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Review

Preventing Catastrophic Failures: A Review of Applying Acoustic Emission Testing in Multi-Bolted Flanges

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Abstract: The integrity of multi-bolted flanges is crucial for ensuring safety and operational efficiency in industrial systems across sectors such as oil and gas, chemical processing, and water treatment. Traditional non-destructive testing (NDT) methods often require operational downtime and may lack sensitivity for early-stage defect detection. This review examines acoustic emission testing (AET), a real-time monitoring technique for detecting acoustic waves generated by material defects. An analysis of 145 studies demonstrated AET's effectiveness in detecting early-stage defects across various materials and industrial applications. Recent advances in sensor technology and signal processing have significantly enhanced AET's capabilities. However, challenges remain regarding environmental noise interference and the need for specialized expertise. The review identifies knowledge gaps and proposes future research directions, including planned laboratory experiments to characterize defect signals in multi-bolted flange systems under different operational conditions. The findings position AET as a transformative solution for industrial inspection and maintenance, offering enhanced safety and reliability for critical infrastructures.

Keywords: non-destructive testing (NDT); acoustic emission testing (AET); multi-bolts connection; flanges; structural health monitoring (SHM)

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1. Introduction

The integrity of multi-bolted flanges and piping systems is of paramount importance across various industrial sectors, including oil and gas, chemical processing, and water treatment. These components serve as critical connections between pipes, valves, and other equipment, thereby ensuring the safe and efficient operation of industrial systems. Failures in these systems can lead to catastrophic consequences such as leaks, explosions, and significant economic losses, underscoring the need for robust inspection and maintenance protocols.

Traditional non-destructive testing (NDT) methods, such as ultrasonic testing (UT), radiography (RT), and visual inspection, have long dominated the inspection landscape.

Although these techniques have proven effective in many applications, they often require operational downtime and may lack the sensitivity to detect early-stage defects. This limitation necessitates the exploration of alternative inspection methods that can provide real-time monitoring capabilities without disrupting operations.

Acoustic emission testing (AET) has emerged as a promising alternative to conventional NDT methods. AET leverages the detection of acoustic waves generated by the rapid release of energy from localized sources within materials such as cracks and voids. This real-time monitoring technique offers several advantages over traditional methods, including continuous assessment capabilities without disrupting operations and heightened sensitivity for detecting incipient defects.

Despite its potential, comprehensive reviews focusing specifically on AET's application to multi-bolted flanges remain limited. This study addresses this gap by synthesizing insights from 145 studies on AET, with a primary focus on its use in multi-bolted flanges. Given the scarcity of direct research on flanges, this review also draws from AET applications in broader piping systems, highlighting the versatility of the technique across industries and materials.

The analysis reveals that while AET has been widely adopted in sectors such as aerospace, automotive, and civil engineering, its implementation in multi-bolted flanges remains underexplored. This discrepancy highlights the need for a targeted review to bridge the knowledge gap and identify opportunities for AET to enhance the flange integrity.

To ensure rigor, studies were systematically selected based on their relevance to AET in flanges or piping, empirical data contribution, and publication in peer-reviewed journals between 2010 and 2024. Quality assessment prioritizes studies with validated experimental designs, clear defect detection methodologies, and industrial applicability.

Building on these insights, this review outlines a roadmap for future investigations. First, controlled laboratory experiments will characterize AE signals from intact and defected (corroded or cracked) multi-bolted flanges under varying pressures to establish baseline patterns for different failure modes. These tests will be extended to diverse materials (e.g., carbon steel and composites) and noisy environments to evaluate AET's robustness. Finally, field validation of operational pipelines and flanges will confirm the practicality of the technique, addressing real-world challenges, such as temperature fluctuations and background noise.

The innovative contribution of this work lies in its focus on translating AET's proven efficacy in related industries to multi-bolted flanges, where safety and reliability are paramount. By highlighting the adaptability of the technique across materials and operational environments, this review not only addresses an underexplored area, but also underscores the broader significance of AET in structural health monitoring (SHM).

2. Multi-Bolted Flange and Piping

Multi-bolted flanges are essential components in piping systems, providing secure connections between pipes, valves, and other equipment [1]. They are widely used in industries such as oil and gas, chemical processing, and water treatment, where the reliable joining of components under various pressure levels is crucial. The integrity of these flanges is vital for the safe and efficient operation of industrial systems because failures can lead to leaks, explosions, and significant economic losses.

These flanges consisted of a circular disk with holes around the perimeter, allowing multiple bolts to fasten the two flanged components together. This design enhances the load-bearing capacity, simplifies the construction and replacement processes, and provides flexibility for easier disassembly and maintenance. This is particularly important in environments such as petrochemical plants, where regular inspection and component replacement are necessary. As shown in Figure 1, these plants contain numerous multi-bolted flanges that require careful attention.

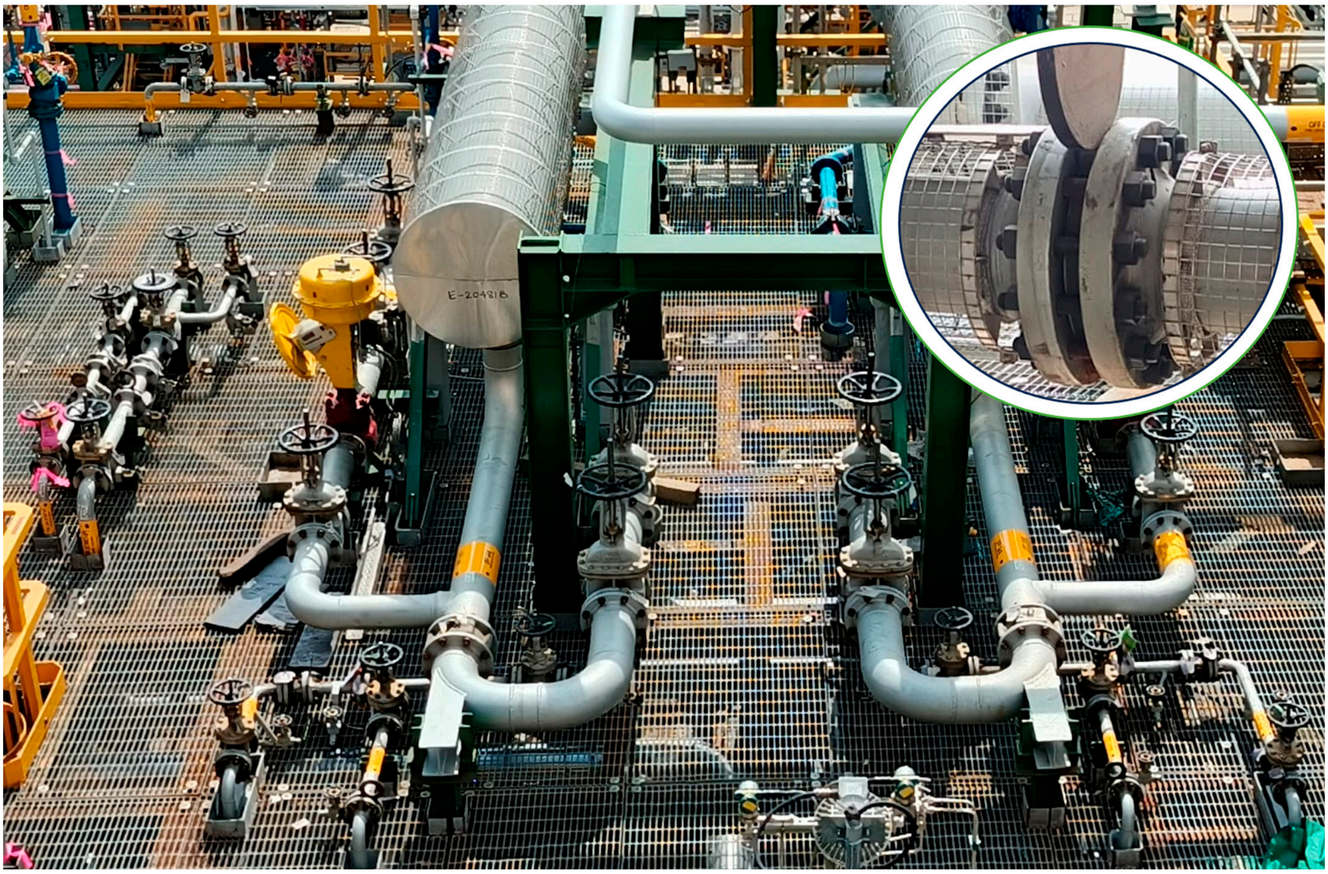

Figure 1. Schematic representation of multi-bolted flanges in industrial piping systems.

2.1. Damage Mechanisms in Multi-Bolted Flange

Multi-bolted flanges are critical components in industrial piping systems, providing secure connections between pipes, valves, and other equipment. Their design allows for the reliable joining of components under various pressure levels, making them essential in industries such as oil and gas, chemical processing, and water treatment. The integrity of these flanges is crucial for the safe and efficient operation of industrial systems because failures can lead to leaks, explosions, and significant economic losses.

2.1.1. Leakage

Leakages in piping systems, particularly at flange joints, present significant operational challenges that can compromise the system integrity [2]. Thermal shock is a critical factor contributing to leakage, as explored by Goyal [3], who analyzed how sudden temperature increases affect flange integrity, leading to joint failure. He proposed strategies to mitigate these risks, such as avoiding abrupt temperature changes and employing spacers to prevent bolt deformations.

Therefore, effective leak detection is crucial. Shi et al. [4] introduced a two-source-four-sensor transient testing method that allows for the virtual isolation of pipe sections, enabling independent leakage analysis. Their transfer matrix approach proved to be highly sensitive, identifying both single and multiple leaks. Bohorquez et al. [5] advanced leak detection by integrating fluid transient analysis with artificial neural networks (ANNs), creating a model that predicts junction locations with an average error of 2.32 m. This data-driven method relies on transient-head data, demonstrating the potential of combining machine learning with fluid dynamics for pipeline monitoring.

Manufacturing and operational issues can also lead to leakages. Noble et al. [6] reviewed the factors leading to failures in welded neck flanges and identified incorrect manufacturing processes and vibration-induced fatigue as the key contributors. Their analyses provided insights into the critical failure mechanisms.

Korlapati et al. [7] categorized leak detection techniques into externally/computationally based and visual/inspection methods, highlighting the evolution of these techniques and the potential for machine learning to improve detection accuracy. Jaszak [8] investigated gasket durability in bolted-flange joints and found that the leakage stabilized at approximately 20% of the energy dissipated during the second bending cycle. Ahmad et al. [9] proposed an integrated approach combining fluid transient analysis with ANNs, introducing a vulnerability index based on acoustic emission hit (AEH) to enhance leak sensitivity, achieving accurate predictions of junction locations.

Momeni and Piratla [10] explored a hydraulic model-based approach for leak detection using pressure data by integrating ANNs and genetic algorithms to predict leakage severity, although they acknowledged the need for better validation in real-world scenarios. Daniyan et al. [11] presented a prototype test rig for detecting oil leakages in pipelines, combining electronic monitoring with Real-Time Transient Model (RTTM) technology for efficient, automated leak detection.

El-Zahab and Zayed [12] reviewed leak detection technologies in water distribution networks, emphasizing the need for effective leak management to prevent resource losses, and analyzed trends in the literature over the past four decades. Gao and Kazama [13] examined the relationship between sealing liquid viscosity and leakage control in flat-flange gasket systems, proposing that controlling sealing part temperatures can reduce leakage and improve flange joint reliability.

In summary, leakage in flange joints is influenced by thermal shock, manufacturing defects, and operational conditions. Innovative detection methods, including transient testing configurations and machine learning (MI) techniques, are being developed to enhance leak detection and mitigate risks.

2.1.2. Bolt Integrity: Challenges of Loosening and Tightening

The integrity of bolted joints is crucial for the reliability of piping systems because improper bolt tension can lead to significant operational failures. Both undertightening and overtightening can compromise joint integrity, making it essential to understand their impact [14,15].

Undertightening results from insufficient preload, leading to joint separation and leakage. Argatov and Sevostianov [16] proposed a method using electrical resistance measurements to assess joint integrity, revealing that the electrical constriction resistance at the contact interface is sensitive to changes in contact pressure. Overtightening induces excessive stress in bolts, leading to material failure [17]. Wang et al. [18] monitored bolt looseness using piezoceramic transducers and a time reversal method, demonstrating real-time detection through energy dissipation analysis.

Zhu et al. [19] examined elastic interactions in bolted flange joints, emphasizing how tightening sequences affect preload distribution and joint performance. Scheepers and Bezuidenhout [20] illustrated through case studies that variations in bolt preload affect creep damage accumulation and fatigue life, thereby confirming that both under- and overtightening can reduce the safe operating life of components.

Schierl et al. [21] focused on the stress state of high-strength bolts in bolted flange connections, finding that yield-point controlled tightening (YCT) provides more reliable preload levels than traditional torque methods, reducing fatigue failure risk. Grzejda et al. [22] investigated preloaded asymmetric multi-bolted connections, ensuring optimal tightening sequences through controlled testing setups.

Wróbel and Walczak [23] analyzed the load conditions in pipe flange connections, revealing that the flange geometry significantly affects the load distribution among bolts, potentially increasing stress and fatigue. Croccolo et al. [24] conducted a literature review on bolted joint optimization, identifying five key techniques—bolt layout, tightening strategies, tightening sequences, bolt size, and stress management—that enhance load distribution and minimize bolt requirements.

Bolt integrity is a critical factor in flange performance and is influenced by both under- and overtightening. Advanced monitoring techniques and optimization strategies are essential to ensure reliable preload distribution and minimize the risk of fatigue and failure.

2.1.3. Corrosion

Corrosion is a critical concern in flange systems, particularly in chemically aggressive environments [25–27]. Understanding the corrosion mechanisms and their implications for flange integrity is essential for effective management [28–31].

Hakimian et al. [32] investigated how variations in gap size between flanges influence corrosion behavior, revealing that larger gaps correlate with increased corrosion rates. This finding suggests that optimized gasket designs can significantly enhance the longevity of the flange joints. Similarly, Ji et al. [33] analyzed the corrosion failure of a pipeline flange in a hydrofluoric acid environment and identified CO_2 corrosion exacerbated by high temperatures and flow rates as the primary cause. This highlights the importance of selecting suitable materials and coatings to mitigate corrosion risks under harsh conditions.

Expanding on this topic, Hakimian et al. [34] provided a comprehensive review of corrosion-related failures in bolted flanged gasket joints and explored the forms of corrosion, such as pitting and crevice corrosion. Their findings underscore the necessity of careful material selection to enhance resistance against these corrosion types.

To further address corrosion prevention, Lyublinski et al. [35] summarized innovative protection strategies for flanges, emphasizing designs that incorporate volatile corrosion inhibitors (VCIs) and desiccants. These strategies significantly reduce corrosion rates, illustrating practical approaches to enhance durability in corrosive environments.

Ossai et al. [36] conducted an analysis of pipeline failures in corrosive settings, reviewing mechanisms such as sweet corrosion and microbiologically induced corrosion (MIC). Their work highlighted the necessity for proactive maintenance and monitoring to prevent loss of integrity.

Finally, Hakimian et al. [37] examined the influence of different gasket materials on the corrosion behavior of stainless steel flanges, demonstrating that graphite gaskets lead to increased corrosion rates compared to PTFE gaskets. This finding emphasizes the critical role of material selection in mitigating corrosion risks.

2.1.4. Fatigue, Failure and Cracks

Fatigue cracks can initiate from manufacturing defects or cyclic loading, leading to flange failure [38]. Understanding the factors that affect the fatigue life is crucial. Okorn et al. [39] provided a comprehensive overview of these factors, emphasizing how geometric imperfections and preload levels influence the fatigue performance of bolted connections. Their findings revealed that discrepancies between the theoretical and actual preloads can result in fatigue failures, highlighting the necessity for precise preload determination in practical applications.

To address specific applications, Lochan et al. [21] reviewed the fatigue performance of M72 bolted connections in offshore wind turbines. They noted the challenges posed by variable-amplitude cyclic loads in harsh marine environments and the lack of experimental data for larger bolts, which hinder the development of reliable fatigue design curves.

Rincón-Casado et al. [40] presented a methodology for estimating the residual fatigue life of in-service wind turbine bolts, focusing on those bolts removed after experiencing significant operational loads. Their experimental approach simulated real-world conditions and provided valuable insights into the bolt performance.

In examining specific materials, Xu et al. [41] investigated cracking in girth welds of duplex stainless steel (DSS S31803) pipes and flange connections. Their analysis determined that fatigue fractures are linked to residual stresses in serrated gaskets, highlighting the importance of the material properties.

Liu and Wang [42] conducted a failure analysis of a steam pipe flange gasket in a petrochemical facility, identifying fatigue fractures as the primary failure mechanism due to residual stress. Their methodology emphasized the need for improved handling of the residual stress during assembly.

Taghipour et al. [43] performed a root cause analysis of premature failure in a welded flange joint in an ammonia plant, attributing the failures to unsuitable welding parameters that resulted in low-strength grain structures.

Otegui and Fazzini [44] investigated flange failures in pressure vessels subjected to dynamic loads. Their analysis revealed that many failures originate from inadequate welding practices and poor reinforcement design, leading to stress concentrations and crack initiation.

Fatigue, failure, and cracks are significant concerns in flange systems and often result from manufacturing defects, cyclic loading, and residual stresses. Comprehensive analysis and improved welding practices are essential to mitigate these risks and enhance flange reliability.

2.2. Current Trends in NDT Inspection on Multi-Bolted Flange and Piping

NDT methods are crucial for detecting and monitoring defects in multi-bolted flanges and piping systems. Several NDT techniques are currently being used to ensure the integrity and reliability of these critical components.

2.2.1. Ultrasonic Guided Wave

Ultrasonic guided waves (UGWs) play a crucial role in NDT for pipeline inspections, particularly in detecting corrosion and assessing structural integrity. The frequency range used in the UGW varies significantly based on inspection requirements, with lower frequencies (below 150 kHz) suitable for long-range inspections over 5 m, while higher frequencies (200 kHz to 1 MHz) are used for shorter ranges, allowing for better resolution of smaller defects.

The recent literature highlights the effectiveness of UGW in various applications. Olisa et al. [45] reviewed UGW techniques, noting their cost-effectiveness but also identifying gaps in understanding the correlation between UGW parameters and combined damage effects. Wu et al. [46] studied wave scattering in steel pipes with welded bends, emphasizing the complexities introduced by pipe geometry in defect detection.

Bai [47] demonstrated UGW's application in detecting fouling in pipelines using FEM to show that guided waves can effectively identify scale formation despite fouling layers. Tan et al. [48] conducted a parametric study on defect detection in bent pipes, revealing that specific modes are more effective for different defect types.

Cawley [49] reviewed UGW principles and noted that while the technology has matured, challenges in signal interpretation remain. El-Hussein et al. [50] focused on UGW's long-range capabilities for detecting damage from third-party impacts, highlighting the need for optimized frequency selection.

Alobaidi et al. [51] explored various ultrasonic techniques in the oil and gas sector, emphasizing the benefits of combining NDT methods to enhance defect detection. Niu et al. [52] investigated UGW excitation and propagation using piezoelectric transducer arrays and optimized the designs for improved defect detection sensitivity.

Raišutis et al. [53] presented a technique for inspecting steel pipe walls with UGW to effectively detect corrosion in hard-to-reach areas. Their work underlined the need for further research on the effectiveness of this technique under varying environmental conditions.

Hatsukade et al. [54] developed a comprehensive UGW inspection system utilizing magnetostrictive methods, achieving effective defect localization but noting environmental noise impacts on signal clarity. Teoh et al. [55] analyzed corrosion detection using torsional UGW, establishing a correlation between defect depth and wave reflection.

Jiang et al. [56] utilized COMSOL Multiphysics version 6.2 to model UGW detection in bent pipes, identifying optimal excitation frequencies for effective corrosion detection. Pattanayak et al. [57] explored UGW for inspecting eccentric annular pipes, highlighting the challenges posed by eccentricity on wave characteristics.

Finally, Huang et al. [58] conducted a bibliometric analysis of ultrasonic inspection techniques, revealing a gap between the theoretical advancements and practical applications. Jiang et al. [59] further explored UGW for defect detection in gas pipelines, demonstrating the integration of ML for enhanced monitoring efficiency.

2.2.2. Nonlinear Ultrasonics

In the context of SHM, the transition from linear guided wave techniques to nonlinear ultrasonics represents a significant leap forward in the detection and assessment of damage in pipelines and pipe flanges. Building on the foundation of linear guided wave methods, nonlinear ultrasonic techniques, especially those involving guided waves, offer enhanced capabilities for identifying early-stage and subtle forms of damage.

Nonlinear ultrasonic guided wave (NUGW) techniques combine the long-range inspection advantages of guided waves with the sensitivity of the nonlinear ultrasonic responses. These techniques are particularly well suited for detecting damage in pipelines and flanged connections, where traditional linear methods may fall short.

Pieczonka et al. [60] reviewed nonlinear vibro-acoustic modulation techniques applied to guided waves. Their work emphasized the potential of these methods in detecting hidden defects in pipelines. NUGW can detect minute damages such as early-stage cracks or corrosion by leveraging harmonic generation and wave mode conversions. This is crucial for an aging infrastructure, where small defects can rapidly escalate into significant safety hazards.

Guan et al. [61] investigated the interaction between fatigue crack propagation and cylindrical guided waves in aluminum pipes. Through numerical simulations and experimental testing, they found that the nonlinear indices derived from the wave responses were correlated with crack growth. This relationship allows for quantitative fatigue-life assessments. NUGW outperforms linear UGW in this regard because it can capture the nonlinear material behavior near crack tips, enabling earlier detection of critical defects.

Niu et al. [62] addressed the challenges posed by environmental factors, particularly thermal stress, in pipeline monitoring. They applied NUGW to detect the thermal stress in continuous welded rails. Their study demonstrated that temperature-induced nonlinearities in guided waves can be used to quantify thermal stress and enhance the reliability of damage detection under dynamic operational conditions.

Nonlinear ultrasonic methods have shown great promise in SHM beyond the application of nonlinear guided wave techniques. Nonlinear ultrasonic techniques have emerged as critical advancements in the field of SHM, particularly for their ability to detect micro-damage and assess the integrity of vital infrastructure such as pipelines and bolted joints. Unlike traditional linear ultrasonic methods, which typically measure the wave speed and amplitude changes, nonlinear methods utilize the unique characteristics of wave interactions with structural defects.

Zhao et al. [63] developed a real-time monitoring method using vibro-acoustic modulation (VAM) to detect early bolt looseness in pipelines. They utilized piezoelectric transducers to generate low-frequency (LF) and high-frequency (HF) waves. The modulation of the HF probing wave by the LF pumping wave could indicate looseness. This method significantly improved sensitivity compared to linear ultrasonic techniques and eliminated the need for baseline data, thus addressing a crucial limitation of traditional methods.

Hong et al. [64] focused on delamination detection in lined anti-corrosion pipes by utilizing nonlinear ultrasonic methods to evaluate structural integrity. By measuring the nonlinear coefficients associated with the ultrasonic responses, they were able to effectively quantify delamination damage, which is critical for maintaining the safety of pipelines in corrosive environments.

Nilsson et al. [65] further explored the nonlinear ultrasonic characteristics of corroded steel plates, particularly relevant to containment liner plates in nuclear power plants. Through rigorous experimentation and analysis, they identified significant increases in acoustic nonlinearity parameters, such as relative quadratic nonlinearity and sideband peak count, in severely corroded regions. These findings indicate that nonlinear ultrasonic methods can effectively detect corrosion-induced defects and enhance the safety of critical infrastructures.

In the realm of impact damage detection, Wang et al. [66] explored linear and nonlinear ultrasonic techniques to assess the damage in carbon fiber-reinforced plastic (CFRP) laminates. Their study demonstrated that while linear ultrasonic methods provided valuable insights, nonlinear parameters, particularly those derived from higher harmonics, offered greater sensitivity to damage that was otherwise undetectable.

Finally, Fierro and Meo [67] presented a novel approach that uses nonlinear wave modulation techniques to estimate the residual fatigue life of metallic components. Their research demonstrated a clear correlation between the nonlinear parameters derived from guided waves and the extent of fatigue damage, allowing baseline-free predictions of the remaining service life.

Together, these studies illustrate the growing application of nonlinear ultrasonic techniques in monitoring the integrity of pipelines and bolted joints, emphasizing their sensitivity to early-stage damage and their potential for real-time monitoring. As research continues to evolve, these methods may lead to more effective strategies for maintaining the safety and reliability of critical infrastructure.

2.2.3. Phased Array Ultrasonic Testing

Phased Array Ultrasonic Testing (PAUT) employs multiple transducers to steer and focus ultrasonic beams, thereby providing detailed images of the internal structures. This technique is particularly effective for detecting and characterizing flaws in complex geometries, such as multi-bolted flanges and piping systems.

Sankar [68] explored the application of PAUT to assess corrosion in flange faces within process industries. This study highlights the effectiveness of PAUT in identifying and quantifying corrosion damage in carbon steel flanges, achieving a probability of detection (POD) of up to 90%. The methodology involved both mock-up tests and in-service inspections, validating the PAUT results against physical examinations. The findings suggest that the PAUT is a reliable non-intrusive method for monitoring flange integrity, particularly in corrosive environments. Tai et al. [69] conducted an experimental investigation on phased array corrosion mapping on hot piping surfaces [70].

Yaacoubi et al. [71] proposed a comprehensive NDT strategy for assessing the structural integrity of nuclear piping by combining UGW, time-of-flight diffraction (TOFD), phased array (PA), and multi-skip (MS) techniques. This study used numerical simulations and in situ tests to validate the effectiveness of these techniques in detecting various defects in nuclear piping.

2.2.4. Radiography Testing

RT uses X-rays or gamma rays to detect internal flaws in materials. This method provides detailed images of the internal structures and is particularly useful for detecting volumetric defects.

Traditional NDT methods often require the removal of insulation layers, which is time-consuming and costly. To address these drawbacks, Xu et al. [72] examined the application of online digital radiographic inspection to pipelines with insulation layers. They detailed the operational principles of digital radiography, including the use of portable X-ray sources and digital imaging plates. Their research demonstrated that this technique effectively identified defects, such as incomplete penetration in circumferential welds, proving to be a time-efficient and cost-effective solution for maintaining the integrity of insulated pipelines.

Based on this, Moreira et al. [73] explored the use of Digital Detector Arrays (DDAs) in the context of RT for offshore pipelines. The authors highlighted the advantages of digital radiography over traditional film-based systems, emphasizing improved sensitivity, faster inspection cycles, and real-time imaging capabilities. Their study demonstrated that DDAs could effectively enhance the defect detection rates in welded pipe joints, making them a viable alternative for quality control in demanding industrial environments.

Mousa et al. [74] contributed significantly to the field of NDT by demonstrating the potential of optimized radiographic techniques in the inspection of water-filled pipes. Their work underscored the importance of addressing the challenges posed by scattered radiation and provided a foundation for future research aimed at enhancing the reliability and efficiency of pipeline inspection.

Xie et al. [75] conducted a comparative experimental study on PAUT versus X-ray detection methods for small-diameter pipe welds. The results indicated that PAUT outperformed the X-ray techniques in terms of defect detection rates and measurement precision. This finding suggests that the PAUT may be a more effective method for inspecting small-diameter pipe welds, offering higher accuracy and reliability in detecting defects.

Amoah et al. [76] focused on the investigation of wall thickness, corrosion, and deposits in industrial pipelines using radiographic techniques. The study employed both the tangential radiographic technique (TRT) and the double-wall technique (DWT) to evaluate welded pipes with known defects. The results showed that the TRT method provided higher measured wall thickness values than the actual thickness, highlighting the influence of magnification effects on radiographic assessments. This finding underscores the need for careful calibration and interpretation of radiographic images to ensure accurate detection of defects.

2.2.5. Hydrostatic Leak Testing

Hydrostatic testing (HT) plays a critical role in ensuring the integrity and reliability of piping systems in various industries. Elwerfalli et al. [77] developed a turnaround maintenance (TAM) model specifically tailored to optimize the performance of critical static equipment in gas plants. Their study emphasized HT as a proactive measure for assessing the integrity of piping systems before commissioning. By combining historical data analysis with predictive modeling, they demonstrated that rigorous HT protocols could significantly reduce the risk of leaks and failures, revealing gaps in the existing maintenance schedules and suggesting a need for more frequent testing in high-pressure environments.

Building on this foundation, Wu et al. [78] investigated the implications of an explosion incident on a styrene plant, highlighting the preventive role of HT. Their forensic analysis integrated hydrostatic pressure tests with material property assessments to identify critical stress points and establish a correlation between inadequate HT and increased failure rates. This study identified a research gap regarding the need for standardized testing protocols that can be universally applied across various industries to enhance safety.

Corrosion is a prevalent damage mechanism in the oil and gas industries. Baby et al. [79] focused on determining corrosion rates and the remaining life of piping systems, utilizing HT as a fundamental component of their assessment strategy. Their innovative methodology combined hydrostatic pressure tests with ultrasonic thickness measurements to effectively quantify the material loss owing to corrosion. The results indicated that HT not only confirmed the integrity of the piping but also provided valuable data for predicting the service life. However, a notable research gap is the absence of real-time monitoring systems capable of continuously assessing piping integrity during operation.

Lee et al. [80] presented a novel work-aid tool for in-service piping inspection, incorporating HT to streamline the inspection process in the oil and gas industry. Their findings revealed that automated HT procedures could enhance the efficiency and accuracy of identifying leaks and weaknesses. Nonetheless, the study highlights the need for greater integration of artificial intelligence to predict failure points based on HT data.

Sidun and Łukaszewicz [81] explored the verification of the ram-press pipe bending processes, emphasizing the importance of HT in validating the integrity of bent pipes. Their methodology combined hydrostatic pressure tests with FEM to predict deformation under pressure, demonstrating that HT can effectively reveal stress concentrations that may lead to failure. A significant research gap emerged regarding the long-term impact of repeated HT on material fatigue over time.

Shih et al. [82] conducted a life cycle guideline study for underground piping systems, underscoring HT as a vital maintenance strategy. Their approach integrated HT with life-cycle cost analysis, demonstrating that regular testing could significantly extend the lifespan of piping systems. The findings revealed that the strategic implementation of HT could lead to substantial cost savings in terms of maintenance and replacement. However, the identified research gap focuses on the need for more empirical data on the long-term benefits of HT under varying environmental conditions.

Grzejda [83] discussed health assessments of multi-bolted connections, specifically focusing on the role of HT in ensuring the integrity of these connections in piping systems. By combining HT with advanced modeling techniques, this study evaluated the performance of bolted joints under pressure. The results indicated that HT could effectively predict potential failure points in multi-bolted configurations; however, the research gap highlighted the necessity for more field studies to validate the theoretical models developed.

Wen et al. [84] examined the impact of HT on the mechanical properties of high-strength pipelines in natural gas applications. They employed experimental burst tests and FEM simulations to assess the integrity of pipelines subjected to hydrostatic pressure.

Their results indicated that microdefects significantly influenced the failure pressure, underscoring the critical role of defect characterization in reliability assessments. However, the authors noted a research gap concerning the lack of standardized testing protocols for varying pipeline materials under different environmental conditions.

Zeng et al. [85] focused on the reliability assessment of HT in pipelines with a 0.8 design factor in the West–East China Natural Gas Pipeline III. They introduced a probabilistic approach to monitor real-time failure probabilities during HT, leveraging Monte Carlo techniques for reliability analysis. Their findings indicated that failure probability increased with increasing water pressure, demonstrating the need for real-time monitoring systems. This study opens avenues for further research on integrating advanced monitoring technologies and developing more resilient pipeline designs under varying operational pressures.

Finally, Mattos et al. [86] provided a comprehensive analysis of the reliability of HT in pipelines used to produce water on offshore platforms. Utilizing elastoplasticity theory, they modeled the relationship between the pressure and yield strength during testing. Their findings suggested that both the yield and burst pressures could be derived from the tensile test data, streamlining the testing process. However, a research gap remains in exploring how these models can be adapted for pipelines subject to environmental factors such as temperature fluctuations and corrosion over time.

3. Acoustic Emission Testing (AET)

AET is an NDT technique that relies on the detection of acoustic waves generated by the rapid release of energy from localized sources within a material. These sources typically include microscopic cracks, voids, or other defects that form and propagate under stress.

When a material is subjected to mechanical stress, it deforms. This deformation can lead to the formation of cracks or the growth of existing defects. As these cracks grow, they release energy in the form of elastic waves, creating acoustic emissions (AEs). These emissions generally occur in the ultrasonic frequency range, typically above 20 kHz, and can be captured using specialized sensors, known as acoustic emission sensors.

The AET mechanism involves several key steps. First, as the material is subjected to loads such as pressure, tension, or bending, internal stresses develop within the material. When these stresses exceed the threshold of the material, defects, such as microcracks, initiate and propagate. The growth of these defects releases energy that generates elastic waves that travel through the material. Depending on the nature of the defect and material properties, these waves can consist of both longitudinal and shear waves.

Specialized sensors were placed on or near the test specimen to detect these AE. These sensors convert the mechanical vibrations into electrical signals. Once the signals are detected, they undergo analysis using various signal-processing techniques to extract meaningful data regarding the presence and characteristics of defects. This process allows for the real-time monitoring and assessment of the structural integrity of the material. Figure 2 illustrates the principle of the AET applied to a multi-bolted connection.

AET offers several advantages that make it particularly suitable for monitoring the integrity of structural components, including multi-bolted flanges. One of the most significant benefits of AET is its ability to provide continuous real-time data on the structural health of a component. This capability allows for the immediate detection of defects, enabling proactive maintenance and timely intervention [87].

Additionally, AET is highly sensitive and capable of detecting defects at very early stages long before they become critical. This sensitivity is essential to prevent catastrophic failures in critical applications. This method is also effective under dynamic loading conditions, where structural components experience fluctuating loads, making it crucial for applications such as piping systems, which frequently undergo pressure and temperature changes.

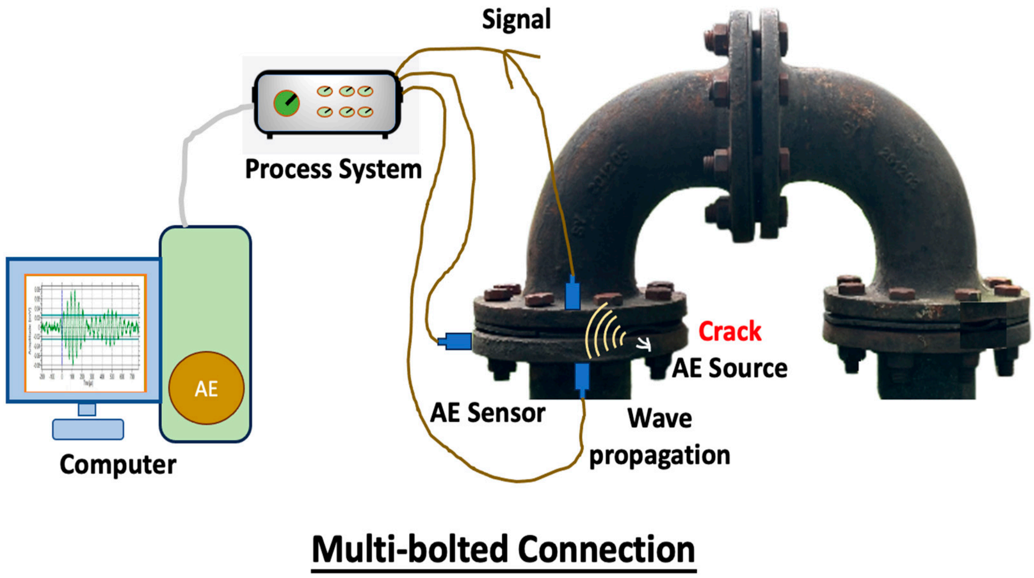

Figure 2. Schematic principle of AET applied to a multi-bolted connection.

Furthermore, as an NDT method, AET does not alter or damage the test material, allowing inspections without compromising the integrity of the component. Finally, AET provides comprehensive data regarding the size, location, and activity of defects, which are invaluable for assessing the overall health of the structure.

3.1. Diverse Applications of AET Across Industries

To achieve a comprehensive understanding, a systematic review of 145 articles with titles containing "AE", "acoustic emission", and "acoustic emission testing" was conducted. AET has demonstrated extensive applicability across various industries, primarily because of its efficacy in the real-time monitoring and early detection of defects. This technology is particularly critical in environments where structural integrity is paramount, as the early identification of flaws can prevent catastrophic failures.

Within the oil and gas sector, the AET is indispensable for monitoring the integrity of pipelines and pressure vessels. This facilitates the detection of leaks and structural failures in high-pressure pipelines, thereby mitigating the risk of environmental disasters. Nguyen et al. [88] introduced a novel approach for leak state detection and size identification in industrial fluid pipelines, employing AE activity intensity index curves based on b-value and random forest algorithms.

The AET also plays a crucial role in monitoring critical infrastructure, including bridges and tunnels. For example, it enables the continuous assessment of bridge component integrity, facilitating the detection of microcracks, which may signify structural weaknesses. Tayfur [89] proposed a novel signal-centric framework designed to enhance the real-time reliability of NDT for concrete damage detection via the AET. This study correlates the mechanical processes in concrete with the AE signal characteristics to evaluate the POD of cracking events. Furthermore, Yu et al. [90] investigated the prediction of fatigue crack growth in steel bridge components using AE monitoring techniques and established a relationship between the AE absolute energy rate and crack growth rate, thereby offering a simplified approach to fatigue life prediction.

In the aerospace sector, AET is used to monitor critical aircraft components, including wings and fuselage structures. Sensors are employed to detect AE arising from stress or fatigue during both flight and ground operations, thereby alerting maintenance crews to issues that necessitate prompt attention and upholding stringent safety standards. Bhuiyan and Giurgiutiu [91] explored the correlation between AE waveforms and fatigue crack propagation in thin metallic plates, particularly in aluminum. Their research classified AE signals into distinct groups based on waveform characteristics, thereby yielding insights into the damage mechanisms associated with fatigue loading. Additionally, Vanniamparambil et al. [92] investigated the identification of crack initiation in aluminum alloys through AE monitoring, utilizing complementary non-destructive evaluation methods such as Digital Image Correlation (DIC) and Infrared Thermography (IRT). Their findings demonstrated that AE signals can reliably indicate the onset of cracking.

In the automotive industry, AET is increasingly being employed to ensure the quality of critical components. During the manufacturing process, it facilitates the identification of defects, such as cracks and material fatigue, in components, such as brakes and chassis. Saeedifar et al. [93] successfully correlated AE signal characteristics with crack growth behavior, establishing reliable methodologies for determining crack tip positions and evaluating interlaminar fracture toughness. Suwansin and Phasukkit [94] presented a novel deep learning-based AE scheme for the non-destructive localization of cracks in train rails under load, achieving high classification accuracy. Brambilla et al. [95] explored the use of AE techniques for diagnosing mechanical failures in historical vehicle engines. This study successfully identified simulated faults, such as clearance issues and wear of piston rings, demonstrating the potential of AE monitoring as a non-destructive diagnostic tool.

In the realm of civil engineering, Bacharz et al. [96] examined the correlation between shrinkage and AE signals in early-age concrete to enhance NDT methodologies for assessing structural integrity. Their study identified a robust relationship between shrinkage strains and AE signals, categorizing the signals to reflect various types of microcracking. By employing logarithmic functions for prediction, the authors provided a valuable framework for monitoring the damage levels in concrete during the critical early hardening phase. Furthermore, Barat et al. [97] explored the application of AE technology for the SHM of walking dragline excavators.

Owing to length constraints, not all the studies can be elaborated upon in detail. Table 1 provides a classification of the additional research on AET applications across diverse fields.

Table 1. Summary of AET applications across diverse industries.

Industrial	Researchers' References
Oil and Gas	[88,98–118]
Automobile	[91,93,95,107,119–181]
Infrastructure	[88–90,94,98,100–106,109,110,117,129,180,182–202]
Aerospace	[91–93,99,104,105,117,119–168,170,171,173–181,185,187,188,196,197,199,203–208]
Energy	[149,180,184,207,209–213]
Manufacturing	[172,214,215]
Mining	[97,214,216–220]
Civil Engineering	[90,96,97,139,144–146,192,217]
Geotechnical	[186,219,220]
Railway	[94,221]
Marine industries	[147]

3.2. Broad Applicability of AET Across Diverse Materials

According to the literature review, AET has been demonstrated to apply to a diverse range of materials. Unlike other NDT methods, which may be restricted to specific material types, AET can be effectively utilized across various materials. For instance, magnetic particle testing (MT) is primarily applicable to ferromagnetic materials, eddy current testing (ECT) is suitable for conductive materials [222], and penetrant testing (PT) is not suitable for porous materials.

The aerospace and automotive industries exhibit a higher volume of research activity, leading to a notable prevalence of composite materials in the literature, particularly CFRP and glass fiber-reinforced polymers (GFRPs). Other composites, such as basalt fiber-reinforced polymers (BFRPs) and natural fiber-reinforced polymers (NFRPs) appear less frequently.

Saeedifar et al. [160] explore the application of acoustic emission techniques to evaluate delamination crack growth in glass/epoxy composite laminates under quasi-static and fatigue loading conditions. Mills-Dadson et al. [167] investigate AE monitoring techniques to identify unstable damage growth in CFRP composites during tensile loading. Huijer et al. [168] demonstrate that both small and large piezoelectric sensors can effectively capture AE signals during loading tests, with distinct frequency ranges indicating varying sensitivities.

Masmoudi et al. [121] examine the efficacy of embedded piezoelectric sensors for AE monitoring in GFRP composites, particularly in laminated and sandwich structures. Liu et al. [223] investigate the mechanical and AE properties of vegetable fiber-reinforced epoxy composites intended for percussion instrument applications. Their study found that while the flexural strengths and moduli of these composites are competitive with those of traditional wood, their acoustic properties, such as dynamic modulus and sound velocity, are comparatively inferior.

In the metal category, carbon steel, including steel structures and piping, has emerged as the predominant research material, whereas stainless steel, aluminum, and other alloys have also been examined. Wisner et al. [164] introduce an innovative AE signal processing framework to detect and identify fracture mechanisms in aluminum alloys. By integrating in situ scanning electron microscope (SEM) observations with advanced AE analysis, this study establishes a robust correlation between AE signals and microstructural damage. Liu et al. [112] investigate the performance of two acoustic emission sensors—Nano30 and VS150-RIC—in monitoring hydrogen-induced cracking (HIC) in carbon steel. Their comparative analysis revealed that the VS150-RIC excels in detecting HIC signals and accurately locating sources, while the Nano30 proved superior for signal classification owing to its broader frequency response.

Agletdinov et al. [178] propose a novel Bayesian framework for analyzing AE data aimed at improving the detection of damage mechanisms in zirconia-coated titanium alloys. This methodology effectively addresses the challenges posed by low signal–noise ratios, enabling the reliable detection of critical moments during material deformation by focusing on identifying transition points in the AE time series generated during scratch testing.

Bui Quy et al. [115] proposed a novel AE-based technique for detecting small leaks in stainless steel 304 water pipeline systems. Their method segments AE signals using a Hanning window with a 50% overlap and employs a k-nearest neighbor (KNN) classifier trained on features extracted from the transformed signals.

The third category of materials pertains to civil engineering and construction industries, including concrete, rock, and granite. Mandal et al. [194] introduce a novel approach to AE monitoring in reinforced concrete, utilizing a series of narrow partial power bands (SN2PB) to effectively identify damage mechanisms during bending tests. Bacharz et al. [96] explore the correlation between shrinkage and AE signals in early-age concrete, aiming to enhance NDT methods for assessing structural integrity. Their study identified a strong relationship between shrinkage strains and AE signals, categorizing the signals to reflect different types of microcracking. Shi et al. [198] investigate the acoustic emission characteristics related to the creep fracture evolution of fine sandstone specimens with pre-existing cracks under uniaxial compression.

Although they represent a smaller proportion of the literature, successful applications of AET have been documented for additional materials including ceramic matrix composites, polymethyl methacrylate, wood, PVC, and marble. These studies further substantiate the versatility of AET across a wide array of materials. Table 2 summarizes the various materials studied by researchers.

Table 2. Summary of diverse materials studied using AET.

Material		Researchers' References
Polymer Matrix Composite	CFRP	[98,119,125,126,128,130,133,135,136,138,140,143–146,148,149,153,158,159,165,167,168,170,171,174,176,180,182,183,188,204]
	GFRP	[93,121–123,125,127,132,138,139,141,147,149,151,152,154,156,160,161,175,201]
	BFRP	[190]
	NFRP	[173]
Ceramic matrix composite	Ceramic matrix composite	[177,181,207]
Metals and Alloys	Steel	[90,94,97,98,102,104,105,109,110,112,131,179,183,187–189,193,197,199,203,208,211,215,221]
	S.Steel	[106,108,114,115,134,163,166]
	Alloys	[99,124,126,178,196,210]
	Aluminum	[91,92,164,166,185,205,206]
	Tungsten carbide anvils	[214]
Construction Materials	Concrete	[89,96,98,120,183,188,191,192,194,195,200,213]
	Rock	[198,216,218]
	Granite	[113,217,219,220]
	Marble	[186]
Polymethyl methacrylate	Polymethyl methacrylate	[184]
	PVC	[118,202]

3.3. Defect Types Detected by AET

AET has emerged as a vital NDT method for identifying various defect types across different materials including composites, metals, and concrete/rock. This subsection reviews the defect types detected by AET as documented in the literature and emphasizes the unique challenges and characteristics associated with each material category.

3.3.1. Composite Materials

Composites, particularly those used in aerospace and automotive applications, are subjected to various types of defects that can significantly affect their performance. The following defects are commonly identified through the AET.

1. Matrix Cracking: Matrix cracks often initiate owing to mechanical stress or impact. AET can detect the AE associated with these cracks as they propagate, providing valuable insights into the integrity of the material.
2. Fiber Breakage: The breakage of fibers within composite materials can lead to a significant loss of strength and stiffness. AET can effectively monitor fiber integrity by capturing the stress waves generated during fiber breakage events.
3. Fiber Debonding: Fiber debonding occurs when the fiber–matrix interface weakens, leading to reduced load transfer efficiency. The AET detects the acoustic signals generated during the debonding process, which can indicate potential failure mechanisms.

4. Delamination: Delamination, or the separation of layers within a composite, is a critical mode of failure. The AET is particularly adept at detecting the onset of delamination, as the AE associated with this defect is often distinct and measurable.
5. Weak Adhesion: Weak adhesion between layers or between fibers and the matrix can lead to premature failure. AET can help identify areas of weak adhesion before they cause significant structural damage.
6. Microcrack Initiation: Microcracks can serve as precursors to more severe damage. An AET can detect early-stage microcracks, allowing proactive maintenance measures to be implemented.
7. Degradation: Environmental factors can lead to material degradation over time. AET can be used to monitor AE related to degradation processes, providing insights into the long-term performance of composite materials.

3.3.2. Metal Materials

Metals are widely used in various engineering applications, and the detection of defects in these materials is crucial to ensure their safety and reliability. The defects identified in metal materials through AET include the following.

1. Fatigue Cracking: Fatigue cracking is a common failure mode in metals that are subjected to cyclic loading. The AET can detect the AE generated during the initiation and propagation of fatigue cracks, providing real-time monitoring of structural integrity.
2. Crack Initiation and Propagation: AET can capture the acoustic signals associated with both the initiation and growth of cracks in metal components. This capability allows for the early detection of potential failure points.
3. Cavitation Erosion: In hydraulic systems, cavitation can lead to the erosion of metal surfaces. The AET can detect the AE generated during the cavitation process, enabling operators to address the issue before significant damage occurs.
4. Corrosion: Corrosion can compromise the structural integrity of metals. AET can monitor AE associated with corrosion processes, providing valuable information about the extent of material degradation.
5. Leak Detection: Leaks can pose serious safety hazards in piping systems. The AET can effectively identify acoustic signatures associated with leaks, allowing for timely maintenance and repair.
6. Welding Imperfections: Welding processes can introduce defects such as incomplete fusion or porosity. An AET can detect AE related to these imperfections, enabling quality assurance in welded structures.
7. Structural Damage: AET can monitor the overall structural health of metal components and detect any AE that indicates damage or degradation, thus facilitating proactive maintenance.

3.3.3. Concrete and Rock Materials

Concrete and rock are essential materials in civil engineering, and monitoring their integrity is vital for ensuring their safety and longevity. The following defects are commonly detected in these materials through AET.

1. Microcracking: Microcracking is a common phenomenon in concrete that often results from shrinkage or thermal effects. AET can effectively capture the AE associated with microcrack formation, providing an early warning of potential structural issues.
2. Rock Fractures: In geological applications, the AET can be used to monitor fractures in rock formations. The AE generated during fracture events can provide insight into the stability of rock structures, which is crucial for construction and mining operations.

3. Fatigue Cracking: Similarly to metals, concrete can experience fatigue cracking under repeated loading conditions. AET can detect AE related to fatigue damage, allowing for real-time assessment of structural integrity.
4. Degradation: Over time, concrete and rock can undergo degradation because of environmental factors. AET can monitor the AE associated with degradation processes, helping to assess the long-term durability of these materials.

AET is a powerful tool for detecting a wide range of defects across different materials, including composites, metals, and concrete/rock. By capturing the AE generated during various failure mechanisms, the AET enables researchers and engineers to monitor material integrity, identify potential failure points, and implement proactive maintenance measures. Figure 3 classifies the types of defects according to the material type for ease of reference.

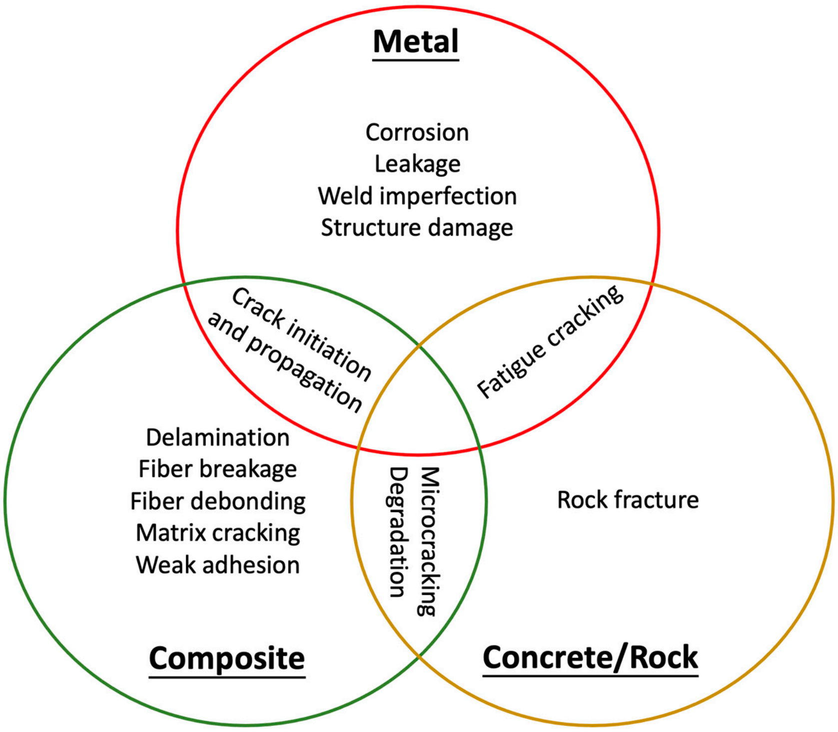

Figure 3. Defect types detected by AET Venn diagram.

3.4. Challenge and Limitation of AET

Despite its numerous advantages, AET has several challenges and limitations that hinder its widespread adoption and accuracy in real-world applications. These challenges span technical, operational, and environmental factors and necessitate ongoing research and innovation.

3.4.1. Noise Interference

Noise interference remains a significant challenge in AET, particularly in industrial environments, where machinery vibrations, electromagnetic interference, and thermal fluctuations can obscure defect-related signals. This noise can originate from various sources, including environmental factors, equipment operations, and material properties, making it difficult to distinguish genuine AE signals from the background noise.

To address this challenge, researchers have developed several noise reduction techniques. Wang et al. [224] employed a hybrid framework combining convolutional neural networks (CNNs) and long short-term memory (LSTM) networks to analyze AE signals, achieving 97% accuracy in predicting valve displacement and fault conditions. Maginga et al. [225] introduced a hybrid CNN-LSTM model combined with wavelet transform to detect maize diseases using Internet of Things (IoT) sensors, achieving 96.39% accuracy in disease classification and 99.98% accuracy in ultrasound anomaly detection. Bettayeb et al. [226] used a hybrid wavelet transform framework and ANNs to enhance flaw detection in steel materials, achieving 97.5% classification accuracy. Davoudabadi and Aminghafari [227] proposed a fuzzy-wavelet denoising technique, combining fuzzy transforms and wavelet thresholding to reduce noise in audio signals, achieving up to 19.57 dB signal–noise ratio (SNR) improvement for bird chirp signals and 19.66 dB for musical signals. Melchiorre et al. [228] introduced a hybrid framework combining the Akaike Information Criterion (AIC) and a convolutional recurrent neural network (CRNN) to detect AE signal onset times, crucial for crack localization, with normalized root mean square errors (NRMSEs) as low as 19.60% for onset time detection.

3.4.2. Signal Processing Complexity

AE signals are inherently nonstationary and multimodal, necessitating sophisticated signal processing to extract meaningful features. Shu et al. [123] used Multivariate Mode Decomposition (MVMD) to isolate damage-related frequency bands in GFRP composites, thereby improving the SNR for crack detection.

Traditional methods often require manual feature extraction and selection, which are time-consuming and subjective. For example, wavelet transforms, which are effective for noise reduction and feature extraction, require expertise in selecting the appropriate wavelet functions and decomposition levels. The complexity increases with the need for real-time processing, where the computational efficiency becomes critical. Wisner et al. [164] employed Gaussian Mixture Model (GMM) clustering to distinguish high-frequency particle fracture (450–550 kHz) from noise in aluminum alloys. Zonzini et al. [144] used Capsule Neural Networks (CapsNetToA) to retain spatial dependencies in composite plate signals, achieving 10$\times$ higher localization accuracy than traditional methods under low SNR.

Advanced techniques, such as deep learning, automate feature extraction but introduce higher computational demands and the need for large annotated datasets. The integration of multiple data sources, such as combining AE data with vibration or thermal data, further complicates the signal processing pipelines.

3.4.3. False Alarms and Signal Ambiguity

False alarms are a common issue in AET and lead to decreased system credibility and operational efficiency. These false alarms can be triggered by non-defect events such as mechanical vibrations, electromagnetic interference, or sensor malfunctions. The complexity of AE signals, which are often nonstationary and multimodal, further complicates the distinction between genuine defect signals and noise. Barat et al. [97] achieved 97% noise reduction in dragline excavators by analyzing wave propagation parameters

To mitigate false alarms, researchers have implemented advanced signal processing and MI techniques. One approach involves combining the data from multiple sensors to validate the signals. For instance, integrating AE sensors with vibration sensors or thermal cameras can help filter out false alarms caused by mechanical vibrations or thermal effects. Monti et al. [129] used k-means clustering and SEM validation to reduce false positives in flax composites by correlating amplitude, energy, and duration.

MI algorithms, particularly supervised learning methods, such as support vector machines (SVMs) and ANNs, have been employed to classify AE signals more accurately. These algorithms were trained on labeled datasets to recognize patterns associated with true defects, thereby reducing the likelihood of false positives. Ahn et al. [229] combined IEA, DWT, and GA-optimized SVM for pipeline leak detection, achieving 97.73% accuracy and reducing false alarms through noise resilience.

Additionally, unsupervised learning techniques such as clustering can identify anomalous signal patterns that deviate significantly from the norm, potentially indicating genuine defects.

3.4.4. Sensor Limitations

Sensor limitations can significantly affect the effectiveness of the AET. Factors such as sensor sensitivity, frequency response, and spatial resolution affect the quality and reliability of the acquired signals. Low-sensitivity sensors may fail to detect weak AE signals from early-stage defects, whereas sensors with narrow frequency ranges may not capture the full spectrum of relevant frequencies, leading to signal distortion or omission. Furthermore, the physical placement and coupling of sensors to the test material can introduce additional challenges, particularly in complex geometries or large structures where uniform coverage is difficult to achieve.

Recent advances in sensor technology have aimed to overcome these limitations. High-sensitivity wideband sensors were developed to improve the detection of subtle AE signals. For example, Liu et al. [112] compared two AE sensors, Nano30 and VS150-RIC, for monitoring HIC in carbon steel and found that VS150-RIC excelled in detecting HIC signals and accurately locating sources, while Nano30 was superior for signal classification because of its broader frequency response. Distributed acoustic sensing (DAS) technology, which uses fiber-optic cables as sensors, offers the advantage of continuous monitoring over large areas with a high spatial resolution. This technology can detect AE signals along the entire length of the fiber, making it suitable for monitoring extensive structures, such as pipelines and bridges.

3.4.5. Cost and Practicality

The implementation of AET can be cost-prohibitive, particularly for small- and medium-sized enterprises (SMEs). This technology requires investment in advanced sensors, data acquisition systems, and specialized software, in addition to the need for trained personnel to operate and interpret the systems. These factors can limit the adoption of AET in certain industrial sectors where budget constraints are a concern.

Recent developments have aimed to address these limitations through the creation of more affordable and user-friendly systems. Commercial AET systems such as those offered by Physical Acoustics Corporation (PAC) [230] and Qawrums [231] provide online monitoring solutions specifically designed to help SMEs overcome financial barriers to implementation. These systems incorporate automated analysis tools that reduce the need for extensive expertise, lower labor costs, and increase efficiency.

However, the actual cost savings and practical benefits of these solutions vary significantly based on the specific context of implementation. Factors such as the scale of operations, frequency of use, complexity of the infrastructure being monitored, and specific defect detection requirements all influence the return on investment. While these commercial solutions represent important progress in making AET accessible to smaller enterprises, their effectiveness and cost-efficiency must be evaluated on a case-by-case basis.

Moreover, the integration of AET with other NDT methods can optimize inspection processes by leveraging the strengths of each technique. This approach distributes the cost burden across multiple inspection capabilities while providing a more comprehensive assessment of structural integrity.

Researchers and industry practitioners continue to explore avenues for further reducing the implementation costs of AET. This includes developing more affordable sensor technologies, creating standardized protocols that minimize customization needs, and establishing clear guidelines that reduce the learning curve for new users.

3.4.6. Regulatory and Validation Challenges

The regulatory landscape for AET implementation remains fragmented, with no universally harmonized standards governing its application, validation, or data interpretation across industries. This lack of uniformity creates significant challenges for widespread AET adoption because compliance with multiple regional or sector-specific regulations is often required. Although several standards exist that partially address aspects of AET, they primarily focus on terminology, test methods, and general guidelines rather than providing comprehensive validation protocols for complex scenarios. Table 3 lists a comparison of ASTM and ISO standards for AET in a multi-bolted flange.

Table 3. Comparison of ASTM and ISO standards for AET in multi-bolted flange inspections.

Standard	Scope	Strengths	Limitations for Flange Inspections	Relevance to Flange Applications
ASTM E750	General AET practices (sensor placement and signal processing).	Establishes foundational protocols for AET implementation.	Lacks guidance for dynamic loading, geometric complexity (e.g., bolted joints), or multi-material interfaces.	Provides baseline procedures but is insufficient for flange-specific challenges.
ASTM E976	Sensor response reproducibility verification.	Ensures consistent sensor performance.	Does not address environmental noise, material variability, or real-world operational conditions.	Critical for sensor calibration but ignores flange-specific noise sources.
ASTM E2374	System performance verification.	Validates AET system accuracy under controlled conditions.	Does not mandate standardized defect simulation (e.g., gasket degradation and bolt loosening).	Useful for system setup but lacks flange-specific validation scenarios.
ASTM E650	Terminology and definitions for AET.	Standardizes reporting terminology.	Does not resolve ambiguities in signal interpretation for complex defects.	Essential for consistency but does not address flange-specific signal analysis.
ASTM E1139	AET in metallic structures.	Guides AET for metals, relevant to flange materials.	Excludes composites, gaskets, or bolted joint dynamics.	Applies to metallic flange components but ignores hybrid material interactions.
ISO 24367	SHM using AET.	Emphasizes sensor integration and data analysis for structural health.	Lacks prescriptive methods for flange-specific defect classification (e.g., bolt loosening).	Provides a general SHM framework but lacks flange-specific guidance.
ISO 18081	General NDT validation principles.	Establishes validation criteria for NDT methods.	Does not address AET's unique challenges (noise and real-time monitoring).	Applies broadly but does not resolve AET-specific gaps in flange inspections.
ISO 24543	AE source localization.	Guides localization techniques, critical for pinpointing defects in flanges.	Does not account for geometric complexity (e.g., bolt holes and gasket interfaces).	Useful for localization but limited by flange geometry.
ISO 23876	AET for pressure equipment.	Aligns with flange integrity assessments in pressure systems.	Lacks guidance on AI-driven signal processing for dynamic flange conditions.	Relevant to pressure-containing flanges but outdated for advanced analytics.
ISO 24489	AE data representation and exchange.	Standardizes data formats for interoperability.	Does not resolve discrepancies in defect classification across industries.	Facilitates data sharing but does not harmonize flange-specific analysis.
ISO 18249	Sensor calibration.	Ensures sensor accuracy and technical compliance.	Does not address operational challenges like environmental noise.	Critical for sensor calibration but ignores real-world noise in flange settings.

Current Regulatory Frameworks

ASTM Standards

- ASTM E750: Provides general practices for AET, including sensor placement, signal processing, and data interpretation. However, detailed guidelines for dynamic loading conditions or geometrically complex components such as flanges are lacking [232].
- ASTM E976: Focuses on verifying the reproducibility of sensor responses but not addressing real-world environmental noise or material variability [233].
- ASTM E2374: Guides system performance verification, but does not mandate standardized defect simulation or validation protocols for industrial applications [234].

- ASTM E650: Establishes terminology for AET, ensuring consistency in reporting but not resolving ambiguities in signal interpretation [235].
- ASTM E1139: Outlines operational practices for AET in metallic structures, excluding composites and unconventional environments [236].
- ISO Standards
- ISO 24367: Focuses on structural health monitoring (SHM) using AET, emphasizing sensor integration and data analysis. However, there are currently no prescriptive methods for flange-specific defect classification [237].
- ISO 18081: Provides general principles for NDT validation but does not address AET's unique challenges, such as noise interference and real-time monitoring [238].
- ISO 24543: Guides AE source localization, critical for flange inspections, but does not account for geometric complexities or dynamic loads [239].
- ISO 23876: Provides details of AET applications for pressure equipment, aligned with flange integrity assessments but lacking guidance on AI-driven signal processing [240].
- ISO 24489: Standardizes AE data representation, enhancing interoperability, but not resolving discrepancies in defect classification across industries [241].
- ISO 18249: Focuses on sensor calibration, ensuring technical accuracy, but not addressing operational challenges such as environmental noise [242].

Key Gaps in Existing Standards

1. Lack of Application-Specific Guidance: Current standards (e.g., ASTM E1139 and ISO 23876) primarily target metallic structures or composites, leaving multi-bolted flanges, a hybrid of metals, gaskets, and underregulated bolts.
2. Absence of Real-Time Monitoring Metrics: Standards such as ASTM E750 and ISO 24367 do not define performance metrics (e.g., POD and false alarm rates) for real-time AET in dynamic environments.
3. Inadequate AI/ML Integration: Emerging AI-driven signal-processing technologies, such as CNN-LSTM networks, are not addressed in the existing standards, creating uncertainty in regulatory compliance for advanced analytics.

3.5. Recent Advancements of AET

In recent years, significant progress has been made in AET technology, driven by innovations in sensor design, signal processing algorithms, and integration with emerging technologies. These advancements address several limitations discussed in the previous section, particularly regarding noise interference, signal interpretation complexity, and the need for specialized expertise. One of the most transformative developments is the integration of artificial intelligence (AI) and machine learning (ML) techniques into AET systems, which has dramatically enhanced their capabilities for noise reduction, feature extraction, and real-time analysis. These AI-driven approaches represent a major step forward in making AET more accessible, accurate, and applicable in diverse industrial settings.

3.5.1. AI-Driven Signal Processing and Deep Learning

The integration of AI and ML into AET has significantly enhanced the field's capabilities, particularly in terms of noise reduction, feature extraction, and real-time analysis. Recent advancements have resulted in the application of various AI techniques, from traditional ML models to state-of-the-art deep learning architectures, each contributing uniquely to the improvement of AET systems.

- Enhanced noise reduction techniques: Deep learning models, particularly those combining CNNs with LSTM networks, have proven effective in denoising AE signals. Wang et al. [224] achieved 97% accuracy in predicting valve displacement and fault conditions by preprocessing signals with wavelet transform before feeding them into a

CNN-LSTM model. Similarly, Maginga et al. [225] integrated wavelet transform with a CNN-LSTM model to detect maize diseases, achieving 96.39% accuracy in disease classification and 99.98% accuracy in ultrasound anomaly detection. These hybrid models leverage the strengths of CNNs for spatial feature extraction and LSTMs for temporal pattern recognition, making them particularly suited for processing the nonstationary and multimodal nature of AE signals.

- Advanced feature extraction and classification: AI-driven approaches have revolutionized feature extraction in AET. Traditional methods rely on handcrafted features, which are time-consuming and require significant domain expertise. Deep learning models, such as CNNs, automatically learn hierarchical features from raw data, thereby reducing the need for manual feature engineering. Guo et al. [145] applied the InceptionTime model, a deep learning architecture designed for time-series classification, to AE signals from composite materials. This model achieved approximately 99% accuracy in classifying damage modes, outperforming traditional methods, such as SVM and decision trees. The InceptionTime model's ability to extract complex features from raw waveforms demonstrates the potential of end-to-end deep learning pipelines in AET.
- Real-time monitoring and localization: The combination of AI with AET has enabled the real-time monitoring and localization of defects, which are critical for applications requiring an immediate response. Melchiorre et al. [228] developed a hybrid model combining the AIC with a CRNN for crack localization in concrete structures. This model achieved 96.37% accuracy on real-world AE data, significantly outperforming traditional methods, such as AIC alone. The CRNN architecture, which combines CNNs for feature extraction and recurrent neural networks (RNNs) for sequence modeling, demonstrated robustness in low SNR environments, making it suitable for real-time applications. Sun et al. [217] used a VGG16-based CNN with Mel-frequency spectrograms to classify rock fracture precursors in real time, achieving 87.68% accuracy.
- Cross-domain applications: AI-driven AET has found applications across various domains, from civil infrastructure to aerospace. Zhao et al. [243] proposed a hybrid model combining singular spectrum analysis, CNNs, and LSTMs to classify microseismic signals. This model achieved an accuracy of 94.56% in distinguishing microseismic events from blasting and mechanical signals, highlighting the versatility of AI techniques in different material and environmental contexts.
- Future directions and emerging trends: The future of AI in AET lies in the development of more efficient and interpretable models. Lightweight architectures, such as mobile CNNs, and self-supervised learning approaches are being explored to reduce computational overhead while maintaining performance. Additionally, physics-informed machine learning, which incorporates the domain knowledge of wave propagation into neural network architectures, promises to improve generalization and reduce the need for extensive labeled datasets.

In summary, AI-driven signal processing has transformed the AET by addressing long-standing challenges in noise reduction, feature extraction, and real-time analysis. The continued advancement of deep learning techniques and their integration with AET systems will further enhance the reliability and applicability of this NDT method across diverse industrial and infrastructural applications.

3.5.2. Integration with IoT Platforms for Smart Maintenance

The integration of AET with Industrial IoT has opened new avenues for real-time monitoring and predictive maintenance, enhancing the efficiency and reliability of industrial systems. In addition to the work of Ullah et al. [100], several other studies and applications highlighted the growing synergy between AET and IoT technologies.

- Smart city infrastructure monitoring: AET combined with IoT enables the continuous health monitoring of critical urban infrastructure. For instance, Saleem et al. [244] developed a real-time pipeline leak detection system using AE signals processed through a CNN-LSTM model. This system achieved 99.69% accuracy in classifying leak-related AE signals, demonstrating its potential for scalable, low-latency monitoring solutions in smart city applications.
- Industrial equipment health monitoring: In manufacturing and heavy industries, AET integrated with IoT platforms allows for the remote monitoring of equipment health. Nair et al. [182] combined unsupervised k-means clustering with supervised ML models to classify AE signals from CFRP-strengthened concrete structures. The framework achieved $\geq$98.6% accuracy in identifying damage mechanisms, illustrating that IoT integration can support proactive maintenance strategies in industrial settings. Ullah et al. [100] developed a Bi-LSTM model for pipeline leak detection, achieving 99.78% accuracy across varying pressures and fluids.
- Predictive maintenance in complex systems: The fusion of AET with IoT facilitates predictive maintenance in systems with multiple components and varying operational conditions. Nguyen et al. [116] introduced an AE activity intensity index (AIIC) combined with an RF classifier to detect and size leaks in fluid pipelines. This approach achieved 100% accuracy in classifying leak sizes, demonstrating how IoT-enabled AET can provide precise, real-time data for maintenance planning.
- Cross-domain applications: The integration of AET with IoT is not limited to specific industries, but extends across multiple sectors. In agricultural monitoring, Maginga et al. [225] used a hybrid CNN-LSTM model with IoT sensors to detect maize diseases and achieved high accuracy in both disease classification and ultrasound anomaly detection. This demonstrates the versatility of AET-IoT integration in diverse application domains.
- Technical advancements and future directions: Advancements in edge computing and sensor networks further enhance the practicality of AET-IoT systems. Researchers are developing lightweight MI models optimized for edge devices, enabling real-time processing with minimal latency. Additionally, DAS technology, which leverages fiber-optic cables as sensors, offers high spatial resolution and scalability for monitoring large structures like pipelines and bridges.

In summary, the integration of AET with IoT platforms represents a significant advancement in SHM. It enables real-time data acquisition, analysis, and predictive maintenance, addressing the challenges in noise reduction, signal processing, and practical implementation. As technology continues to evolve, the synergy between AET and IoT is likely to expand, offering even more robust solutions for ensuring the safety and reliability of industrial systems.

3.5.3. Advanced Sensor Technologies

Advancements in sensor technology bolster AET by enhancing its signal capture capabilities. High-sensitivity, wide-bandwidth sensors detect weaker AE signals for early-stage defect identification. Liu et al. [112] compared Nano30 and VS150-RIC sensors in monitoring hydrogen-induced cracking, finding VS150-RIC excellent for signal detection and localization, while Nano30 was better for signal classification. These sensor technologies have expanded AET's application possibilities. In summary, recent AET progress in AI-driven processing, IoT integration, and sensor technology has boosted detection accuracy in noisy environments and practical feasibility, providing robust support for future SHM and maintenance strategies.

4. Summary and Discussion

The integration of AET into the monitoring and maintenance of piping systems and flanges represents a significant advancement in ensuring structural integrity across various industries. This discussion synthesizes the insights gained from the previous sections, focusing on the implications of AET applications, challenges, and future directions.

4.1. Literature Review Summary

To achieve a comprehensive understanding, a systematic review of 145 articles with titles containing "AE", "acoustic emission", and "acoustic emission testing" was conducted. AET has demonstrated extensive applicability across various industries, primarily owing to its efficacy in the real-time monitoring and early detection of defects. This technology is particularly critical in environments where structural integrity is paramount, as the early identification of flaws can prevent catastrophic failures.

The distribution of AET applications across industries demonstrates a pronounced emphasis on the automotive and aerospace sectors, which together account for more than 61% of the total references. Specifically, the automotive sector constitutes 27.80% of the references, whereas the aerospace sector comprises 33.20%. Following these sectors, the infrastructure and oil and gas industries collectively represent an additional 24.90% of the references, with infrastructure accounting for 15.77% and oil and gas accounting for 9.13%. The remaining sectors, including energy (3.73%), manufacturing (1.24%), mining (2.90%), civil engineering (3.73%), geotechnical (1.24%), railway (0.83%), and marine industries (0.41%), collectively account for only 14.08% of the references, as illustrated in Figure 4.

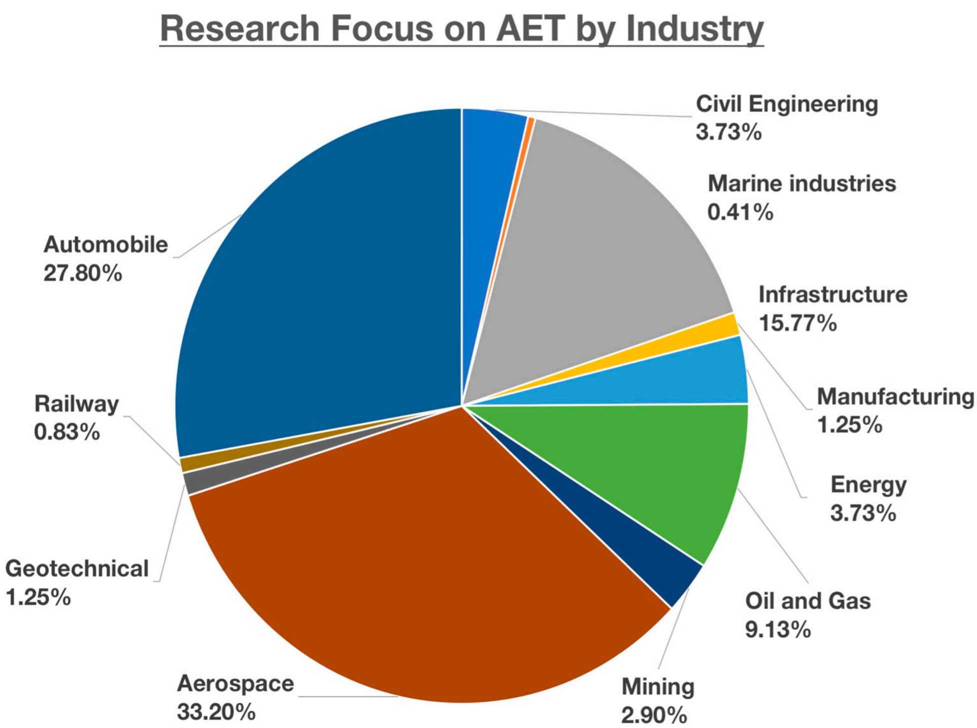

Figure 4. Distribution of AET applications across industries.

A review of the recent literature reveals a diverse application of AET across a spectrum of materials; Polymer Matrix Composites (PMCs) dominate the research landscape, accounting for 43.2% of all the AET studies. Within this category, CFRP leads with a significant share of 25.6%, highlighting its critical role in high-performance applications such as the aerospace and automotive industries. GFRP follows 16%, reflecting its widespread use in construction and marine applications. BFRP and NFRP represent a minimal portion at 1%, indicating niche but potentially growing areas of research.

Ceramic Matrix Composites (CMCs), known for their high-temperature stability, constitute 2.4% of the research focus. This percentage underscores their specialized applications in extreme environments, such as aerospace engines.

The metals and alloys category, which is essential in numerous industries, accounts for 36% of the research. Steel, with its versatility, captures 19.2% of the focus, whereas aluminum and stainless steel each represent 5.6%, reflecting their importance in diverse applications. Alloys of 4.8% and tungsten carbide anvils constitute 0.8% of the research, indicating specialized uses.

Construction materials, which are crucial for infrastructure development, represent 16% of the AET studies. Concrete, the most ubiquitous construction material, accounts for 9.6%, whereas rock, granite, and marble each represent a smaller portion, reflecting their use in specific structural applications.

Lastly, polymers and plastics, with their broad applications, constitute 2.4% of the research. Polyvinyl Chloride (PVC), with its versatility, accounts for 2%, while polymethyl methacrylate (PMMA) accounts for 1.6%, highlighting its use in transparent structural applications, as illustrated in Figure 5.

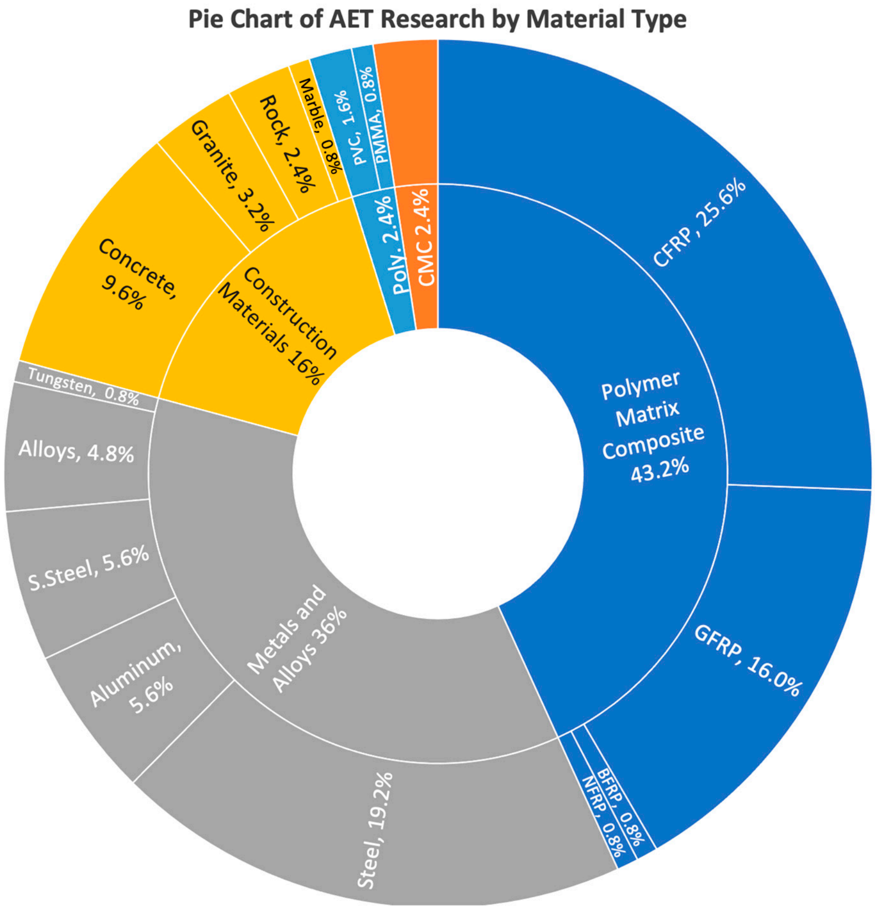

Figure 5. Distribution of diverse materials studied using AET.

This distribution of research efforts across various materials underscores the critical role of AET in ensuring the safety, reliability, and longevity of materials for diverse industrial applications. The focus on PMCs and metals and alloys, in particular, reflects their widespread use and the need for robust integrity assessment methods.

4.2. Discussion

In industrial systems, the integrity of piping and flange connections is important for ensuring safety, reliability, and operational efficiency. As industries face increasing pressure to minimize downtime and enhance safety protocols, the evolution of inspection technologies has become crucial. This section discusses the current trends in NDT methods, particularly focusing on AET and its position among other inspection techniques.

Recent advancements have propelled AET to the forefront of SHM, enabling the real-time detection of developing defects. The integration of AET into inspection protocols not only enhances the reliability of assessments but also supports proactive maintenance strategies that can prevent catastrophic failures.

However, the application of AET is challenging. The need for skilled operators, environmental noise considerations, and the complexity of signal interpretation present barriers to its widespread adoption. This discussion explores these trends, advancements, and challenges in detail, providing a comprehensive understanding of the current landscape of pipeline and flange inspection technologies.

4.2.1. Current Trend in Pipeline and Flange Inspection

The inspection of multi-bolted flanges poses unique challenges because of their complex geometry, dynamic loading conditions, and susceptibility to localized defects such as corrosion, cracks, and gasket degradation. The existing NDT methods, although effective for pipelines, face limitations when applied to flanges. Below is a revised analysis of the current techniques and their applicability to multi-bolted flanges.

Guided Wave Ultrasonic Testing (UGW): UGW is widely used for long-range pipeline inspections, where it efficiently detects corrosion and cracks by propagating waves along the length of the pipe. However, its application in multi-bolted flanges is constrained by the following:

- Geometric Complexity: Flange bolt holes, gaskets, and abrupt transitions scatter guided waves, reducing the signal clarity and defect detectability.
- Mode Conversion: The complex geometry of flanges causes wave-mode conversions, complicating signal interpretation.
- Short-Range Limitations: High-frequency UGW (200 kHz–1 MHz) used for detailed imaging has a limited penetration depth, making it unsuitable for thick flanges or buried components.

Despite these challenges, the UGW can complement other flange inspection methods in specific scenarios. For example, a low-frequency UGW (<150 kHz) may still provide baseline integrity assessments for flanges in simpler configurations.

Nonlinear Ultrasonics: Nonlinear ultrasonic techniques, such as vibro-acoustic modulation and harmonic generation, exploit nonlinear wave interactions to detect early-stage defects in flanges. These methods can identify microcracks, corrosion, and fatigue damage in bolted joints where linear methods struggle. Guan et al. [61] demonstrated that nonlinear cylindrical waves can quantify fatigue crack growth in aluminum pipes, a finding that is applicable to flange components. However, nonlinear ultrasonics requires specialized equipment and advanced signal processing, which limits their widespread adoption.
Phased Array Ultrasonic Testing (PAUT): PAUT is used for flange corrosion mapping and weld inspection owing to its ability to steer ultrasonic beams and generate high-resolution images. Sankar achieved 90% POD for the corrosion of carbon steel flanges using

PAUT. Despite this success, PAUT requires meticulous calibration and operator expertise, particularly for complex flange geometries with bolt holes and gasket interfaces.
Radiography Testing (RT): RT effectively detects CUI and weld defects in flanges but is constrained by radiation safety protocols and the need to remove insulation. Xu et al. and Moreira et al. advocated digital radiography as a safer alternative, although its use in live industrial environments remains limited by operational disruptions.
Hydrostatic Testing (HT): HT is critical for verifying flange joint integrity under pressure but requires system shutdown and extensive preparation. Grzejda highlighted HT's role in assessing bolted connections but noted its inability to detect incipient defects during normal operation, necessitating complementary methods such as AET.

Challenges Specific to Flange Inspection

- Geometric Complexity: Flange bolt holes and gasket interfaces scatter ultrasonic waves, reducing the signal clarity for the UGW and PAUT.
- Dynamic Loading: Pressure and temperature fluctuations in operational flanges introduce noise that masks defect-related signals.
- Accessibility: Bolted joints often require disassembly for visual inspection, which increases downtime and cost.

Table 4 provides a summary of NDT techniques for multi-bolted flange inspection.

Table 4. NDT techniques for multi-bolted flange inspection.

Technique	Application in Flanges	Advantages	Limitations	References
Guided Wave Ultrasonic Testing (UGW)	Baseline integrity assessment for flanges in simple configurations; corrosion detection in pipelines connected to flanges	Long-range capability; cost-effective; minimal downtime	Severely limited by flange geometry (wave scattering and mode conversion); low resolution for complex defects	[45,49]
Nonlinear Ultrasonics	Detection of microcracks, corrosion, and fatigue damage in flanges and bolted joints	High sensitivity to early-stage defects; works under dynamic loading	Requires specialized equipment and signal processing; limited field applications	[60]
Phased Array Ultrasonic Testing (PAUT)	Corrosion mapping, weld defect detection in flanges	High-resolution imaging; suitable for complex geometries	Operator skill-dependent; calibration-intensive; limited to accessible areas	[68,69]
Radiography Testing (RT)	Detection of corrosion under insulation (CUI) and weld flaws in flanges	High accuracy for volumetric defects; non-contact	Radiation hazards; requires insulation removal; limited to static inspections	[72,73]
Hydrostatic Testing (HT)	Verification of flange joint integrity under pressure	The gold standard for leak detection; comprehensive validation under load	Requires system shutdown; time-consuming; unable to detect incipient defects	[77,83]

4.2.2. Advancements in AET Technology

AET has undergone significant advancements, positioning it as a transformative solution for the real-time monitoring of multi-bolted flanges. These advancements have addressed the critical limitations of traditional NDT methods, particularly in complex flange geometries and dynamic operational environments. Below is a structured overview of key innovations in AET.

AI-Driven Signal Processing and Deep Learning

The integration of AI and ML has revolutionized AET's capabilities, enabling robust noise reduction, automated feature extraction, and real-time defect classification.

- Noise Mitigation: Hybrid models, such as CNN-LSTM networks [224] and fuzzy-wavelet denoising, suppress environmental noise and improve SNR in industrial settings [227].
- Feature Learning: Deep learning architectures such as InceptionTime [145] and Capsule Neural Networks automatically identify subtle defect patterns in AE signals, thereby reducing reliance on manual feature engineering [144].

- Real-Time Localization: The CRNN model achieves sub-millimeter crack localization in flanges under dynamic loading, leveraging temporal and spatial feature learning [228].

IoT Integration for Smart Maintenance

AET's integration with the Industrial IoT enables scalable, remote monitoring of multi-bolted flanges.

- Edge Computing: Lightweight models optimized for edge devices enable real-time leak detection in pipelines connected to flanges, thereby reducing latency and computational overhead [244].
- Predictive Maintenance: Hybrid frameworks combining AE data with IoT sensors predict flange failures by analyzing trends in pressure, temperature, and AE activity [100].
- Distributed Sensing: Fiber-optic DAS technology provides the continuous monitoring of large flange networks, enhancing spatial resolution and coverage [112].

Advanced Sensor Technologies

Innovations in sensor design have enhanced AET's sensitivity to early-stage defects in flanges.

- Wide-bandwidth sensors: High-sensitivity sensors such as VS150-RIC detect low-amplitude AE signals from microcracks in carbon steel flanges, whereas Nano30 sensors excel in high-frequency signal classification [112].
- Embedded sensors: Piezoelectric transducers embedded in flanges enable the in situ monitoring of bolt loosening and gasket degradation, overcoming accessibility challenges [121].

Nonlinear Acoustic Emission (NAE) for Micro-Damage Detection

Recent research has explored nonlinear acoustic emission (NAE) to detect micro-damage that is undetectable by traditional linear AET.

- Higher-Harmonic Analysis: NAE techniques analyze frequency shifts and wave interactions to identify incipient cracks and corrosion in the flanges [61].
- Vibro-Acoustic Modulation: Zhao et al. demonstrated real-time bolt looseness detection using nonlinear ultrasonic modulation, outperforming linear methods in noise-prone environments.

Advantages Over Traditional NDT Methods

Advancements in AET address critical gaps in flange inspection.

- Real-Time monitoring: Unlike HT or RT, AET operates during normal flange operation, minimizing the downtime.
- Dynamic load compatibility: AET detects defects under pressure/temperature fluctuations, whereas PAUT and UGW struggle with signal stability.
- Sensitivity to early defects: Unlike visual inspection or hydrostatic testing, AI-driven AET identifies microcracks and corrosion at incipient stages.

4.2.3. Challenges and Limitations of AET for Flange Inspection

Despite these advancements, AET faces challenges that hinder its adoption. Environmental noise, particularly in industrial settings, can obscure AE signals, necessitating sophisticated noise reduction techniques. Signal interpretation complexity, compounded by the nonstationary nature of AE data, requires skilled operators and advanced ML algorithms. In addition, sensor limitations, such as sensitivity and spatial coverage, and the absence of standardized validation protocols for diverse materials and environments, remain barriers. Addressing these challenges will require ongoing research on AI-driven signal processing, robust sensor design, and regulatory harmonization.

4.3. Future Directions

Building on these foundational findings, this review proposes a structured roadmap to advance AET's practical implementation. Initially, controlled laboratory testing will systematically characterize AE signatures from both intact and defective (corroded or cracked) multi-bolted flange assemblies under dynamic pressure conditions. These experiments will establish baseline patterns for distinct failure modes, serving as a reference for anomaly detection in industrial settings.

To ensure robustness, the methodology will be extended across diverse material systems (e.g., carbon steel and composite alloys) and simulated noisy environments to evaluate AET's resilience against extraneous vibrations and electromagnetic interference. Finally, field validation campaigns on operational pipelines and flanges will address real-world challenges such as temperature fluctuations and variable background noise to confirm the reliability of the technique in industrial contexts. This iterative approach bridges the theoretical potential with actionable solutions, positioning the AET as a cornerstone of predictive maintenance frameworks for critical infrastructure.

Following the completion of the laboratory and field validation phases, the next phase will focus on integrating AI/ML to address the persistent challenges in AE signal interpretation. Specifically, deep learning models such as CNNs and RNNs have been developed.

1. Suppress nonstationary noise in AE datasets, improving the signal–noise ratios for defect identification.
2. Classify complex failure modes with higher precision by leveraging transfer learning from pretrained models.
3. Enable real-time adaptive monitoring by incorporating online learning algorithms to account for environmental variability.

This computational framework enhances AET's sensitivity to incipient defects while reducing false positives, thereby ensuring its scalability for large-scale industrial applications. By merging experimental validation with AI-driven analytics, this study aimed to create a self-calibrating, intelligent system capable of autonomous decision making in critical safety scenarios.

5. Conclusions

AET has established itself as a groundbreaking NDT technique, particularly for the inspection and continuous monitoring of multi-bolted flanges in critical industrial applications. The capacity of the technology for real-time monitoring, combined with its exceptional sensitivity to detect incipient defects, makes it an indispensable tool for maintaining structural integrity and preventing catastrophic failures across various industries.

To further advance the understanding and application of AET, an experimental study is currently being conducted to characterize and learn defect signals in multi-bolted flange systems. This experiment aimed to systematically analyze the AE signatures associated with various types of defects, including corrosion, cracks, and loosened bolts under different operational conditions. By collecting comprehensive datasets of acoustic signals from both intact and defective flange assemblies, this study established baseline patterns for distinct failure modes, enhancing our ability to accurately identify and classify defects in real-world industrial settings.

The integration of advanced sensor technologies and ML has significantly enhanced the AET capabilities, enabling more efficient and precise inspections. High-sensitivity sensors can detect subtle acoustic signals from early-stage defects, whereas sophisticated signal processing algorithms can improve the interpretation of complex acoustic data. The collected experimental data will be used to train and validate the ML models, further improving the accuracy and reliability of defect detection and classification.

Despite these advancements, several challenges must be addressed to fully realize AET's potential. The interpretation of AET results requires specialized expertise, and environmental noise in industrial settings can interfere with signal clarity. Future research should focus on developing more robust signal processing techniques, improving sensor technology to enhance detection capabilities, and establishing standardized protocols that account for the diverse operational conditions encountered in flange systems.

The ongoing evolution of AET promises the delivery of safer and more reliable industrial operations. By enabling the effective monitoring and maintenance of critical components, such as multi-bolted flanges, AET contributes to enhanced operational performance and risk reduction across sectors. As industries increasingly prioritize safety and efficiency, the importance of AET in SHM will continue to grow, driving further innovation and the application of this vital technology.

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