverse mechanisms involved in the piezoelectric sensing process, which is useful for monitoring structures.

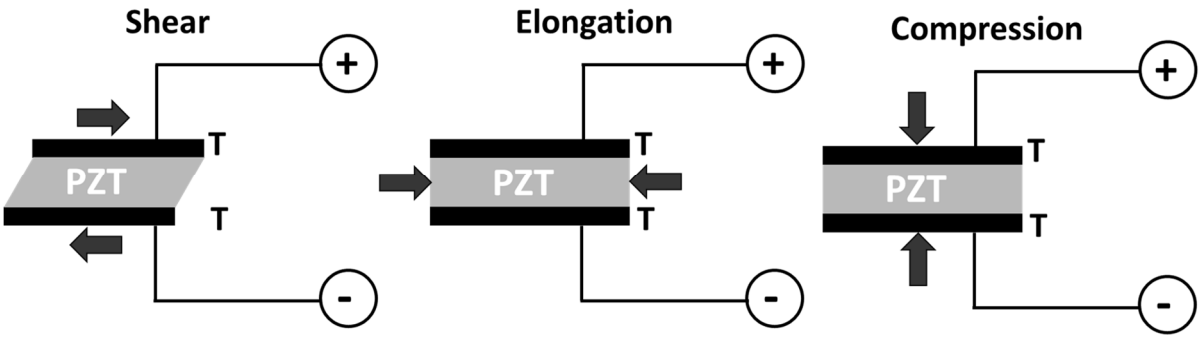

Figure 1. PZTs deformation modes.

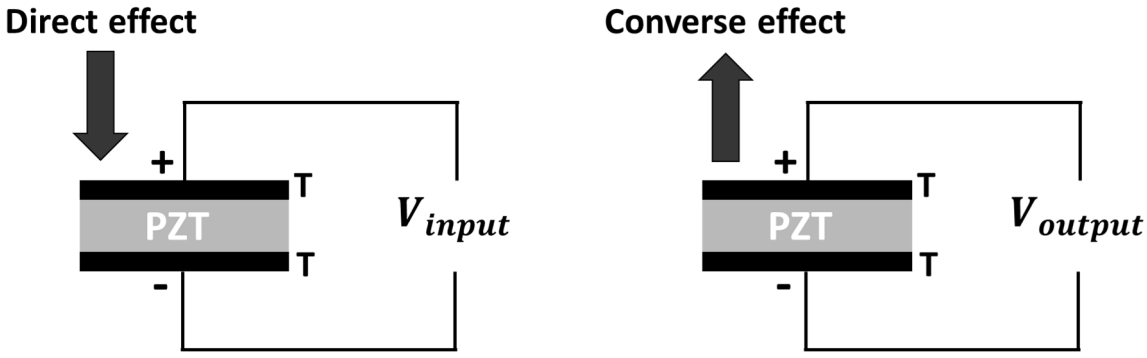

Figure 2. The direct and inverse response principle in the PZTs effect.

LWs inspection relies on waves moving through flat structures, and these waves react to any damage present. To detect changes in the LWs responses, first need to collect baseline signals that show what it looks like when there's no damage.

LWs offer several advantages for NDT. They can propagate over significant distances, even within high-attenuation materials like composites. Furthermore, LWs are highly sensitive to internal interference, enabling the efficient inspection of large areas such as aircraft wing skins [5]. Unlike surface-level methods, LWs can detect both surface and internal defects by utilizing various modes to access the material's full thickness. In summary, LW-based detection provides five key benefits: (1) the ability to inspect large structures through coatings or insulation; (2) full cross-sectional coverage over long distances; (3) the elimination of expensive structural probing; (4) the capacity to identify multiple defects simultaneously; and (5) low energy consumption and operational costs [5]. By analyzing LW data, engineers can diagnose, locate, and characterize the severity of fatigue damage in fiber-reinforced polymer (FRP) structures, ultimately providing more accurate estimates of their remaining useful life.

Next, looked into the various LWs methods that have been developed for detecting damage in composite structures over the years. Also, explored key topics like where to best place sensors, telemetry approaches, system identification techniques, and the use of finite element (FE) methods. One of the highlights is the use of ANNs, which have become a go-to method for predicting fatigue damage in composite structures recently.

Before diving into how fatigue damage detection works in composite materials with LWs, there are a few important points to consider. First, one needs to have a solid grasp of the composite materials themselves, including their failure mechanisms and fatigue behaviors, as well as what influences them. Then, should take a close look at the methods used to detect fatigue damage in these structures, particularly NDT techniques. Finally, it's crucial to review previous research on the topic to establish a basis for comparison.

1.1. Composite materials

The adoption of composite materials has increased significantly in recent years, driven primarily by their superior specific strength, stiffness, fatigue resistance, and damage tolerance. These advantageous properties have led to their widespread integration across the construction, automotive, aerospace, marine, and sporting goods industries. In aerospace specifically, composites are utilized for critical components such as radomes, wing panels, and stabilizers. A primary example of this shift is the Boeing 787 Dreamliner, which features an airframe composed largely of composite materials, as illustrated in **Figure 3** [6].

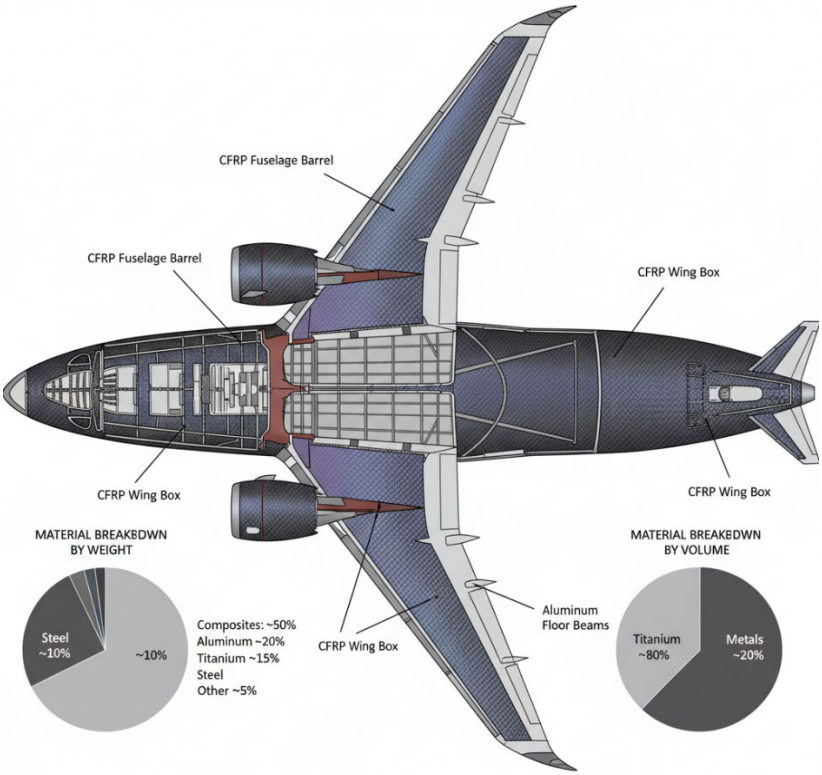

Figure 3. The composite materials percentages in Boeing 787.

When it comes to composite materials, key mechanical traits like strength, stiffness, and fatigue life are crucial. Figuring out the integrity and reliability of these structures is a must. Over the past few decades, composite structures have posed significant research challenges, mainly because they have been used more and more across different applications, from mechanical setups to structural systems. These

composites often face both static and fatigue loads. In fact, it's been noted that around 80% of failures in mechanical and structural components relate to fatigue [7].

1.2. The mechanisms of failure

Because composite materials are anisotropic, they can experience various failure modes either at the same time or one after another before the entire structure gives way.

Typically, when composites face static loading, they fail due to a mix of different interacting mechanisms that ultimately lead to a break. For laminates, as well as single layers, different types of damage mechanisms can be observed. Often, the failure happens at the point where the matrix meets the reinforcement, which is known as debonding, especially at defects that are almost always present in composites, largely because of how it's made. Other frequent failure modes include matrix cracking, fiber rupture, delamination (in laminates), and buckling (especially under compression) [8].

Fatigue damage in composite materials initiates early in the loading cycle. The fundamental mechanisms governing fatigue behavior under both uniaxial [9–12] and multiaxial [13–15] loading are well-documented and consistent. This damage typically progresses through three distinct stages: matrix cracking (Phase I), the initiation of local delaminations from those cracks (Phase II), and the coalescence of delaminations leading to ultimate failure (Phase III). Correspondingly, the structural stiffness exhibits three similar phases: a rapid initial degradation during the first 10–20% of the fatigue life due to matrix cracking, followed by a gradual, near-linear decline. In the final stage, damage accumulates exponentially, leading to a 'sudden death' failure [16], as illustrated in **Figure 4** [17].

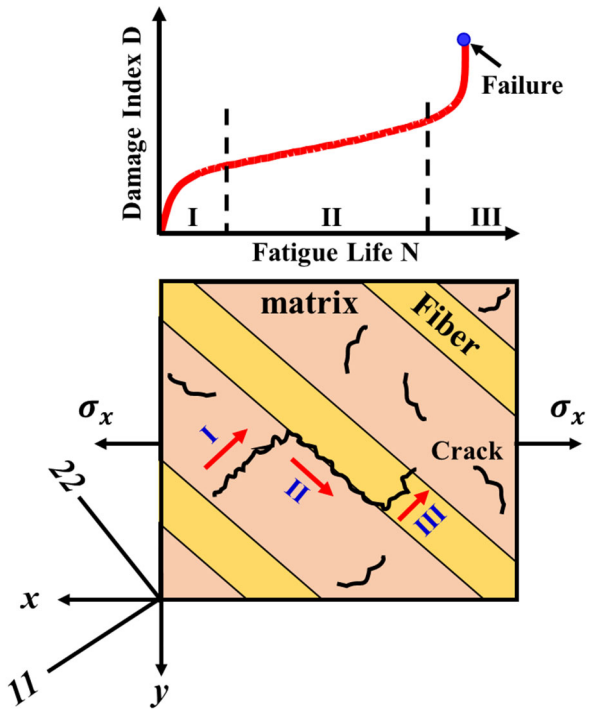

Figure 4. The Failure mechanisms phases.

Schulte et al. [18,19] were the first to mention this three-phase stiffness reduction, and since then, it's been seen in a variety of composite materials, including woven composites [20,21].

Fiber-reinforced composites are made up of three different phases, and because of that, failure can happen in any one of those phases or at the boundaries where they meet. So, the types of failures in these composites include fiber breaks, cracks in the matrix, debonding, and delamination (**Figure 5**).

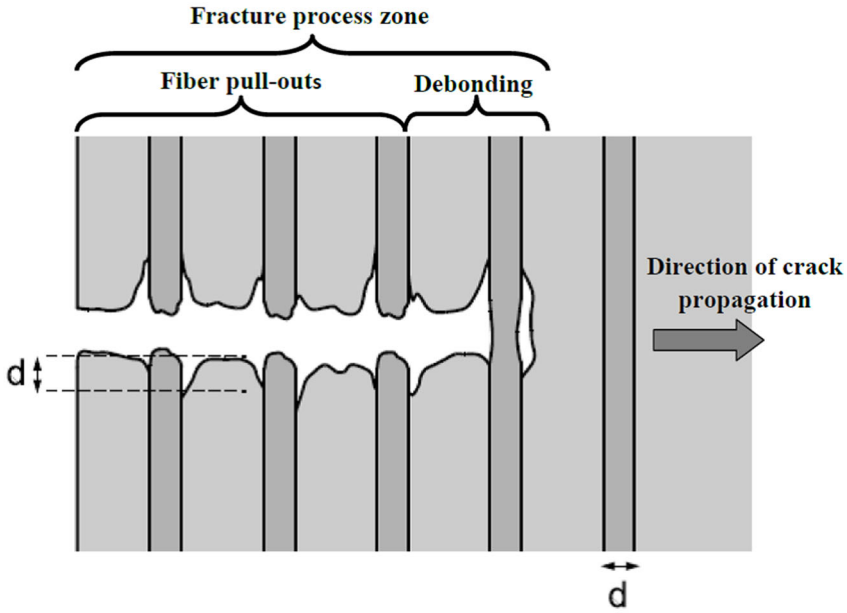

Figure 5. Failure modes on a laminate.

1.3. The fatigue behavior

The fatigue behavior of composite materials is inherently complex due to their anisotropic and heterogeneous nature. Despite extensive research into these characteristics, design methodologies often continue to rely on exhaustive fatigue testing and conservative safety factors. For unidirectional (UD) composites under axial tension-tension loading, fatigue resistance is governed by the interaction between the fibers, matrix, and their respective interfaces. These damage mechanisms are typically characterized using a Fatigue Life Diagram (FLD), which partitions fatigue behavior into three distinct regions. The specific morphology of these regions on the FLD depends on the constituent properties and interfacial bonding, as illustrated in the schematic representation in **Figure 6**.

Within the FLD, Region I represents the quasi-static failure scatter band, which remains independent of cyclic loading and is not solely governed by the matrix. In contrast, Regions II and III are primarily influenced by the fatigue properties of the matrix, though they are also affected by fiber stiffness, interfacial bonding, matrix inelasticity, and the specific loading conditions. Specifically, in Region II, stiffer fibers can impede the growth of fiber-bridged cyclic cracks, thereby extending fatigue life. Furthermore, high-stiffness fibers more effectively arrest matrix fatigue cracks, increasing the fatigue limit, a trend indicated by the arrows in **Figure 6**. A comparison between glass-epoxy (GFRE) and carbon-epoxy (CFRE) composites in **Figure 7**

clearly demonstrates this effect; the transition from glass to carbon fibers results in a significant shift of Region II toward a longer fatigue life.

The two regions, Regions II and III, in FLD are significantly influenced by some other critical factors, and these can be ranked based on their impact on FLD: (1) loading types [22,23], (2) loading frequency [24–26], (3) volume fraction (V_f) [27–29], (4) fiber orientation [30,31], (5) mean stress and stress ratio [32,33], (6) environmental factors [34,35], (7) sizing and stress gradient [36,37], (8) surface finish [38,39], and (9) stress concentration [36,40] (9) adhesive joint type [41,42], (10) thermal and other factors [43,44].

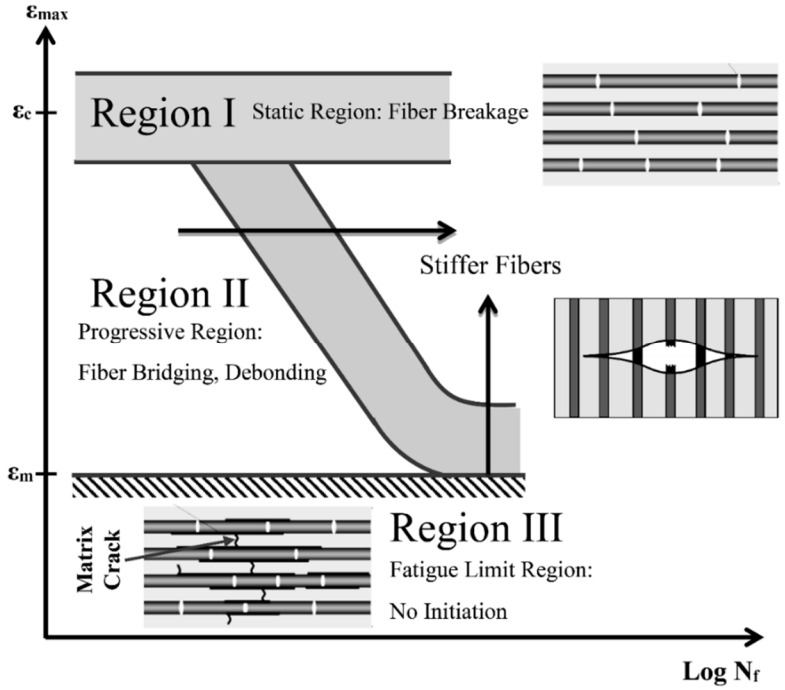

Figure 6. UD composites fatigue life diagram (FLD) (axial tension–tension loading).

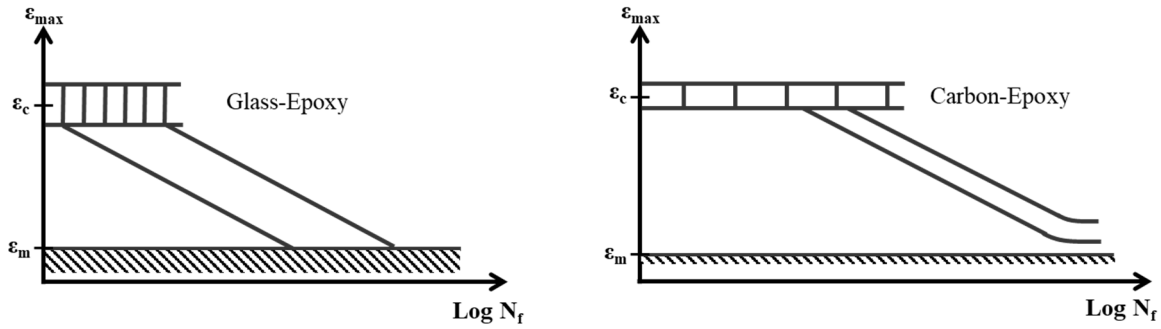

Figure 7. FLD for GFRE (left) and CFRE (right) at three fiber volume fractions [23].

1.4. Fatigue failure criteria

Under fatigue loading, materials experience stress levels below their ultimate static strength; however, cyclic loading causes a progressive deterioration of material properties. Failure occurs when the residual strength degrades to the level of the

applied stress. Numerous researchers have utilized polynomial failure criteria to estimate the fatigue life of composites [45–50]. Rather than relying on static strength, these models incorporate fatigue strength as a function of cycle count within the denominator of the failure criteria, a method that significantly enhances the detection and prediction of fatigue damage. For over thirty years, global research has focused on developing such failure models to elucidate damage mechanisms. As illustrated in **Figure 8**, various theories offer different perspectives on failure, where interacting stress components collectively influence the structural integrity of the composite system. Consequently, the suitability of a specific criterion depends on the material properties and the loading conditions. In these equations, the left side represents the local stress components normalized by their respective strengths, defined as Relative Damage (R.D.), while the right side is conventionally set to unity.

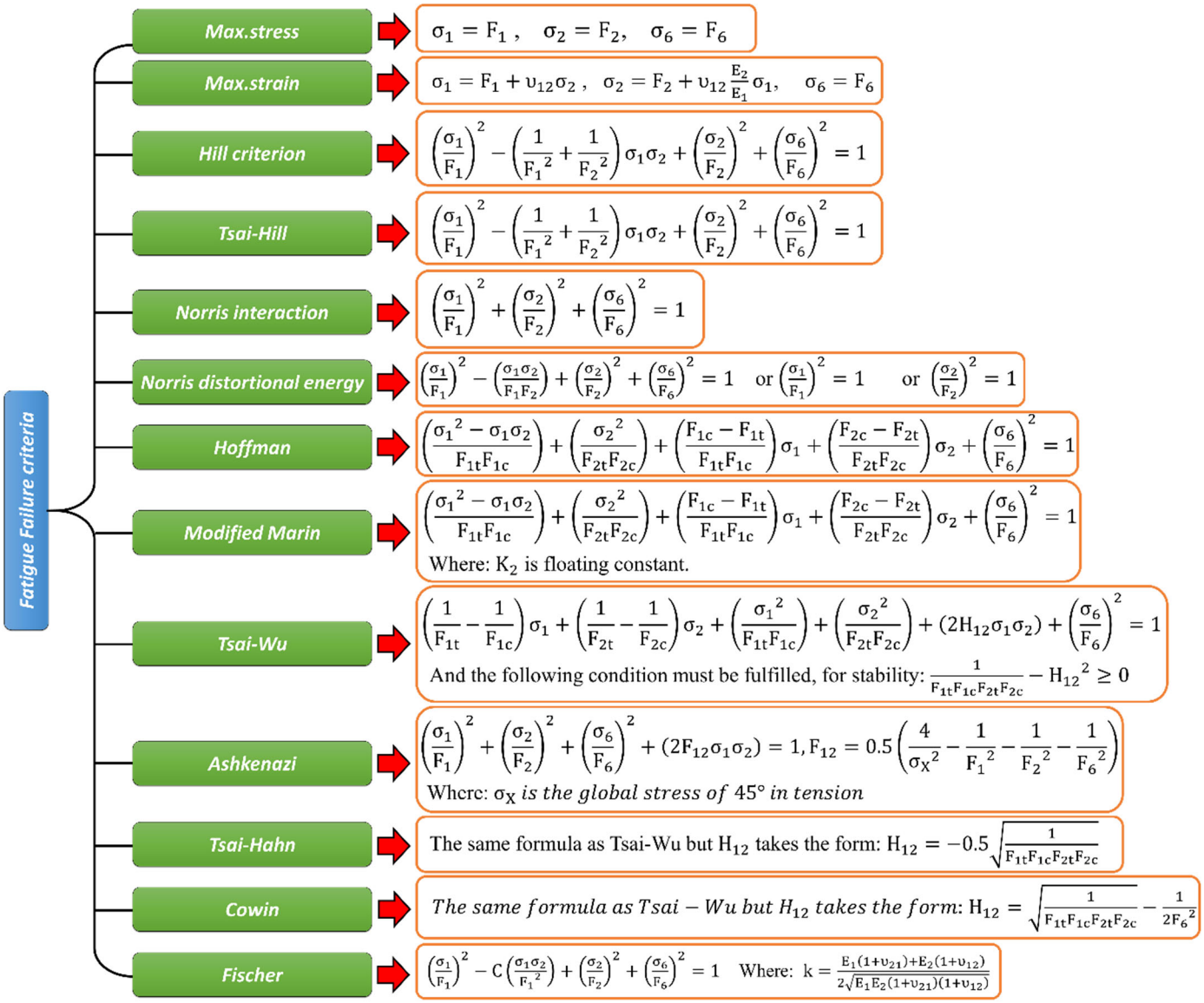

Figure 8. Failure Criteria / Theories of Failure.

2. Fatigue damage detection

A standardized classification system for damage states has gained significant traction within the structural health monitoring (SHM) community. This framework characterizes damage by addressing five fundamental levels: (1) Existence: determining if damage is present; (2) Location: identifying the exact position within the structure; (3) Type: characterizing the nature of the defect; (4) Extent: assessing the severity of the damage; and (5) Prognosis: estimating the remaining useful life of the system [51].

To figure out what kind of damage a structure has and how bad it is, one usually needs to know how that structure behaves under different failure conditions. This is often done using analytical models. For instance, when monitoring the structure while it's in use, compare the modal parameters of the damaged structure to those of the structure when it’s intact. This process is known as global diagnosis. If find that there’s damage, can then use a model of the damaged structure to identify where the damage is located, which is referred to as local diagnosis [52].

Fatigue damage monitoring in composite materials is generally categorized into destructive testing (DT) and NDT. DT methodologies encompass laboratory and in-situ assessments designed to evaluate material limits through tensile, compression, interlaminar shear, and fracture toughness testing. Furthermore, DT characterization often involves specialized techniques such as sectioning, de-plying, and fractography to analyze internal failure mechanisms.

NDT techniques have proven quite effective for evaluating composite structures on-site, especially when it comes to checking the integrity of laminate composites. Lately, as shown in **Figure 9**, several methods have been applied to monitor these laminate structures, including: (1) Ultrasonic testing [53–59]; (2) X-Ray Radiography [60–63]; (3) Thermography [64–68]; (4) Acoustic Emission [69–73]; (5) Vibrography [74–77]; (6) Eddy Currents [78]; (7) Optical-based NDT methods like embedded Optical Fiber Sensors [79–82]; and (8) Lamb Waves techniques [83–93].

There are quite a few different NDE techniques available for monitoring fatigue damage in composite structures, each with its own strengths and weaknesses. While each method works best in its own area, they may overlap when it comes to the size of the defects that can be found, how accurately they can be detected, and which types of damage they can pick up. For instance, ultrasonics are good at finding delaminations, but acoustic emission is capable of detecting both delaminations and fiber failures. Yet, it’s important to note that no single technique can identify every type of fatigue damage out there [94]. **Figure 10** presents the different types of fatigue damage that these NDE techniques can detect in laminate composite structures.

As illustrated in **Figure 10**, no single NDT method is capable of fully capturing the diverse fatigue damage states inherent in laminate composites. A multi-modal NDE approach is essential to obtain a comprehensive assessment of damage types and their impact on residual mechanical properties. For instance, integrating data from ultrasonic testing and X-ray radiography can facilitate a three-dimensional reconstruction of the intricate damage networks within the composite.

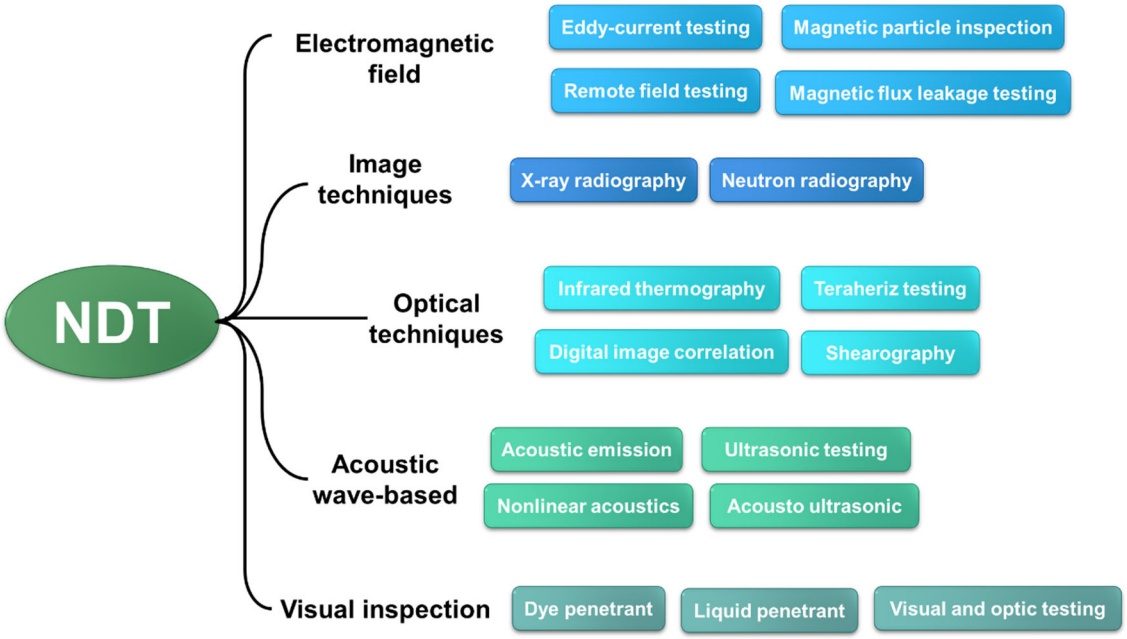

Figure 9. NDT Types for laminated composite structures.

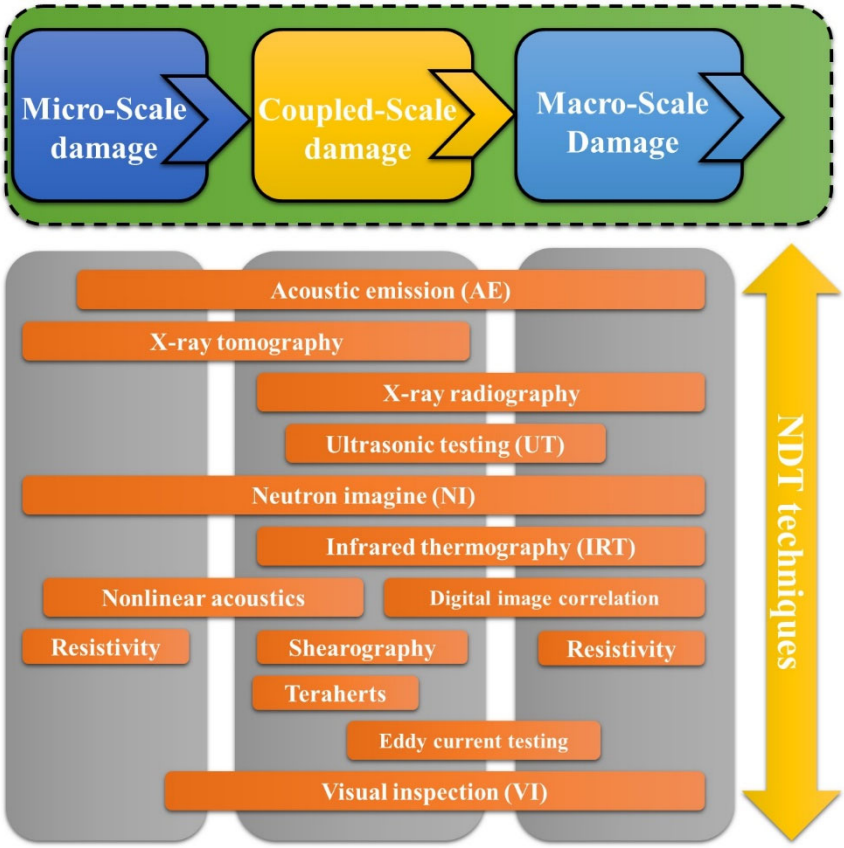

Figure 10. Overview of NDT Methods capabilities for SHM in laminated composite structures.

3. Damage detection-based lamb waves technique

LWs are a class of GWs that propagate through plate or shell-like structures. Over the past two decades, significant research and development have been driven by an

increasing interest in utilizing LWs for structural damage monitoring. The technology is approaching maturity for diverse engineering applications, offering a cost-effective solution for continuous and automated structural health monitoring. However, in contrast to traditional NDT methods such as ultrasonic scanning and radiography, which have been refined over fifty years, LW-based detection remains an emerging field. Several technical challenges must still be addressed before it achieves widespread industrial adoption.

LWs techniques are highly effective for NDT because they travel long distances through energy-absorbent composite materials. Their sensitivity to path interference allows for rapid screening of large areas, such as composite wing skins, while the use of different LW modes enables the detection of both surface and subsurface defects. Key advantages include non-invasive testing through insulation, comprehensive cross-sectional assessment, and cost-effective operation with minimal energy requirements [95]. Consequently, LW data analysis serves as a robust tool for diagnosing and quantifying fatigue damage, facilitating reliable estimates of the remaining useful life of composite structures.

3.1. History and literatures

LWs, which were first identified by Horace Lamb back in 1917, can be found in thin, plate-like materials like panels, plates, and small beams that have parallel edges [95]. Mindlin was the pioneer in creating a detailed theory for plates, and he worked alongside Schoch and Frederick during the 1950s and 60s [96]. Then, in 1961, Worlton [97] introduced the idea of using LWs for detecting damage. Together, these contributions have paved the way for the current use of LWs in NDT.

Saravanos and Birman [98] were the first to apply LWs to composite materials, showing through both analysis and experiments that it's possible to detect delamination in composite beams using these waves. Percival and Birt [99] reached similar conclusions, directing their research toward the two main modes of LWs. As well as the other types of damage in composite materials were explored, with Seale and Smith [100] looking at fatigue and thermal damage, while Tang and Henneke [101] studied how sensitive LWs propagation is to fiber fractures.

Alleyne and Cawley [102] were the first to look at how LWs interact with defects for NDT. Following that, Saravanos et al. [103] came up with a method to detect delamination in composite materials by using LWs along with embedded PZTs. They used piezoelectric patches to generate the first anti-symmetric LWs mode.

Subsequent research into LWs techniques has focused on comparative performance against alternative composite damage detection strategies. Studies have evaluated the durability, efficacy, and sensitivity of LWs, establishing their capability for precise damage localization [104–111]. While LWs are highly effective at identifying local structural defects, their primary limitation is the requirement for an active power supply to facilitate signal generation. Furthermore, high data acquisition rates are essential to maintain adequate signal resolution. Despite these challenges, LWs offer superior sensitivity and accuracy compared to traditional methods. To optimize power consumption and data storage, researchers suggest integrating LWs into a hybrid SHM system alongside passive methods, such as Frequency Response

Functions (FRF) or spectral analysis. Additionally, employing wavelet transform-based analysis in the time-frequency domain has been shown to enhance the precision of damage evaluation [112–117].

Over the last decade, research has increasingly focused on overcoming the inherent challenges of using LWs for fatigue damage detection in composites. Significant efforts have been directed toward enhancing the sensitivity and localization capabilities of these techniques. For example, Yeum et al. [89] developed a novel, reference-free LW technology specifically for delamination detection. This approach enables the identification of defects along a single propagation path without requiring prior baseline data or predefined decision boundaries. By utilizing circular PZTs for wave excitation, the researchers analyzed the interaction between a single wave mode and delamination through both numerical simulations and experimental validation. Their findings demonstrate that structural integrity can be accurately assessed without the need for comparative baseline signals or multi-path data fusion.

LWs propagation can be simulated via FE analysis using platforms such as ANSYS and ABAQUS. Researchers often develop 2D cross-sectional plate models to characterize LW responses and assess fatigue-related damage, specifically debonding and delamination. Various numerical methods have been employed to model these phenomena in the time domain, including the two-dimensional Fast Fourier Transform (2D FFT) [118], wavelet transforms [119], and Semi-Analytical FE (SAFE) or Wave FE (WFE) methods [121]. FEA is frequently used to validate experimental results; for instance, Baid [122] utilized FEA to corroborate findings on skin-core interface damage in woven composite and honeycomb sandwich panels. Furthermore, Shen and Giurgiutiu [93] developed a Combined Analytical FE Approach (CAFA) for the efficient simulation of 2D LW interaction with damage. Their results, validated against scanning laser Doppler vibrometry (SLDV) data, demonstrated that CAFA offers superior computational accuracy and versatility compared to full-scale multiphysics simulations.

3.2. Modelling and simulation

LWs are ultrasonic waves that travel between two parallel surfaces, and they have been studied quite a bit for their potential in detecting damage. The materials or structures' defects can be detected by looking at the changes in phase and group velocities, along with the drop in amplitude of LWs when comparing damaged versus undamaged specimens. These waves come in two modes: symmetrical (*S*) and anti-symmetrical (A) modes (check out **Figure 11**). In *S* modes, the displacements of the plate are symmetrical around its center, but in some modes are anti-symmetrical. There are actually an infinite number of both S and A modes present in a plate [123].

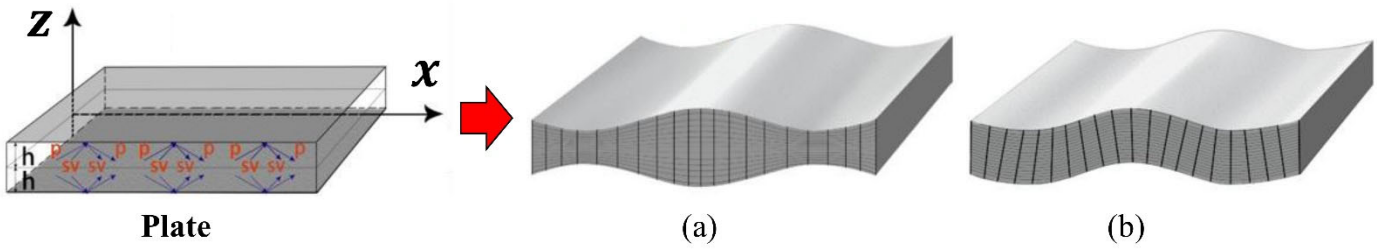

Figure 11. (a) Symmetric and (b) anti-symmetric LWs modes.

LWs propagation traits are illustrated through dispersion curves, as seen in **Figure 12**. These curves plot phase and group velocities against the frequency-thickness product, which get it by solving the equations related to LWs.

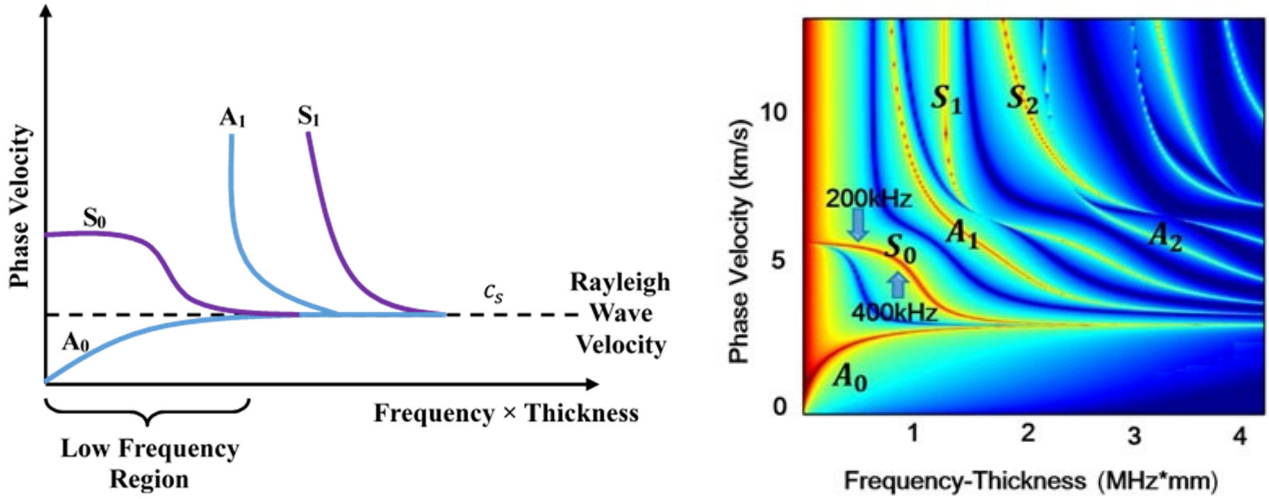

Figure 12. LWs phase velocity dispersion curve.

The LWs dispersion curves illustrate how wavenumber relates to circular frequency ω (or can use linear frequency f based on the equation $\omega = 2\pi f$). The longitudinal wave velocity c_L , and the transverse (shear) wave velocity c_T. For isotropic plates, there's actually an analytical formula to calculate these LWs dispersion curves. These curves can be got from solving the Rayleigh-Lamb equation for a plate of thickness *2h*, for two distinct types of modes: Symmetric (S) and Anti-symmetric (A), [124,125] as follows:

1) Symmetric (S):

$$\frac{\tan(\beta h)}{\tan(\alpha h)} = -\left[\frac{4k^2\alpha\beta}{(k^2-\beta^2)^2}\right] \quad (1)$$

2) Anti-symmetric (A):

$$\frac{\tan(\beta h)}{\tan(\alpha h)} = -\left[\frac{(k^2-\beta^2)^2}{4k^2\alpha\beta}\right] \quad (2)$$

where: $\alpha^2 = (\omega^2/{c_T}^2) - k^2$and $\beta^2 = (\omega^2/{c_L}^2) - k^2$. c_S represent the vertical wave numbers for longitudinal and transverse waves, respectively.

LWs behavior in non-homogeneous composite plates tends to be trickier than in homogeneous isotropic plates, mainly because of the varying material properties. In a standard anisotropic composite plate, how the material behaves is influenced by factors like the fiber and matrix characteristics, the orientation of the fibers, and the thickness and arrangement of the layers throughout the plate.

The dispersion curves for composite plates can be calculated in basically two ways: using exact solutions or approximate ones [126]. The exact methods depend on 3D elasticity theory and are tackled through matrix techniques, like the transfer matrix method and the global matrix method [127–129]. These approaches break down the layered plates into a matrix form, capturing both stresses and displacements at the surface, along with the amplitudes of incoming and outgoing waves. On the other hand, when it comes to approximate solutions, the FE Method comes into play for figuring out dispersion curves of waveguides with various shapes. And in the case of anisotropic composite plates, the averaged material properties are actually used for each layer in the plates.

3.3. SHM-based lamb waves technique

SHM is an evolving field derived from the study of smart materials and structures. It has garnered significant attention recently, particularly for applications in civil infrastructure and aerospace vehicles. The primary objective of SHM is to develop automated systems capable of continuous monitoring and damage detection, thereby reducing reliance on manual inspection. As illustrated in **Figure 13**, a typical SHM architecture comprises three core components: (i) a sensory system, (ii) a data processing system, encompassing acquisition, transmission, and storage, and (iii) a health assessment system utilizing diagnostic algorithms and information management. Some advanced frameworks also incorporate a fourth component dedicated to structural repair functionalities [130–135].

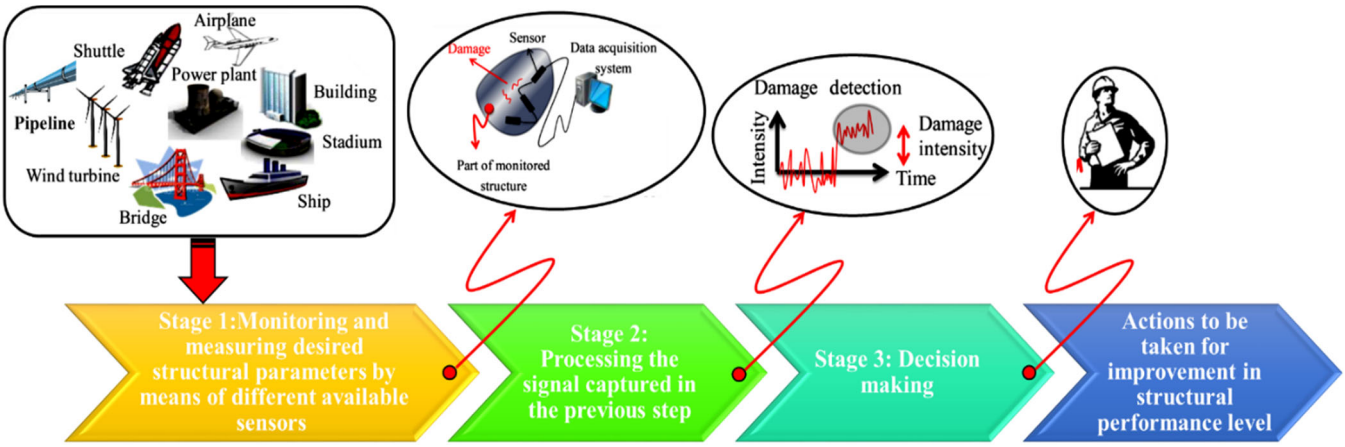

Figure 13. SHM Strategy.

SHM utilizing LWs is categorized into passive and active systems. Passive SHM relies on sensors to detect LWs generated internally by damage events. Conversely, active SHM systems employ actuators to introduce controlled LWs into the structure, which are subsequently captured by sensors. As illustrated in **Figure 14**, these signals

provide critical data regarding structural integrity. While passive SHM is primarily utilized for damage localization, active SHM enables the selection of specific modes and frequency ranges, significantly streamlining the signal processing required for damage detection.

There are a variety of transducers that can both generate and detect LWs in composite structures. Some of these include ultrasonic transducers [136], laser transducers [137], optical fiber transducers [138], interdigital or comb transducers [139], and speckle interferometry [140]. However, PZTs are the most commonly used for employing the LWs technique to detect and locate fatigue damage in composite structures. This is mainly because they offer a strong force output at fairly low voltages, are lightweight, easy to integrate, work across a wide frequency range, are cost-effective, and respond well even at low frequencies [141–151].

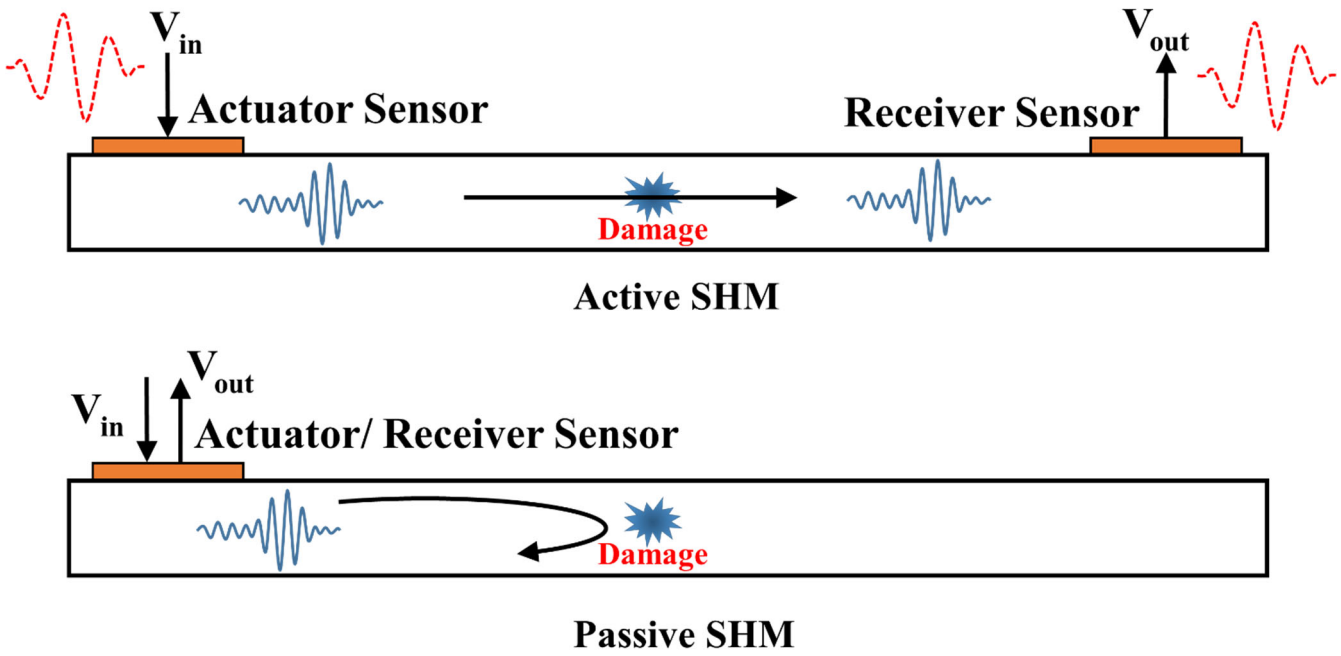

Figure 14. Active and passive SHM set up for damage detection.

3.4. Damage detection process

The picked method for detecting damage using LWs needs to handle noise, vibrations from the structure, and the fact that multiple modes can overlap. Now, there are three detection methods that can be classified based on signal processing: time domain analysis [152], frequency domain analysis [153], and time-frequency domain analysis [154]. When it comes to detecting fatigue damage in composite structures with LWs techniques, the time domain correlation method is typically used for processing wave signals. With these time domain methods, the damage can be estimated by looking at the time histories of inputs, which allows for the detection of damage events both on a global scale and in specific local areas.

The damage detection model works by analyzing wave signals and comparing them to baseline measurements taken under conditions with no damage. This baseline helps remove boundary effects from getting signals when there's damage, as illustrated

in **Figure 15**. The tricky part is that it's tough to keep this baseline data consistent since it can shift due to environmental changes.

There are two detection methods that focus on the time domain: direct time and time reversal methods. In direct time domain analysis, a time series signal typically captures the propagation history of LWs moving through a structure. This gives clear insights into the waves, such as different wave modes, moving speed, attenuation and dispersion over distance, and scattering off boundaries or damages (check out **Figure 15**). The Time Reversal Method (TRM) was initially introduced to counteract the dispersion of LWs, but it has recently found a role in diagnosing damage as well. One of the big advantages of using TRM over traditional methods is that it doesn't require a baseline database [155], which can help reduce false alarms about damage because of changing environments and operational factors. So far, TRM has been effective in monitoring damage and pinpointing where it is, and it even has the potential to assess how severe and what type of damage.

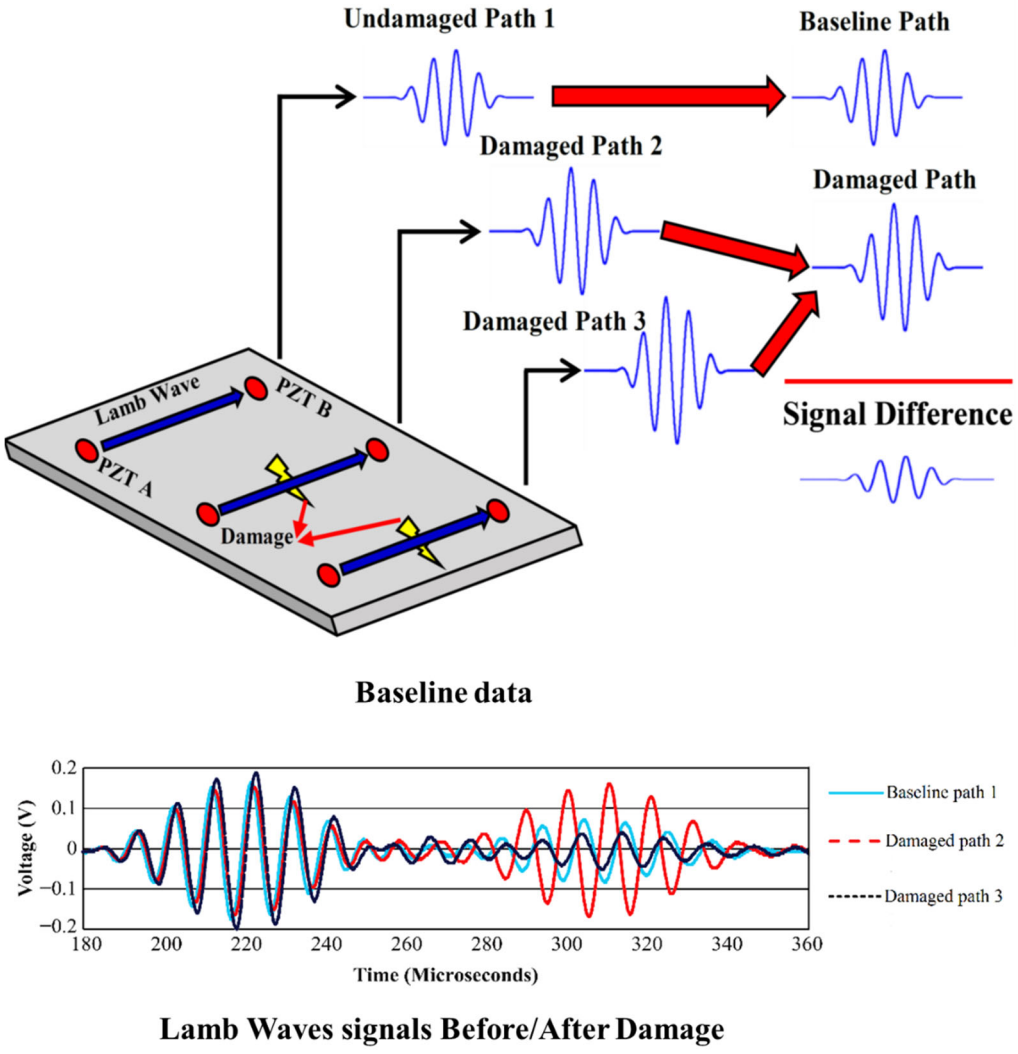

Figure 15. The difference between the fabric Plate (Baseline) path 1 and changing the damage Path 2& Path 3.

To grasp the TRM method for detecting damage, take a look at **Figure 16**. Here, a transducer array is set up on the structure, where one transducer sends out a signal

that another one picks up. Each transducer needs to act both as a sensor and an actuator, which is why PZTs are commonly used. The time reversal process shown in **Figure 16** begins with a signal being sent from PZT A and recorded by PZT B. The signal received at PZT B gets flipped in time (that is, V_B (t) $\rightarrow$ V_B (−t)), and it's then sent back from PZT B to PZT A, where it's recorded again. Finally, the signal at PZT A is reversed in time and compared to the original one.

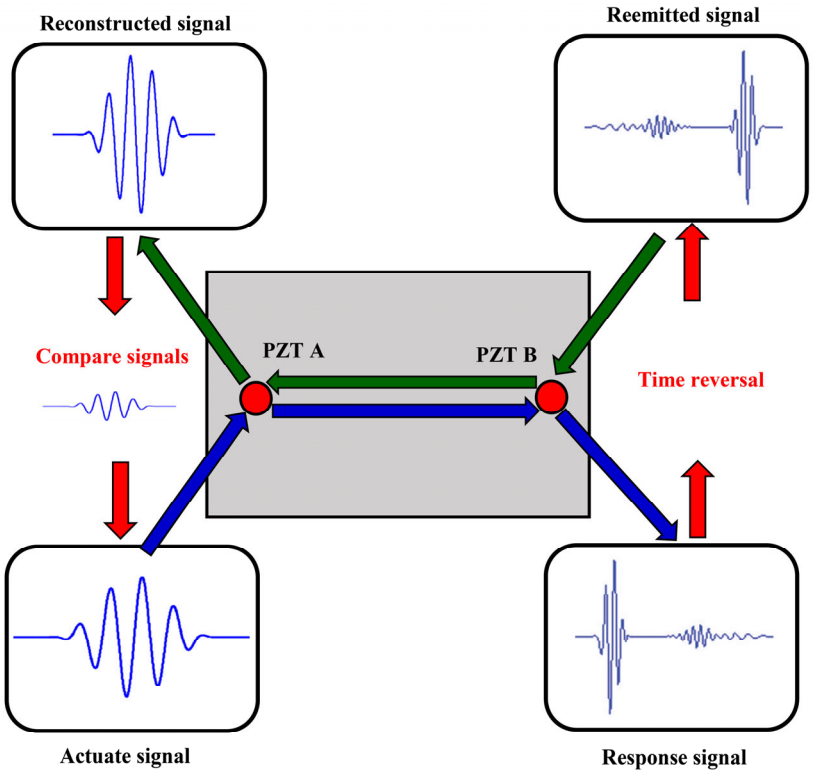

Figure 16. Time reversal processes.

Because of the importance of the TRM, the researchers addressed improving the performance of the TRM by several methods, such as a standard reemitted signal (SRS) crossing the damage again. When the SRS is resubmitted with the damage, its effects on the SRS are compared in extensive patterns to the traditional TRM. Therefore, the SRS contains additional information on damage (such as wave velocity) that can be extracted for damage range detection. For more details of the recent studies on improving the performance of TRM, see **Figure 17**.

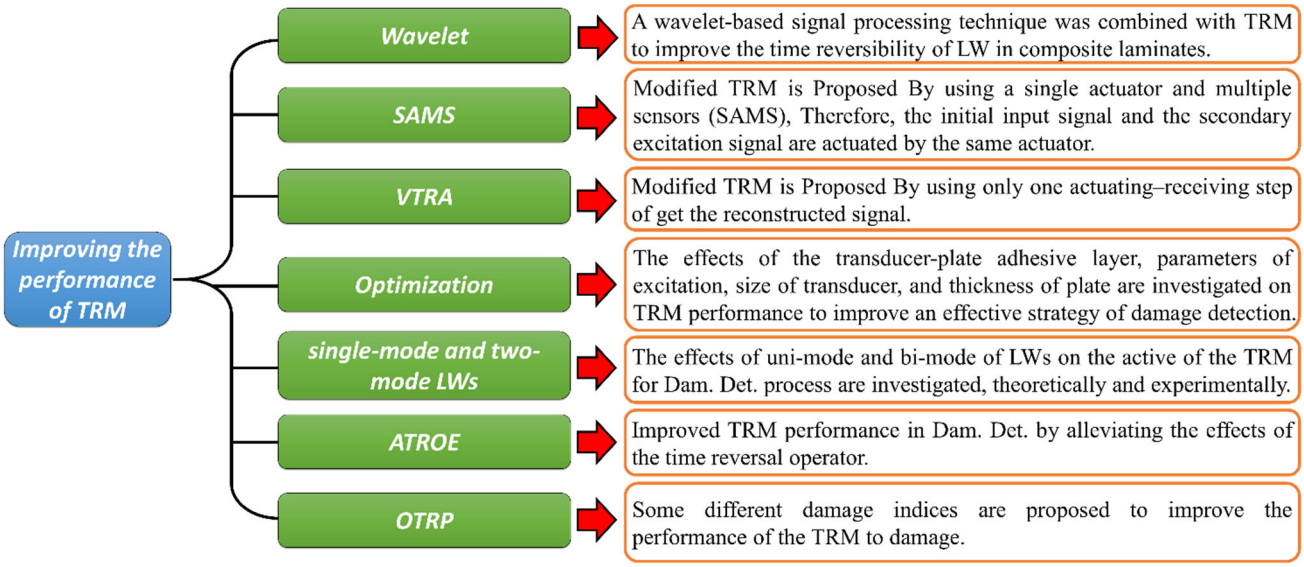

Figure 17. A comparison between recent methods for improving the performance of TRM in the LWs technique.

3.5. Damage localization

The damages can be localized using methods like triangulation [156], tomography techniques [157], and time reversal [158]. There's also a more complex approach that uses AI algorithms, which requires a lot of data on damage simulations to train the algorithm [159]. But if the training conditions change, the algorithm might not perform well. Additionally, the damages can be located based on how energy travels through LWs [160].

Multiple studies have addressed damage localization through various algorithmic frameworks. Rautela et al. [161] introduced a hybrid classification-regression method, highlighting the efficacy of Deep Learning (DL) in modeling guided wave behavior for damage detection. Similarly, Miorelli et al. [162] developed an automated approach for localizing and sizing damage by training a Convolutional Neural Network (CNN) on simulated signals, later validating its performance with both synthetic and experimental data. Wu et al. [163] integrated deep CNNs with continuous wavelet transforms to identify internal delamination in CFRP materials, demonstrating high precision in pinpointing defects. To improve localization efficiency using minimal sensor arrays, Liao et al. [164] proposed a multiscale CNN incorporating a self-attention module, which significantly enhanced performance on guided wave testing platforms. Furthermore, comparative studies by Feng et al. [165] on anisotropic CFRP plates indicated that ANN-based algorithms outperform probabilistic approaches in Time of Flight (ToF) analysis. Yelve et al. [166] corroborated this by utilizing Damage Index (DI) values derived from root mean square deviation, concluding that ANNs provide reliable localization. While image-based signal processing captures subtle details, it necessitates high data resolution and complicates storage requirements. Conversely, ToF and DI-based methods offer reduced computational demand but risk omitting critical signal information. Despite these advancements, achieving accurate localization across the entire structural domain—particularly at the boundaries of the sensor network—remains a significant challenge.

The time window is the period of time between T_{start} and T_{end} which are given in Equations (3) and (4), respectively:

$$T_{start} = T_1 + \text{ToF} - \frac{1}{2}T_0 \tag{3}$$

$$T_{\text{end}} = T_1 + \text{ToF} + \frac{1}{2}T_0 \tag{4}$$

where T_1 denotes the wave excitation time of the actuator, T_0 is the time window, ToF is the time of flight from the receiver to the actuator, and T_0 is the period of the excitation wave envelope. The time window is demonstrated in **Figure 18**.

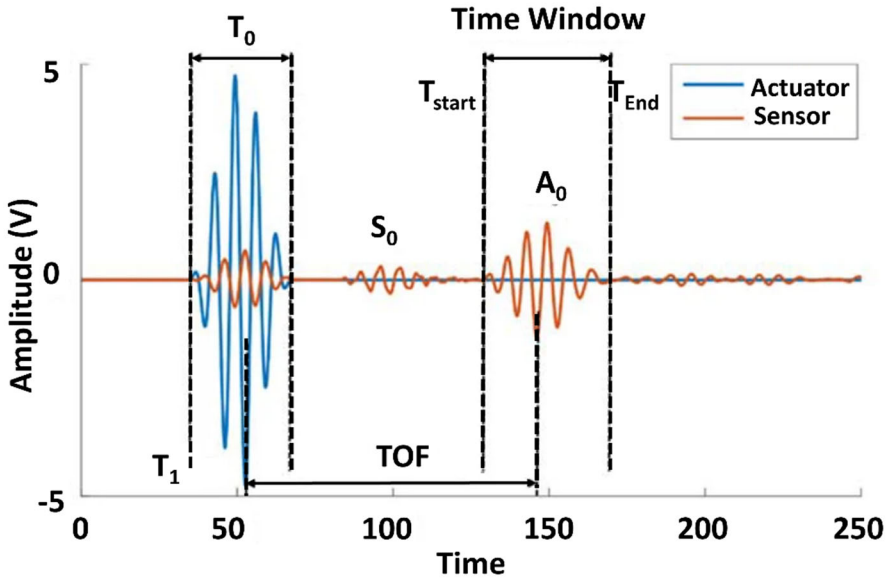

Figure 18. Failure modes on a laminate.

4. Fatigue damage prediction with AI algorithms

Overall, damage detection and characterization using LWs present significant challenges. Even in simple geometries, response signals can become highly complex. Signal integrity is further complicated by fluctuations in transducer coupling conditions, which alter the amplitude of the captured data. Moreover, the generation of high-order modes at boundaries or structural discontinuities results in intricate signals that are difficult to interpret. Due to the difficulty of developing accurate physical models for LW interaction with damage in metallic and composite materials, various Artificial Intelligence (AI) algorithms, including Artificial Neural Networks (ANN), Machine Learning (ML), and Deep Learning (DL), have been proposed. These data-driven approaches facilitate structural diagnosis directly from measured signals without the need for complex physics-based modeling.

4.1. Artificial neural networks (ANNs)

ANNs are a method used in AI that mimics how our brains work, sitting alongside other techniques like expert systems, genetic algorithms (GA), fuzzy logic, and Bayesian networks. It's found a lot of use in various fields such as medicine, business,

and engineering, like speech recognition, diagnosing hepatitis, fixing telecom issues from faulty software, recognizing images, and monitoring failures in laminated composite materials. The reason NNs have gained popularity is their capability to tackle non-linear problems and their resilience in noisy environments, which makes them a solid choice for these kinds of applications [167].

The main goal of ANNs is to find patterns and identify trends in complex or unclear data that are often too intricate for humans or other computer methods to catch.

ANNs come in various forms, each with its own training and testing methods. At their core, though, it usually includes numerous simple processing units called nodes or neurons [167]. These neurons affect how the others work through something called a weight. Basically, each neuron calculates a nonlinear weighted sum of its inputs and sends that result along to other neurons. The functioning of the entire network relies heavily on how these neurons interact with each other. Typically, an NN is made up of several layers of neurons: the input layer, one or more hidden layers, and the output layer, as presented in **Figure 19**. The input layer takes in the data and passes it on to the hidden layers, which handle all the complex calculations. Finally, the results are sent to the output layer, where presented to the user.

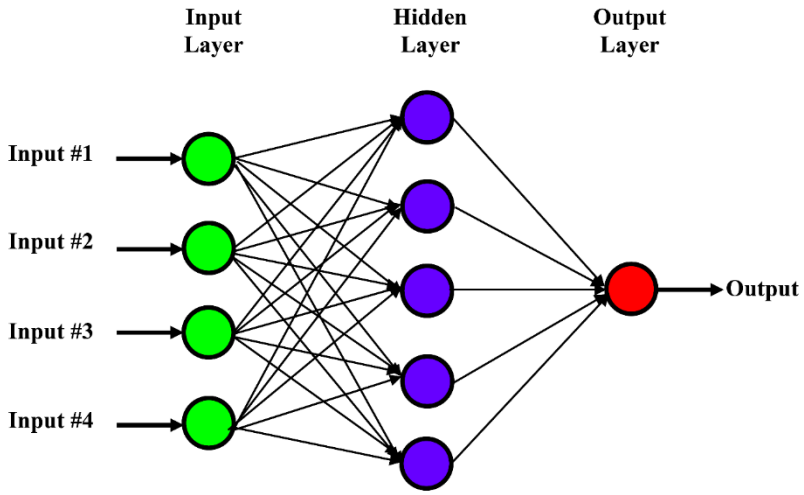

Figure 19. A simple ANNs.

Distinguishing between various ANNs architectures involves more than selecting a linear or nonlinear activation function; it also depends on the specific connectivity between neurons. This topology, among other design factors, defines the network structure and dictates the appropriate learning algorithms. Among the diverse architectures explored in recent research, multilayer feedforward neural networks (FFNNs) remain the most widely utilized.

These multilayer FFNNs have one or more hidden layers sitting between the input and output layers. In this setup, data moves forward from the input units to the output units without any feedback loops. This means there's no way for outputs from one layer to feed back into the inputs of the same or a previous layer. **Figure 20** below illustrates a multilayer FFNN architecture. Each layer contains a weight matrix W, a bias vector, and an output vector. To keep things organized, a layer number as a superscript is added to the variables to clarify which layer is intended.

Multilayer FFNNs possess significant computational power. Specifically, a two-layer network, utilizing a sigmoid activation function in the hidden layer and a linear function in the output layer, can approximate any functional mapping with a finite number of discontinuities. In these multilayer architectures, each layer serves a distinct functional purpose in the data transformation process.

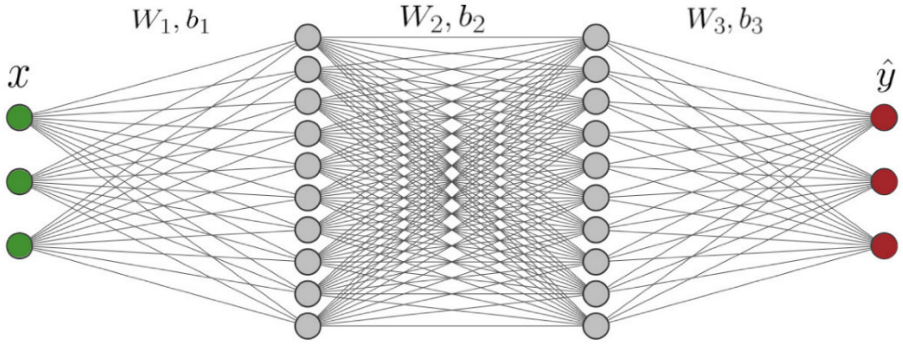

Figure 20. Multilayer FFNNs.

4.2. Machine learning (ML)

ML, a subset of Artificial Intelligence, enables systems to identify patterns and facilitate autonomous decision-making by learning from data rather than following explicit, task-specific programming. Through the processing of extensive datasets, these algorithms iteratively refine their performance. ML powers diverse applications, including recommendation engines, image recognition, and predictive analytics, utilizing common algorithms such as linear and logistic regression, decision trees, ANNs, K-Means clustering, K-Nearest Neighbors (KNN), and Support Vector Machines (SVMs). The standard ML training workflow involves defining the input-output architecture, acquiring vibration signals, preprocessing raw data, extracting relevant features, selecting and implementing the appropriate model, and conducting final post-processing of the results.

4.3. Deep learning (DL)

DL is a more advanced branch of Machine Learning that uses multilayered ANNs to tackle tough problems, kind of like how our brains work when processing information. It is the driving force behind modern AI, including voice assistants, self-driving cars, and generative AI like large language models (LLMs). The popular DL architectures include CNNs for image processing, Recurrent Neural Networks (RNNs)/LSTM (Long Short-Term Memory) for time-series, and Generative Adversarial Networks (GANs) for generative tasks. These structures enable state-of-the-art performance in computer vision, natural language processing, and generative AI by utilizing specialized layers like convolutions, attention mechanisms, or encoder-decoder structures.

4.4. Damage identification

On the side, data-driven methods use AI techniques like ML and DL to pull out complex insights from large sets of monitoring data. These techniques train classifiers

to assess damage conditions or regressors to pinpoint where the damage is located. [168–177]. Such as, Altabey et al. [178] employed a CNN to detect water absorption in BFRP composite pipes by extracting the material's dielectric features. They monitored the change in electrical capacitance corresponding to the water absorption rate from start to saturation of the BFRP. The primary CNN relates the absorption rate to the absorption time by applying the Fickian Diffusion Model (FDM); the CNN takes the potential difference between the electrodes as its input. Using the same pipe for their "case study," Altabey [179] introduced a long-term creep thermo-mechanical fatigue behavior for CNN training, aiming to speed up the learning convergence compared to the basic steepest descent approach, and verify his network on another case study of BFRP composite plate employed by Altabey et al. [180].

Wu et al. [181] converted raw low-frequency wave signals into time-frequency scalograms via continuous wavelet transform, subsequently employing a 2D-CNN to evaluate structural integrity. In a separate study, Lee et al. [182] utilized pre-processed ultrasonic guided wave signals to train an autoencoder-based deep learning model. This architecture facilitates the extraction of damage-sensitive features from the autoencoder's latent feature space to identify fatigue in laminated composites.

Krawczuk et al. [183] investigated the integration of GA and ANNs for the detection and characterization of delamination within a numerical model of a multilayered GFRP beam. Their methodology employed two distinct approaches for identifying damage location and size: FE model updating to isolate modeling errors, and the evaluation of diverse damage scenarios. They utilized an objective function based on shifts in the first four natural frequencies, incorporating the Damage Location Assurance Criterion (DLAC) by Messina et al. [184]. While the GA successfully converged within a reasonable number of generations, the authors proposed that incorporating elitism could further optimize performance. Conversely, the ANNs demonstrated difficulty in accurately identifying the through-thickness position of the delaminated layer, a limitation attributed to an insufficient number of training cases.

Hatem et al. [185] integrated GA and ANNs to detect damage in CFRP cantilever beams. Their study categorized four distinct damage types: circular holes, delaminations, linear surface cracks, and through-thickness cracks, each varying in size, location, and orientation. To classify these defects, the researchers employed a multi-network architecture consisting of five models: a generalized regression network (GRN), a linear network, two back-propagation networks (standard and regularized), and a radial basis network. The GRN proved most effective for classification, achieving accuracy rates between 85% and 98%. Following identification, specific ANNs or GAs were utilized to quantify damage parameters. The authors concluded that while damage size could be predicted with high precision, results for location and orientation were less consistent.

Zheng et al. [186] merged computational mechanics with ANNs, particularly applying the back-propagation technique to forecast delamination in CFRP beams. They trained the ANNs on FE models that looked at various sizes and positions of delaminations, using the first five natural frequencies as their input. The team discovered that the ANNs could effectively predict both the size and the location of delamination, with just a small margin of error.

Haj-Ali et al. [187] investigated the utility of ANNs in developing nonlinear micromechanical models, identifying fiber-matrix interfacial cracking as a critical factor in damage assessment. Utilizing unit cell (UC) models for a unidirectional metal-matrix composite, they established the crack angle as a primary damage parameter. The ANN architectures were trained using data from 3D FE simulations to generate stress-strain constitutive models integrated with damage variables. This research was among the first to demonstrate the efficacy of ANNs in creating damage-inclusive micromechanical material models. Notably, however, their ANN was restricted to monotonic loading behavior and tailored specifically to a boron-aluminum metal matrix composite.

Chakraborty [188] investigated the influence of embedded delamination parameters, specifically size, geometry, and location, on the natural frequencies of FRP composite laminates. To generate a comprehensive dataset, 201 3D-FE models were developed, each featuring unique delamination configurations. Through these numerical simulations, the first ten natural frequencies were extracted for each case. This study provides a robust data-driven framework for understanding how structural modal responses are altered by internal delamination characteristics. They adjusted the numbers to fit between 0.1 and 0.9. Out of the total, they randomly picked 165 data sets to train the network, while the remaining sets were saved for testing.

Roseiro et al. [189] put forward a method that uses ANNs to detect and measure damage. They based their approach on data from PZTs, feeding this information into a FFNN. Their method employed a higher-order FE formulation, which helped capture the response of laminated composite plates and collect the necessary electrical signals from the sensors. To demonstrate how this works, they included a numerical example involving a simply supported laminated composite plate. Karnik et al. [190] looked into how delamination behaves based on different drilling parameters at the entry points of CFRP plates. For their study on high-speed drilling, they used an ANNs model that took into account factors like spindle speed, feed rate, and point angle. They went with a multilayer feed-forward ANN and trained it using the error-back-propagation training algorithm (EBPTA) to get the job done.

Roseiro et al. [189] proposed a methodology utilizing ANNs for damage detection and quantification. Their approach integrated PZT data into an FFNN, leveraging a higher-order FE formulation to accurately capture the electromechanical response of laminated composite plates. The efficacy of this method was demonstrated through a numerical example of a simply supported composite plate. In a separate study, Karnik et al. [190] investigated delamination behavior during high-speed drilling of CFRP plates. They developed a multilayer FFNN trained via the error back-propagation training algorithm (EBPTA) to analyze the influence of spindle speed, feed rate, and point angle on delamination at the entry points.

There are numerous other data-driven techniques out there, including ANN [191,192], Bayesian models [193,194], clustering algorithms [195], and various evolution algorithms [196], like extreme learning machines [197], Gaussian process regression [198], gated recurrent units [199], Kalman filters [200], random forests [201], stacked autoencoders [202], support vector machines [203], and transfer learning [204]. These methods can be categorized into shallow ML models and DL models. While shallow models can work well, their success often hinges on manual

feature extraction, which is both tedious and calls for a lot of specialized knowledge [205]. Plus, different goals like damage detection, severity evaluation, and location identification each need separate feature engineering. On the other hand, DL models automatically pull out specific features needed for tasks right from raw data, making them adaptable to various objectives. So, DL-based approaches can potentially compete with, or even outdo, physics-based methods, all while needing less specialized knowledge. That said, the limited amount of monitoring data under damaged conditions might cause data-driven models to overfit, which can affect how accurately they detect and locate damage. Consequently, their reliability continues to be a point of discussion, especially in cases where data is scarce. The recent studies of AI algorithms application in SHM of composite structures are listed in **Figure 21**.

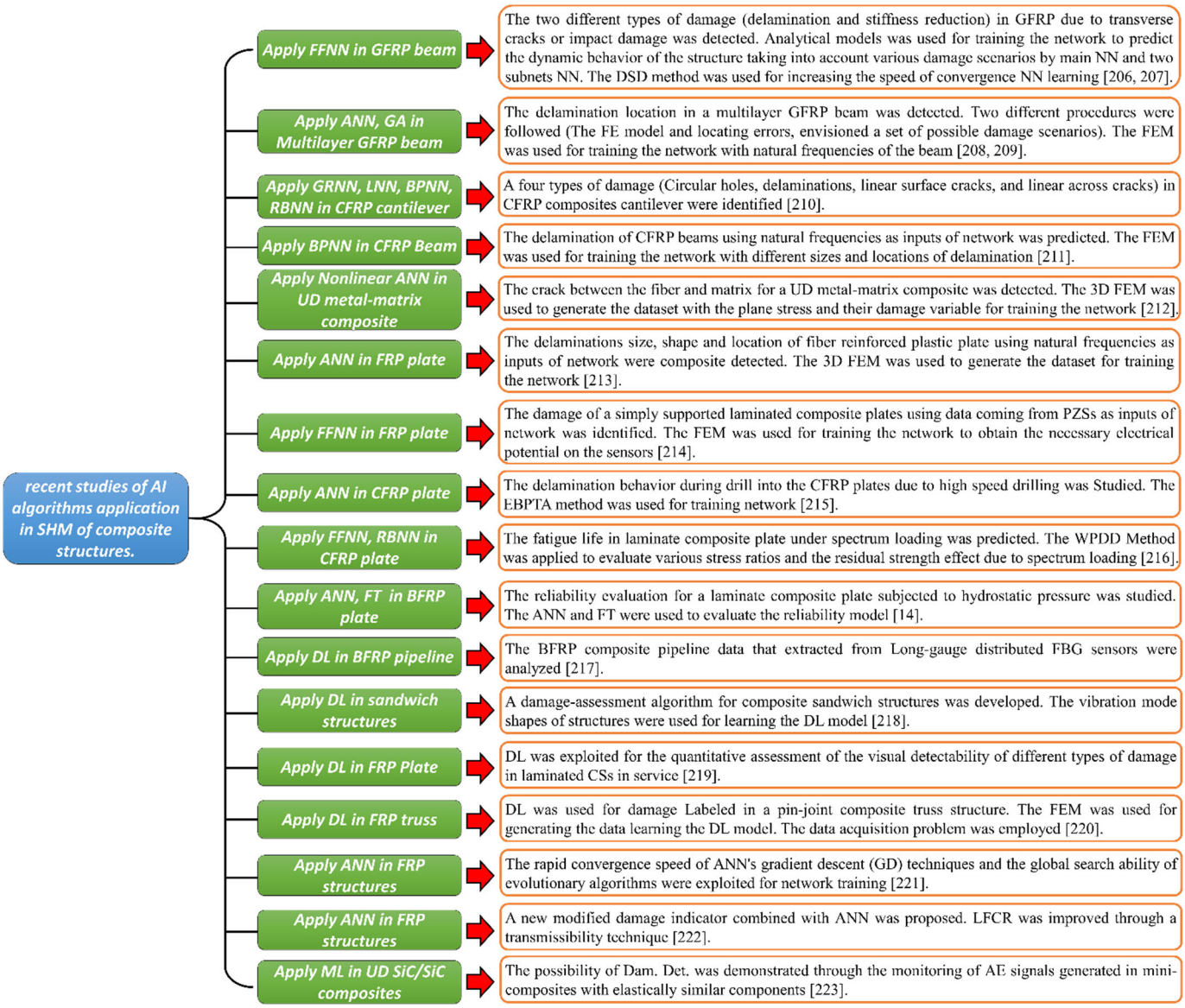

Figure 21. Some recent studies of AI algorithms application in SHM of composite structures [206-223].

5. Summary

This review looks at various aspects of SHM-based LW to identify damage in composite structures subjected to fatigue loads. First, covered different failure mechanisms, fatigue behavior, fatigue loading criteria, the advancements in SHM for composite structures, as well as SHM technologies that rely on NDT and PZT. Then, explored using the LW method for damage identification and the role of AI in SHM and damage detection. In total, we went through 223 papers, with 109 of them being published from 2020 onward. Of these, 70 papers were published between 2022 and 2023, most of which were published in 2024 and 2025, as illustrated in **Figure 22**.

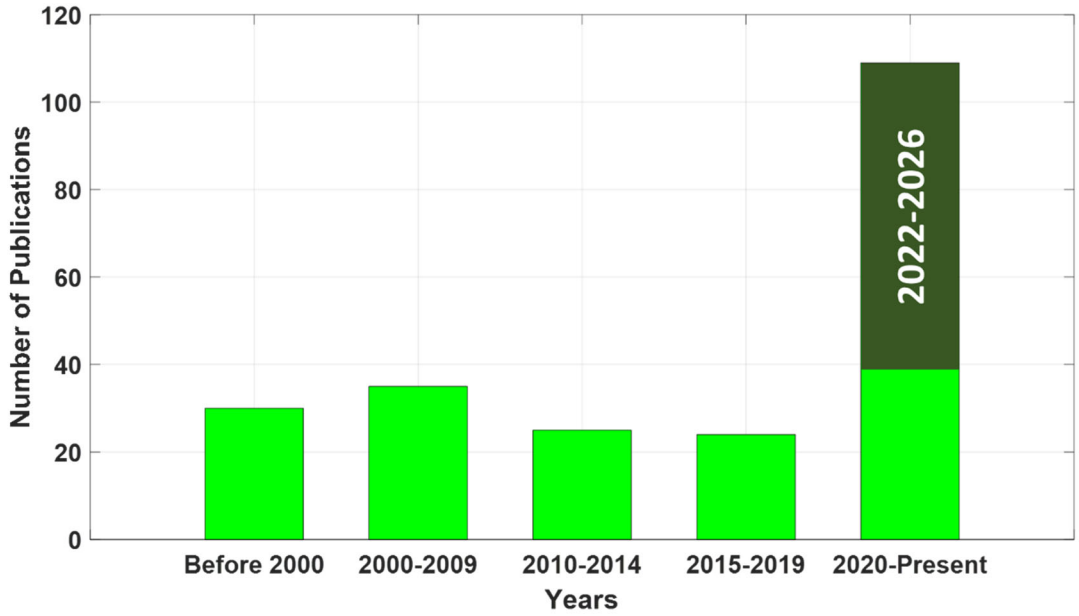

Figure 22. Number of Publications in Google Scholar on damage identification based on guided waves in Composite structures with AI schemes, beginning from 2000 to 2026.

6. Discussions

In this review study, we examined LWs behavior, modeling approaches, and applications, specialized in fatigue damage detection for composite structures. This review is structured around three core components:

Part 1: In this part, we discussed the composite materials fundamentals and material overview of analyzed composite structures, failure mechanisms, and fatigue behaviors. We found that the damage progression was identified as a three-phase fatigue failure process:

3) Phase I: Matrix cracking initiation,
4) Phase II: Local delaminations developing from cracks,
5) Phase III: Delamination consolidation leading to final failure.

Fatigue Life Diagram (FLD) is visualized as three fatigue regions influenced by fiber, matrix, and interface properties (**Figure 6**). The Key FLD affected Factors were summarized in Loading types, frequency, volume fraction (V_f), fiber orientation, mean

stress/stress ratio, environmental conditions, sizing, stress gradient, surface finish, and stress concentration.

Part 2: In this part, we discussed the damage monitoring techniques, especially the NDT methods and evaluated various NDT techniques with different sensitivities, such as Ultrasonic testing, X-Ray Radiography, Thermography, Acoustic Emission, Vibrography, Eddy Currents, Optical Fiber Sensors, and Lamb Waves (LWs), and introduced the detection tolerance of these techniques through **Figure 10** of the comparative analysis presented. Then we focused on the advantages of LWs technique for the damage monitoring in composite structures, which are limited to:

1) Large Area Coverage: Sparse transducer setup enables extensive monitoring with minimal area loss,
2) Cross-Section Inspection: Multiple wave modes facilitate internal and surface defect monitoring,
3) Damage Classification: Wave mode variations enable differentiation of damage types,
4) High Sensitivity: Superior detection accuracy rates,
5) Accessibility: Effective for enclosed/insulated structures (e.g., underwater pipelines),
6) Integration Potential: Compatible with structural health monitoring (SHM) systems for automated online detection,
7) Efficiency Benefits: Reduced energy consumption and operational costs (requires advanced signal processing),

In summary, we found LWs demonstrate significant potential for composite damage identification. Method adaptability allows customization for various damage scenarios. Presents a viable alternative to traditional NDE approaches. The revised format maintains all technical content while improving readability through logical grouping and consistent bullet-point structure.

Part 3: In this part, we discussed the integration with AI for enhancing the composite damage identification. We found that combining LWs with AI algorithms (ANNs, ML, DL) creates an optimized damage identification system, where as:

1) AI models trained on LWs data can effectively predict damage location and severity with minimal error,
2) Simplifies complex signal relationships while saving processing time and resources,
3) Enables power-efficient, real-time monitoring with reduced data storage requirements,
4) Requires simulated damage data for effective training of AI models.

Overall Recommendation: The study concludes that Lamb Wave technology, when integrated with AI-driven SHM systems, provides a highly accurate and efficient solution for fatigue damage detection in composite structures, offering significant advantages in sensitivity, coverage, and operational efficiency.

7. Conclusion

In the end, Fatigue in composites progresses through three phases—matrix cracking, delamination, and final failure—governed by material properties and loading

conditions. LWs techniques offer superior structural health monitoring, providing large-area, automated, and deep-penetration damage detection compared to traditional methods. Integrating LW data with AI algorithms (ANNs, ML, DL) enables accurate damage localization while optimizing computational efficiency.

The study concludes that LWs technology, when integrated with AI-driven SHM systems, provides a highly accurate and efficient solution for fatigue damage detection in composite structures, offering significant advantages in sensitivity, coverage, and operational efficiency.

8. Future outlook

The future outlook for AI-integrated guided wave damage identification in composite structures focuses on transitioning from simple detection to autonomous, real-time diagnostic and prognostic systems. Current trends emphasize moving beyond localization to full damage characterization (size, shape, and type) and the prediction of Remaining Useful Life (RUL).

Conflict of interest: The author declare no conflicts of interest to report regarding the present study.

References

1. Farrar CR, Worden K. An introduction to structural health monitoring. Philosophical Transactions of the Royal Society A: Mathematical, Physical and Engineering Sciences. 2007; 365: 303-315.
2. Diamanti K, Soutis C. Structural health monitoring techniques for aircraft composite structures. Progress in Aerospace Sciences. 2010; 46: 342-352.
3. Santoni G. Fundamental Studies in the LAMB-WAVE Interaction Between Piezoelectric Wafer Active Sensor and Host Structure During Structural Health Monitoring. PhD thesis. College of Engineering and Information Technology, University of South Carolina; 2010.
4. Vizzini AG. Damage Detection in Blade-Stiffened Anisotropic Composite Panels Using Lamb Wave Mode Conversions. Master's thesis. Arizona State University; 2012.
5. Su Z, Ye L, Lu Y. Guided Lamb waves for identification of damage in composite structures: A review. Journal of Sound and Vibration. 2006; 295: 753-780.
6. Al-Tabey WA. The Fatigue Behavior of Woven-roving Glass Fiber Reinforced Epoxy under Combined Bending Moments and Internal Hydrostatic Pressure. PhD Thesis. Alexandria University; 2015.
7. Bannantine JA, Comer JJ, Handrock JL. Fundamentals of Metal Fatigue Analysis. Prentice Hall; 1990.
8. Altabey WA. A novel framework to identify delamination location/size in BFRP pipe based on convolutional neural network (CNN) algorithm hybrid with capacitive sensors. International Journal of Lightweight Materials and Manufacture. 2025; 8(3):393-401. doi:10.1016/j.ijlmm.2024.12.002
9. Altabey WA. The fatigue damage monitoring of composite pipeline based on frequency domain analysis of electrical capacitance sensor system measurements. International Journal of Lightweight Materials and Manufacture. 2025; 8(6):779-792. doi:10.1016/j.ijlmm.2025.06.002
10. Altabey WA. A novel material model of BFRP laminated composite diaphragms for nano electro mechanical sensors. Journal of Polymer Science and Engineering. 2026; 9(1):11915. doi:10.24294/jpse11915
11. Altabey WA. Composite Materials and Structures, Artificial Intelligence-Based Structural Health Monitoring. De Gruyter Brill; September 8, 2025. ISBN: 978-3-11-914546-6. doi:10.1515/9783112213094
12. Altabey WA. Structural Reliability and Health Monitoring of Composite Structures with Artificial Intelligence. Elsevier Inc.; June 26, 2026. ISBN: 9780443510953.
13. Khan SA, Rahimian Koloor SS, King Jye W, Siebert G, Tamin MN. A fatigue model to predict interlaminar damage of FRP composite laminates subjected to mode I load. Polymers. 2023; 15: 527. doi:10.3390/polym15030527

14. Odeh A, Al-Shugaa MA, Al-Gahtani HJ, Mukhtar F. Analysis of laminated composite plates: A comprehensive bibliometric review. Buildings. 2024; 14: 1574. doi:10.3390/buildings14061574
15. De Giorgi M, Nobile R, Palano F. CFRP fatigue damage detection by thermal methods. Materials. 2022; 15: 3787. doi:10.3390/ma15113787
16. Guedes RM. Creep and Fatigue in Polymer Matrix Composites. Woodhead Publishing Series in Composites Science and Engineering. Woodhead Publishing; 2011: 366-405.
17. Georg Karl Kocur. From detection to prediction of damage in thin-walled structures: A review on engineering acoustics and machine-learning methods. Sound and Vibration. 2026; 641: 119906. doi:10.1016/j.jsv.2026.119906
18. Ding Y, Chen S, Xie F, Zhang C, Jiang W, Jing X. Hybrid fiber reinforced polymer composites: Recent advances in manufacturing methods, hybridization strategies and service performance. Composites Part A: Applied Science and Manufacturing. 2026; 209: 109934. doi:10.1016/j.compositesa.2026.109934
19. Altabey WA. The laminated pipeline material delamination identification based on artificial intelligence schemes. In: 2024 10th International Conference on Advances in Machinery, Materials Science and Engineering Applications (MMSE 2024). Paris, France; July 27-28, 2024. Advances in Transdisciplinary Engineering. IOS Press; 2024; 58: 827-834. doi:10.3233/ATDE240713
20. Altabey WA, Kouritem SA, Al-Moghazy MA. Apply frequency response function schemes for damage detection in composite nanoscale-pipes under transient conditions. Nano-Structures & Nano-Objects. 2024; 39: 101259. doi:10.1016/j.nanoso.2024.101259
21. Altabey WA, Kouritem SA, Al-Moghazy MA. A new diagnostic system for damage monitoring of BFRP plates. e-Prime - Advances in Electrical Engineering, Electronics and Energy. 2023; 15: 100258. doi:10.1016/j.prime.2023.100258
22. Duggan TV, Byrne J. Fatigue as a Design Criterion. McMillan Press Ltd.; 1977. ISBN: 0-333-21488-9.
23. Kim HC, Ebert LJ. Axial fatigue failure sequence and mechanisms in unidirectional fiberglass composite. Journal of Composite Materials. 1978; 12: 139-152.
24. Ellyin F, Kujawski D. Fatigue testing and life prediction of fiber glass-reinforced composites. In: Neale KW, Labossière P, eds. First International Conference on Advanced Composite Materials in Bridges and Structures (ACMBS-I). Sherbrooke, Québec, Canada: Canadian Society for Civil Engineering; 1992: 111-118.
25. Kujawski D, Ellyin F. Rate/frequency-dependent behaviour of fiberglass/epoxy laminates in tensile and cyclic loading. Journal of Composites. 1995; 26(10):719-723.
26. Lee BL, Liu DS. Cumulative damage of fiber-reinforced elastomer composites under fatigue loading. Journal of Composite Materials. 1994; 28(13):1261-1286.
27. Chamis CC. Mechanics of Load Transfer at the Fiber/Matrix Interface. NASA TN D-6588; February 1972.
28. Soden PD, Kitching R, Tse PC, Tsavalas Y, Hinton MJ. Influence of winding angle on the strength and deformation of filament-wound composite tubes subjected to uniaxial and biaxial loads. Composites Science and Technology. 1993; 46(4):363-378.
29. Keck S, Fulland M. Effect of fibre volume fraction and fibre direction on crack paths in flax fibre reinforced composites. Engineering Fracture Mechanics. In press. Available online April 13, 2016.
30. Ghamarian N, Hanim MA, Penjumras P, Majid DL. Effect of fiber orientation on the mechanical properties of laminated polymer composites. Reference Module in Materials Science and Materials Engineering. Current as of July 22, 2016.
31. Chawla N, Liaw PK, LaraCurzio E, Ferber MK, Lowden RA. Effect of fiber fabric orientation on the flexural monotonic and fatigue behavior of 2D woven ceramic matrix composites. Materials Science and Engineering: A. 2012; 557(15):77-83.
32. El Kadi H, Ellyin F. Effect of stress ratio on the fatigue of unidirectional fibre glass-epoxy composite laminae. Journal of Composite Materials. 1994; 25(10):917-924.
33. Fujii T, Shiina T, Okubo K. Fatigue notched sensitivity of glass woven fabric composites having a circular hole under tension/torsion biaxial loading. Journal of Composite Materials. 1994; 28: 234-251.
34. Athijayamani A, Thiruchitrambalam M, Natarajan U, Pazhanivel B. Effect of moisture absorption on the mechanical properties of randomly oriented natural fibers/polyester hybrid composite. Materials Science and Engineering A. 2009; 517: 344-353.
35. Merah N, Nizamuddin S, Khan Z, Al-Sulaiman F. Effects of harsh weather and seawater on glass fiber reinforced epoxy composite. Journal of Reinforced Plastics and Composites. 2010; 29(20):3104-3110.
36. Kaynak C, Mat O. Uniaxial fatigue behavior of filament-wound glass-fiber/epoxy composite tubes. Composites Science and Technology. 2001; 61(13):1833-1840.
37. Wisnom MR. Size effects in composites. Reference Module in Materials Science and Materials Engineering. Current as of

October 28, 2015.
38. Zerbst U, Vormwald M, Pippan R, Gänser HP, Sarrazin-Baudoux C, Madia M. About the fatigue crack propagation threshold of metals as a design criterion–A review. Engineering Fracture Mechanics. 2016; 153: 190-243. doi:10.1016/j.engfracmech.2015.12.002
39. Subramanian S, Elmore IS, Stinchcomb WW, Reifsnider KL. Influence of fiber–matrix interphase on the long-term behavior of graphite/epoxy composite. In: Deo RB, Saff CR, eds. Composite Material: Testing and Design. ASTM STP 1274. American Society for Testing and Materials; 1996; 12: 69-87.
40. Hochard C, Miot S, Thollon Y. Fatigue of laminated composite structures with stress concentrations. Composites Part B: Engineering. 2014; 65: 11-16.
41. Venkatappagari S, Mutra RR, Mallikarjuna RD. State-of-the-art in adhesive joint technology: A comprehensive review of recent progress. Journal of Materials Research and Technology. 2025; 37: 2593-2615. doi:10.1016/j.jmrt.2025.06.166
42. Hiremath VS, Mallikarjuna RD. Effect of CFRP pin reinforcement and manufacturing technique on shear and dynamic properties of flat-joggle-flat composite joints. Materials Letters. 2024; 357: 135733. doi:10.1016/j.matlet.2023.135733
43. Hiremath VS, Reddy MD, Mutra RR, Sanjeev A, Dhilipkumar T, Naveen J. Thermal degradation and fire retardant behaviour of natural fibre reinforced polymeric composites—A comprehensive review. Journal of Materials Research and Technology. 2024; 30: 4053-4063. doi:10.1016/j.jmrt.2024.04.085
44. Balaji S, Rajesh M, Naveen J, Reddy DM, Dhilipkumar T, Sathyaseelan P, Murali AP. Effect of 3-aminopropyl-trimethoxysilane functionalization and co-cure manufacturing on enhancing the structure properties of GFRP composite joint. Materials Letters. 2025; 383: 138053. doi:10.1016/j.matlet.2025.138053
45. Sims DF, Brogdon VH. Fatigue behavior of composites under different loading modes. In: Reifsnider KL, Lauraitis KN, eds. Fatigue of Filamentary Materials. ASTM STP 636. 1977: 185-205.
46. Hahn HT. Fatigue behavior and life prediction of composite laminates. In: Tsai SW, ed. Composite Materials: Testing and Design (Fifth Conference). ASTM STP 674. 1979: 383-417.
47. Hashin Z. Fatigue failure criteria for unidirectional fiber composites. Journal of Applied Mechanics. 1981; 48: 846-852.
48. Hashin Z. Fatigue failure criteria for combined cyclic stress. International Journal of Fracture. 1981; 17(2):101-109.
49. Tennyson RC, Hansen JS, Heppler GR, Mabson G, Wharram G, Street KN. Computation of influence of defects on static and fatigue strength of composites. AGARD-CP-355. 1983: 14-17.
50. Wu CML. Thermal and mechanical fatigue analysis of angle-ply CFRP laminates. Second International Composites Conference and Exhibition. Ottawa, Ontario, Canada; 1993: 631-638.
51. Altabey WA. Innovative intelligent and expert system of bridges damage identification via wavelet packet energy curvature difference method integrated with artificial intelligence algorithms. Sound & Vibration. 2025; 59(2). doi:10.59400/sv2372
52. Wang CG, Song XY, Zhang YW, Han QK, Chen LQ. Semi-analytical modeling and vibration analysis of thin-walled plate structures with arbitrary geometric profiles. Thin-Walled Structures. 2026; 221: 114420. doi:10.1016/j.tws.2025.114420
53. Amaro AM, Santos JB, Cirne JS. Delamination depth in composites laminates with interface elements and ultrasound analysis. Strain. 2011; 47: 138-145.
54. ZengHua L, HongTao Y, CunFu H, Bin W. Delamination damage detection of laminated composite beams using air-coupled ultrasonic transducers. Science China: Physics, Mechanics & Astronomy. 2013; 56(7):1269-1279.
55. Alem B, Abedian A. Fatigue damage detection in large thin wall plate based on ultrasonic guided wave by using a piezoelectric sensor network. In: 29th Congress of the International Council of the Aeronautical Sciences. St. Petersburg, Russia; September 7-12, 2014.
56. Liu Z, Yu H, He C, Wu B. Delamination detection in composite beams using pure Lamb mode generated by air-coupled ultrasonic transducer. Journal of Intelligent Material Systems and Structures. 2014; 25(5):541-550.
57. Park B, An Y, Sohn H. Visualization of hidden delamination and debonding in composites through noncontact laser ultrasonic scanning. Composites Science and Technology. 2014; 100(21):10-18.
58. Kersemans M, Martens A, Degrieck J, et al. The ultrasonic polar scan for composite characterization and damage assessment past, present and future. Applied Sciences. 2015; 58(6):1-15.
59. Lissenden CJ, Liu Y, Rose JL. Use of non-linear ultrasonic guided waves for early damage detection. Insight - Non-Destructive Testing and Condition Monitoring. 2015; 57(4).
60. De Albuquerque VC, Tavares JRS, Durão LMP. Evaluation of delamination damage on composite plates using an artificial neural network for the radiographic image analysis. Journal of Composite Materials. 2010; 44(9):1139-1159.

61. Tompson CG, Johnson WS. Determination of the nontraditional lay-up influence and loading configuration on fatigue damage development under bearing-bypass loading conditions using radiography. Journal of Composite Materials. 2011; 45(22):2259-2269.
62. Aidi B, Philen MK, Case SW. Progressive damage assessment of centrally notched composite specimens in fatigue. Composites Part A: Applied Science and Manufacturing. 2015; 74: 47-59.
63. Jespersen KM, Lowe T, Withers PJ, Zangenberg J, Mikkelsen LP. Micromechanical time-lapse X-ray CT study of fatigue damage in uni-directional fibre composites. In: 20th International Conference on Composite Materials. Copenhagen; July 19-24, 2015.
64. Szwedo M, Bednarz J, Paćko P, Pieczonka Ł, Uhl T. Approach to thermographical damage detection in composite plates. In: Uhl T, ed. Selected Problems of Modal Analysis of Mechanical Systems. Publishing House of the Institute for Sustainable Technologies – National Research Institute (ITeE-PIB); 2009.
65. Kêdziora P. Detection of interlinear cracks in composite structures with the use of piezoelectric sensors and thermography. In: III ECCOMAS Thematic Conference on Computational Methods in Structural Dynamics and Earthquake Engineering. Corfu, Greece; May 25-28, 2011.
66. Colombo C, Libonati F, Vergani L. Fatigue damage in GFRP. International Journal of Structural Integrity. 2012; 3(4):424-440.
67. Toscano C, Riccio A, Camerlingo F, Meola C. Lock in thermography to monitor propagation of delamination in CFRP composites during compression tests. In: 11th International Conference on Quantitative InfraRed Thermography. Naples, Italy; June 11-14, 2012.
68. Schmutzler H, Alder M, Kosmann N, Wittich H, Schulte K. Degradation monitoring of impact damaged carbon fibre reinforced polymers under fatigue loading with pulse phase thermography. Composites Part B: Engineering. 2014; 59: 221-229.
69. Davijani AAB, Hajikhani M, Ahmadi M. Acoustic emission based on sentry function to monitor the initiation of delamination in composite materials. Materials and Design. 2011; 32: 3059-3065.
70. Altabey WA, Noori M, Wu Z, Al-Moghazy MA, Kouritem SA. Studying acoustic behavior of BFRP laminated composite in dual-chamber muffler application using deep learning algorithm. Materials. 2022; 15(22):807. doi:10.3390/ma15228071
71. Altabey WA, Noori M. Mathematical modeling of BFRP laminated composite double-chamber mufflers based acoustic transmission loss optimization. In: Proceedings of the International Conference of Steel and Composite for Engineering Structures (ICSCES 2023). Lecture Notes in Civil Engineering. Vol 486. Springer; April 2024. doi:10.1007/978-3-031-57224-1_6
72. Saeedifar M, Fotouhi M, Najafabadi MA, Toudeshky HH. Prediction of delamination growth in laminated composites using acoustic emission and cohesive zone modeling techniques. Composite Structures. 2015; 124: 120-127.
73. Saeedifar M, Fotouhi M, Najafabadi MA, Toudeshky HH, Minak G. Prediction of quasi-static delamination onset and growth in laminated composites by acoustic emission. Composites Part B: Engineering. 2016; 85: 113-122.
74. Lakhdar M, Mohammed D, Boudjemâa L, Rabiâ A, Bachir M. Damages detection in a composite structure by vibration analysis. Energy Procedia. 2013; 36: 888-897.
75. Altabey WA, Noori M, Silik A. Measuring structural vibration behavior via deep learning and wavelet transform in laminated composite plates with nonlinearity in dimensions and boundary conditions. In: Noori M, Rainieri C, Gentile C, eds. Operational Modal Analysis: Developments and Applications. CRC Press, Taylor & Francis; March 6, 2026: 185-207. doi:10.1201/9781003516941-13. ISBN: 9781032851754.
76. Domagalski Ł, Kowalczyk I. Application of machine learning models in predicting vibration frequencies of thin variable thickness plates. Materials. 2026; 19: 205. doi:10.3390/ma19010205
77. Prusty JK, Papazafeiropoulos G, Mohanty SC. Free vibration analysis of sandwich plates with cut-outs: An experimental and numerical study with artificial neural network modelling. Composite Structures. 2023; 321: 117328.
78. Heuer H, Schulze MH, Meyendorf N. Non-destructive evaluation (NDE) of composites: Eddy current techniques. In: Non-Destructive Evaluation (NDE) of Polymer Matrix Composites. Chapter 3. 2013. ISBN: 978-0-85709-344-8.
79. Liu C, Wang X, Noori M, et al. Innovative design and sensing performance of a novel large-strain sensor for prestressed FRP plates. Developments in the Built Environment. 2024; 20: 100567. doi:10.1016/j.dibe.2024.100567
80. Takeda N, Okabe Y, Mizutani T. Damage detection in composites using optical fibre sensors. Proceedings of the Institution of Mechanical Engineers, Part G: Journal of Aerospace Engineering. 2007; 221: 497.
81. Peng Q, Zhang X, Huang C, Carter EA, Lu G. Hierarchical fiber-optic delamination detection system for carbon fiber reinforced plastic structures. Modelling and Simulation in Materials Science and Engineering. 2012; 18: 1-14.

82. Zuluaga-Ramírez P, Arconada Á, Frövel M, Belenguer T, Salazar F. Optical sensing of the fatigue damage state of CFRP under realistic aeronautical load sequences. Sensors. 2015; 15: 5710-5721.
83. Dayal V, Kinra VK. Leaky Lamb waves in an anisotropic plate. II—Nondestructive evaluation of matrix cracks in fiber-reinforced composites. Journal of the Acoustical Society of America. 1991; 89(4):1590-1598.
84. Kessler SS, Spearing SM, Soutis C. Damage detection in composite materials using Lamb wave methods. Smart Materials and Structures. 2002; 11: 269-278.
85. Yashiro S, Takatsubo J, Toyama N. An NDT technique for composite structures using visualized Lamb-wave propagation. Composites Science and Technology. 2007; 67: 3202-3208.
86. Hu N, Liu Y, Li Y, Peng X, Yan B. Optimal excitation frequency of Lamb waves for delamination detection in CFRP laminates. Journal of Composite Materials. 2010; 44(13).
87. Yeum CM, Sohn H, Ihn JB, HJ. Delamination detection in a composite plate using a dual piezoelectric transducer network. Composite Structures. 2012; 94: 3490-3499.
88. Gopalakrishnan S. Lamb wave propagation in laminated composite structures. Journal of the Indian Institute of Science. 2013; 93(4):699-713.
89. Yeum CM, Sohn H, Lim HJ, Ihn JB. Reference-free delamination detection using Lamb waves. Structural Control and Health Monitoring. 2014; 21: 675-684.
90. Keulen CJ, Yildiz M, Suleman A. Damage detection of composite plates by Lamb wave ultrasonic tomography with a sparse hexagonal network using damage progression trends. Shock and Vibration. 2014: 1-8.
91. Spiegel MD. Damage Detection in Composite Materials Using PZT Actuators and Sensors for Structural Health Monitoring. Master's thesis. Department of Electrical and Computer Engineering, University of Alabama; 2014.
92. Qiao P, Fan W. Lamb wave-based damage imaging method for damage detection of rectangular composite plates. Structural Monitoring and Maintenance. 2014; 1(4):411-425.
93. Shen Y, Giurgiutiu V. Combined analytical FEM approach for efficient simulation of Lamb wave damage detection. Ultrasonics. 2016; 69: 116-128.
94. Mouritz AP. Non-destructive evaluation of damage accumulation. In: Harris B, ed. Fatigue in Composites. Woodhead Publishing Series in Composites Science and Engineering. Chapter 8. 2003. ISBN: 978-1-85573-608-5.
95. Ng CT, Veidt M. A Lamb-wave-based technique for damage detection in composite laminates. Smart Materials and Structures. 2009; 18: 074006. doi:10.1088/0964-1726/18/7/074006
96. Chimenti DE. Guided waves in plates and their use in materials characterization. Applied Mechanics Reviews. 1997; 50: 47-284.
97. Worlton DC. Experimental confirmation of Lamb waves at megacycle frequencies. Journal of Applied Physics. 1961; 32: 967-971.
98. Saravanos DA, Birman V. Detection of delaminations in composite beams using piezoelectric sensors. In: Proceedings of the 35th Structures, Structural Dynamics and Materials Conference of the AIAA. 1994.
99. Percival WJ, Birt EA. A study of Lamb wave propagation in carbon-fibre composites. Non-Destructive Testing and Condition Monitoring. 1997; 39: 728-735.
100. Seale MD, Smith BT. Lamb wave assessment of fatigue and thermal damage in composites. Journal of the Acoustical Society of America. 1998; 103: 2416-2424.
101. Tang B, Henneke EG. Lamb wave monitoring of axial stiffness reduction of laminated composite plates. Materials Evaluation. 1989; 47: 928-934.
102. Alleyne DN, Cawley P. The interaction of Lamb waves with defects. IEEE Transactions on Ultrasonics, Ferroelectrics and Frequency Control. 1992; 39(3):381-397.
103. Saravanos DA, Birman V, Hopkins DA. Detection of delaminations in composite beams using piezoelectric sensors. In: Proceedings of the 31st AIAA/ASME/ASCE/AHS/ASC Structures, Structural Dynamics and Materials Conference. 1994: 181-191.
104. Kessler SS, Spearing SM, Atalla MJ. In-situ damage detection of composites structures using Lamb waves methods. In: Proceedings of the 1st European Workshop on Structural Health Monitoring. Ecole Normale Supérieure, Cachan, Paris, France; 2002: 374-381.
105. Su Z, Ye L, Bu X. Evaluation of delamination in laminated composites based on Lamb waves methods: FEM simulation and experimental verification. In: Proceedings of the 1st European Workshop on Structural Health Monitoring. Ecole Normale

Supérieure, Cachan, Paris, France; 2002: 328-335.
106. Lee BC, Staszewski WJ. Modelling of acousto-ultrasonic wave interaction with defects in metallic structures. In: Proceedings of the International Conference on Noise and Vibration Engineering (ISMA 2002). Leuven, Belgium; 2002: 319-327.
107. Ricci F, Banerjee S, Mal AK. Health monitoring of composite structures using wave propagation data. In: Proceedings of the 2nd European Workshop on Structural Health Monitoring. Forum am Deutschen Museum, Munich, Germany; 2004: 1035-1042.
108. Toyama N, Okabe T. Effects of tensile strain and transverse cracks on Lamb-wave velocity in cross-ply FRP laminates. Journal of Materials Science. 2004; 39: 7365-7367.
109. Sundararaman S, Adams DE, Rigas EJ. Characterizing damage in plates through beamforming with sensor arrays. In: Proceedings of the 23rd International Modal Analysis Conference (IMAC XXIII). Orlando, Florida, USA; 2005. Paper no. 249.
110. Kim BH, Stubbs N, Park T. Flexural damage index equations of a plate. Journal of Sound and Vibration. 2005; 283: 341-368.
111. Harri K, Guillaume P, Vanlanduit S. On-line damage detection on a wing panel using transmission of multisine ultrasonic waves. NDT & E International. 2008; 41(4):312-317.
112. Mansi A, Dunai L, Cao M. Wavelet-based denoising of structural health monitoring strain measurements. Measurement: Sensors. 2025; 42: 101974. doi:10.1016/j.measen.2025.101974
113. Mehrabadi FA, Nguyen A, Zarfam P, Bitaraf M, Aziminejad A. Data-efficient anomaly detection in bridge structures using weighted k-nearest neighbor classifier. Smart Materials and Structures. 2025; 34(11):115044. doi:10.1088/1361-665X/ae1bed
114. Lin YZ, Nie ZH, Ma HW. Structural damage detection with automatic feature-extraction through deep learning. Computer-Aided Civil and Infrastructure Engineering. 2017; 32(12):1025-1046. doi:10.1111/mice.12313
115. Azizi T. Comparative analysis of statistical, time–frequency, and SVM techniques for change detection in nonlinear biomedical signals. Signals. 2024; 5: 736-755. doi:10.3390/signals504004
116. Silik A, Noori M, Wu Z, Altabey WA, Dang J, Farhan NSD. Wavelet-based vibration denoising for structural health monitoring. Urban Lifeline. 2024; 2: Article 15. doi:10.1007/s44285-024-00025-0
117. Altabey WA. The nonlinear study of composite plates natural frequency using RNN-LSTM combined with wavelet transform features. International Journal of Mechanical Engineering and Robotics Research. 2026; 15(2):197-210. doi:10.18178/ijmerr.15.2.197-210
118. Hurlebaus S, Niethammer M, Jacobs LJ. Automated methodology to locate notches with Lamb waves. Journal of the Acoustical Society of America: Acoustics Research Letters Online. 2001; 2(4):97-102.
119. Altabey WA. The damage identification in laminated composite plate under fatigue load through wavelet packet energy curvature difference method. Composites Part C: Open Access. 2022; 9: 100304. doi:10.1016/j.jcomc.2022.100304
120. Su Z, Ye L. Identification of Damage Using Lamb Waves: From Fundamentals to Applications. Springer-Verlag Berlin Heidelberg; 2009.
121. Migot A, Saaudi A, Giurgiutiu V. Delamination depth detection in composite plates using the Lamb wave technique based on convolutional neural networks. Sensors. 2024; 24: 3118. doi:10.3390/s24103118
122. Baid HK. Detection of Damage in a Composite Structure Using Guided Waves. PhD thesis. Mechanical Engineering, University of California, Los Angeles; 2012.
123. Ratassepp M, Klauson A. Curvature effects on wave propagation in an infinite pipe. Ultragarsas. 2006; 59(2):19-25.
124. Chakraborty A. Modeling of Lamb waves in composite structures. In: Encyclopedia of Structural Health Monitoring. Chapter 49. John Wiley & Sons; 2009: 923-939.
125. Nayfeh A, Chimenti D. Free wave propagation in plates of general anisotropic media. Journal of Applied Mechanics. 1989; 56(4):881-886.
126. Lowe MJS. Matrix techniques for modeling ultrasonic waves in multilayered media. IEEE Transactions on Ultrasonics, Ferroelectrics and Frequency Control. 1995; 42(4):525-542.
127. Nayfeh AH. Wave Propagation in Layered Anisotropic Media with Applications to Composites. Elsevier Science B.V.; 1995.
128. Alleyne DN, Cawley P. A 2-dimensional Fourier transform method for the quantitative measurement of Lamb modes. In: Proceedings of IEEE Ultrasonics Symposium. 1990; 2: 1143-1146.
129. Hayward G, Hyslop J. Determination of Lamb wave dispersion data in lossy anisotropic plates using time domain finite element analysis, part I: Theory and experimental verification. IEEE Transactions on Ultrasonics, Ferroelectrics, and Frequency Control. 2006; 53(2):443-448.
130. Altabey WA. The response of the composite circular diaphragms under thermo-mechanical stresses via bulge testing. Journal

of Polymer Science and Engineering. 2026; 9(1):11929. doi:10.24294/jpse11929
131. Spencer BF Jr, Sim SH, Kim RE, Yoon H. Advances in artificial intelligence for structural health monitoring: A comprehensive review. KSCE Journal of Civil Engineering. 2025; 29(3):100203. doi:10.1016/j.kscej.2025.100203
132. Altabey WA. The advanced structural health monitoring by non-destructive self-powered wireless lightweight sensor. Structural Durability & Health Monitoring. 2025; 19(6):1529-1545. doi:10.32604/sdhm.2025.069003
133. Altabey WA. A novel sensors technologies for structural health monitoring of civil structures. Journal of Dynamic Disasters. 2025; 1: 100053. doi:10.1016/j.jdd.2026.100053
134. Altabey WA. An intelligent system for pavement health monitoring using perception sensors aided deep learning algorithms. Structural Durability & Health Monitoring. Published online December 2, 2025. doi:10.32604/sdhm.2025.073949
135. Altabey WA. A framework based on deep learning and the intelligent sensors for pavement assessment condition. Sound & Vibration. 2025; 59(6):3458. doi:10.59400/sv3458
136. Toyama N, Takatsubo J. Lamb wave method for quick inspection of impact-induced delamination in composite laminates. Composites Science and Technology. 2004; 64: 1293-1300.
137. Schulz MJ, Pai PF, Inman DJ. Health monitoring and active control of composite structures using piezoceramic patches. Composites Part B: Engineering. 1999; 30: 713-725.
138. Altabey WA, Wu Z, Noori M, Fathnejat H. Structural health monitoring of composite pipelines utilizing fiber optic sensors and an AI-based algorithm—A comprehensive numerical study. Sensors. 2023; 23(8):3887. doi:10.3390/s23083887
139. Schmidt D, Heinze C, Hillger W, Szewieczek A, Sinapius M, Wierach P. Design of mode selective actuators for Lamb wave excitation in composite plates. Proceedings of SPIE. 2011; 7984: 798409.
140. Koh YL, Chiu WK, Rajic N. Effects of local stiffness changes and delamination on Lamb wave transmission using surface-mounted piezoelectric transducers. Composite Structures. 2002; 57: 437-443.
141. Kouritem AK, Altabey WA. Ultra-broadband natural frequency using automatic resonance tuning of energy harvester and deep learning algorithms. Energy Conversion and Management. 2022; 272: 116332. doi:10.1016/j.enconman.2022.116332
142. Afshar H, Kamran F, Shahi F. Recent progress in energy harvesting technologies for self-powered wearable devices: The significance of polymers. Polymers for Advanced Technologies. 2025; 36: e70187. doi:10.1002/pat.70187
143. Ali A, Ali S, Shaukat H, et al. Advancements in piezoelectric wind energy harvesting: A review. Results in Engineering. 2024; 21: 101777. doi:10.1016/j.rineng.2024.101777
144. Sohail A, Ali A, Shaukat H, et al. Integrating self-powered medical devices with advanced energy harvesting: A review. Energy Strategy Reviews. 2024; 52: 101328. doi:10.1016/j.esr.2024.101328
145. Ali A, Ashfaq M, Qureshi A, et al. Smart detecting and versatile wearable electrical sensing mediums for healthcare. Sensors. 2023; 23(14):6586. doi:10.3390/s23146586
146. Hu K, Wang M. Broadband piezoelectric energy harvester based on coupling resonance frequency tuning. Micromachines. 2023; 14: 105. doi:10.3390/mi14010105
147. Ganie AS, Bano S, Bashar N, Sabir S, Khan MZ, Rahman MM. Piezoelectric ceramics: Advanced applications in electrochemical and electronic fields. In: Singh S, Kumar P, Mondal DP, eds. Advanced Ceramics for Versatile Interdisciplinary Applications. Elsevier Series in Advanced Ceramic Materials. Elsevier; 2022: 167-179. doi:10.1016/B978-0-323-89952-9.00006-3
148. Shaukat H, Ali A, Ali S, Altabey WA, Noori M, Kouritem SA. Applications of sustainable hybrid energy harvesting: A review. Journal of Low Power Electronics and Applications. 2023; 13: 62. doi:10.3390/jlpea13040062
149. Li Z, Roscow J, Khanbareh H, Haswell G, Bowen C. Energy harvesting from water flow by using piezoelectric materials. Advanced Energy and Sustainability Research. 2024; 5(5):2300235. doi:10.1002/aesr.202300235
150. Liu X, He L, Liu R, Hu D, Zhang L, Cheng G. Piezoelectric energy harvesting systems using mechanical tuning techniques. Review of Scientific Instruments. 2023; 94(3):031501. doi:10.1063/5.0120778
151. Radeef ZS, Jweri ARK, Alsayah AM, Alshukri MJ, Khaled M. Advances in piezoelectric energy harvesting: Materials, configurations, and power optimisation strategies. Results in Engineering. 2025; 28: 107782. doi:10.1016/j.rineng.2025.107782
152. Kim YH, Kim DH, Han JH, Kim CG. Damage assessment in layered composites using spectral analysis and Lamb wave. Composites Part B: Engineering. 2007; 38: 800-809.
153. Paget CA, Grondel S, Levin K, Delebarre C. Damage assessment in composites by Lamb waves and wavelet coefficients. Smart Materials and Structures. 2003; 12: 393-402.
154. Zhao X, Zhang G, Gao H, et al. Active health monitoring of an aircraft wing with embedded piezoelectric sensor/actuator

network: I. Defect detection, localization and growth monitoring. Smart Materials and Structures. 2007; 16: 1208-1217.
155. Jha R, Watkins R. Lamb wave based diagnostics of composite plates using a modified time reversal method. In: Proceedings of 50th AIAA/ASME/ASCE/AHS/ASC Structures, Structural Dynamics, and Materials Conference. Palm Springs, California; May 4-7, 2009.
156. Gao Y, Sun L, Song R, et al. Damage localization in composite structures based on Lamb wave and modular artificial neural network. Sensors and Actuators A: Physical. 2024; 377: 115644. doi:10.1016/j.sna.2024.115644
157. Souza PR, Nobrega EGO. Lamb wave based damage detection and localization using two ring-shaped arrangement of piezo transducers. IFAC-PapersOnLine. 2015; 48(21):646-651. doi:10.1016/j.ifacol.2015.09.600
158. Nzouatchoua CB, Bentahar M, Montresor S, et al. Damage localization on composite structures based on the delay-and-sum algorithm using simulation and experimental methods. Sensors. 2023; 23: 4368. doi:10.3390/s23094368
159. Azad MM, Munyaneza O, Jung J, Sohn JW, Han JW, Kim HS. Damage localization and severity assessment in composite structures using deep learning based on Lamb waves. Sensors. 2024; 24: 8057. doi:10.3390/s24248057
160. Zeng X, Hu N, Liu Y, et al. Prediction and evaluation of projectile damage in composite plates using the neural network-cloud model. Frontiers in Materials. 2023; 10: 1164090.
161. Rautela M, Gopalakrishnan S. Ultrasonic guided wave based structural damage detection and localization using model assisted convolutional and recurrent neural networks. Expert Systems with Applications. 2021; 167: 114189.
162. Miorelli R, Fisher C, Kulakovskyi A, et al. Defect sizing in guided wave imaging structural health monitoring using convolutional neural networks. NDT & E International. 2021; 122: 102480.
163. Wu J, Xu X, Liu C, et al. Lamb wave-based damage detection of composite structures using deep convolutional neural network and continuous wavelet transform. Composite Structures. 2021; 276: 114590.
164. Liao Y, Wang Y, Zeng X, et al. Multiscale 1DCNN for damage localization and quantification using guided waves with novel data fusion technique and new self-attention module. IEEE Transactions on Industrial Informatics. 2024; 20(1):492-502.
165. Feng B, Pasadas DJ, Ribeiro AL, et al. Locating defects in anisotropic CFRP plates using ToF-based probability matrix and neural networks. IEEE Transactions on Instrumentation and Measurement. 2019; 68(5):1252-1260.
166. Yelve NP, Mulla IB. Locating damage in thin metallic plates using Lamb waves and artificial neural network. In: International Conference on Nascent Technologies in Engineering (ICNTE). IEEE; 2017: 1-7.
167. Hen Y, Hwang JN. Handbook of Neural Network Signal Processing. CRC Press; 2001.
168. Azad MM, Cheon Y, Raouf I, Khalid S, Kim HS. Intelligent computational methods for damage detection of laminated composite structures for mobility applications: A comprehensive review. Archives of Computational Methods in Engineering. 2024: 1-29.
169. Azad MM, Rehman Shah AU, Prabhakar MN, Kim HS. Deep learning-based fracture mode determination in composite laminates. Journal of Computational Structural Engineering Institute of Korea. 2024; 37: 225-232.
170. Azouz Z, Honarvar Shakibaei Asli B, Khan M. Evolution of crack analysis in structures using image processing technique: A review. Electronics. 2023; 12: 3862. doi:10.3390/electronics12183862
171. Huang Z, Chang D, Yang X, Zuo H. A deep learning-based approach for crack damage detection using strain field. Engineering Fracture Mechanics. 2023; 293: 109703. doi:10.1016/j.engfracmech.2023.109703
172. Altabey WA, Noori M, Wu Z. Deep learning-based crack, location and area identification for a pipeline by the convolutional neural network based on crack contour network method. In: 5th ECCOMAS Thematic Conference on Uncertainty Quantification in Computational Sciences and Engineering (UNCECOMP 2023). Athens, Greece; June 12-14, 2023. doi:10.7712/120123.10644.20187
173. Altabey WA, Noori M, Wu Z, Silik A, Farhan NSD. Effective technique for structures damage detection based on the structural frequency maps. In: 5th ECCOMAS Thematic Conference on Uncertainty Quantification in Computational Sciences and Engineering (UNCECOMP 2023). Athens, Greece; June 12-14, 2023. doi:10.7712/120123.10645.21865
174. Altabey WA. An artificial intelligence-based scheme for structural health monitoring in CFRE laminated composite plates under spectrum fatigue loading. Structural Durability & Health Monitoring. 2025; 19(5):1145-1165. doi:10.32604/sdhm.2025.068922
175. Oh S, Song J, Kim T. Deep learning-based modularized loading protocol for parameter estimation of Bouc–Wen class models. Engineering Structures. 2025; 339: 120458. doi:10.1016/j.engstruct.2025.120458
176. Altabey WA, Noori M, Wang T, Ghiasi R, Kuok S, Wu Z. Deep learning-based crack identification for steel pipelines by extracting features from 3D shadow modeling. Applied Sciences. 2021; 11(13):6063. doi:10.3390/app11136063

177. Yang C, Zheng F, Kapelan Z, Savic D, Pan G, Feng Y, Ma Y. Automated quantification of sewage pipe cracks using deep learning for urban water environment management. Tunnelling and Underground Space Technology. 2025; 155(Part 2):106195. doi:10.1016/j.tust.2024.106195
178. Altabey WA. A comprehensive study of a long-term creep thermo-mechanical fatigue behavior monitoring of BFRP composite pipeline using electrical capacitance sensors and deep learning algorithm. International Journal of Fatigue. 2024; 184: 108277. doi:10.1016/j.ijfatigue.2024.108277
179. Altabey WA, Noori M, Wu Z, Al-Moghazy MA, Kouritem SA. A deep-learning approach for predicting water absorption in composite pipes by extracting the material's dielectric features. Engineering Applications of Artificial Intelligence. 2023; 121: 105963. doi:10.1016/j.engappai.2023.105963
180. Tomás M, Jalali S, Silva de Vargas A. Creep evaluation and temperature dependence in self-sensing micro carbon polymer-based composites for further development as an Internet of Things sensor device. Journal of Composite Materials. 2022; 56(6):961-973. doi:10.1177/00219983211058805
181. Azad MM, Jung J, Kim HS, Munyaneza O, Sohn JW, Huang B. An integrated multi-task transfer learning for damage detection, localization, and severity assessment of laminated composite plate. Composite Structures. 2025; 371: 119478. doi:10.1016/j.compstruct.2025.119478
182. Lee H, Lim HJ, Skinner T, Chattopadhyay A, Hall A. Automated fatigue damage detection and classification technique for composite structures using Lamb waves and deep autoencoder. Mechanical Systems and Signal Processing. 2022; 163: 108148.
183. Krawczuk M, Ostachowicz W, Kawiecki G. Detection of delaminations in cantilevered beams using soft computing methods. In: Proceedings of the European COST F3 Conference on System Identification and Structural Health Monitoring. Madrid, Spain; 2000: 243-252.
184. Messina A, Jones IA, Williams EJ. Damage detection and localization using natural frequency changes. In: Proceedings of the 1st Conference on Identification. Cambridge, England, UK; 1992: 67-76.
185. Hatem TM, Foutouh MNA, Negm HM. Application of genetic algorithms and neural networks to health monitoring of composite structures. In: Proceedings of the 2nd European Workshop on Structural Health Monitoring. Forum am Deutschen Museum, Munich, Germany; 2004: 616-623.
186. Zheng D. Low Velocity Impact Analysis of Composite Laminated Plates. PhD Thesis. Graduate Faculty of the University of Akron, USA; 2007.
187. Haj-Ali RM, Pecknold DA, Ghaboussi J, Voyiadjis GZ. Simulated micromechanical models using artificial neural networks. Journal of Engineering Mechanics. 2001; 127(7):730-738.
188. Chakraborty D. Artificial neural network based delamination prediction in laminated composites. Materials and Design. 2005; 26: 1-7.
189. Roseiro L, Ramos U, Leal R. Neural networks in damage detection of composite laminated plates. In: Proceedings of the 6th WSEAS International Conference on Neural Networks. Lisbon, Portugal; June 16-18, 2005: 115-119.
190. Karnik SR, Gaitonde VN, Rubio JC, Correia E, Abrão AM, Davim JP. Delamination analysis in high speed drilling of carbon fibre reinforced plastics (CFRP) using artificial neural network model. Materials and Design. 2008; 29(9):1768-1776.
191. Tran-Ngoc H, Khatir S, Ho-Khac H, De Roeck G, Bui-Tien T, Abdel Wahab M. Efficient artificial neural networks based on a hybrid metaheuristic optimization algorithm for damage detection in laminated composite structures. Composite Structures. 2021; 262: 113339.
192. Zara A, Belaidi I, Khatir S, Oulad Brahim A, Boutchicha D, Abdel Wahab M. Damage detection in GFRP composite structures by improved artificial neural network using new optimization techniques. Composite Structures. 2023; 305: 116475.
193. Corbetta M, Sbarufatti C, Giglio M, Saxena A, Goebel K. A Bayesian framework for fatigue life prediction of composite laminates under co-existing matrix cracks and delamination. Composite Structures. 2018; 187: 58-70.
194. Cantero-Chinchilla S, Chiachío J, Chiachío M, Chronopoulos D, Jones A. A robust Bayesian methodology for damage localization in plate-like structures using ultrasonic guided-waves. Mechanical Systems and Signal Processing. 2019; 122: 192-205.
195. Doan DD, Ramasso E, Placet V, Zhang S, Boubakar L, Zerhouni N. An unsupervised pattern recognition approach for AE data originating from fatigue tests on polymer–composite materials. Mechanical Systems and Signal Processing. 2015; 64-65:465-478.
196. Vo-Duy T, Ho-Huu V, Dang-Trung H, Nguyen-Thoi T. A two-step approach for damage detection in laminated composite structures using modal strain energy method and an improved differential evolution algorithm. Composite Structures. 2016;

147: 42-53.
197. Lu S, Jiang M, Jia L, Sui Q, Sai Y. CFRP damage identification system based on FBG sensors and ELM method. Optical Review. 2015; 22: 46-51.
198. An H, Youn BD, Kim HS. A methodology for sensor number and placement optimization for vibration-based damage detection of composite structures under model uncertainty. Composite Structures. 2022; 279: 114863.
199. Zhuang L, Luo K, Yang Z. A multimodal gated recurrent unit neural network model for damage assessment in CFRP composites based on Lamb waves and minimal sensing. IEEE Transactions on Instrumentation and Measurement. 2024; 73: 3506911.
200. Soman R, Ostachowicz W. Kalman filter based neutral axis tracking for damage detection in composites structures under changing axial loading conditions. Composite Structures. 2018; 206: 517-525.
201. Sarr CAT, Chataigner S, Gaillet L, Godin N. Nondestructive evaluation of FRP-reinforced structures bonded joints using acousto-ultrasonic: Towards diagnostic of damage state. Construction and Building Materials. 2021; 313: 125499.
202. Li Z, Wang Z, Li Y, Han S. SN-SAE: A new damage diagnosis method for CFRP using Lamb wave. Measurement Science and Technology. 2023; 34: 095020.
203. Lu S, Jiang M, Sui Q, Sai Y, Jia L. Damage identification system of CFRP using fiber Bragg grating sensors. Composite Structures. 2015; 125: 400-406.
204. Tavares A, Di Lorenzo E, Cornelis B, Peeters B, Desmet W, Gryllias K. Machine learning approaches to damage detection in composite structures combining experimental and simulation domains. Mechanical Systems and Signal Processing. 2024; 215: 111412.
205. Azad MM, Kim S, Kim HS. Autonomous data-driven delamination detection in laminated composites with limited and imbalanced data. Alexandria Engineering Journal. 2024; 107: 770-785.
206. Hanagud S, Luo H. Damage detection and health monitoring based on structural dynamics. In: Structural Health Monitoring, Current Status and Perspectives. Stanford University, Palo Alto, California, USA; 1997: 715-726.
207. Luo H, Hanagud S. Dynamic learning rate neural network training and composite structural damage detection. AIAA Journal. 1997; 35(9):1522-1527.
208. Ganjdoust F, Kefal A, Tessler A. Delamination detection and localization in vibrating composite plates and shells using the inverse finite element method. Sensors. 2023; 23: 7926. doi:10.3390/s23187926
209. Páleník M, Musil M, Úradníček J. Detection, localisation and quantification of structural damage using changes in modal characteristics. Applied Sciences. 2023; 13: 10777. doi:10.3390/app131910777
210. Miller B, Ziemiański L. Accelerating multi-objective optimization of composite structures using multi-fidelity surrogate models and curriculum learning. Materials. 2025; 18: 1469. doi:10.3390/ma18071469
211. Setoodeh AR, Malekzadeh P, Nikbin K. Low velocity impact analysis of laminated composite plates using a 3D elasticity based layerwise FEM. Materials & Design. 2009; 30(9): 3795-3801. doi:10.1016/j.matdes.2009.01.031
212. Hochster H, Bernikov Y, Meshi I, Lin S, Ranatunga V, Waas AM, Shemesh NNY, Haj-Ali R. Refined nonlinear micromechanical models using artificial neural networks for multiscale analysis of laminated composites subject to low-velocity impact. International Journal of Solids and Structures. 2023; 264: 112123. doi:10.1016/j.ijsolstr.2023.112123
213. Okafor AC, Chandrashekhara K, Jiang YP. Delamination prediction in composite beams with built-in piezoelectric devices using modal analysis and neural network. Smart Materials and Structures. 1996; 5(3): 338. doi:10.1088/0964-1726/5/3/012
214. Saadatmorad M, Jafari-Talookolaei RA, Pashaei MH, Khatir S. Damage detection on rectangular laminated composite plates using wavelet based convolutional neural network technique. Composite Structures. 2021; 278: 114656. doi:10.1016/j.compstruct.2021.114656
215. Fard MG, Baseri H, Azami A, Zolfaghari A. Prediction of delamination defects in drilling of carbon fiber reinforced polymers using a regression-based approach. Machines. 2024; 12: 783. doi:10.3390/machines12110783
216. Altabey WA, Kouritem SA, Al-Moghazy MA. Application of intelligent perception, management and maintenance of pavement. In: 2025 10th International Conference on Intelligent Transportation Engineering (ICITE 2025). Beijing, China; October 24-26, 2025. Advances in Transdisciplinary Engineering. IOS Press; 2026; 84: 495-502. doi:10.3233/ATDE251520
217. Impraimakis M. Deep recurrent-convolutional neural network learning and physics Kalman filtering comparison in dynamic load identification. Structural Health Monitoring. 2025; 24(3):1752-1782. doi:10.1177/14759217241262972
218. Meruane V, Aichele D, Ruiz R, López Droguett E. A deep learning framework for damage assessment of composite sandwich structures. Shock and Vibration. 2021; 2021: 1483594.
219. Fotouhi S, Pashmforoush F, Bodaghi M, Fotouhi M. Autonomous damage recognition in visual inspection of laminated

composite structures using deep learning. Composite Structures. 2021; 268: 113960.

220. Seventekidis P, Giagopoulos D. A combined finite element and hierarchical deep learning approach for structural health monitoring: Test on a pin-joint composite truss structure. Mechanical Systems and Signal Processing. 2021; 157: 107735.
221. Elsisi A, Abdel-Monsef S, Salim H. Artificial intelligence in the design and optimization of laminated FRP composites: A review of methodologies and applications. Journal of Composites Science. 2025; 9: 654. doi:10.3390/jcs9120654
222. Zenzen R, Khatir S, Belaidi I, Le Thanh C, Wahab MA. A modified transmissibility indicator and artificial neural network for damage identification and quantification in laminated composite structures. Composite Structures. 2020; 248: 112497.
223. Muir C, Swaminathan B, Fields K, et al. A machine learning framework for damage mechanism identification from acoustic emissions in unidirectional SiC/SiC composites. npj Computational Materials. 2021; 7: 146.