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Crack Detection of Metal Components Based on Acoustic Emission Method: A Review

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Abstract: Acoustic emission (AE) refers to transient elastic waves generated by the rapid release of localized strain energy during crack initiation, propagation or plastic deformation in stressed materials. Due to its remarkable capacity to identify internal microcracks in metallic substances, AE method serves as a crucial element in the monitoring of mechanical structure integrity. This paper summarizes key studies on the use of the AE technique to diagnose cracks in metal components. It describes the time-frequency characteristics and energy evolution patterns of AE signals during crack development, as well as the mechanisms of AE. Furthermore, it offers an overview of the progress in various intelligent recognition models, feature extraction techniques, and signal denoising methods. It subsequently analyzes the deficiencies and implementation challenges of existing technologies alongside case studies of typical industrial apparatus. This study presents new approaches, such as multi-source signal integration, large model evaluation, and real-time monitoring systems, to tackle issues such as noise disruption, insufficient model generalization, and a lack of consistent standards. The scholarly achievements in this domain are encapsulated in this paper, which additionally provides suggestions and citations for further investigation.

Keywords: Acoustic emission; Metal components; Crack detection; Intelligent recognition.

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1.Introduction

Metal components are especially susceptible to crack damage in operation due to factors such as material defects and stress concentration. Under severe conditions, fissures can easily lead to safety incidents as they significantly reduce the load-bearing strength of mechanical frameworks. The initiation and propagation of cracks are vital stages in the failure of mechanical systems, making precise and real-time observation of these phenomena critically important from both engineering and theoretical perspectives. Conventional detection methods generally exhibit low efficacy and insufficient accuracy when addressing complicated components and initial microcracks. AE method is a prevalent non-destructive evaluation method capable of continuously and accurately monitoring the complete progression of internal damage in metallic materials. It offers essential utility in identifying initial fractures and evaluating the state of mechanical apparatus. This paper provides a comprehensive review the practical applications of AE method in crack detection. It begins with the signal generation process, common processing algorithms, feature extraction methodologies, and standard engineering application contexts, then objectively assesses the limitations of existing technologies, identifies potential avenues for future advancement, and provides valuable insights for additional research and engineering applications in this field.

1.1 Overview of AE Method and Its Applications in Machinery Fault Detection

AE refers to transient elastic waves generated by the rapid release of localized strain energy during crack initiation, propagation or plastic deformation in stressed materials. In microscopic phenomena such as crack initiation, propagation, and fracture, transient elastic waves are generated within the material and released outward. The elastic- wave signals are captured and analyzed by piezoelectric sensors installed on the component surface, which enables dynamic and continuous monitoring of damage evolution, source identification, and pattern recognition. It serves as a core technical approach in the fields of fatigue damage assessment and structural safety early- warning [1,2].

The history of AE method is vast. In early 19th century, Researchers in mining engineering and seismology documented the auditory events occurring during the stress-induced rock and metal collapse. However, hampered by the sensor and signal-processing technology of the time, significant investigations were relegated to qualitative representations of phenomena and fragmented across numerous fields. Failing to establish a systematic technological framework or cohesive academic vocabulary [3,4]. The official inception of contemporary AE method can be traced to the 1950s. In 1950, German materials scientist Joseph Kaiser [5] systematically conducted tensile tests on different metallic substances, such as zinc, aluminum, and copper. He noted for the first time that no significant AE signal was produced until the external load exceeded the material's historical maximum stress level. AE activity would only recommence once the stress exceeded the prior peak value. This event became known as the "Kaiser Effect" after it occurred. This research, for the first time, quantified the relationship between AE signal characteristics and the progression of internal material damage, thereby establishing a fundamental theoretical basis for AE method. Consequently, Kaiser is regarded in academia as the pioneer of contemporary AE detection methods. In the late 1950s, American researchers Schofield and Tatro conducted a series of studies that elucidated the physical basis and practical significance of AE. Schofield's comprehensive tests on single-crystal metals indicated that AE

during plastic deformation is mostly caused by the collective movement of dislocations. [6]. Simultaneously, Tatro systematically explored the mechanisms of AE, establishing that it is fundamentally an internal volume phenomenon rather than a surface phenomenon in materials [7]. He was a trailblazer in proposing that AE could be a valuable tool for examining the intricate mechanical properties of engineering materials. This propelled the growth of AE research from basic materials mechanics to engineering applications [8]. The 1960s saw a crucial shift for AE method. Green et al. pioneered the application of AE method in non-destructive testing (NDT) engineering. Showcasing its practicality for identifying fatigue cracks in aerospace metal structures and welded components. This transcends the technological limitations that had restricted this method to fundamental laboratory investigations [9]. Simultaneously, Harold L. Dunegan developed the methodical use of AE method for monitoring the integrity of pressure vessel hydrostatic tests. This approach confirmed its efficacy in detecting and pinpointing flaws like internal fissures or leaks in pressure vessels. It also created a foundational technical structure for AE testing of pressure vessels, which provided a pragmatic basis for its later extensive engineering implementation [10]. In the 1960s and 1970s, the designation “Acoustic Emission” became a widely accepted academic term in the international scholarly community. In 1969, the American Society for Testing and Materials (ASTM) released the inaugural technical standard for AE testing, marking the official onset of this technology's standardization and engineering utilization. Following that, a comprehensive technical framework was created, which included signal capture, feature parameter extraction, damage source location, damage mode detection, and residual life evaluation. AE method has been widely used in major engineering domains, including pressure vessels, steel bridges, critical aero-engine components, and wind power systems [1,3].

Nowadays, with the evolution of the AE method, it exhibits major technical merits. It requires no disassembly of components to conduct continuous online monitoring. Its core advantage lies in its superior capacity for early microcrack recognition in comparison to in-situ detection approaches such as infrared thermography and digital imaging [11]. Consequently, the AE method has been successfully and competently applied in fault detection across a diverse range of mechanical equipment. It has particularly shown considerable potential in the early identification of cracks [12]. It has gradually evolved into a core technical tool in the fields of non-destructive testing and structural health assessment [1,2].

1.2 Hazards of Crack Failures and Detection Challenges

The existing literature indicates that fatigue fractures and stress corrosion cracks are the primary causes of abrupt failures in essential metallic service components such as transmission gears, wind turbine bearings, aero-engine turbine disks, and pressure pipelines. These metallic components often operate in demanding conditions characterized by high temperatures, corrosive chemicals, and repetitive stress. Under prolonged coupled erosion, microcracks initiate at intergranular imperfections and rapidly progress to unstable fractures following a phase of stable growth. The issue lies in the fact that the fissures are difficult to detect with the naked eye or other conventional inspection methods throughout their entire developmental phase. The overall load-bearing ability of the structure has significantly reduced by the time observable macroscopic defects appear. This often leads to equipment degeneration, operational halts, and crucially potential grave safety events and significant financial losses. This viewpoint is further supported by fracture mechanics and engineering failure data, indicating that early microcrack

defects overlooked in a timely manner contribute to 50% to 90% of fracture failures in metallic engineering components [13]. Consequently, early detection of cracks is crucial for ensuring that equipment operates safely throughout its lifespan.

All widely used non-destructive testing methods possess inherent limitations. Although ultrasonic, X-ray, and magnetic particle inspections can access internal structures, offline testing requires halting equipment functionality. In scenarios requiring continuous monitoring, this is nearly impossible. The risks connected with X-ray radiation and the potential secondary contamination of precision components from magnetic particle residues are significant drawbacks. Visual inspection is restricted to surface-level macro-cracking and useless for finding hidden interior damage. Traditional testing methods have hysteresis, resulting in a diminished response to micron-scale nascent fractures. By the time these imperfections are detected, they have evolved into macroscopic defects at the millimeter scale, rendering the damage irreparable. While this is still a disputed issue, the risks associated with hysteresis are considerable for precise technology such as aerospace.

An option is offered by AE method. This method is a non-intrusive dynamic surveillance method that can directly capture the elastic stress waves emitted by materials during the formation and spread of fractures without requiring external stimulation. AE phenomena result from both plastic deformation and interfacial friction inside the material. These occurrences cause changes to signal amplitude, energy, and spectrum features, which generally exhibit specific quantitative correlations with crack propagation velocities and levels of damage. Consequently, AE can adjust for the spatial and temporal constraints of offline testing and exhibits heightened sensitivity to superficial micro-damage. However, issues such as the superposition of multi-source noise, attenuation of signal propagation, and the convergence of various damage sources significantly restrict the precision of quantitative detection.

1.3 Motivation

During the last decades, several review works have provided key foundations for theoretical research and engineering practice, and have expanded the knowledge of AE method and its use in structural damage detection. However, so far there are still few targeted and thorough studies of AE-based crack detection in metallic components.

Early in 1998, Huang et al. [14] released a seminal review of AE method for fatigue and fracture materials research. It comprehensively outlined the main principles of classical AE parametric analysis (including counts, peak amplitude and energy) in tensile, fatigue and corrosion tests. Source function modeling and elastic wave propagation theory were preliminarily introduced . Because of the technological development at that time, this effort did not include sophisticated signal processing or pattern recognition approaches. It is not explicitly aimed at crack detection scenarios for industrial metallic components.

More recently, Holford et al. [15] summarized the main challenges of AE fatigue fracture detection in complex aerospace environments in terms of industrial scenarios. It summarized the progress of source localization and signal classification methods. In this study, an automatic detection methodology combining AIC-based arrival time correction with spatial clustering was proposed.However, this work solely focused on the aerospace field and metallic fatigue. It did

not conduct a horizontal comparison across various industrial fields and include the latest advances in deep learning technologies.

Carrasco et al. [16] provided a brief review of AE crack monitoring technologies across materials. It described the main waveform parameters and typical application fields. However, the description of the metallic fatigue fractures was not enough as the length was limited. It also lack of systematic comparison of the signal processing techniques and engineering-oriented application analysis.

The use of AE method to stress corrosion cracking (SCC) for particular failure types was investigated by Calabrese et al. [17]. They carefully analyzed the AE source processes in SCC advancement and the waveform feature recognition methods. They developed multivariate statistical analysis and neural network methods for SCC damage detection. However, this evaluation is confined to the only failure mode of stress corrosion. Typical failure modes of mechanical components such as common fatigue fracture and contact fatigue are not included.

Regarding data-driven intelligent methods, Ciaburro and Iannace [18] gave a systematic review of the machine learning methods for AE testing. They classified the clustering algorithms, artificial neural networks, convolutional neural networks and recurrent neural networks. The detection accuracy and applicable scenarios were compared. However, this review was organized by categories of algorithms, not by harm mechanisms. It did not particularly separate out the application of intelligent approaches for fracture detection in metallic components. The engineering bottlenecks hindering industrial implementation were not examined.

Despite extensive research and industrial practice over recent decades, three core scientific challenges remain fundamentally unresolved in AE-based crack diagnosis for metallic components. It also constitutes the main bottlenecks restricting further engineering popularization of this technology.

First, the source aliasing problem. AE signals originating from crack propagation and interfacial friction. Plastic deformation and environmental noise are often mixed and superimposed in practical scenarios, making it difficult to accurately isolate and identify crack-specific signal signatures.

Second, the quantitative mapping gap. It remains difficult to establish a stable, generalizable quantitative relationship between AE characteristic parameters and actual crack size, depth and growth rate. That is restricting the AE method from qualitative detection to quantitative evaluation.

Third, the generalization bottleneck. The detection models and evaluation thresholds were trained under specific materials, structural geometries and operating conditions. It often suffers severe performance degradation when transferred to other scenarios. The robust cross-domain adaptability is significantly discounted.

Overall, existing reviews have promoted the development of AE method from different dimensions. There is still a lack of a systematic framework that focuses on crack detection in

metallic components and covers the full chain from generation mechanism, signal processing, intelligent recognition to industrial application and development prospects. To address this gap, this paper presents a comprehensive review of AE-based crack detection technology for metallic components. The work sorts out the AE generation mechanisms and signal characteristics during crack initiation and propagation. It also compares and analyzes the technical routes for signal denoising, feature extraction, and intelligent pattern recognition. The application status and the performance bottleneck in typical industrial domains, including transportation, aircraft, energy and petrochemical infrastructure was summarized. Finally, the development directions of frontier such as multi-source information fusion, large model intelligent decision-making and real-time monitoring system were discussed. This review is expected to serve as a reference for researchers and engineers in the field of structural health monitoring, and to promote the engineering application and standardization of AE crack detection technology.

1.4 Literature Search Strategy

To ensure comprehensiveness, objectivity and reproducibility of the literature coverage in this narrative review. A structured literature search method was implemented prior to preparation of this publication. It is important to point out that this work does not attempt to be a systematic review that strictly adheres to PRISMA. The following search protocol was developed to avoid subjective selection bias and to cover the mainstream research landscape in the topic.

A literature search was performed in the most commonly used academic databases in the subject of mechanical engineering and structural health monitoring, including Web of research, Scopus, ScienceDirect, IEEE Xplore, Google Scholar, CNKI, and Open research in global networks (Tsinghua University Library). Backward snowballing was also carried out on the reference lists of highly cited review papers and classic monographs to locate seminal publications that might be overlooked by keyword-based retrieval.

The search was based on Boolean operator combinations. The basic keyword groupings represented three dimensions:

(1) acoustic emission method: (“acoustic emission” OR “AE”);

(2) research object: (“crack detection” OR “fatigue crack” OR “crack propagation”) AND (“metallic components” OR “metal structures”) NOT (“rock” OR “concrete”);

The publication time range was set from 2020 to 2026, with particular attention paid to last 5 years studies to reflect the latest advances in intelligent signal processing and industrial applications. Classic theoretical works on AE generation mechanisms were not restricted by this time range to ensure the integrity of the theoretical framework.

The inclusion criteria were defined as follows:

(1) peer-reviewed full-length journal articles published;

(2) studies focusing on AE-based crack detection, damage characterization or life prediction in metallic materials or components;

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(3) studies supported by experimental validation, including laboratory tests or industrial case studies.

The exclusion criteria included:

(1) studies focusing solely on composite materials, ceramics or polymers;

(2) conference abstracts, short communications, book chapters and editorial materials;

(3) duplicate publications of the same study from different venues.

The screening process consisted of two consecutive stages. The first stage involved the screening of titles and abstracts to exclude obviously unrelated records. The second stage was a full-text assessment to determine eligibility for inclusion and exclusion criteria. Finally, roughly 116 sample papers were selected to be included in this review. It covers four fundamental topics: AE generation mechanisms during crack propagation, signal denoising and feature extraction methods, intelligent pattern recognition algorithms, and industrial engineering applications.

The manuscript follows the hierarchical technological chain shown in Fig. 1.1 to systematically organize the reviewed research and make the logical linkages across physical mechanisms, signal processing approaches, industrial applications and frontier prospects clearer.

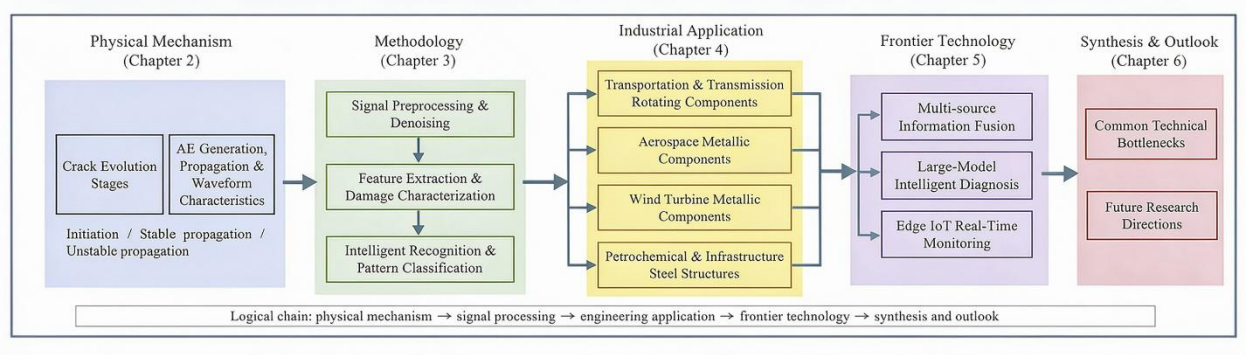

Fig. 1. A Review Framework of AE-based Crack Detection in Metallic Components

In addition, this work provides a cross-comparison and critical synthesis of the evaluated approaches and their practical implementations. It identifies generic technological barriers and outlines possible future research routes.

On the basis of this framework, this paper conducts a horizontal comparison and critical synthesis of numerous approaches and applications. It points out common technological constraints and promising future research areas. The rest of the paper is structured as follows. Chapter 2 provides the physical process of creation and propagation of AE during fatigue crack growth in metallic components. It defines the differential AE signal properties during crack initiation, stable and unstable propagation stages. Chapter 3 reviews the AE signal processing and intelligent diagnosis methodology system. The processes of signal preprocessing and denoising, feature extraction and damage characterization, and intelligent pattern recognition are illustrated. Finally, it performs a comparative analysis of the performance and applicability of

typical methods. Chapter 4 studies the engineering practice of AE-based crack detection in four main industrial sectors. The transportation and transmission rotating components, aerospace metallic components, wind turbine metallic components, and petrochemical and infrastructure steel structures are covered in this chapter. The scenario-specific technical bottlenecks were summarized for each field. In Chapter 5, we introduce some emerging frontier research directions such as multi-source information fusion, large-model intelligent diagnosis and edge IoT real-time monitoring. The entire review is concluded in Chapter 6. The typical technical constraints across the entire technological chain are summarized, and targeted future research prospects are proposed.

2. AE Signal Generation Mechanisms and Crack Characteristic Analysis

This chapter is the physical basis of the whole AE-based crack detection system. It elaborates on the generation and propagation mechanisms of AE signals accompanying fatigue crack evolution in metallic components. The differentiated signal features across different damage stages are characterized, which provides a mechanical basis for designing subsequent signal processing algorithms and diagnostic models.

The beginning of cracks, plastic deformation, and continued crack growth are fundamental AE sources associated with damage. It is closely correlated with structural failure in metal components during their operational lifespan. Differences in crack classification, geometric measurements, propagation velocity, and substrate material influence the temporal, spectral, energetic, and additional characteristics of the signals. A fundamental prerequisite for achieving accurate crack detection is analyzing the physical mechanisms of AE throughout the crack development process, distinguishing signal patterns associated with different crack types, and evaluating the impacts of signal propagation and environmental disturbances.

2.1 AE Generation Mechanisms during Crack Initiation and Propagation

The primary origins of AE signals at the crack initiation phase are microscopic phenomena such as dislocation movement, microvoid amalgamation, and the interlinking of microcracks inside the material. When a fatigue fracture enters the propagation phase, energy is continuously emitted, allowing the AE technique to effectively monitor dynamic crack growth conditions [19-21]. Signal energy, event frequency, and peak amplitude during fracture formation can be used to calculate the component's current damage level and crack propagation rate [21-23]. Integrating previous research findings with multi-parameter AE analysis allows for effective differentiation between the three unique stages of macroscopic crack initiation, stable propagation, and unstable propagation [20-22].

Relevant experiments have demonstrated a quantitative correlation between the energy of the AE signal and the velocity of crack propagation, a relationship that remains consistent across different stress ratio conditions. This conclusion gives theoretical support for the quantitative estimation of crack size [20]. Interface cracks have very different fracture mechanics than homogeneous metal cracks. Using metrics like median frequency and signal information entropy, it is possible to assess whether a fracture deviates along or violates the interface [24]. Overall, defining the energy release patterns during fracture propagation is critical for interpreting AE data and enhancing diagnostic accuracy.

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2.2 Temporal, Spectral and Energy Characteristics of AE Signals for Different Crack Types

Fatigue fractures generate AE signals with similar waveform amplitudes as they gradually propagate under cyclic stress. Academics denote such recurring signals originating from a singular source as “Acoustic Multiplets”. At the microscopic scale, these signals relate to gradual crack propagation and friction between the surfaces of the crack, occurring within a specific load range [25]. AE method serves as an effective instrument for early damage detection because it is more sensitive to the to the initiation and early propagation of fatigue cracks compared to traditional vibration detection methods [25–26].

Surface cracks, subsurface cracks, and through-thickness cracks represent the three classifications of fractures in metallic components. It is defined in engineering methodology based on their geometric configurations. The temporal, spectral, and energetic attributes of the AE produced by these three types of fractures often exhibit significant differences.

(1) Surface fatigue fractures are visible on the surface of the component. Stress waves have short propagation distances and little attenuation since they do not need to travel through complex material. The signal has a quick rising time and a large peak amplitude in the temporal domain. The spectral energy is concentrated in the mid-to-high frequency range. The energy released during a single event is moderate, and the frequency of repeated multiple waves remains stable. These are mostly due to frictional interactions between crack surfaces.
(2) Subsurface cracks refer to fatigue fractures that are integrated within the matrix. The phenomena of scattering, dispersion, and time-delay occur as stress waves propagate through them. As a result, the core frequency drops and the waveforms take on a “stretched” appearance with pronounced following tails. The energy of individual events demonstrates significant variability. Numerous wave signals are often infrequent and easily masked by the background noise of equipment during the gradual crack propagation stage.
(3) Through-thickness cracks significantly enlarge the dimensions of the fracture plastic zone by entirely bisecting the component's cross-section. Their time-domain signals exhibit the most concentrated ring-down counts alongside the highest peak amplitudes. The energy for each individual event is markedly greater than that of the previous two categories, and the frequency domain span is exceptionally extensive. Through-thickness cracks often indicate unstable growth. A rapid release of energy occurs alongside the vanishing of several wave signals.

However, geometric morphology by itself is inadequate for distinction. The energy distribution patterns in the time-frequency of the signals can be altered by loading conditions such as combined high-low temperature settings, consistent stress ratios, and fluctuating amplitude loads. This elucidates why contemporary studies [21] generally advocate for a multi-parameter joint methodology to characterize the extent of crack development, incorporating amplitude, rise time, duration, total event energy, and center frequency. While the boundaries of sample applicability require further elucidation, scholars globally have conducted comparative analyses utilizing engineering metals such as 304L stainless steel and aerospace aluminum alloys. They effectively substantiate the generalizability of multi-parameter AE characterization techniques for detecting fatigue damage in various materials [27–29].

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AE can continuously document the complete signal sequence of crack development under stress. Conventional ultrasonic phased array testing technology can provide static geometric imaging of cracks but fails to capture the entire dynamic propagation process. A comprehensive analysis of both static crack measurements and dynamic propagation characteristics is facilitated by the inherent complementarity of these two methods [30]. Due to noise and signal degradation, depending exclusively on a single parameter in AE signal analysis is susceptible to inaccuracies. A reliable analytical approach for assessing component damage levels and trends in failure progression is cross-analysis employing multi-dimensional indicators across the time domain, frequency domain, and energy. It facilitates precise identification of crack types and measurement of propagation rates [21].

According to the crack evolution process, AE signals exhibit distinct differences across three stages.

In the crack initiation stage, the signals are characterized by very low amplitude, sparse event occurrence, and high randomness. It is easily confused with background noise and interfacial micro-friction signals. This is the hardest part to get right. The steady propagation stage is characterized by periodically recurring acoustic multiplets of very regular parametric behavior and is the best characterized damage stage to date. However, operational parameters like load variation and lubrication conditions may cause disturbance in this. The unstable propagation stage is related to the instantaneous violent release of strain energy. The peak amplitude and event density increase sharply and acoustic multiplet characteristics disappear. At this level, signals are quite identifiable, but the duration is very short. It puts tremendous requirements on the real-time response of the detection systems.

There is no completely definite dividing line between the qualities of the three stages. The coupling effect of operating conditions further complicates accurate stage discrimination. This is one of the primary rationales for widespread use of multiparameter joint characterization methodologies. Noise and propagation attenuation affect single parameters, which can lead to mis-estimations. But the overall cross-analysis of several dimensions such as time domain, frequency domain and energy can effectively distinguish the types of cracks and quantify the propagation rate. It can provide a valid analytical approach for assessing the damage and development trend of failure of components. This approach provides a sound analytical basis for evaluating the extent of damage and the propagation tendencies of failure in structural components.

2.3 AE Signal Propagation Characteristics and Environmental Influence Factors

In the transmission of elastic stress waves produced by AE sources in a metallic matrix, four fundamental propagation phenomena such as dispersion, waveform distortion, multi-path reflection, and energy attenuation. The dispersion effect denotes the occurrence in which elastic wave components of varying frequencies traverse a medium at disparate velocities. Higher frequency components move more slowly, leading to the elongation and widening of the initial pulse waveform following extensive transmission. It thereby distorting critical time-domain metrics like rise time and peak values. The waveform distortion effect pertains to the occurrence in anisotropic substances like orthotropic plates and laminated metals, where wave velocity varies with the direction of propagation. The combination of dispersion and scattering effects

leads to a level of waveform distortion that significantly surpasses that of uniform carbon steel elements. The multi-path propagation phenomenon pertains to the reflection and refraction of stress waves at the internal and external surfaces of components, welding joints, and bolted connections. Signals produced by a singular damage source reach the sensor via various routes at distinct intervals, resulting in multiple time-separated waveforms of identical origin. It can be mistakenly interpreted as several damage locations. The energy attenuation phenomenon denotes the gradual dissipation of energy by stress waves as they travel, attributed to internal friction within the material and scattering at grain boundaries. As the distance of propagation increases, the attenuation of both signal amplitude and overall energy becomes more pronounced. This rendering signals produced by subsurface fractures often exceedingly faint and challenging to detect upon reaching the sensor. The original waveform is considerably altered and deformed due to the individual or combined influence of these various effects. It impairing the precision of crack source localization and damage feature extraction. Li et al. [31] validated via AE damage localization experiments on orthotropic steel plates. He found the previously mentioned multiple propagation coupling interferences considerably exacerbate the time difference localization error of AE sources. This hindering the ability to achieve precise engineering localization.

Besides the waveform distortion resulting from the medium's intrinsic propagation properties, the initially gathered waveforms are also affected by the operational circumstances and the supporting conditions of the testing apparatus. The primary sources of disruption can be categorized into three distinct groups. The initial category encompasses environmental electromagnetic and mechanical noise. The functioning of motors, gear interactions, and fluid collisions produce persistent interference waveforms coincide with the spectrum of micro-crack signals. It concealing subtle damage characteristics. The second category pertains to losses resulting from sensor coupling conditions. Inadequate thickness of the coupling medium between the sensor and the component surface, or contamination of the contact surface, leads to a loss in stress wave transmission. It considerably diminishing the SNR of the acquisition. The third category pertains to disruptions caused by intrinsic material defects. Inherent voids in the base material and the release of residual welding stress generate extraneous AE events. It merge with crack propagation signals will lead to erroneous fault identification.

In response to the aforementioned challenges, scholars both domestically and internationally have formulated a range of adaptive signal processing algorithms. Aiming at mitigating propagation interference and enhancing the clarity of effective crack signals. The EWT is a traditional technique that utilizes the distribution of the signal spectrum to adaptively partition frequency bands. It can independently decompose various dispersion modes and autonomously identify significant feature components closely associated with crack damage. This method can precisely determine the arrival time difference of each modal signal at the sensor, effectively reducing the impact of multi-path reflection and frequency dispersion distortion on localization calculations. In complex steel structure crack monitoring scenarios such as orthotropic isotropic steel plates, compared to traditional threshold methods, the positioning error of this algorithm is significantly reduced. [31].

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3. AE Signal Processing and Crack Feature Extraction

Based on the physical characteristics of AE signals described in Chapter 2, this chapter structures the AE signal processing and intelligent diagnosis methodology into three consecutive layers. The preprocessing and denoising, feature extraction and damage characterization, and intelligent pattern classification are introduced respectively. A comparative study is made for typical procedures in terms of performance, applicability and inherent shortcomings.

The majority of noise in industrial settings is complex. The critical step in fracture feature extraction is to remove interfering noise from raw signals in order to obtain reliable damage characteristics. There are two layers of AE data evaluation including fundamental analysis and advanced analysis. Fundamental analysis is divided into two phases. The first phase uses a variety of techniques, such as filters, EMD, EEMD, and VMD, to preprocess signals and reduce noise. It can reduce interference and distortion caused by ambient and circuit elements. The following step employs multidimensional analysis, including time-domain, frequency-domain, and entropy assessments based on the revised waveforms. It can generate quantitative metrics that define the crack damage situation. Conventional fault detection uses the previously described derived feature characteristics to recognize qualitative cracks and assess damage severity. In recent years, advanced analytical techniques that use feature data and rely on machine learning and deep learning have emerged. Using comprehensive features to perform automatic crack classification, propagation rate fitting, and remaining lifespan prediction can significantly enhance detection automation and quantitative precision. It also reduces the workload of manual comparative assessment and establishes a feasible technical framework for intelligent online monitoring. This approach drives the evolution of AE crack detection from retrospective analysis to a new engineering application paradigm characterized by real-time alerts and full-life-cycle quantitative assessment.

To maintain uniformity across the review, all diagnostic performance indicators offered in the following chapters are based on consistent definitions and evaluation criteria. It is used for all quantitative performance data provided in the manuscript.

Detection accuracy: the ratio of correctly identified samples to the complete test data set, which shows the overall accurate rate of the diagnosis model.

Precision: True crack samples divided by the total number of crack samples predicted by the model. It measures the false alarm level of detection technologies . More precision means less false positive alerts.

Recall: The ratio of the number of successfully detected crack samples to the total number of true crack samples in the test set. It measures the level of missed detection. The higher the recall, the lesser the missed crack occurrences.

F1-score: The harmonic mean of precision and recall; gives an overall measure of categorization performance that balances both accuracy and recall. It is referred as:

$$F1 = 2 \times \frac{Precision \times Recall}{Precision + Recall} \quad (1)$$

It spans from 0 to 1, and is more resilient than overall accuracy in measuring AE fracture identification under imbalanced sample distributions with substantial background noise .

Unless otherwise stated, all performance results are derived from controlled laboratory tests on standard metallic specimens using either pre-formed or fatigue-cracked specimens.

3.1 AE Signal Preprocessing and Denoising Methods

AE signals gathered in situ frequently overlap with operational noise from equipment, electromagnetic interference, and background noise from the sensor acquisition circuitry. These interference signals can readily obscure pertinent damage waveform data associated with crack progression, thereby diminishing the precision of feature extraction and fault detection. To tackle these challenges, it is essential to implement a tiered preprocessing framework with uniform calibration and noise reduction as the primary components. Standardized calibration functions as an initial foundational procedure aimed at rectifying diverse waveform distortions that arise during the acquisition phase. Primarily encompassing four methods such as baseline drift adjustment, amplitude normalization, trigger threshold calibration, and multi-channel time-delay synchronization. These four methods of signal preprocessing have developed into a well-established framework. Gradual waveform baseline shifts caused by long-term alternating loads, environmental temperature fluctuations, and micro-slippage at the sensor interface, can be eliminated by methods such as moving average and least squares fitting. This approach can remove low-frequency trend components to restore the authentic amplitude baseline of the signal. Amplitude discrepancies arising from variations in sensor gains and probe coupling conditions can be rectified via normalization methods. It facilitating horizontal comparison of multi-channel data. Adjusting the event trigger threshold in real time based on the circuit's background noise recorded under no-load conditions enables systematic elimination of non-significant low-amplitude events. Timing discrepancies induced by hardware sampling and transmission lines can be consistently adjusted across all channels via time-delay alignment. After the aforementioned standardized preprocessing, AE signals undergo initial frequency-domain denoising via methods such as bandpass filtering and wavelet filtering. Initial waveform purification is achieved by separating extraneous components such as low-frequency mechanical vibrations and high-frequency electromagnetic coupling interference through frequency band differentiation. [32-33].

In complex high-noise scenarios such as aero-engines and heavy-load transmission components, relying solely on basic preprocessing and simple filtering is quite unreliable. Adaptive modal decomposition methods such as Empirical Mode Decomposition (EMD), Ensemble Empirical Mode Decomposition (EEMD), and Variational Mode Decomposition (VMD) have been extensively researched and used to reduce secondary noise. Conventional EMD is susceptible to mode mixing issues [34]. EEMD mitigates this by consistently introducing auxiliary white noise and averaging various decomposition outcomes. VMD utilizes variational constraints for adaptive signal frequency domain separation and can iteratively determine the optimal mode count k and constraint coefficient α. In current studies, the kurtosis criterion is frequently commonly used to find effective modes, which improves the distinction between crack signals and noise [35–36]. According to relevant research, this strategy outperforms standard decomposition strategies in terms of clutter suppression [37].

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At present, the research is mainly based on the basic preprocessing workflow combined with intelligent optimization and information entropy discrimination methods. This multi-level joint processing framework is conducive to improving the effectiveness of waveform purification in complex interference environments. Zheng Qinwen [32] significantly improved the denoising capability of AE signals during aircraft engine operation by using this framework. She first applied basic signal preprocessing methods such as baseline correction, then used an advanced Dung Beetle Optimizer to adaptively select the optimal wavelet threshold. Zhou et al. [38] proposed a wavelet packet preprocessing system incorporating Kullback-Leibler relative entropy (KLRE). They utilized multi-scale wavelet packet decomposition to conduct comprehensive hierarchical preprocessing, and adopted entropy values to quantify the chaotic characteristics of waveforms. Through this method, the continuous crack propagation waveforms were effectively distinguished from unstable interference signals. This solved the waveform distortion problem arising from the variation of working conditions. With the development of more advanced algorithms, the preprocessing and denoising of AE signals have been greatly increased.

Table 3.1 Performance comparison of typical AE signal preprocessing and denoising methods

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Method Category	Core Techniques	Applicable Interference Types	Denoising Performance	Computational Complexity	Real-Time Capability	Main Limitations
Normalization and Calibration	Baseline drift correction, amplitude normalization, trigger threshold calibration, multi-channel time-delay alignment	Systematic errors, channel gain mismatch, baseline drift	N/A (noise separation not applicable)	Very low	Excellent	Only corrects acquisition-induced systematic errors; no capability to separate noise from damage signals.
Basic Frequency-Domain Filtering	Band-pass filtering, wavelet filtering	Steady-state mechanical vibration, electromagnetic coupling interference	Moderate	Low	Good	Poor adaptability to non-stationary crack signals; strong denoising may distort weak early-stage damage waveforms.
Adaptive Mode Decomposition	EMD, EEMD, VMD with kurtosis-based effective mode selection	Non-stationary noise, high background noise scenarios	Relatively high	High	Relatively poor	Intrinsic mode mixing and end effects; high computational load; difficult for online deployment.
Intelligent Hybrid Denoising	Adaptive wavelet thresholding, entropy-guided wavelet packet processing, intelligent	Variable operating condition fluctuations, strong noise environments	Good	Very high	Poor	Relies on empirical parameters or training data; cross-condition generalization remains to be verified.

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Method Category	Core Techniques	Applicable Interference Types	Denoising Performance	Computational Complexity	Real-Time Capability	Main Limitations
	algorithms					

In general, the four types of preprocessing and denoising algorithms have obvious performance trade-offs in application contexts, computing cost and denoising effectiveness. Normalization and calibration techniques are a common front-end step with just modest computing overhead. It addresses systematic acquisition artifacts rather than actual noise interference. In engineering practice, the most often used basic frequency-domain filters are simple and stable. However, they are unable to deal with non-stationary AE signals resulting from varying loads or progressive crack propagation. Adaptive mode decomposition algorithms can distinguish damage patterns from non-stationary background noise far more effectively.The drawback is the cost of substantially increased computational complexity and degraded real-time performance. Intelligent hybrid methods are the most reliable in a wide range of operating conditions, but they are hard to use in different industrial settings because they depend on tuning parameters or historical data.

From an engineering application perspective, there are two typical obstacles for the present AE denoising technologies. First, there is an inherent compromise between the strength of denoising and the integrity of the signal. The aggressive denoising algorithms tend to remove weak AE signals from incipient crack initiation as noise, resulting in missed detection. Second, the optimal parameters of most methods are tuned under specific operating settings. The insufficient flexibility under the conditions of load, speed or lubrication is one of the main reasons for the high false alarm rate in the field application.

3.2 AE Feature Extraction and Damage Assessment Methods

The processed and noise-reduced AE signals encompass comprehensive damage data of materials. The choice of feature-extraction methods serves as a fundamental connection between raw signal analysis and damage-state assessment. It directly influencing the sensitivity of damage detection, the accuracy of quantitative evaluations, and the precision of pattern differentiation. Currently, the technical framework for AE feature extraction exhibits multi-dimensional complementarity among statistical features in the time domain, features in the time-frequency domain, and entropy-based features. When integrated with multi-parameter joint-analysis methods, an extensive and multi-tiered characterization of component fatigue-damage conditions can be achieved.

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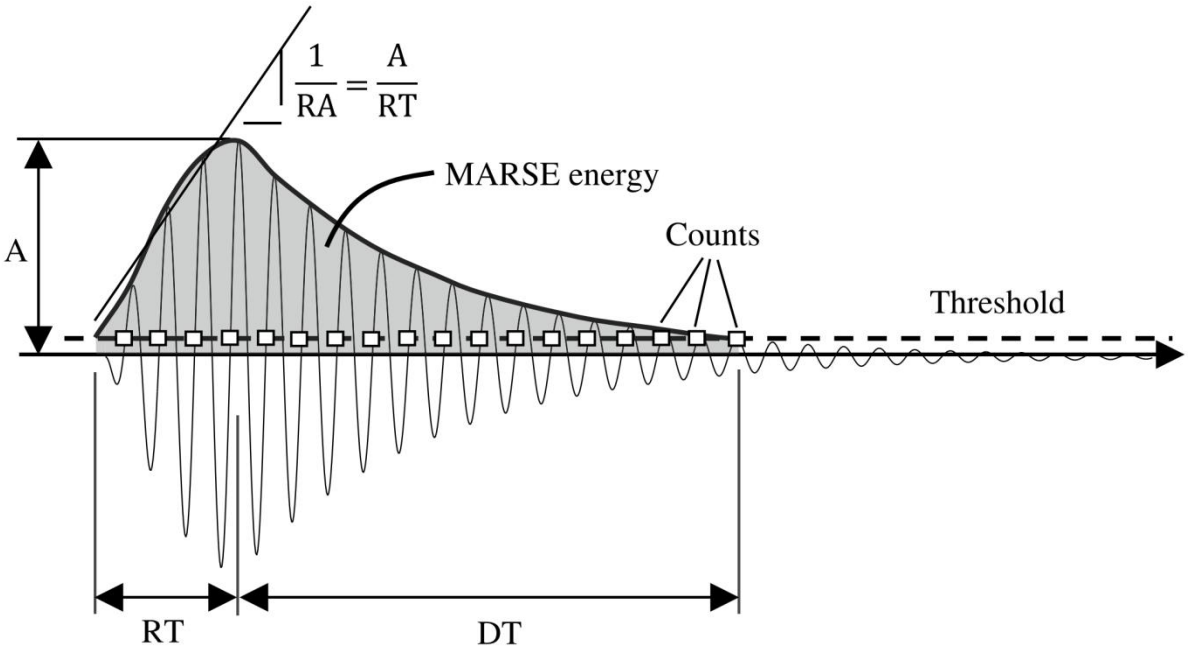

Fig. 2 Characteristic Parameters of a Typical AE Burst Signal(Adapted from Carrasco et al. [16])

All AE feature indicators cited throughout this review follow the unified definitions and calculation conventions specified below. The indicators are classified into three categories. The core formulas provided for key parameters.

1. Event-based characteristic indicators

These parameters are extracted from individual AE burst events and directly correspond to the energy release behavior during crack initiation and propagation, and their physical meanings correspond to the labels in Fig. 3.1.

- Peak amplitude (A): The maximum absolute value of the burst signal waveform

$$A = \max(|y|) \tag{2}$$

- Rise time (RT): From burst start to peak amplitude, where the start is defined by crossing a set threshold.

- Downtime (DT): From the peak amplitude to the burst end, where the end is defined by crossing down the set threshold.

- Signal duration (D): The total time length of a single burst event between the first and last threshold crossing.

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$$D = RT + DT \tag{3}$$

- AE event count: The number of burst signals whose amplitude exceeds the preset threshold within a unit time

- MARSE energy: measured area under the rectified signal envelope

$$\text{MARSE} = \int_0^D e\,(t)\mathrm{d}t \tag{4}$$

(where e(t) is the envelope of the AE signal.)

-True energy: area under the squared signal envelope

$$\text{TrueEnergy} = \int_0^D e^2\,(t)\mathrm{d}t \tag{5}$$

2. Time-domain statistical indicators

These parameters describe the amplitude distribution and statistical properties of AE waveforms in a statistical window.

-Mean value: The arithmetic average of signal amplitudes in the analysis window

$$\bar{y} = \frac{1}{n}\sum_{i=1}^{n} y_i \tag{6}$$

(where n is the total number of sampling points, and (y_i) is the signal amplitude of the i-th sampling point.)

-Root mean square (RMS): Reflects the effective energy level of the signal.

$$\text{RMS} = \sqrt{\frac{\sum_{i=1}^{n}(y_i)^2}{n}} \tag{7}$$

-Kurtosis: The fourth standardized moment of the signal, reflecting the sharpness of the amplitude distribution.

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$$K = \frac{E[(y-\mu)^4]}{\sigma^4} = \frac{\frac{1}{n}\sum_{i=1}^{n}(y_i-\bar{y})^4}{\left(\frac{1}{n}\sum_{i=1}^{n}(y_i-\bar{y})^2\right)^2} \tag{8}$$

where μ is the mean value of the signal and σ is the standard deviation of the signal.

- Impulse factor: The ratio of the signal peak to the rectified mean (mean absolute value), which characterizes the relative intensity of impulsive components in the signal.

$$X_I = \frac{A}{\frac{1}{n}\sum_{i=1}^{n}|y_i|} \tag{9}$$

- Margin factor: The ratio of the signal peak to the square root amplitude, where the square root amplitude is defined as the square of the arithmetic mean of the square root of the absolute signal values.

$$X_M = \frac{A}{\left(\frac{1}{n}\sum_{i=1}^{n}\sqrt{|y_i|}\right)^2} \tag{10}$$

3. Entropy-based indicators

These indicators quantify the disorder and complexity of AE signal sequences and are sensitive to subtle changes in damage characteristics under strong background noise.

- Information entropy: Measures the uncertainty of signal amplitude distribution.

$$H = -\sum_{i=1}^{n} p_i \log_2 p_i \tag{11}$$

(where p_i is the probability of the signal amplitude falling within the i-th interval.)

Conventional time-domain statistical characteristics constitute the most essential and commonly utilized feature category in acoustic-emission analysis systems. Common metrics include average value, maximum value, RMS, kurtosis, impulse factor, margin factor, and others. The peak value and RMS effectively represent the overall amplitude and energy intensity of AE signals. It also correlating with the total magnitude of strain energy released during damage occurrences. Kurtosis serves as a quantitative measure of signal-shock properties, demonstrating notable discriminative capacity for burst transient signals at the onset of cracking. It also commonly utilized for the swift identification of sudden damage occurrences. Nonetheless, these global statistical characteristics exhibit significant constraints in application. Initially, they characterize the overall statistical properties of signals within a specified analytical time

window.They neglect to account for transient evolutionary nuances of micro-damage events during crack propagation. Also demonstrating poor sensitivity to progressively developing early-stage fatigue micro-cracks. Secondly, feature values are vulnerable to disruptions like acoustic attenuation during propagation, sensor coupling circumstances, and variations in external loads. It leads to diminished detection reliability in intricate operational environments. Thirdly, relying solely on amplitude and energy statistics fails to distinguish between different damage mechanisms such as plastic deformation, crack propagation, and interface friction, which complicates the accurate identification of damage modes.

To address the intrinsic limitations of time-domain statistical features, time-frequency analysis techniques such as Short-Time Fourier Transform (STFT), Wavelet Transform (WT), and Hilbert-Huang Transform (HHT) have progressively been incorporated into AE feature extraction. They serve as essential instruments for elucidating dynamic damage-evolution patterns [39]. The STFT performs segmented Fourier analysis on signals using sliding time windows, yielding the time-varying distribution of signal spectra. It is appropriate for signal examination during the stable growth period of deterioration. Constrained by the uncertainty principle of fixed-window functions, its temporal and frequency resolutions cannot be enhanced concurrently.Its efficacy for extremely short burst signals generated by micro-cracks is limited. The WT possesses multi-resolution capabilities for time-frequency localization. It disaggregates AE signals into various frequency band components via multi-scale decomposition. This approach attains superior frequency resolution in the low-frequency range and exceptional time resolution in the high-frequency range. It closely matching the transient, non-stationary characteristics of AE signals. This method can precisely identify the timing of damage events and distinguish between different damage-source mechanisms based on variations in energy distribution across frequency bands. It represents the predominant technical approach for extracting AE features in the time-frequency domain currently. HHT is primarily utilized to determine the instantaneous amplitude and frequency of analytical signals. When integrated with adaptive signal-decomposition algorithms like EMD, it can accurately detect instantaneous-frequency variations during the unstable crack-propagation phase. This facilitates early warning of critical damage-failure conditions. These three aforementioned methodologies have distinct focuses and mutually enhance one another, jointly forming a sophisticated technical framework for time-frequency-domain feature extraction.

Entropy-based characteristics, including information entropy and permutation entropy, evaluate the severity of fatigue damage by measuring the complexity and level of disorder in AE signals. It shows significant benefits in identifying stages of damage evolution [40-41]. The progression of material fatigue damage is fundamentally a dynamic phenomenon where internal microstructures shift from an ordered state to a disordered one. Consequently, the intricacy of AE signals escalates incrementally with the accumulation of damage, and entropy-derived attributes can offer ongoing and precise quantitative assessment for this phenomenon. Information entropy indicates the extent of damage dispersion by assessing the uniformity of energy distribution within signal spectra. As fatigue damage builds up, the frequency bands of signals expand progressively and energy distribution becomes more dispersed. This results in a consistently rising trend of information entropy. Permutation entropy quantifies the dynamic alterations of systems by assessing the probabilities of permutation configurations in time-series

data. It offers low computational cost, strong noise resistance, and high sensitivity to subtle state fluctuations. It can detect subtle dynamic anomalies in the initial stage of crack formation and is suitable for early warning of incipient fatigue deterioration in structures. In contrast to traditional amplitude-dependent characteristics, entropy-based features remain unaffected by absolute signal amplitude and propagation loss. Owing to this, it demonstrates superior adaptability to fluctuating load conditions. They have become essential quantitative metrics for assessing fatigue damage severity.

In addition to the previously stated characteristics, traditional event-related metrics such as acoustic-emission event count, true energy, signal duration, rise time, and amplitude exhibit distinct physical relationships with crack-propagation phenomena. All of these serve as essential core parameters for quantitative damage assessment. Studies have shown the escalation rates of cumulative event count and cumulative energy are directly related to crack-propagation rates. The inflection points on their curve slopes typically indicate shifts between damage phases. The duration of a signal and its rise time can indicate the extent of crack development and are frequently utilized to differentiate between micro-crack initiation and macroscopic crack propagation. However, it must be acknowledged that individual feature parameters are susceptible to interference from testing conditions and rarely meet the requirements for high-precision quantitative damage assessment. Conversely, multi-parameter joint analysis can significantly enhance the dependability and precision of evaluation outcomes via multi-dimensional information integration and cross-validation [42-43]. Pertinent experimental investigations demonstrate that factors like signal amplitude and energy display unique reactions to surface and deep-seated cracks. It can act as distinctive foundations for estimating crack depth [44]. Crack length prediction models developed using multi-feature parameters integrate multi-dimensional data including amplitude, energy, frequency spectrum, and entropy metrics. Their prediction accuracy markedly exceeds single-factor models, facilitating quantitative monitoring of fatigue damage progression processes.

Table 3.2 Performance comparison of typical AE feature extraction and damage assessment methods

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Method Category	Core Indicators & Techniques	Applicable Damage Stages	Sensitivity to Early Damage	Robustness to Operating Fluctuations	Main Limitations
Time-domain statistical features	Mean value, peak amplitude, RMS, kurtosis, crest factor, margin factor	All stages; most sensitive to unstable crack propagation	Low	Poor	Cannot capture transient details of micro-crack evolution; susceptible to wave attenuation, coupling variation and load fluctuations; unable to distinguish damage mechanisms.
Time-frequency domain features	STFT, WT, HHT	All stages; particularly suitable for dynamic damage evolution	Moderate	Moderate	STFT suffers from inherent time-frequency resolution trade-off; WT involves high computational cost and relatively poor real-time performance.
Entropy-based features	Information entropy, permutation entropy, etc	All stages; particularly effective for early damage warning	High	Good	Only reflect signal complexity rather than direct crack geometry; physical interpretation of damage mechanisms is relatively weak.
Event parameters & multi-feature fusion	Hit count, cumulative energy, signal duration, rise time; multi-parameter joint assessment models	Quantitative damage assessment and remaining life prediction	Moderate	Relatively good	Single parameters are vulnerable to detection conditions; fusion models rely on calibrated data with limited generalization across different structures.

The four types of AE feature extraction methods have different features of application and complimentary performances. The simplest and most generally used method is the time-domain statistical characteristics, which have the advantages of simplicity and obvious physical meaning. Its performance in early damage detection and under variable operating conditions is poor. While

time-frequency domain approaches enable multi-resolution characterization of non-stationary damage signals and identification of diverse damage causes. This approach comes at the cost of higher computational complexity. Entropy-based features are insensitive to absolute signal amplitude and propagation attenuation. Owing to their greater sensitivity to nascent damage and stronger robustness against load fluctuations, they are highly useful for early fatigue warning. Event-based parameters provide the physical basis for quantitative damage assessment, while multi-feature fusion models can significantly improve evaluation accuracy by leveraging complementary information and enabling cross-validation.

There are still two bottlenecks for the present AE feature assessment technology. Firstly, there is no uniform quantitative mapping model between AE feature parameters and the actual geometric parameters of cracks (length, depth, propagation rate) in general. Most assessment methods are empirically calibrated rather than analytically derived, which limits their cross-component generality. Secondly, feature values typically drift with changes in operating parameters, such as load level and sensor coupling status. It remains a key source of inaccurate assessment in practical industrial scenarios.

3.3 Crack Pattern Identification and Classification via Machine Learning and Deep Learning

Leveraging the swift advancement of AI technology, machine learning and deep learning algorithms have emerged as prevalent instruments for recognizing crack patterns in AE signals. As a quintessential example of conventional machine learning, the Support Vector Machine (SVM) continues to occupy a significant role in contemporary research. Zuo [45] illustrated via comparative experiments on aluminum tube bending that SVM exhibits considerable stability with small to medium-sized datasets. Nonetheless, in the context of multi-feature fusion, the overall efficacy of SVM is inferior to that of deep learning models exemplified by CNN.

One-dimensional Convolutional Neural Networks (1D CNN) have been widely applied to detect fatigue fractures in railway axles in recent years. For example, Sun Zijie [46] introduced VMD decomposition integrated with permutation entropy for the identification and reconstruction of AE characteristics. A refined-parameter 1D CNN was applied to accurately distinguish three signal categories: axle fractures, impacts, and ambient noise. Tian Ying [47] employed the Morlet wavelet to extract characteristics from fatigue fractures, impacts, and auditory disturbances. These wavelet features were subsequently integrated into a DBN model consisting of three stacked restricted Boltzmann machines (RBM). Compared to individual DBN and WT-1DCNN models, the detection accuracy on the test dataset increased to 99.0%. Li Kun [48] integrated expansive convolutional pooling units with a multi-layer residual architecture to develop an enhanced 1D CNN model. It directly analyzes three categories of 1D AE time-series signals: axle fractures, impacts, and ambient noise. Multiple controlled experiments confirmed that this model achieves higher recognition accuracy than standard 1D-CNN, VGG16, and LSTM.

With the advancement of machine learning technologies, fusion networks represented by CNN-LSTM can simultaneously extract spatial and temporal features, giving them an advantage in crack detection and service-life prediction. Li Daguang [49] developed a one-dimensional

convolutional CNN-LSTM hybrid model for local damage feature extraction. By validating on real datasets, the model can effectively isolate split cracks, environmental noise, and impact interference signals. Feng Sen [50] developed a temporal forecasting model that combines BiLSTM with CRF constraints. Comparative analysis across multiple models and validation on sample sets demonstrated that this model delivers lower prediction errors and improved generalization robustness. Peng Qingwei [51] introduced a hybrid deep learning architecture known as HCNN-BiLSTM. It uses a dual convolution module to extract spatial features, and then analyzes temporal dependencies in both forward and backward directions via a two-layer BiLSTM with Dropout. The framework distinguishes fatigue cracks in axles from noise and impact interference signals through classification and dual prediction sub-models. Evaluated across multiple independent axle AE datasets, the model achieves higher recognition accuracy and lower waveform prediction error than algorithms such as DBN, LSTM, and BiLSTM. IIt demonstrates strong cross-sample generalization capability. Furthermore, numerous prior studies have integrated CNN with DBN. They employ wavelet transformation for feature extraction and the particle swarm optimization (PSO) method to dynamically refine key hyperparameters, including the number of hidden layer nodes, learning rate, and iteration counts of the deep belief network. For example, Zhu Xiaoxiao [52] and Tang Xiaowen [53] used PSO to optimize DBN hyperparameter combinations. They successfully mitigate the local optimum problem in network training and reduce the computational burden associated with high-dimensional AE feature matrices.

In practical engineering contexts, labeled samples are often insufficient. To address industry challenges such as limited samples and class imbalance in AE fault datasets, transfer learning (TL) and generative adversarial networks (GAN) have advanced considerably. TL leverages pre-trained models on established datasets and adapts them to new operational scenarios. This approach effectively addresses fatigue crack detection issues in low-sample settings. Wu Xiangdi [54] utilized multi-scale residual networks for the identification of axle cracks, while Shen Zihan [55] applied basic CNNs in conjunction with TL for the same purpose. They verified that this method can repurpose previous characteristics from source operating conditions, substantially mitigating model overfitting due to limited samples in new operating conditions, achieving cross-domain fault detection accuracies surpassing 91%. Nonetheless, both approaches were validated only on laboratory constant-load datasets, without evaluation in real operational environments featuring complex noise, temperature fluctuations, and varying loads. Moreover, domain alignment solely executed numerical distribution matching without integrating physical constraints derived from fracture mechanics. Owing to the tendency of TL techniques to generate physically nonsensical feature pseudo-alignment, generative adversarial networks (GAN) and their variant, conditional generative adversarial networks (CGAN), offer a viable alternative. Zhang Qiusheng and colleagues [56] developed a CGAN model and integrated operational condition limitations into every layer of the network. They successfully executed interpolation expansion on three categories of AE feature samples for bearings (normal, cracked, and rubbing). They enhanced the balance of the training set and mitigated model overfitting in limited-sample situations. Simultaneously, the comparative analysis in this study showed that incorporating CGAN-augmented samples into the classification model increased the mean fault detection accuracy to 93.12%. Nonetheless, generative adversarial networks exemplified by CGAN encounter challenges, including the struggle of produced waveforms to adhere to the authentic

physical principles governing crack evolution. Sample imbalance and fluctuations in operating conditions can both reduce generation quality. Furthermore, the model tuning process is complex, and it lacks constraints grounded in mechanical mechanisms, which results in limited interpretability.

Accordingly, the research community has recently proposed numerous innovative algorithmic integrations, including data augmentation, multi-scale feature fusion, and attention mechanisms, to enhance model robustness and generalization. Monika [57] employed STFT to convert time-domain AE signals of high-strength steel into time-frequency spectrograms as CNN inputs. Monika's evaluation of different data augmentation techniques on model accuracy revealed that horizontal flipping and rotation can expand the sample set without degrading recognition performance. She further developed a lightweight SpecNet to achieve accurate binary classification of crack and normal signals. Wang et al. [58] utilized the Sentry function to enable simultaneous annotation of AE and mechanical loads. They also introduced an improved MFCC feature extraction technique tailored for ultrasonic high-frequency signals. By employing an LSTM temporal network with a sliding window, they achieved phased real-time early detection of steel fatigue fractures. Cui et al. [59] developed a comprehensive deep learning architecture integrating 1D convolution, LSTM, and temporal attention, and applied a Gaussian noise data augmentation technique to enrich the sample dataset. Their research showed that this model could accurately identify the three phases of crack initiation, propagation, and fracture. Zhang Chunlong [60] introduced a dual-channel hybrid deep learning approach that integrates SE-Inception and CNN-BiLSTM. This method successfully converted one-dimensional time-series AE signals from axles into grayscale images to generate dual-input samples. By leveraging SE attention, multi-scale Inception, and temporal BiLSTM to concurrently extract spatial and temporal features. This approach not only achieved high-accuracy classification of three signal types (cracks, impacts, and noise) but also performed regression prediction of the remaining fatigue life of axles by adjusting the output layer and loss function. Zhang Chunpeng [61] introduced the CBAM attention module to enhance the saliency of 1D AE features. It integrated a TCN-GRU parallel network to simultaneously capture local short-term features and long-term dependencies. This ultimately enabled classification of axle crack faults and prediction of remaining fatigue life. Moreover, the current body of literature persistently presents novel advancements. The incorporation of various network architectures, including Transformer-TCN [62], Improved Deep Residual Shrinkage Network (IDRSN) [63], YOLO [64], and KAN-LSTM [65], offers distinct advantages in feature extraction, noise resistance, temporal modeling, and other aspects. These approaches enhance AE fault identification systems.

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Table 3.3 Performance comparison of typical AE feature extraction and damage assessment methods

Method Category	Core Architectures & Techniques	Typical Application Scenarios	Training Data Requirement	Cross-condition Generalization	Computational Complexity	Main Limitations
Traditional Machine Learning	classical statistical classifiers such as SVM	Small-sample, steady-state crack classification; simple damage mode discrimination	Low	Moderate	Low	Relies heavily on manual feature engineering; limited performance on multi-feature fusion and complex non-stationary signals.
Basic Deep Learning	CNN, LSTM, DBN,GRU	One-dimensional AE time series classification; crack / noise / impact signal discrimination	Moderate	Relatively good	Moderate	Mainly captures local spatial features; limited ability to model long-term temporal dependencies of crack evolution.
Hybrid & Sequence Modeling Architectures	CNN-LSTM, HCNN-BiLSTM Sequence labeling architectures: BiLSTM-CRF	Simultaneous crack pattern classification and waveform prediction / remaining fatigue life prediction	Moderate to high	Good	High	Relatively complex network structure; requires sufficient labeled sequential data for training.
Small-Sample & Data	TL, GAN, CGAN	Scarcely labeled datasets; class-imbalanced	Very low	Moderate	Moderate to high	Transfer learning may produce physically

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Method Category	Core Architectures & Techniques	Typical Application Scenarios	Training Data Requirement	Cross-condition Generalization	Computational Complexity	Main Limitations
Augmentation		samples; cross-working-condition recognition				meaningless feature alignment; GAN-generated waveforms may not conform to real fracture mechanics.
Advanced Optimized Architectures	Enhancement techniques: (CBAM, SE-Inception, multi-scale feature fusion); Novel backbone architectures(TCN-GRU, Transformer)	High-accuracy classification; remaining life prediction; anti-interference under complex noise	Moderate to high	Good	Very high	High computational cost; black-box nature with weak interpretability; lack of systematic field validation.

In general, AE-based crack pattern identification technologies have developed from classical machine learning that relies on manual feature engineering to end-to-end deep learning architectures. Their classification accuracy, anti-interference ability and multi-task adaptability have been continuously improved. Small-sample and simple scenario applications can still use traditional machine learning approaches due to their low compute cost and great interpretability. Basic deep learning models, such as 1D CNN, perform better than traditional algorithms on one-dimensional AE time series. But they have difficulties in predicting the temporal evolution of damage. The hybrid architectures combining CNN for spatial feature extraction and recurrent networks for temporal dependency modeling produce the best overall performance in both classification and prediction tasks. It is the mainstream technical way at present. TL and GAN serve as effective solutions to the widespread industrial issue of insufficient labeled fault samples. However, their generalizability and physical rationality still require further improvement. Advanced optimized structures such as attention mechanisms enhance feature capture capabilities and generalization, though at the expense of increased model complexity.

There are three common barriers in the industrial adoption of AE intelligent identification methods. First, most models are evaluated on laboratory datasets under controlled settings, and their performance typically deteriorates significantly in real industrial environments with heavy background noise and variable operating conditions. Second, deep learning models typically suffer from a black-box problem with poor physical interpretability, which limits engineering acceptance and trust. Third, there are no uniform benchmark datasets or evaluation criteria across different components and working conditions, making it difficult to conduct horizontal comparisons and fair evaluations of alternative algorithms.

4. Application and Performance Bottlenecks of AE Method in Crack Fault Detection

Chapter 3 establishes a methodical framework. Based on this system, the engineering practice of AE-based crack detection in four major industrial fields is reviewed in this chapter. Technical adaptability, field performance, and bottlenecks in each application scenario are assessed case by case.

The AE method, owing to its high sensitivity and real-time monitoring capabilities, has been widely used for detecting micro-crack damage in various industrial equipment such as gears, bearings, aero-engines, wind turbines, bridges, and pipelines. Nevertheless, it is important to objectively acknowledge that the main obstacles hindering the implementation of this method remain. The complex on-site signal interference, challenges in identifying subsurface cracks, and the impact of harsh environments on signal transmission remain notable challenges. Therefore, further advancements are needed in areas such as signal processing, feature extraction, and multi-source integration.

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4.1 Transportation and Transmission Industry: Metallic Rotating Components Crack Detection

Since gears and bearings are critical components in rotating machinery, fatigue crack propagation is their common failure mode. Conventional vibration monitoring lacks sensitivity to nascent micro-cracks, whereas the AE method exhibits heightened sensitivity to high-frequency stress waves. This renders it exceptionally adept at detecting early signs of crack formation.

According to existing research literature on gear crack faults, Crivelli [66] experimentally demonstrated that AE signals undergo noticeable changes once root crack propagation reaches a specific number of cycles. Thereafter, by combining the 110–120 kHz frequency range with bandpass FFT, Chebyshev moment feature extraction, and sliding Shannon entropy analysis, extensive waveform data can be compressed while minor signal anomalies are detected. It thereby enhances the sensitivity of early crack detection and enables online monitoring. Cui et al. [67] proposed a gear AE fault detection method integrating WOA-VMD with RFE-SVM. They used the Whale Optimization Algorithm (WOA) to dynamically determine the key parameters of VMD for signal denoising. High-sensitivity features were selected through Recursive Feature Elimination (RFE) to reduce dimensional redundancy. These features were integrated with PSO-optimized SVM for fault identification, achieving an experimental detection accuracy of 98.75%. Single-source signals are prone to issues such as failing to detect early faults and lacking precision in assessing damage severity. Therefore, research is progressively shifting toward multi-source signal integration. The fusion of signals from multiple sources can mitigate the limitations of single signals and improve the ability to detect subtle gear defects. Zhou Yaohui and colleagues [68] integrated vibration and AE signals, manually extracted time-domain and frequency-domain features from multi-condition gear simulation data. They effectively employed BP neural networks for the identification of gear cracks and broken teeth.

The AE method can also facilitate the early detection of surface cracks and subsurface micro-crack damage in rolling bearings. Sha Yundong and colleagues [69] developed a WPD-KI-HED fusion algorithm that initially performs wavelet packet decomposition and kurtosis filtering to reconstruct signals. They then applied Hilbert demodulation to identify fault frequencies. This method accurately detects defects in the inner and outer rings of bearings on both standard test rigs and complex acoustic transmission systems of aero-engines, ultimately keeping the characteristic frequency accuracy error within ±1 Hz. Zhang Xiaotao [70] introduced a diagnostic method for bearing AE that integrates SVD denoising with Fast Kurtogram, effectively isolating the characteristic frequencies of artificial fissures on both the inner and outer rings of bearings. Hidle et al. [71] introduced a pulse integration detection method grounded in prior knowledge. It utilizes the periodic likelihood ratio index and pulse integration spectrum validation to preemptively identify 0.5 mm subsurface fatigue micro-cracks in bearings, outperforming the conventional root mean square index.

In the fault detection of harmonic reducers, Zhao Yongqiang [72] developed a detection system that integrates sound and AE signals. It utilizes the VMD-SVM method to analyze knocking sound signals for swift identification of reducer damage, achieving an accuracy rate of 95.03%. Integrating the PCA outlier accumulation algorithm to assess performance degradation trends enables a fault warning threshold to be established 700 hours in advance. Moreover, by

leveraging AE energy and variations in average levels, the equipment's life cycle can be effectively divided into four phases: undamaged, crack initiation, stable propagation, and unstable propagation.

AE method is capable of not only detecting crack damage but also offers significant benefits in detecting other minor impairments. Guo Fuping [73] employed AE method to detect wear defects on the inner and outer ring surfaces. They developed HMM input features based on wavelet packet energy and classified four bearing conditions (normal, inner ring wear, outer ring wear, and rolling element surface wear) via likelihood probability analysis. Song Yuqin [74] proposed a method for automatically determining the optimal K value of VMD decomposition based on an energy difference criterion. This method extracted sample entropy and permutation entropy to construct feature vectors and applied fuzzy C-means clustering to identify mechanical impact faults, including normal bearing, inner ring wear, rolling element wear, outer ring local pitting, and minor spalling. Zhao Yuanxi [75] employed the AE method to monitor surface pitting degradation of the bearing's inner ring, outer ring, and rolling elements. It achieved fault pattern identification based on harmonic wavelet packet and BP networks, with a fault detection accuracy of 92.5%.

For rotating equipment components such as gears and bearings, the AE method is more sensitive to incipient fatigue microcracks than conventional vibration monitoring. Hence, it is highly suitable for detecting early warning signals at the time of crack initiation. Combined with time-frequency feature extraction, intelligent classification algorithms, and multi-source signal fusion methodologies, it can accurately identify fracture damage. However, this application scenario also faces common bottlenecks. Signal source aliasing is usually caused by multiple interference sources, such as gear meshing, interface friction, and lubrication state variations. Low-speed operating conditions are mainly associated with insufficient signal strength. Moreover, detection models generally exhibit poor generalization when applied to diverse field operating conditions.

4.2 Aerospace Industry: Metallic Structural Component Crack Detection

Due to the prolonged operation of aero-engine turbine disks and blades under severe conditions of high temperature, high rotational speed, and heavy load. Fatigue damage directly and significantly undermines the operational safety of aviation equipment [76]. High temperatures and structural connection interfaces often cause AE signal degradation and distortion, complicating the subsequent analysis process [77].

Currently, numerous academic studies focus on identifying crack depths in turbine disks. Pulsed eddy current technology has achieved high-precision quantitative measurement in laboratory settings. However, its effectiveness in the intricate operational environments of aero-engines remains unverified [78-79]. Moreover, the ultrasonic longitudinal wave reflection detection technique faces challenges including structural blind spots, the need for shutdown and disassembly for inspection, and inadequate detection rates for micro-cracks [80]. The AE method presents an alternative approach. Chen [81] developed a fatigue crack growth prediction model that integrates crack-tip constraints with AE data. This method leverages AE energy and the stress intensity factor, demonstrating that cumulative AE energy accurately reflects the

progression of crack damage. A calculation formula for the plastic zone, accounting for the yield-to-tensile ratio, was derived from three-dimensional elastoplastic finite element calibration. A streamlined machine learning component with physical constraints was implemented to correct prediction deviations in the later stages of the model. This approach effectively reduces systematic forecasting errors during the advanced phases of crack propagation, enhances overall predictive accuracy, and preserves the physical interpretability of the underlying fracture mechanics framework. Zuo Yichao [82] fused multi-source signals including acoustic emission and vibration to classify three types of contact fatigue spalling morphology, and characterized lifetime characteristics via the Weibull distribution. He also constructed a standardized dataset based on damage evolution stages defined by AE energy and vibration RMS index. He developed a serial fusion prediction model combining ResNet and C-Transformer. It can accurately identify early damage and predict remaining lifetime. With the development of multi-modal detection technologies, Liu et al. [83] proposed the VAE-MAM model with CLIP-based cross-modal alignment and mixed attention mechanisms. He constructed the ViAED benchmark dataset with 1755 paired image-AE samples. The model achieves an F1-score of 98.05%, significantly enhancing the discriminative capability of the features. However, the method is only validated on laboratory riveted plate specimens, not on complex geometries. It also requires line-of-sight optical access, hindering deployment inside enclosed cavities. Its high computational cost restricts real-time on-site applications.

For aero-engine turbine disks and related structural components operating under extreme conditions, the AE method offers a feasible non-disassembly approach for fatigue crack characterization and remaining life prediction. It can be integrated with fracture mechanics models, multi-physical signal fusion strategies and even visual multi-modal frameworks to improve detection accuracy and early warning capability. However, high temperatures and interface effects often cause signal attenuation and waveform distortion. Most detection models are validated on simplified laboratory specimens rather than real engine components. Their generalization ability under variable load conditions remains insufficient. These are among the most pressing challenges in crack monitoring of aero-engine parts [84].

4.3 Power and Energy Industry: Wind Turbine Metallic Component Crack Detection

In wind power systems, metal drive-train components such as gearboxes and bearings are the leading causes of unplanned downtime and maintenance costs. Conventional vibration monitoring exhibits low sensitivity to early and subsurface cracks under low-speed, heavy-load, and variable-torque operating conditions. As a result, the AE method has been recognized as a preferred approach for the structural health assessment of wind turbines [85-86].

Shi Qing [86] focused on wind turbine pitch bearings and developed a comprehensive AE monitoring framework. The method quantifies the AE characteristics of cracks through time-frequency analysis and EMD after wavelet denoising. An AR-GCC-PHAT time-delay estimation algorithm is proposed to achieve accurate damage localization in ring bearings. Starting from the physical mechanisms, Li Ting [87] proposed a crack detection method for pitch bearings that integrates AE with the STFT. Field experiments verified that persistent impact features in the 90–140 kHz frequency range can be used to differentiate cracks. This method demonstrates

stronger resilience against operational condition disturbances compared to singular time-frequency analysis. Liu [88] proposed some specific AE and vibration diagnostic methods for weak defect signals and high background noise. For AE denoising, a discrete/random separation based cepstrum editing liftering (DRS-CEL) approach combined with morphological closing envelope was proposed. For the fluctuating-speed vibration processing, Bayesian Augmented Lagrangian analysis was introduced. The methods have been validated on natural damaged industrial scale pitch bearings with more than 15 years of operation with an effective fault identification. AE has outperformed traditional vibration analysis for incipient damage diagnosis under low speed condition. However, validations are mostly dependent on test rig and field validation under wind load disturbances and blade flapping interference is still not enough. Focusing on 42CrMo pitch bearing steel, Liu Yubin [89] introduced a CEEMDAN denoising method that employs a kurtosis criterion for selecting IMF components. He transformed AE time series into images through Gramian Angular Fields and developed a ResNet18 model integrated with a CBAM attention module. This method can precisely identify five categories of damage: no wear, trace wear, stable wear, severe wear, and outer ring cracking.

For planetary support bearings in gearboxes, Naumann [90] identified the lubrication regime as a critical confounding factor for AE monitoring on a full-scale test rig replicating wind turbine loading conditions. When the specific film thickness ratio λ falls below 1.1, asperity contact generates abundant transient AE events that mask incipient defects and invalidate traditional time-domain metrics. A multi-stage processing framework combining wavelet packet decomposition, cepstrum analysis and Mahalanobis outlier detection was proposed. It successfully detected 100 μm-wide seeded inner race defects under mixed lubrication. For source localization, the neural network approach outperforms the time-of-arrival method and ΔT mapping. However, all tests were conducted under constant load and speed, and generalizability to variable wind conditions remains unvalidated.

Regarding sub-surface bearing damage such as white etching cracks, Fuentes et al. [91] proposed an AE detection methodology combined with Gaussian mixture probabilistic modelling. The approach was validated on a full-scale bearing rig and was able to differentiate sub-surface damage from the undamaged baseline even under changing operating conditions. It extends AE detection capability to the pre-spalling stage. This advance is of great significance for predictive maintenance. However, the technology currently only enables qualitative detection, without quantitative assessment of crack size and depth.

The AE method is more effective than the usual vibration monitoring in detecting incipient and sub-surface fractures in wind turbine metallic drive-train components. It provides early warning of deterioration and aids the qualitative identification of subsurface defects that precede spalling. However, the main scenario-specific interference factors are the changes in lubricant condition and wind loads. Most of the approaches are validated under steady-state operating conditions, with limited field verification. There is no quantitative assessment of fracture size and depth available. Practical deployment is hindered by signal attenuation between tower and flange structures. At present, steady improvements are being made by measuring structural attenuation patterns, optimizing algorithms, and developing new network models [92]. A new

development direction is the integration of large models and IoT technology for wind turbine monitoring.

4.4 Petrochemical and Infrastructure Industry: Metallic Structure Crack Detection

Beyond the applications mentioned above, the AE method is also widely used for crack detection in structures such as steel plates, railway wheelsets, high-pressure vessels, pipelines, and valves [93].

Björn Abeln and colleagues [94] used the Crest Factor as an AE feature index to characterize the distinct kurtosis signals of steel plates across the stages of micro-crack initiation, propagation, and macroscopic fracture. This approach demonstrates that AE can detect micron-scale early micro-damage sooner than conventional detection techniques. Huang et al. [95] investigated tensile fractures in Q23 low-carbon steel and developed the MF-DBSCAN unsupervised clustering algorithm. It integrates multifractal characteristics with Pareto-optimized DBSCAN. By employing fractal spectrum width and height to assess the four-stage damage progression of base materials and welded components, this method achieves real-time detection of crack propagation phases without needing pre-labeled datasets.Yin Jin [96] developed a CDAE-CNN joint denoising and localization model for identifying fatigue fractures in bridge steel plates.It combines an improved AFPSO particle swarm optimization algorithm with a convolutional neural network. This approach achieves a notable localization accuracy of 99.2% in low signal-to-noise ratio environments.

For crack assessment of shaft-like structures, Liu Xujie [97] developed a detection methodology integrating wavelet threshold denoising, wavelet packet feature extraction, and PCA-PNN recognition.It enables real-time crack identification during the shaft straightening process. Bench tests verified that this method achieves a detection accuracy of 98% and effectively eliminating errors caused by mechanical knocking signals. Ren Yifei [93] enhanced the time-difference algorithm for railway wheelset detection and developed an AE damage detection system. This system incorporates adaptive grey wolf optimization, VMD denoising, STA/LTA with refined AIC for first-arrival identification. This approach significantly improves the localization accuracy of damage sources by utilizing Geiger 3D time-difference localization with initial position refinement.

For high-pressure vessel apparatus, Zeng Degang and colleagues [98] devised a hardware and software system for the real-time surveillance of fissures in fracturing pump valve boxes utilizing AE ring-down counts. Fatigue simulation tests determined optimal parameters for acquisition threshold and data transmission interval, and this method can effectively detect initial cracks of 0.2 mm. Zhang Peng [99] tackled feeble AE signals resulting from internal leakage in hydraulic cylinders and subsequently developed four varieties of intelligent diagnostic algorithms. SVM is adopted for small-sample recognition. The integration of CEEMDAN-HHT time-frequency diagrams and CNN achieves accurate classification under diverse operating conditions. PSOSA-optimized DBN facilitates real-time online monitoring. DBN feature extraction coupled with a two-layer BiLSTM enables complementary fusion of multi-sensor information. All models achieved satisfactory recognition results on a laboratory fixed-pressure test rig. Franziska Baensch and colleagues [100] performed four-point bending experiments on

notched S355J2H steel pipes, developed a dynamic threshold AE signal processing framework. They introduced the Weighted Peak Frequency (WPF) to distinguish between micro-crack ((>400 kHz) and macro-crack/friction (<400 kHz) signals, demonstrating that AE can detect crack initiation earlier than the DCPD potential method. Yang Jing and colleagues [101] employed wavelet packet decomposition to analyze AE signals from valve leakage. The ratio of frequency band energy is assessed to differentiate between two leakage types (insufficient sealing and perforation/crack). Viability of this identification method was confirmed through laboratory and field assessments.

In the petrochemical and infrastructure sectors, the AE method enables early crack identification, damage stage classification, and source localization for diverse structural forms. It can detect nano-scale nascent damage earlier than existing approaches and provides online monitoring without requiring disassembly. However, complex signal propagation channels, diverse damage mechanisms, and fluctuating field conditions are major industrial obstacles that hinder further improvements in detection accuracy and quantitative performance.

5. Frontier Technologies and Industrial Development Trends

Chapter 4 highlights the main technical barriers shown in industrial applications and analyzes three major frontier research paths of AE crack monitoring. In this chapter, we introduce multi-source information fusion, large-model intelligent diagnosis, and edge IoT real-time monitoring. We examine current scientific advances and remaining practical challenges for each direction.

Driven by major advances in artificial intelligence, big data, and the Internet of Things, the AE method is progressively moving toward integrated multi-source information, intelligent analysis, and remote online monitoring. These technologies have significantly improved diagnostic accuracy and system performance. However, inconsistent data standards remain a key barrier to their broad industrial application.

5.1 Multi-source Information Fusion and Hybrid Diagnostic Methods

A single AE signal cannot fully represent the overall operating state of machinery, while vibration signals are more sensitive to external influences and structural changes, making them inherently complementary. Combining diverse signals such as AE and vibration has therefore become a prominent research direction in this field. Chen Xiaoxin [102] first revealed the fault coupling characteristics of AE and vibration signals through auto- and cross-correlation analysis, then proposed the GAF-SGE-DCNN single AE diagnostic model and the Attention-1DCNN acoustic-vibration multi-level fusion network. Research indicated that the integration of multi-source signals can enhance the accuracy of bearing fault detection to 97.75%. Chi et al. [103] integrated the time-frequency attributes of AE and vibration sensors, developed an all-encompassing screening index for feature optimization. They introduced a Mahalanobis distance multi-source feature fusion technique as a health indicator and applied it with the envelope spectrum to accurately identify early bearing faults. Their research showed that the two signal types are complementary, and this method achieves higher fault detection accuracy than traditional statistical and machine learning approaches. Li et al. [104] integrated dual-source

monitoring signals from AE and infrared temperature, and developed an LSTM-VAE unsupervised feature compression model. This approach applies monotonicity loss to control feature trends. It uses weighted least squares to construct health indicators. Accurate remaining fatigue life prediction for stainless steel specimens under multi-stress conditions was achieved via a sample similarity algorithm. Its effectiveness has been fully validated in fields such as rotating machinery, aviation equipment, and wind energy systems.

Presently, common fusion techniques can be classified into two categories: feature-level fusion and decision-level fusion. Zaman [105] indicated that by transforming AE and vibration signals into time-frequency representations and inputting them into a parallel convolutional network. A dual-input parallel ResNet-50 convolutional network was built using an interleaved feature fusion method to simultaneously detect various milling machine faults under both idle and operational conditions. The achieved detection accuracy reached 99.07%, outperforming unimodal and conventional fusion models. Wang Liuyang [106] further validated this perspective. To address the challenge of insufficient diagnostic precision of individual sensors, a multi-speed, variable-load bearing test rig was constructed to simultaneously acquire vibration and AE data. Using 1D CNN dual-channel cross-feature fusion combined with continuous wavelet transform (CWT) to generate time-frequency samples, an enhanced 2D CNN model was developed. Studies revealed that the diagnostic precision following multi-source signal integration was markedly enhanced compared to individual vibration or AE signals. The model's identification performance under comprehensive operating conditions with varying speeds and loads outperformed conventional models such as 1D CNN, SVM, and BP. Currently, methods like multi-layer feature stacking and cross-feature fusion have been widely applied in the fault detection of bearings and motors, achieving favorable results.

However, significant research gaps and engineering challenges remain in the industrial translation of this technical trend. Most existing fusion frameworks are primarily validated in laboratory environments with well-defined damage modes under controlled interference, while their actual performance in field conditions with variable operating conditions and coupled multi-source noise remains largely uncharacterized. Furthermore, most current data-driven fusion architectures lack a mechanistic foundation for the cross-modal physical coupling of AE wave propagation, structural vibration response, and damage evolution. This results in limited physical interpretability and generalizability to other structural configurations. From the engineering deployment perspective, practical adoption is further hindered by high retrofitting costs for synchronized multi-sensor systems, the absence of standardized cross-modal calibration techniques, and a lack of uniform industry-wide performance evaluation metrics.

5.2 Intelligent detection and decision support based on large models

Large models exhibit formidable capabilities in processing substantial volumes of text and information. In recent years, they have found diverse applications in the field of equipment fault detection. Typically, large models are trained using operational and maintenance data, fault cases, and technical documentation. The construction of knowledge graphs clarifies the connections between signals and fault characteristics, ultimately yielding interpretable fault detection results [107]. Currently, large models for industrial equipment monitoring and fault diagnosis are mainly

categorized into five primary technical approaches including in-context learning, fine-tuning, retrieval-augmented generation, multimodal models, and time-series large models [108].

Li et al. [109] proposed a Multi-Scale Transformer architecture for railroad axle fatigue crack recognition. It introduces the multi-scale convolutional local perception modules with the Transformer global dependency modeling with supervised contrastive learning. The solution overcomes the insufficient ability of typical Transformers to extract fine-grained transient characteristics in non-stationary AE signals and achieves a classification accuracy of 99.19%. That outperforms CNN, LSTM, and baseline Transformer benchmarks on a dedicated axle fatigue dataset. However, the model is proven only on laboratory axle specimens. Its transferability to different structural geometries and field situations has not been investigated thus far. Li et al. [110] presented a physics-guided deep learning framework for high-strength bolted joint condition evaluation by integrating CNN supervised classification with Gaussian mixture model (GMM) unsupervised clustering. The framework is built on AE features extracted via empirical wavelet transform. By leveraging prior knowledge of bolt loading damage mechanisms, it distinguishes overlapping damage signatures from static friction, sliding, constrained, and failure stages. It efficiently identifies four damage types and enhances diagnostic reliability under conditions of limited labeled data. However, this framework is purpose-built for bolted joint configurations and cannot be easily generalized to general fatigue crack propagation scenarios. Gou et al. [111] proposed an unsupervised learning framework incorporating prior knowledge of material mechanics. Using multiple gradient supervision models as base learners, they designed a knowledge aggregation loss function to automatically separate mixed AE signals of metal dislocations and cracks. Verified through porous stainless steel tensile tests, this method can identify coexisting deformation mechanisms in real time and achieve early warning of material failure based on avalanche statistics laws. Its generalization and identification accuracy are superior to traditional clustering and supervised recognition algorithms.

Except for the above studies, the following are especially representative. Lu et al. [112] presented a lightweight dual-stream Transformer LDS-Former, which is structurally consistent with the transient-evolutionary duality of AE fracture signals. The design separates the high-frequency transient detail preservation and low-frequency damage trend modeling by independent processing streams that are fused by an adaptive gating technique. It achieves a detection accuracy of 95.05% with only 0.199 million parameters, and has been applied on STM32 edge microcontrollers for real-time on-site monitoring. This work demonstrates the possibility of large AE diagnostic models for deployment at the edge, validating that the lightweight architecture can meet the real-time inference latency and memory requirements on resource-constrained embedded devices. However, full field deployment on operating offshore steel structures has not yet been carried out and is a direction for future industry validation.

Large models can assist in feature interpretation, automatically generate diagnostic reports, recommend maintenance strategies, and perform remaining life prediction in AE analysis. Therefore, their application in this field is well-justified. However, real-world applications undeniably face core challenges, including scarce industrial data and difficulties in edge deployment. Large models should develop progressively through three stages including

knowledge augmentation, task-oriented execution, and autonomous learning. Going forward, domain-specific foundational models, multi-source integration, and efficient edge deployment will form the main research directions [108].

5.3 Real-Time Monitoring, IoT and Industrial Application Prospects

At present, the integration of IoT technology with AE monitoring has become an emerging developmental trend. By deploying sensors, communication devices, and edge computing units to form a distributed monitoring network, it is possible to realize real-time signal acquisition, remote transmission, online analysis, and proactive fault warning. Zhu Decheng [113] developed an 8-channel domestic AE acquisition platform incorporating FPGA and PCIe transmission. Validated through lead break tests and rolling vibration table assessments, this system can accurately detect initial minor damage in train components. Gao et al. [114] employed a point-to-point wireless AE acquisition device to collect real-time high-cycle fatigue data of high-strength stainless steel. They derived time-series characteristics like energy and ring counts, and differentiated the three phases of crack initiation, propagation, and fracture according to feature progression. Saleem et al. [115] presented a hybrid deep learning system for real-time pipeline leak detection from AE data. The pipeline transforms the time-domain AE waveforms into the time-frequency scalograms using CWT. It applies Gaussian filtering to reduce background noise, then feeds the enhanced images into a CNN-LSTM hybrid network for joint spatial-temporal feature extraction. A genetic algorithm further optimizes the feature subset, and a fully connected layer performs the final binary classification of leak versus non-leak. The effectiveness of the proposed framework is validated on real-world test data from stainless steel pipelines, achieving a detection accuracy of 99.69% that outperforms single-branch models. However, the current technique only supports binary state identification, lacking the functions of accurate leak localization and quantitative leakage rate estimation. Furthermore, the generalization ability of the model for varied pipe diameters, fluid media and operating pressures is to be validated. It is encouraging that Sayyaf [116] has developed a Wireless Crack Detection System (WCDS) based on the theory of AE sensing. The hardware architecture consists of piezoelectric AE sensors, a microprocessor for signal processing, amplification and analog-to-digital conversion, and a GPS module for microsecond-level time synchronization for multi-node source localization. The system uses the MQTT protocol over Wi-Fi for data transmission with an edge gateway for local preprocessing and cloud relay, and Node-RED for real-time data viewing. The study verifies the technical feasibility of integrating AE methods with IoT architecture for continuous wireless monitoring, and demonstrates advantages in low power consumption and scalable multi-node deployment. However, the technology remains at the laboratory prototype stage and has not undergone long-term field validation in industrial environments. Furthermore, it relies on classical amplitude thresholding for event identification, making it insufficiently robust against ambient noise and varying operating conditions.

There are still three fundamental barriers to be addressed before the AE method can achieve widespread industrial adoption. First, robust signal denoising and source identification capabilities under complex industrial noise must be developed to reduce false alarm rates. Second, the long-term reliability of low-power wireless sensor nodes under high-temperature, high-humidity, and corrosive conditions requires validation. Third, standardized data interfaces and evaluation criteria are needed to enable interoperability between diverse monitoring systems.

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5.4 Standardization Status and Existing Challenges

Despite the benefits of the AE method, the lack of standardized global industry norms and international regulations for AE testing leads to inconsistencies in sampling rates, gain settings, filtering criteria, and data storage formats across different manufacturers and research institutions. As a result, experimental data cannot be exchanged, and relevant results are difficult to compare directly.

Simultaneously, the lack of standardized performance evaluation metrics and benchmark datasets for crack detection and life prediction necessitates the establishment of a comprehensive standard system covering data acquisition, algorithm specifications, equipment calibration, and performance evaluation. This system will facilitate the industrialization of the AE method and enhance compatibility across various systems.

6. Conclusions and Prospects

This paper presents a comprehensive review of research outcomes concerning the AE method for crack detection in mechanical structures. It offers an extensive overview covering the mechanisms of AE generation from cracks, the time-frequency and energy characteristics of signals, signal processing, feature extraction, intelligent recognition algorithms, and their practical applications in diverse engineering contexts. Current research on AE damage detection has established a comprehensive technical framework encompassing signal denoising, feature extraction, and fault identification. Relevant methods have undergone thorough laboratory and field validation across various critical equipment scenarios. Numerous test results indicate that AE monitoring can deliver accurate and timely alerts regarding structural damage, significantly reducing equipment maintenance frequency and overall lifecycle operation and maintenance costs. Current research has developed wireless real-time AE acquisition systems for localized online monitoring of specimens. However, most detection methodologies still rely primarily on offline laboratory sampling and standalone wired acquisition methods, lacking distributed networking with multi-node collaboration and IoT remote management frameworks. It is anticipated that the requirements for comprehensive equipment operation and maintenance will drive the emergence of integrated health monitoring systems. It leverages the IoT, distributed sensor networks, and real-time AE data collection as a foundational technical solution for standardized lifecycle management of high-end equipment in the energy, rail transit, and aerospace industries.

In conclusion, four primary challenges are clearly identified from existing literature and engineering practices. Firstly, the complex conditions at industrial sites complicate the extraction of subtle damage signals. Secondly, the multifaceted nature of cracks and the nonlinearity of signals pose challenges to quantitative assessment. Thirdly, existing models are developed under specific conditions, resulting in insufficient generalization. Finally, the lack of standardized industry protocols hinders technological advancement and the sharing of research findings. Integrating current deficiencies with industry demands, future research may focus on the following avenues:

(1) Investigating into damage mechanisms and examining the interrelations between crack progression and AE signals across varying loads, temperatures, and environmental conditions, and improving physical models.
(2) Formulating signal processing algorithms with robust anti-jamming properties to improve the extraction of subtle features and accommodate intricate industrial environments.
(3) Enhancing intelligent models by integrating transfer learning and few-shot learning to bolster cross-condition generalization. Employing time-frequency analysis and multi-scale networks to differentiate various phases of crack development.
(4) Performing investigations into the coupling of thermal-mechanical-acoustic multi-physics fields, integrating finite element simulations to address monitoring difficulties in harsh environments.
(5) Advocate for the amalgamation of AE method with the IoT, and establish a digital monitoring platform that consolidates data collection, analysis, and early warning systems.

For future comprehensive industrialization, this method will necessitate enhancements in algorithms and hardware, which will lower application costs and improve system stability. Simultaneously, the profound amalgamation of the Internet of Things, artificial intelligence, and AE method inherently offers a remarkable opportunity to establish standardized, interconnected, and intelligent systems for monitoring equipment health, thus enhancing the safety of industrial operations.

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Conflict of Interest Statement

The authors declare no conflicts of interest.

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