Friction

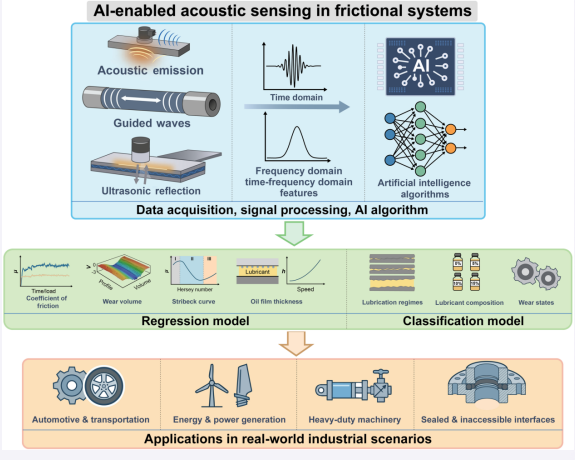
Review Article

AI-enabled acoustic sensing in frictional systems: Methods, progress, and perspectives

Song Yang[1], Dong Qiang[1], Pan Dou[1,2], Tonghai Wu[2], Tom Reddyhoff[1,✉], Min Yu[1,✉]

Cite this article: Yang S, Qiang D, Dou P, et al. *Friction* 2026, **14**: 9441267. https://doi.org/10.26599/FRICT.2026.9441267

ABSTRACT: Acoustic sensing for friction and lubrication monitoring involves the use of acoustic emission, guided waves, and ultrasonic reflection or transmission techniques to probe frictional and lubricated interfaces in a nonintrusive manner. It is particularly important for sealed or in-service mechanical systems, where direct access to the contact zone is limited or impossible. However, traditional acoustic sensing approaches often struggle with the complexity, nonlinearity, and nonstationary nature of friction-induced signals, making reliable interpretation and quantitative analysis challenging. Recent advances in artificial intelligence (AI) have significantly enhanced the ability to extract meaningful information from complex acoustic signals generated by friction, lubrication, and wear processes. This review surveys the current state of AI-enabled acoustic sensing for friction and lubrication monitoring in tribological systems. The sensing principles and data acquisition characteristics of acoustic emission, guided waves, and ultrasonic techniques are first summarized. Common signal processing and feature representation strategies are then reviewed, followed by key learning-based methods, including regression and classification frameworks, for quantitative prediction of friction, lubricant film thickness, and wear indicators, as well as identification of lubrication regimes, frictional states, and their transitions. Representative engineering applications in automotive systems, energy and power generation equipment, heavy-duty machinery, and sealed or inaccessible frictional interfaces are also discussed, demonstrating the broad applicability of AI-enabled acoustic sensing under practical operating conditions. Recent findings further indicate a growing shift from purely data-driven models toward physics-guided and mechanism-informed learning, with improved robustness, generalization, and interpretability. The review highlights both the capabilities and limitations of existing approaches and outlines emerging opportunities for intelligent and reliable tribological monitoring.



KEYWORDS: acoustic sensing; friction and lubrication; artificial intelligence (AI); tribological interfaces

1 Introduction

Friction and lubrication conditions fundamentally govern the operational reliability, energy efficiency, and safety of mechanical systems [1–3]. Deviations from optimal lubrication states can lead to sharp increases in frictional losses [4, 5], accelerated wear [6, 7], and irreversible surface damage [8], often triggering cascading failure processes within complex assemblies. In critical components such as bearings [9, 10], seals [11, 12], gears [13, 14], and automotive powertrain systems [15, 16], uncontrolled friction and lubrication breakdown are among the primary causes of premature failure, unplanned downtime, and significant economic loss [17–19]. In severe cases, friction-induced degradation can compromise structural integrity and operational safety, with consequences that extend beyond component-level damage [20, 21]. Reliable monitoring of frictional behavior and lubrication conditions is therefore not only a matter of performance optimization but also a prerequisite for safe operation and long-term system reliability. As engineering systems continue to operate under increasingly demanding conditions, the ability to detect early-stage changes in interfacial behavior before macroscopic failure occurs has become a central challenge in tribology and mechanical engineering.

A wide range of techniques has been developed to monitor friction and lubrication processes based on different physical principles. Direct measurements using force and torque sensors

[1] Department of Mechanical Engineering, Imperial College London, London SW7 2AZ, UK. [2] Key Laboratory of Education Ministry for Modern Design and Rotor-Bearing System, Xi'an Jiaotong University, Xi'an 710049, China.

✉ Corresponding authors. E-mail: T. Reddyhoff, t.reddyhoff@imperial.ac.uk; M. Yu, m.yu14@imperial.ac.uk

Received: February 27, 2026; Revised: May 12, 2026; Accepted: May 20, 2026

© The Author(s) 2026. This is an open access article under the terms of the Creative Commons Attribution 4.0 International License (CC BY 4.0, http://creativecommons.org/licenses/by/4.0/).

provide accurate information on frictional behavior and are widely used in laboratory studies, but their application in real engineering systems is often limited by intrusive installation and integration constraints [22]. Optical techniques, including interferometry, fluorescence methods, and imaging-based approaches, enable high-resolution measurements of lubricant film thickness and contact phenomena but typically require transparent interfaces or carefully controlled experimental environments [23, 24]. Electrical methods such as electrical contact resistance and capacitance measurements have also been extensively employed to infer lubrication regimes and film formation in rolling and sliding contacts [25, 26]. Although these methods have significantly advanced the understanding of tribological mechanisms, their deployment in industrial systems is frequently restricted by limited accessibility, sensitivity to environmental conditions, and challenges in long-term operation [27].

Acoustic approaches, including acoustic emission (AE), ultrasonic sensing, and guided waves (GWs), provide an alternative means for monitoring friction and lubrication processes without direct access to the contact interface [28–30]. These techniques are particularly attractive for in-service components, as they are capable of probing subsurface and interfacial phenomena in sealed or inaccessible systems. Previous studies have shown that acoustic signals are sensitive to frictional events, lubrication regime transitions, wear development, and changes in contact dynamics. However, the interpretation of acoustic responses remains challenging [31, 32]. Signals generated during friction and lubrication are typically nonstationary and span multiple temporal and spatial scales, reflecting the combined influence of surface interactions, material properties, lubrication conditions, and operating parameters [33, 34]. Comprehensive physics-based models that directly link acoustic signatures to specific tribological states are still limited, especially under realistic operating conditions [35–37]. This complexity has motivated the increasing use of learning-based analysis, which enables informative patterns to be extracted from high-dimensional acoustic data and practical relationships to be established between measured signals and underlying tribological behavior [38–40]. In this context, artificial intelligence plays an increasingly important role by providing systematic and scalable tools to interpret complex acoustic responses and to bridge the gap between measured signals and tribological state characterization [41, 42].

This review examines recent progress in acoustic-based monitoring of friction and lubrication processes, with particular emphasis on learning-assisted interpretation. Acoustic sensing offers a nonintrusive means to probe frictional interfaces that are sealed, inaccessible, or operating in service. Compared with vibration- and optical-based approaches, it is more sensitive to localized interfacial and subsurface phenomena, making it especially suitable for tribological monitoring of difficult-to-access interfaces. Accordingly, the role of artificial intelligence in acoustic sensing is often to establish the relationship between complex acoustic responses and tribological states. However, conventional acoustic analysis methods often rely on handcrafted features and simplified physical assumptions, which struggle to cope with the nonlinear, nonstationary, and strongly coupled nature of friction-induced signals. These limitations motivate the integration of artificial intelligence techniques. To clarify this development, the review is structured as follows. First, three major acoustic sensing approaches, namely, acoustic emission, guided waves, and ultrasonic sensing, are introduced, with emphasis on their sensing principles, theoretical foundations, and data acquisition characteristics in tribological systems. Second, commonly used signal processing and representation methods are reviewed. Third, learning-based frameworks for regression and classification are summarized for predicting frictional behavior, estimating lubricant film thickness and wear indicators, and identifying lubrication states and their transitions. Finally, recent advances in engineering applications are presented, including automotive systems, energy and power generation equipment, heavy-duty machinery, and sealed or inaccessible frictional interfaces. Through this overview, the review aims to clarify the capabilities and limitations of acoustic sensing for friction and lubrication monitoring and to demonstrate the potential of artificial intelligence for intelligent, robust, and interpretable tribological monitoring.

2 Acoustic-based sensing and data acquisition for frictional interfaces

Acoustic sensing provides an effective and nonintrusive means to probe frictional interfaces by capturing stress waves generated during friction and lubrication. In this section, three representative acoustic sensing approaches are introduced, together with their sensors, data acquisition characteristics, and basic theoretical foundations in tribological applications. For acoustic emission, the measured signal can be viewed as the structural response to localized transient events at the frictional interface. For guided wave and resonant acoustic methods, the response is governed by elastic wave equations, dispersion relations, and interfacial boundary conditions. For ultrasonic reflection (UR) and transmission techniques, the signal is determined by the partition of incident wave energy across interfaces with different mechanical impedances. Microphone-based sound acquisition has also been used in friction-related monitoring, but it mainly captures airborne sound over a relatively limited frequency range and is generally less directly linked to localized interfacial phenomena. For this reason, the present section focuses on the three acoustic sensing approaches that are more directly associated with frictional interface characterization. A brief introduction to their underlying theoretical basis helps clarify the origin of the signals and the type of interfacial information that can be extracted in tribological applications.

2.1 Acoustic emission methods

During friction and lubrication, localized and transient interfacial events generate AE signals. In sliding and rolling contacts, these events may arise from asperity interactions, plastic deformation, microfracture initiation, tribofilm formation and rupture, as well as the generation and entrainment of wear debris [43, 44]. Under lubricated conditions, lubricant film breakdown, boundary film shearing, and intermittent solid contact can further contribute to acoustic activity. The resulting stress waves propagate through the contacting bodies and surrounding structure and are detected as AE signals [45, 46]. Owing to its sensitivity to microscale and mesoscale interfacial processes, AE is particularly suitable for monitoring frictional interfaces where direct observation is difficult [47], as illustrated in Fig. 1(a).

From a theoretical perspective, AE can be regarded as transient stress/displacement waves generated by the rapid release of energy from localized sources within a material. In linear elastodynamics, the resulting displacement field can be described by the balance of linear momentum with an equivalent source term, which may be written in a simplified form as Eq. (1) [45]:

$$\rho \frac{\partial^2 u}{\partial t^2} = \nabla \cdot \sigma + f(x,t) \tag{1}$$

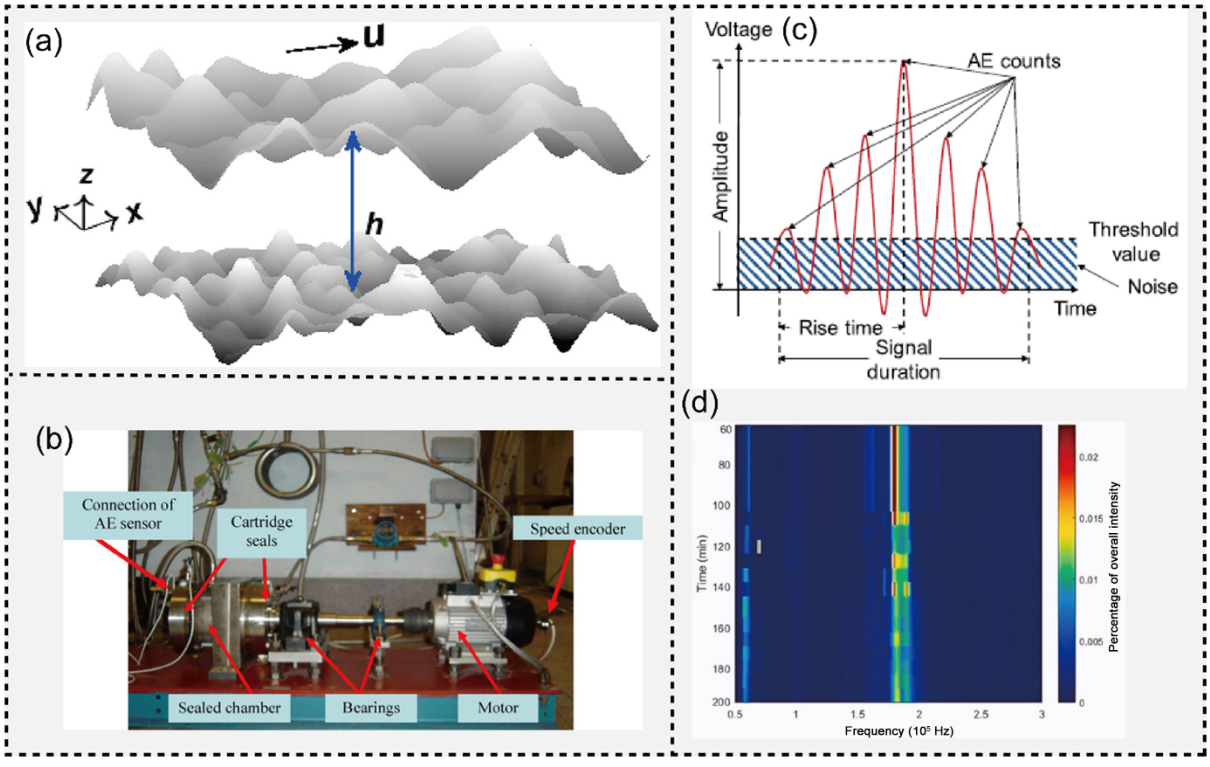


Fig. 1 Representative illustrations of acoustic emission phenomena associated with frictional interfaces. (a) Physical origins of acoustic emission arising from localized interfacial processes during friction and lubrication. (b) Typical sensor configuration illustrating stress wave propagation from frictional contact to externally mounted acoustic emission sensors. (c) Time domain acoustic emission response showing temporal evolution of acoustic activity during frictional interaction. (d) Frequency domain characterization highlighting spectral features associated with acoustic emission generated at frictional interfaces. Reproduced with permission from Ref. [47] for (a), © Elsevier Ltd. 2020; from Ref. [52] for (b), © Elsevier B.V. 2009; from Ref. [60] for (c), © Elsevier Ltd. 2020; from Ref. [61] for (d), © The Author(s) 2023.

where ρ is the material density; u is the displacement field; σ is the stress tensor; $f(x,t)$ represents friction-induced transient source terms. In practice, the measured AE signal is further shaped by propagation and sensing effects and can be expressed conceptually as Eq. (2):

$$s(t) = g(t) \times h(t) \times r(t) \tag{2}$$

where $g(t)$ denotes the source–time function; $h(t)$ is the structural transfer-path response; $r(t)$ is the sensor response. This equation highlights that the measured signal is influenced not only by the interfacial source but also by wave propagation, reflections, and sensor characteristics.

In tribological monitoring, AE is commonly measured using piezoelectric sensors mounted near the frictional interface, such as on specimen holders, bearing housings, seal casings, or machine frames. Sensor selection depends on the frequency range of interest, with commonly used sensors operating from several tens to several hundreds of kilohertz [48, 49]. Lower-frequency sensors are often preferred in large-scale components because of lower attenuation, whereas higher-frequency sensors provide greater sensitivity to localized damage and microscale frictional events [50]. Signal quality is strongly affected by sensor placement and coupling since AE measurements are influenced by wave propagation paths, reflections, and structural resonances [51, 52], as schematically shown in Fig. 1(b). In some cases, multiple sensors are used to improve robustness or capture spatial variations in acoustic activity [53–55].

AE data acquisition in friction and lubrication studies typically involves high sampling rates and strongly nonstationary signals [56, 57]. Sampling frequencies from hundreds of kilohertz to several megahertz are commonly adopted to capture transient emission events. Depending on the application, data may be acquired continuously to monitor long-term frictional evolution or by threshold triggering to isolate burst-type events [58, 59]. At the acquisition stage, time-domain descriptors such as root mean square amplitude, signal energy, peak amplitude, and hit count are widely used to quantify acoustic activity [60], as shown in Fig. 1(c), while frequency-domain analysis is employed to identify characteristic spectral bands [61], as shown in Fig. 1(d). These descriptors often correlate with friction level, lubrication regime, and wear severity, but they are also affected by load, speed, material properties, and lubrication conditions, which complicates direct interpretation [62].

Overall, AE provides rich information about frictional interfaces, but the measured signals are often complex because they reflect the combined influence of source generation, wave propagation, and operating conditions. As a result, conventional descriptor-based analysis may not fully capture the underlying tribological information. This limitation has motivated the increasing use of data-driven and learning-based approaches to extract informative patterns from AE signals and relate them to friction and lubrication behavior.

2.2 Guided wave and resonant acoustic methods

Elastic wave propagation in solid structures has long been used to probe material and interfacial conditions. Guided wave and resonant acoustic methods build on this concept through the controlled excitation and propagation of elastic waves in bounded structures, where wave behavior is governed by material properties, geometry, and boundary conditions [63–65]. In frictional systems, contact interfaces, lubrication films, and surface

interactions modify local stiffness, damping, and mechanical impedance, thereby affecting wave dispersion, attenuation, reflection, and mode coupling. Unlike acoustic emission, which mainly captures transient energy release events, guided wave and resonant methods rely on repeatable excitation and deterministic wave propagation, making them suitable for monitoring gradual, distributed, or quasistatic changes at frictional interfaces [66].

From a theoretical perspective, guided wave propagation can be formulated within the framework of linear elastodynamics. For a homogeneous and isotropic elastic solid without body forces, the displacement field is governed by the Navier–Cauchy equation, as given by Eq. (3) [67, 68]:

$$\rho \frac{\partial^2 u}{\partial t^2} = (\lambda + \mu) \nabla (\nabla \cdot u) + \mu \nabla^2 u \tag{3}$$

where ρ is the material density, u is the displacement field, and λ and μ are the Lamé constants. In bounded structures, the admissible wave modes are constrained by geometry and boundary conditions, leading to dispersion relations of the form shown in Eq. (4):

$$\omega = \omega(k) \tag{4}$$

where ω is the angular frequency and k is the wavenumber. These relations determine key measurable quantities such as phase velocity, group velocity, attenuation, and modal behavior. In tribological systems, changes in interfacial stiffness and damping alter these wave characteristics, providing the physical basis for guided wave and resonant acoustic sensing.

Guided wave measurements are typically implemented using piezoelectric transducers that act as both actuators and receivers. Depending on the geometry and application, these transducers may be surface bonded or embedded. In friction-related studies, sensors are commonly mounted on plates, rods, shafts, or bearing housings to excite longitudinal, shear, or Lamb wave modes that interact with the contact interface [69, 70]. Under suitable excitation frequencies and boundary conditions, guided wave interrogation may also exploit resonant responses, where specific wave modes become particularly sensitive to interfacial stiffness and damping variations [71], as shown in Fig. 2(a). Sensor placement and excitation configuration are therefore designed to maximize wave interaction with the frictional interface while maintaining signal repeatability [72–74].

The signals obtained from guided wave and resonant acoustic measurements are typically narrowband and mode specific. Useful information is encoded in parameters such as wave velocity, amplitude, phase shift, attenuation, and frequency response, as illustrated by the sensing configuration in Fig. 2(b) [75, 76]. Resonant responses are often characterized by resonance peaks, modal damping, and quality factors, which reflect changes in contact stiffness, lubrication regime, or interfacial energy dissipation. In practical structures, however, guided wave propagation is also influenced by dispersion, multimode interference, and environmental variability, resulting in complex responses in both the time and frequency domains, as shown in Figs. 2(c) and 2(d) [77].

Overall, guided wave and resonant acoustic methods provide structured and repeatable measurements for characterizing frictional interfaces. Their sensitivity to interfacial stiffness, damping, and lubrication-related changes makes them a useful complement to acoustic emission in tribological monitoring.

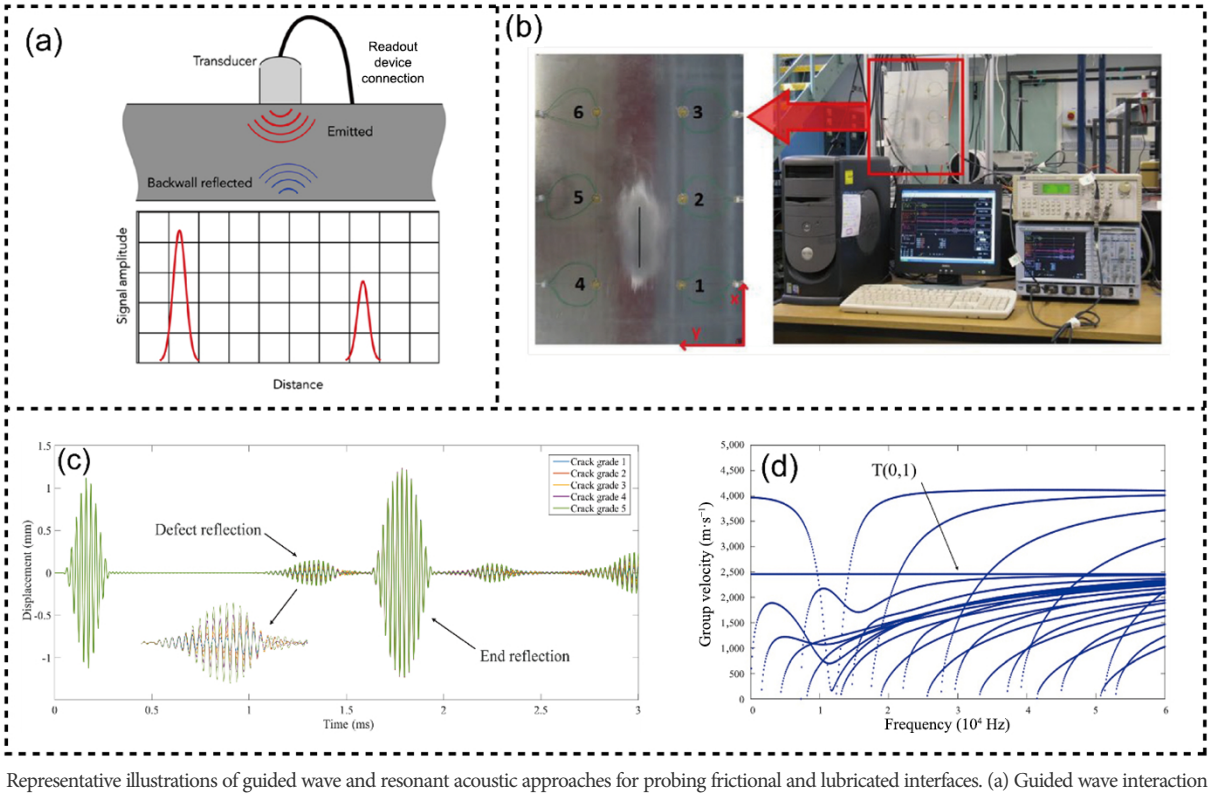


Fig. 2 Representative illustrations of guided wave and resonant acoustic approaches for probing frictional and lubricated interfaces. (a) Guided wave interaction with a lubricated interface, illustrating wave emission, propagation, and reflection governed by interfacial conditions. (b) Experimental configuration for guided wave excitation and sensing using surface-mounted transducers. (c) Typical guided wave signals in time domain showing reflections associated with interfacial features and structural boundaries. (d) Dispersion characteristics of guided wave modes highlighting their sensitivity to structural geometry and interfacial conditions. Reproduced with permission from Ref. [71] for (a), © The authors 2022; from Ref. [76] for (b), © Elsevier Ltd. 2023; from Ref. [77] for (c, d), © Elsevier Ltd. 2022.

2.3 Ultrasonic reflection and transmission techniques

Ultrasonic reflection and transmission techniques are active acoustic methods in which high-frequency elastic waves are introduced into a structure and their interaction with frictional interfaces is evaluated through reflected and transmitted signals. When an ultrasonic wave impinges on a solid contact interface or a lubricated layer, part of the incident energy is reflected, and part is transmitted, with the energy partition governed by the mechanical impedance contrast across the interface, as illustrated in Fig. 3(a) [32]. In frictional systems, variations in contact pressure, surface roughness, lubrication regime, and interfacial stiffness alter this impedance contrast and lead to measurable changes in ultrasonic responses [78, 79]. This sensitivity provides the physical basis for using ultrasonic techniques to interrogate frictional and lubricated interfaces in a nonintrusive manner.

From a theoretical perspective, the reflection and transmission behavior at an interface can be described in simplified form by the reflection coefficient (R), as given by Eq. (5):

$$R = \frac{Z_2 - Z_1}{Z_2 + Z_1} \tag{5}$$

and the transmission coefficient (T) is calculated using Eq. (6):

$$T = \frac{2Z_2}{Z_2 + Z_1} \tag{6}$$

where Z_1 and Z_2 are the acoustic or mechanical impedances of the two media. At tribological interfaces, the effective interfacial impedance is influenced by the lubricant film thickness, contact stiffness, surface roughness, and pressure distribution. As a result, changes in lubrication or contact conditions can be inferred from variations in reflected and transmitted ultrasonic signals.

In practical applications, ultrasonic measurements are typically performed using piezoelectric transducers in pulse-echo or pitch-catch configurations [80]. Depending on the accessibility of the contact region and the component geometry, transducers may be mounted on one or both sides of the interface, enabling either single-side reflection measurements or through-interface transmission measurements. In tribological studies, ultrasonic probes have been integrated into bearing housings, seal casings, and dedicated test specimens to monitor contact conditions without direct access to the interface [81, 82]. Owing to this configuration, ultrasonic techniques generally provide localized interrogation of the contact region with relatively high spatial resolution over short propagation distances, as shown in Fig. 3(b) [83, 84].

The acquired ultrasonic signals are commonly analyzed in both the time and frequency domains. In the time domain, features such as echo amplitude, time of flight, phase shift, and signal bin statistics provide direct information on wave reflection and transmission under different lubrication conditions, as shown in Fig. 3(c) [85]. Frequency-domain analysis further reveals changes in spectral content and attenuation associated with variations in lubricant film thickness and interfacial stiffness, as illustrated in Fig. 3(d) [86]. These ultrasonic features have been correlated with lubricant film thickness, contact stiffness, and real contact area, making ultrasonic reflection and transmission techniques attractive for quantitative assessment of lubrication conditions [87–89]. However, the measured responses are also affected by coupling conditions, temperature, and alignment, which can introduce additional uncertainty [90]. Ultrasonic reflection and transmission techniques thus offer a physically grounded and localized means of probing lubricated frictional interfaces. Their sensitivity to impedance-related interfacial changes makes them especially suitable for quantitative tribological monitoring.

Despite their distinct physical principles, acoustic emission,

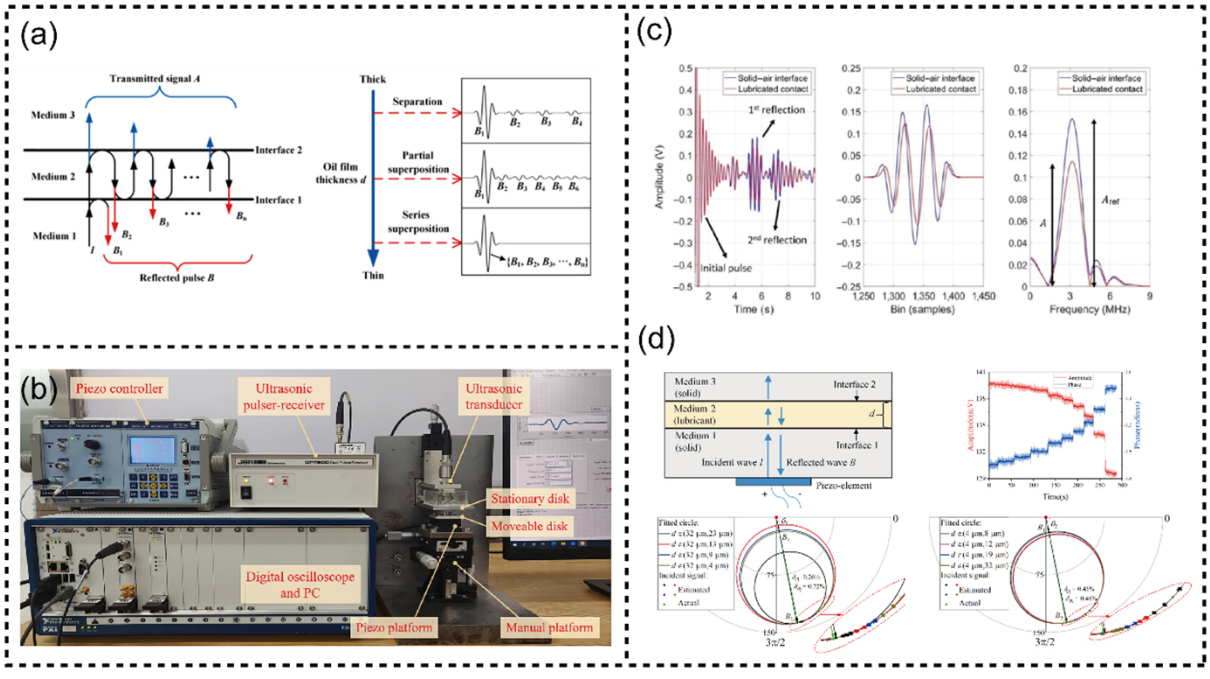


Fig. 3 Ultrasonic reflection and transmission techniques for probing lubricated frictional interfaces. (a) Schematic illustration of fundamental principle of ultrasonic reflection at a lubricated contact, showing interaction between incident waves and lubricant film separating solid surfaces. (b) Representative experimental setup for ultrasonic reflection and transmission measurements in a controlled frictional contact. (c) Time-domain ultrasonic signals illustrating interface-related reflections and their evolution under different lubrication conditions. (d) Frequency-domain analysis of ultrasonic responses highlighting spectral features associated with changes under lubricated contact conditions. Reproduced with permission from Ref. [32] for (a), © Elsevier Ltd. 2021; from Ref. [84] for (b), © Elsevier Ltd. 2023; from Ref. [85] for (c), © The author(s) 2024; from Ref. [86] for (d), © Elsevier Ltd. 2024.

清華大学出版社 Tsinghua University Press | SciOpen

guided waves, and ultrasonic reflection and transmission techniques share several common challenges in frictional systems. Acoustic responses under different contact conditions and lubrication regimes arise from multiple coupled mechanisms, which hinders the establishment of unified and transferable physics-based models linking signals to specific tribological states. In addition, the effective measurement capability of these methods is closely related to their resolution characteristics, which are inherently method dependent. Acoustic emission generally provides high temporal resolution for capturing transient interfacial events, but its spatial resolution is often constrained by propagation-path complexity unless multiple sensors and source-localization strategies are employed. Guided wave methods offer a broader interrogation range, while their spatial resolution depends on the excitation frequency, wavelength, wave mode, and structural dispersion. Ultrasonic reflection and transmission techniques provide strong local sensitivity to interfacial stiffness, gaps, or lubricant film thickness, but their effective sensing region is usually limited by the transducer size and acoustic path.

Another important practical issue is that signal quality and interpretability are strongly influenced by sensor installation and arrangement. For all three methods, sensor placement, coupling condition, alignment, propagation path, and structural boundary effects can significantly affect the measured responses, the effective resolution, and the reliability of signal interpretation. Therefore, the effective resolution of acoustic sensing cannot be represented by a single universal metric because it depends strongly on the sensing principle, excitation frequency, structural geometry, and propagation conditions. As a result, existing analytical descriptions are often system specific and rely on strong simplifying assumptions. In this context, artificial intelligence provides a complementary, rather than substitutive, framework for learning data-driven relationships from complex acoustic responses, enabling scalable interpretation where unified analytical models remain unavailable.

3 Data-model codesign for AI-enabled acoustic tribological monitoring

The effectiveness of acoustic sensing for tribological monitoring depends not only on data acquisition but also critically on how acoustic signals are interpreted and linked to physically meaningful tribological quantities. Acoustic responses from frictional interfaces are inherently high-dimensional and nonstationary, arising from the coupled effects of contact mechanics, lubrication dynamics, and wave propagation, which limits the generality of purely analytical models. These challenges make learning-based approaches particularly attractive for extracting informative relationships between acoustic signatures and frictional states. In this context, AI-enabled acoustic tribological monitoring can be formulated as a representation-to-state mapping process, in which the raw acoustic signal $x(t)$ is first transformed into an input representation X through preprocessing and feature extraction, as given by Eq. (7):

$$X = \Phi(x(t)) \tag{7}$$

and then mapped to the target tribological output through a learning model using Eq. (8):

$$y = f_\theta(X) \tag{8}$$

where $f_\theta(\cdot)$ denotes the AI model and y represents either a continuous tribological quantity or a discrete state label. Accordingly, this section focuses on learning-assisted mapping strategies that relate acoustic signals to friction, lubrication, and contact-related quantities, with emphasis on regression and state identification.

3.1 Learning-based mapping from acoustic signals to physical quantities

Within a data-model codesign framework, a key objective is to establish quantitative links between acoustic responses and physically meaningful tribological quantities. Given the high dimensionality and nonstationary nature of acoustic signals, learning-based approaches provide an effective means to infer friction, lubrication, and contact-related parameters from acoustic features.

3.1.1 Regression of friction, film thickness, and contact indicators

A substantial body of work has employed regression-based learning to map acoustic signatures to continuous tribological quantities such as friction, lubricant film thickness, and contact-related indicators. These studies collectively demonstrate that data-driven regression models can extract quantitative interfacial information from complex acoustic responses across a wide range of operating conditions.

Early learning-based studies in acoustic tribological monitoring focused on establishing quantitative relationships between acoustic emission signals and friction. Gutierrez et al. [91] developed a continuous regression framework linking AE signals to the coefficient of friction in a high-frequency reciprocating steel–steel contact, as shown in Fig. 4(a). Acoustic emission signals acquired at high sampling rates were represented using multiple time- and frequency-domain features, enabling time-resolved friction prediction across varying loads, reciprocating frequencies, and stroke lengths, with correlation coefficients approaching 0.8. This study demonstrated that frictional behavior can be inferred directly from AE measurements without relying on direct force sensing or optical access.

Subsequent work extended AE-based regression beyond friction prediction toward broader lubrication characterization. Yang et al. [92] reconstructed the complete Stribeck curve by regressing both the Stribeck number and the coefficient of friction from AE signals acquired on a high-frequency reciprocating rig, as shown in Fig. 4(b). By systematically varying lubrication conditions to traverse the boundary, mixed, and full-film regimes, this work showed that learning-based interpretation of AE signals can capture physically meaningful lubrication transitions rather than merely reproducing empirical friction trends.

Regression-based acoustic learning has also been extended to practical engineering systems for estimating lubrication- and degradation-related quantities that are difficult to measure directly in operation. For lubricant film thickness estimation, recent studies have combined ultrasonic sensing with learning-based signal interpretation to improve robustness under noisy and dynamically varying conditions. By identifying usable ultrasonic echoes and suppressing motion- and wave-induced disturbances, reliable oil film thickness estimation becomes possible even when conventional deterministic analyses are unreliable [93], as illustrated in Fig. 4(c).

In parallel, acoustic signals have been increasingly used for learning-based prediction of wear evolution in sliding components. Acoustic features sensitive to mixed lubrication and asperity contact have enabled continuous regression of wear progression in sliding bearings, even when experimental degradation data are limited [94], as shown in Fig. 4(d). These

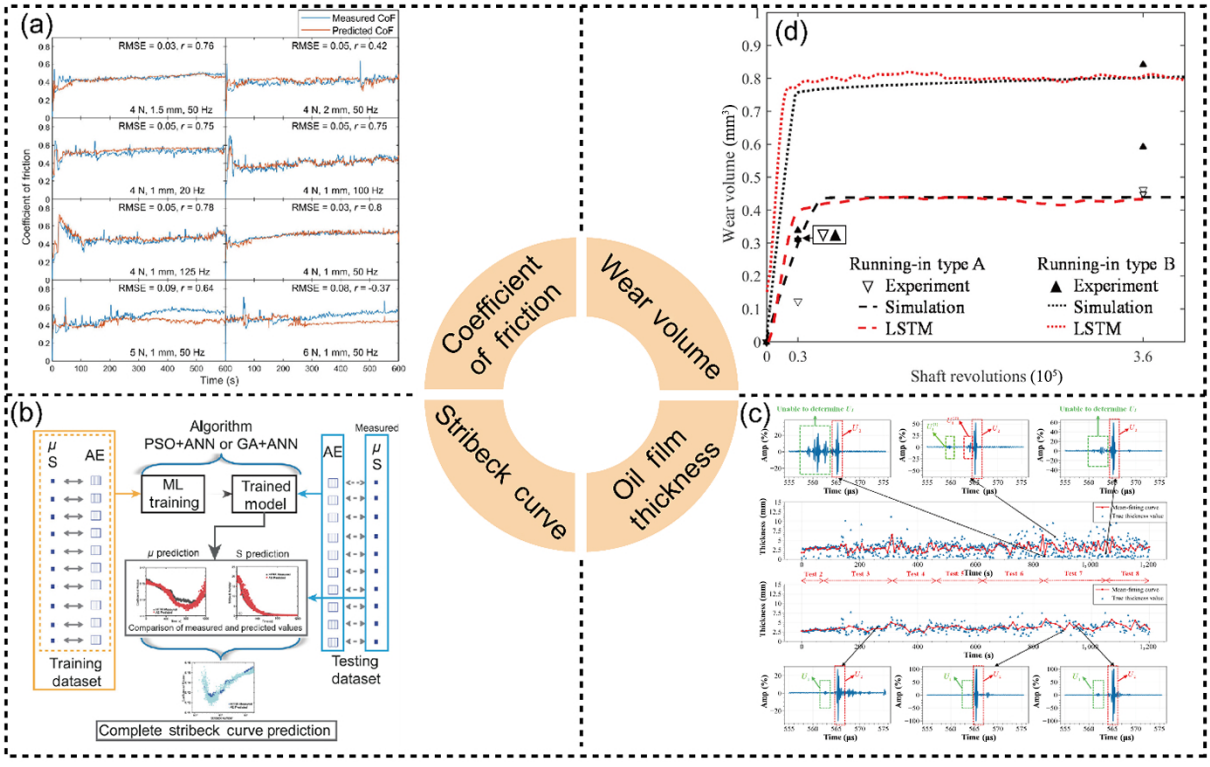


Fig. 4 Representative illustrations of regression-based acoustic learning for quantitative tribological monitoring. (a) Supervised prediction of coefficient of friction from acoustic signals, illustrating time-resolved friction estimation under varying operating conditions. (b) Learning-based reconstruction of Stribeck curve from acoustic signatures, capturing systematic friction evolution across lubrication regimes. (c) Machine learning-assisted acoustic inference of lubricant oil film thickness under dynamic operating conditions. (d) Data-driven prediction of wear volume evolution using acoustic emission features and machine learning models. Reproduced with permission from Ref. [91] for (a), © The author(s) 2024; from Ref. [92] for (b), © Elsevier Ltd. 2025; from Ref. [93] for (c), © 2025 Published by Elsevier Ltd.; from Ref. [94] for (d), © Elsevier B.V. 2021.

studies collectively indicate that acoustic sensing, when coupled with learning-based models, can move beyond condition monitoring toward quantitative inference of frictional degradation processes.

Collectively, these studies demonstrate that the integration of acoustic sensing with learning-based models enables quantitative regression of key tribological quantities, including the coefficient of friction, the Stribeck curve, lubricant oil film thickness, and wear volume, from complex acoustic responses that are otherwise difficult to interpret using analytical approaches alone. Across these studies, a common theme is that learning-based models are not primarily employed to maximize predictive accuracy but to extract physically relevant information embedded in high-dimensional and nonstationary acoustic signals. Together, these developments motivate the emergence of more advanced data-driven and hybrid regression strategies.

3.1.2 Data-driven and hybrid regression models

While regression-based acoustic learning has shown promise for predicting friction, lubrication, and wear, purely data-driven models often suffer from limited robustness across operating conditions. This has motivated the development of data-driven and hybrid regression models that incorporate physical insight into the learning process.

One representative direction is the incorporation of physically meaningful variables and dimensionless groups into data-driven regression frameworks. Issa et al. [95] developed a Gaussian process regression model for predicting central and minimum lubricant film thickness in elastohydrodynamic elliptical contacts using datasets generated from finite element simulations, as shown in Fig. 5(a). Instead of relying on raw operating parameters, their model employed conventional elastohydrodynamic lubrication (EHL) dimensionless groups as inputs, substantially reducing input dimensionality while preserving physical relevance. This strategy enabled quasi-instantaneous film thickness prediction with accuracy exceeding that of classical analytical equations. Although the approach remains data-driven in nature, the explicit use of physics-based descriptors illustrates an effective pathway for embedding domain knowledge into regression models.

Beyond input-level physical embedding, structured learning strategies have been proposed to constrain the regression process using prior knowledge of acoustic wave behavior. Haywood-Alexander et al. [96] introduced structured machine learning tools for guided wave feature modeling, where Gaussian process regression was informed by known attenuation and propagation characteristics of guided waves, as shown in Fig. 5(b). By incorporating physical understanding into the covariance structure and feature-space modeling, their approach achieved improved robustness and uncertainty quantification compared with unconstrained data-driven models. Although developed in a structural health monitoring context, this framework is directly relevant to acoustic tribological regression, where wave–interface interactions similarly govern signal evolution and model extrapolation.

While regression-based acoustic learning has shown promise for predicting friction, lubrication, and wear, the reliability of quantitative estimation remains a major concern in practical applications. As shown in Fig. 5(c), recent work has addressed this issue by combining data-driven ultrasonic measurements with statistical validation for lubricant film thickness estimation [97]. Such approaches place emphasis not only on predictive capability

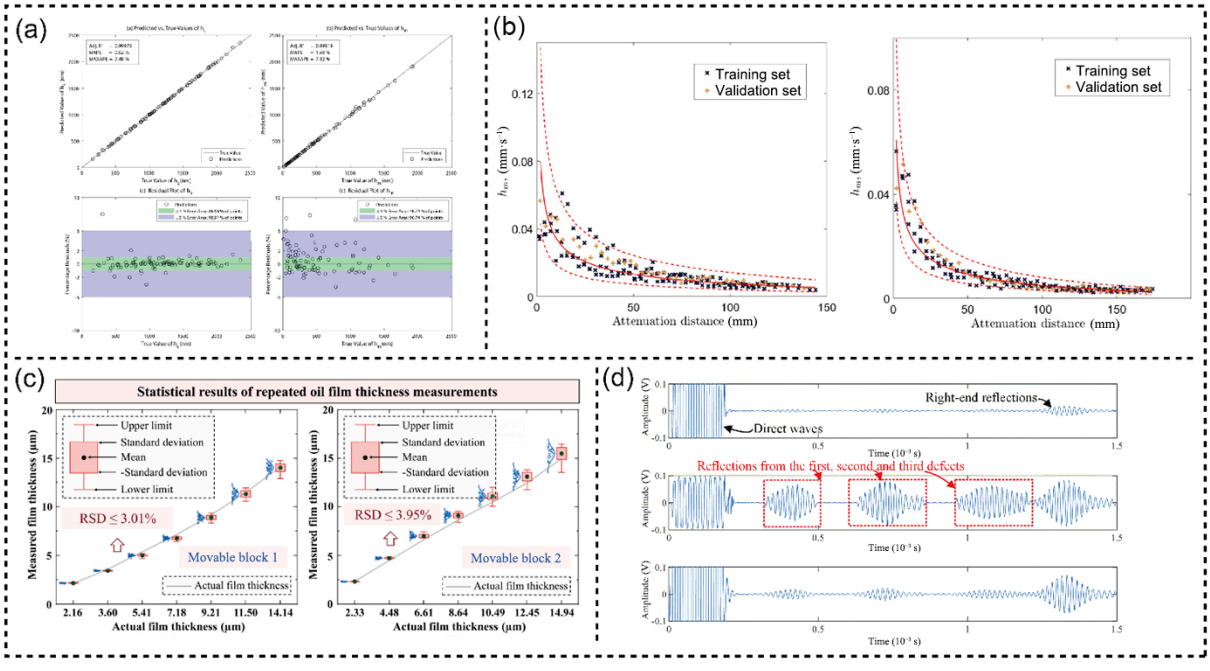


Fig. 5 Data-driven and physics-informed strategies for quantitative tribological parameter estimation. (a) Physics-embedded machine learning regression of lubricant oil film thickness based on physically meaningful inputs and simulation-generated training data. (b) Structured Gaussian process regression of guided-wave features with physical constraints and uncertainty-aware prediction. (c) Learning-assisted ultrasonic estimation and statistical validation of lubricant oil film thickness. (d) Physics-informed deep learning framework for acoustic signal enhancement under low signal-to-noise conditions. Reproduced with permission from Ref. [95] for (a), © The authors 2023; from Ref. [96] for (b), © Elsevier Ltd. 2021; from Ref. [97] for (c), © Elsevier Ltd. 2025; from Ref. [98] for (d), © 2023.

but also on repeatability and measurement consistency under repeated experiments. This is particularly relevant in tribological systems, where measured acoustic responses often reflect both interfacial changes and experimental uncertainty. By integrating data-driven prediction with systematic validation, these methods provide a useful route toward more reliable and robust acoustic monitoring.

More recently, physics-informed deep learning approaches have further extended hybrid regression concepts by integrating simulated physics with data-driven models. Li et al. [98] proposed a physics-informed deep filtering framework for ultrasonic guided waves, in which neural networks were trained using simulation-generated template signals to enhance weak, defect-related wave packets, as shown in Fig. 5(d). By embedding wave propagation physics into the training process, the model demonstrated strong generalization to experimental data without retraining. Although primarily focused on signal enhancement rather than direct parameter regression, this work exemplifies a broader trend toward physics-informed hybrid models, suggesting promising opportunities for future acoustic tribological regression that combines simulation, sensing, and learning within a unified framework.

Overall, data-driven and hybrid regression models provide a practical pathway to enhance robustness and physical consistency in acoustic tribological prediction tasks. Building on these quantitative mapping strategies, Section 3.2 shifts focus from continuous regression to learning-based identification of tribological states and transitions [99].

3.2 State and stage identification from acoustic signatures

While regression-based approaches aim to quantify tribological parameters from acoustic signals, many practical applications require identifying discrete operating states and transitional stages rather than continuous physical values. Acoustic signatures are often highly sensitive to changes in lubrication regimes, contact conditions, and wear evolution, making them well suited for state and stage identification tasks. Accordingly, this section focuses on learning-based methods that classify tribological states and track their temporal transitions using acoustic information.

3.2.1 Classification of lubrication regimes, wear states, and lubricant types

Building on the strong sensitivity of acoustic responses to interfacial contact conditions, classification-based approaches have become an effective tool for identifying discrete tribological states. Instead of estimating continuous physical parameters, these methods aim to recognize characteristic acoustic patterns associated with different lubrication regimes, wear conditions, and material interactions [100].

Acoustic signals have been widely shown to be sensitive to changes in lubrication regimes and can therefore be used to classify boundary, mixed, and hydrodynamic lubrication conditions. In journal bearing systems, acoustic emission features extracted from time–frequency representations were combined with artificial neural networks and genetic algorithm-based feature optimization to classify lubrication regimes under varying loads, speeds, and lubricant viscosities, demonstrating that lubrication state information is intrinsically encoded in acoustic responses [51], as shown in Fig. 6(a).

Beyond lubrication regimes, acoustic and machine learning approaches have also been applied to classify lubricant-related conditions and variations in lubricant composition. Changes in lubricant properties, such as contamination-induced viscosity variation or differences in formulation, alter oil film shear behavior and interfacial dynamics, which are reflected in acoustic signatures. Recent studies have demonstrated that acoustic emission signals, combined with advanced feature extraction and deep learning models, can be used to classify lubricant condition states, including contamination levels and lubrication degradation, with high reliability [101], as shown in Fig. 6(b). In addition,

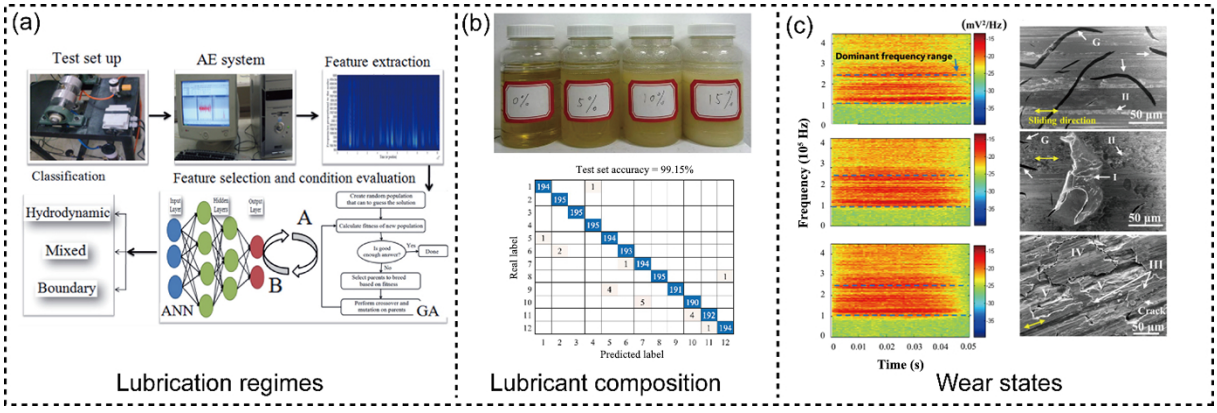


Fig. 6 Identification of lubrication regimes, lubricant-related conditions, and tribological state transitions from acoustic signatures. (a) Acoustic emission-based classification of lubrication regimes using supervised learning. (b) Acoustic machine learning classification of lubricant composition and condition variations. (c) Machine learning-based identification of scuffing-related tribological states from acoustic signatures. Reproduced with permission from Ref. [51] for (a), © Elsevier Ltd. 2015; from Ref. [101] for (b), © The Author(s) 2025; from Ref. [102] for (c), © Elsevier Ltd. 2015.

friction-induced acoustic signals have been exploited to distinguish lubrication-related contact conditions associated with different surface textures and lubrication environments, highlighting the capability of acoustic-based classification to capture lubricant- and formulation-related variations beyond purely mechanical regimes [102].

Acoustic signatures combined with machine learning have also been widely used for classifying wear-related states and contact conditions in tribological systems. In controlled sliding experiments, supervised learning models based on acoustic emission features successfully identified different tribological states associated with scuffing progression, indicating that wear-related interfacial processes can generate distinctive acoustic fingerprints suitable for classification tasks [102, 103], as shown in Fig. 6(c). These classification strategies have been further extended to more complex systems, such as bearings and joint-like contacts, where acoustic-based models were used to differentiate healthy, degraded, and damaged states or to identify spatially distinct wear regions under realistic operating conditions, confirming the applicability of acoustic AI classification frameworks to practical tribological interfaces [104, 105].

Collectively, these studies demonstrate that acoustic signals combined with machine learning enable reliable classification of lubrication regimes, lubricant-related conditions, and wear states across diverse tribological systems. This classification capability provides a foundation for stage-aware and transition-sensitive modeling, where the temporal evolution and interaction between identified states become the primary focus.

3.2.2 Stage-aware and transition-sensitive modeling

While static classification captures discrete snapshots of tribological conditions, many friction and wear processes evolve through identifiable stages characterized by both gradual transitions and abrupt changes. Because acoustic signals are inherently time-resolved and highly sensitive to interfacial dynamics, they provide a natural basis for stage-aware and transition-sensitive modeling of tribological processes.

Early studies established the physical foundation for stage-level interpretation by directly linking acoustic responses to contact state transitions. Fantetti et al. [106] demonstrated that ultrasonic reflections vary systematically within a single vibration cycle, enabling clear discrimination between stick, microslip, and gross slip regimes in metallic friction joints. By synchronizing ultrasonic measurements with friction hysteresis loops, their results revealed that acoustic signals capture transient contact stiffness variations associated with stick-slip transitions, providing physically interpretable markers of contact stages rather than average friction states, as illustrated in Fig. 7(a).

Building on this physical insight, learning-based approaches have been developed to segment and identify tribological stages from long-duration acoustic measurements. In run-to-failure experiments, sequence-based clustering and stage-aware classification methods have been applied to acoustic emission data to distinguish successive phases such as running-in, stable operation, and accelerated degradation. These approaches exploit temporal patterns in acoustic energy and spectral evolution to track contact progression without dense manual labeling, enabling automated identification of stage transitions over extended operating periods, as shown in Fig. 7(b) [107].

Further advances have incorporated explicit temporal modeling to enhance sensitivity to stage transitions. By combining waveform similarity analysis with learning-based segmentation, acoustic data can be partitioned into coherent stages that reflect evolving damage mechanisms and lubrication breakdown. Such methods are particularly effective in identifying emerging transitions during long-term operation, where wear develops gradually and changes in acoustic characteristics are subtle, as demonstrated in Fig. 7(c) [108].

More advanced strategies further integrate physical insight into acoustic analysis to improve robustness and interpretability. Rather than relying solely on conventional signal descriptors, these approaches exploit nonlinear acoustic responses arising from interfacial contact conditions to extract physically meaningful information. Recent studies have shown that contact acoustic nonlinearity under vibro-acoustic modulation can generate characteristic nonlinear features that are sensitive to interfacial state changes. By establishing a clearer link between nonlinear wave interaction mechanisms and measurable acoustic responses, such methods provide a physically grounded complement to data-driven identification, as illustrated in Fig. 7(d) [109].

Overall, stage-aware and transition-sensitive modeling enables acoustic signatures to be interpreted in a temporally structured manner, capturing both discrete states and their evolution during tribological processes. Section 3.3 further examines physics-guided and interpretable considerations within such learning-based frameworks.

3.3 Physics-guided and interpretable modeling considerations

Physics-guided modeling has emerged as a key strategy for

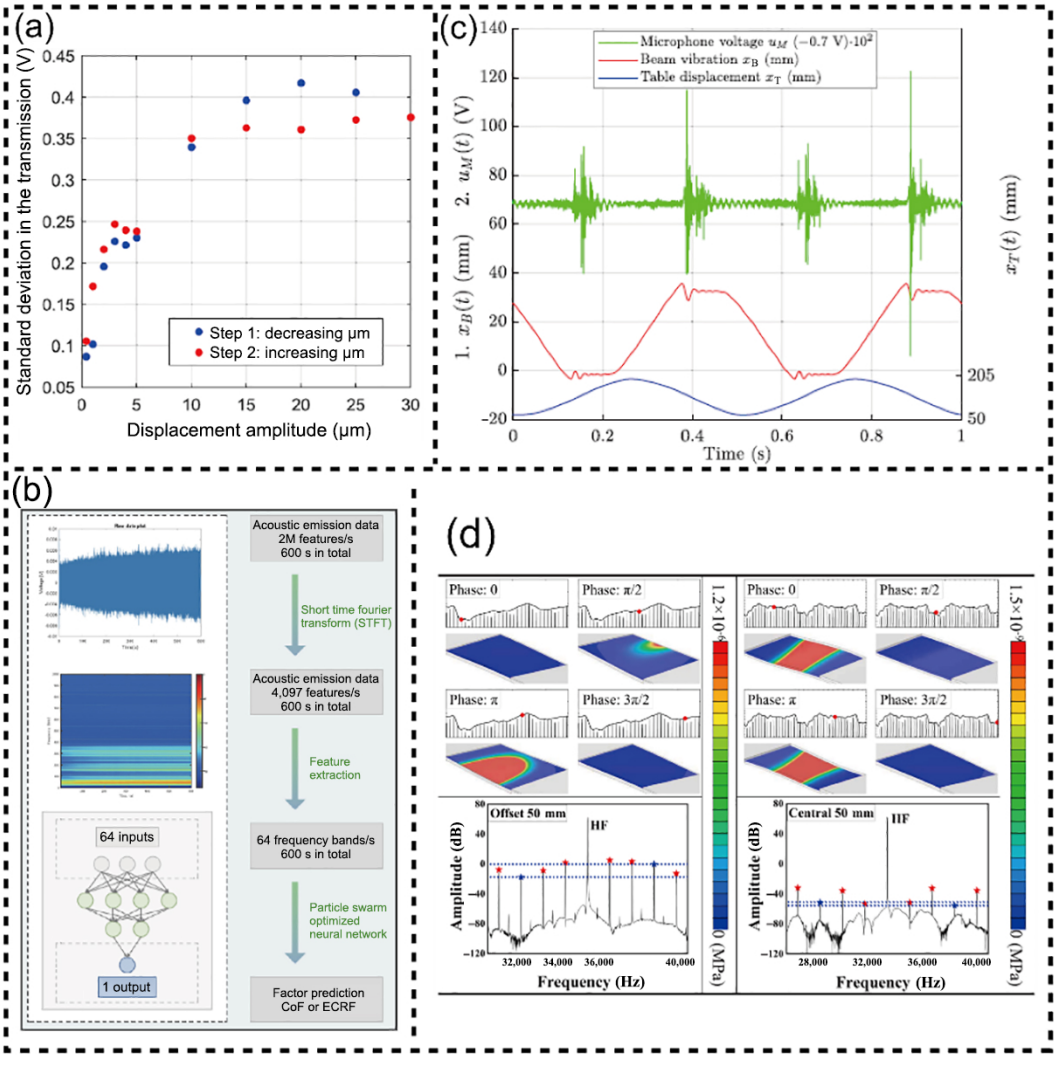


Fig. 7 Stage-aware and transition-sensitive identification of tribological processes using acoustic data. (a) Ultrasonic identification of stick-slip transitions within a single vibration cycle, illustrating stage-dependent acoustic variability. (b) Stage-aware acoustic emission and machine learning framework for joint identification of tribological stages and lubricant conditions. (c) Acoustic signatures associated with frictional instabilities and stick-slip transitions, highlighting transition-sensitive spectral characteristics. (d) Physics-based analysis of contact acoustic nonlinearity using vibro-acoustic modulation, highlighting nonlinear responses induced by interfacial contact conditions. Reproduced with permission from Ref. [106] for (a), © The Author(s) 2021; from Ref. [107] for (b), © Elsevier Ltd. 2025; from Ref. [108] for (c), © The Author(s) 2025; from Ref. [109] for (d), © Elsevier Ltd. 2021.

improving the generalization of acoustic and AI-based tribological monitoring across varying operating conditions. Instead of learning arbitrary input–output mappings, these approaches embed physical knowledge of wave propagation, contact mechanics, and lubrication behavior into the representation or learning process. By constraining feature extraction, network structure, or optimization objectives using physically meaningful quantities, acoustic learning models can focus on signaling components that are intrinsically linked to frictional interactions and interfacial dynamics [110, 111]. As a result, such models are less sensitive to changes in load, speed, sensor placement, or lubrication environment, enabling more reliable predictions beyond the specific conditions seen during training.

Importantly, physics-guided acoustic AI models are not purely black-box systems but retain interpretability at different levels of analysis. Physical insight can be incorporated through physics-informed features, structured model architectures, or hybrid learning frameworks that explicitly relate acoustic responses to contact stiffness, oil film behavior, or damage evolution. This integration allows learned representations to be interpreted in terms of known tribological mechanisms, facilitating diagnostic trust and model validation [112]. Moreover, when data availability is limited or operating conditions deviate from laboratory settings, physics-guided learning provides a principled way to maintain predictive stability while preserving sensitivity to meaningful acoustic signatures [113].

Overall, the combination of acoustic sensing, artificial intelligence, and physical knowledge enables tribological monitoring models that are both generalizable and interpretable. By bridging data-driven learning with physics-based understanding, these approaches provide a robust foundation for reliable decision-making in complex and evolving tribological systems.

4 Application of AI-enabled acoustic sensing in frictional systems

Sections 2 and 3 focus on acoustic sensing principles and data-driven modeling for friction and lubrication monitoring, primarily under controlled laboratory conditions. Building on these methodological foundations, acoustic sensing combined with learning-based analysis has increasingly been translated into *in*

situ engineering applications, where frictional interfaces are monitored directly within operating mechanical systems. In contrast to *ex situ* studies conducted under simplified or controlled environments, *in situ* applications address real-time monitoring in complex and often inaccessible systems.

This section therefore reviews representative *in situ* applications of acoustic-based monitoring in frictional systems, covering automotive components, energy-related equipment, heavy duty machinery, and sealed or inaccessible interfaces operating under practical service conditions.

4.1 Automotive and transportation systems under variable friction and lubrication conditions

Automotive and transportation systems comprise multiple tribological interfaces, including gears, bearings, engines, and tire–road contacts, which operate under highly variable loads, speeds, and lubrication conditions. Monitoring friction and lubrication in these systems is challenging due to limited accessibility and continuously changing operating environments, motivating the use of nonintrusive acoustic sensing combined with data-driven analysis.

Acoustic sensing has been widely applied to bearings and engine-related components, where lubrication regime transitions play a critical role in friction and wear evolution. In both sliding and rolling bearings, changes from hydrodynamic to mixed or boundary lubrication are accompanied by distinct variations in acoustic signatures [60]. Studies have demonstrated that acoustic emission and ultrasonic sensing, together with machine learning models, enable the identification of insufficient lubrication, wear progression, and surface damage under variable speed and load conditions. Importantly, recent work has shown that lubrication-related information can be extracted even using low-cost acoustic sensors when appropriate feature extraction and learning strategies are employed, highlighting the potential for practical deployment in automotive systems [114, 115], as shown in Fig. 8(a).

Beyond bearings and engine-related components, acoustic sensing has also shown strong potential in transmission systems such as gearboxes and automotive drivetrains, where frictional degradation and lubrication failure can lead to rapid fault development and severe secondary damage. Recent studies have shown that acoustic emission signals are highly sensitive to gear meshing conditions, surface damage, and fault severity in gearbox systems [116]. By extracting nonlinear acoustic features and applying machine learning classifiers, different fault types and severity levels can be reliably identified even under complex operating conditions [117, 118], as shown in Fig. 8(b). These results indicate that acoustic sensing combined with data-driven methods can capture early-stage friction and wear signatures that are difficult to detect using conventional vibration-based approaches.

At the vehicle and infrastructure level, friction-induced acoustic phenomena are also central to tire–road interactions and traffic monitoring. Tire–road noise is strongly influenced by surface texture, frictional properties, and environmental conditions, making it a valuable indirect indicator of road conditions and vehicle dynamics. Data-driven studies have demonstrated that acoustic features combined with machine learning can be used to classify road surface states, assess driving conditions, and estimate vehicle speed using passive acoustic measurements [119, 120], as shown in Fig. 8(c). These approaches extend acoustic tribological monitoring from component-level applications to system-level transportation sensing.

Overall, existing studies demonstrate that AI-enabled acoustic sensing provides an effective and nonintrusive framework for monitoring friction, lubrication, and wear across complex mechanical systems operating under variable and demanding conditions [121]. The remaining challenges related to robustness, long-term stability, and transferability motivate further investigation of acoustic-AI monitoring in larger-scale and more severe operating environments.

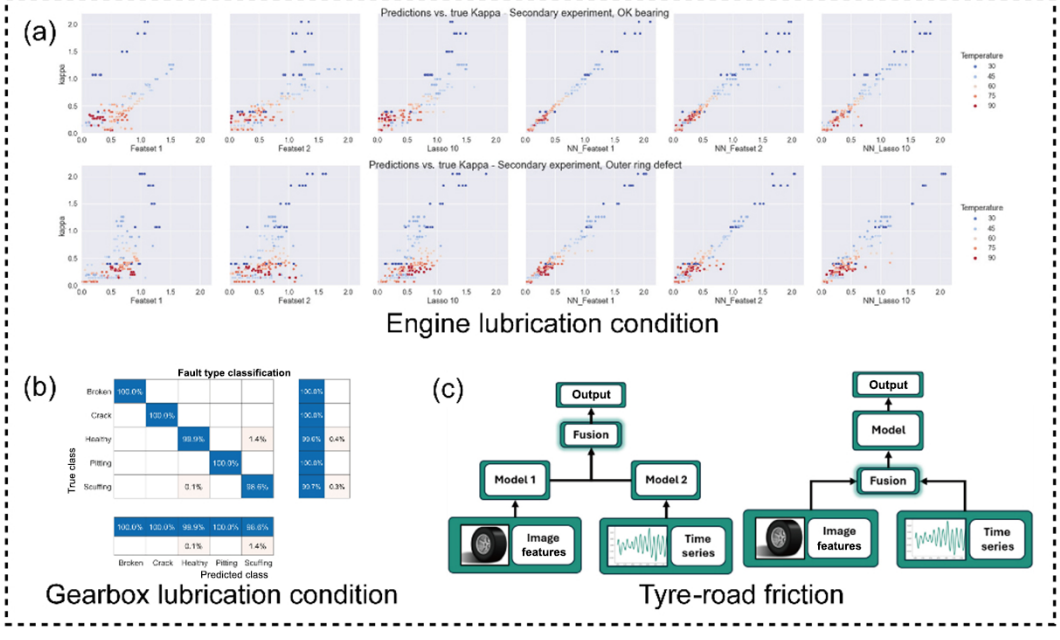


Fig. 8 AI-enabled acoustic monitoring of friction and lubrication in automotive and transportation systems. (a) Acoustic-based assessment of engine lubrication conditions. (b) Acoustic monitoring of gearbox lubrication conditions. (c) Acoustic characterization of tire–road friction during vehicle operation. Reproduced with permission from Ref. [114] for (a), © The Author(s) 2025; from Ref. [118] for (b), © The Author(s) 2024; from Ref. [119] for (c), © The Author(s) 2025.

清華大学出版社 Tsinghua University Press | SciOpen

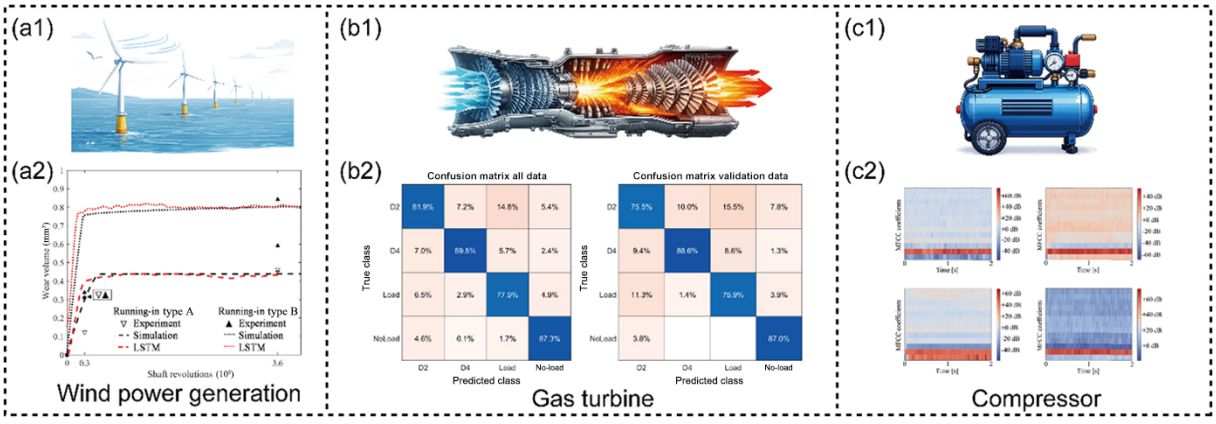


Fig. 9 Acoustic sensing and data-driven assessment of frictional degradation in energy and power generation equipment. (a1, a2) Schematic illustration of a wind turbine system and corresponding acoustic-based evaluation of frictional evolution, including variation of friction-related indicators with shaft revolutions and comparison among experimental results, simulation, and long short-term memory (LSTM) prediction under different running-in conditions. (b1, b2) Schematic illustration of a gas turbine system and corresponding data-driven condition classification results, showing confusion matrices for all data and validation data under different operating states. (c1, c2) Schematic illustration of a compressor system and corresponding acoustic feature maps under different operating regimes for condition characterization. Reproduced with permission from Ref. [94] for (a1, a2), © Elsevier B.V. 2021; from Ref. [126] for (b1, b2), © The Author(s) 2023; from Ref. [128] for (c1, c2), © The Authors 2025.

4.2 Energy and power generation equipment with long-term frictional degradation

Energy and power generation equipment, including wind turbines, gas turbines, and compressors, typically operate under continuous or cyclic loading over long service lifetimes, during which frictional degradation and lubrication deterioration accumulate gradually. Failures in such large-scale assets are often associated with slow damage evolution and high maintenance costs, making early and reliable condition monitoring essential for safe and economical operation [122].

In wind energy systems, tribological degradation frequently occurs in long-life drivetrain components such as gearboxes and bearings [94]. Acoustic emission techniques have been widely investigated for detecting bearing faults and lubrication-related damage in wind turbine drivetrains, where early-stage frictional events generate high-frequency acoustic signatures before macroscopic failures develop [123]. In addition to drivetrain components, acoustic emission monitoring has also been applied to fatigue damage detection in wind turbine blades, enabling the identification and localization of crack initiation and propagation under realistic cyclic loading conditions [124]. These studies demonstrate the suitability of acoustic sensing for capturing long-term frictional and fatigue-induced degradation in wind energy equipment, as shown in Fig. 9(a).

Gas turbines represent another important class of energy equipment in which frictional degradation, wear, and lubrication-related faults develop under extreme thermal and mechanical conditions. Acoustic emission-based monitoring frameworks have been proposed to characterize turbine health states and detect incipient faults associated with bearings, seals, blade rubbing, and fluid-induced instabilities [125]. By combining signal processing techniques with machine learning and deep learning models, reliable classification of turbine operating conditions has been achieved across different loads and rotational speeds [126], as shown in Fig. 9(b). Compared with conventional vibration-based approaches, acoustic emission signals show enhanced sensitivity to localized frictional events.

Acoustic sensing has also been extensively explored for long-term condition monitoring of compressors used in the power and process industries. Frictional degradation in compressor valves, bearings, and sliding interfaces can significantly affect efficiency and reliability over extended operation periods [127]. Studies using acoustic emission or airborne acoustic signals combined with data-driven methods have demonstrated effective fault detection and condition classification, even in noise-intensive industrial environments [128], as shown in Fig. 9(c). These results highlight the practicality of acoustic-based monitoring for energy equipment with limited accessibility to internal components.

Overall, existing studies indicate that AI-enabled acoustic monitoring provides an effective and nonintrusive approach for tracking long-term frictional degradation and lubrication-related damage in energy and power generation equipment. Such approaches offer strong potential for early fault detection, reduced maintenance costs, and improved reliability in large-scale energy systems.

4.3 Heavy-duty and off-highway machinery operating in severe frictional environments

Heavy-duty and off-highway machinery, such as construction, mining, and tunneling equipment, typically operates under extreme loads, harsh environments, and long duty cycles, where severe frictional interactions and lubrication degradation accelerate wear and increase failure risks [46, 129]. Reliable condition monitoring is therefore essential for ensuring safe operation and minimizing costly downtime.

In hydraulic systems widely used in heavy-duty machinery, frictional degradation occurs in pumps, valves, cylinders, seals, and bearings under high pressure and cyclic loading [130]. Wear and degradation of hydraulic seals can lead to internal leakage, efficiency loss, and unstable motion in hydraulic cylinder systems, thereby motivating the use of acoustic-based condition monitoring for seal integrity assessment [131], as shown in Fig. 10(a). Acoustic emission-based monitoring has been shown to be sensitive to friction-induced microevents associated with seal wear, bearing damage, and internal leakage, enabling early identification of lubrication deterioration in complex hydraulic circuits [132]. While acoustic emission dominates current *in situ* applications, ultrasonic techniques have also been explored in localized inspections of hydraulic components, although their deployment is often constrained by coupling conditions and signal attenuation in large-scale systems.

Tunnel boring machines represent a typical class of off-highway equipment exposed to extreme frictional and abrasive

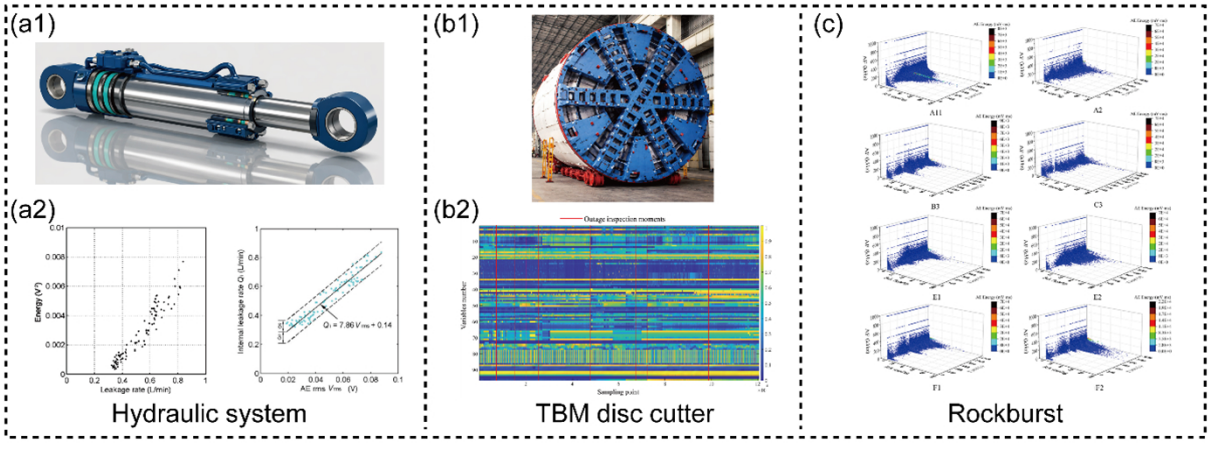


Fig. 10 Condition monitoring of heavy-duty and off-highway machinery using acoustic and learning-based approaches. (a1, a2) Schematic illustration of a hydraulic cylinder system and corresponding acoustic emission-based condition assessment results for seal integrity monitoring. (b1, b2) Schematic illustration of a tunnel boring machine and corresponding time-resolved acoustic feature map for operational state characterization. (c) Acoustic characterization results under multiple operating conditions, showing variation of time–frequency or feature distributions across different machinery states. Reproduced with permission from Ref. [131] for (a1, a2), © Elsevier Ltd. 2005; from Ref. [134] for (b1, b2), © Elsevier Ltd. 2025; from Ref. [136] for (c), © Institute of Rock and Soil Mechanics, Chinese Academy of Sciences 2013.

environments. During excavation, disc cutters experience continuous contact with heterogeneous rock masses, leading to progressive and sometimes anomalous wear [133]. Acoustic and vibration-based monitoring combined with machine learning has been applied to estimate cutter wear levels and detect abnormal wear patterns in real time, providing effective support for cutter replacement decisions and excavation efficiency optimization [134], as shown in Fig. 10(b). In contrast, ultrasonic and guided wave methods remain largely limited to off-line or component-level assessments in such applications due to the difficulty of establishing stable wave propagation paths under highly variable contact and loading conditions.

Beyond component-level degradation, severe frictional environments in heavy-duty operations are often coupled with strong interactions between machinery and surrounding geological media. Acoustic emission monitoring has been extensively used to investigate damage evolution and microcrack activity in surrounding rock during tunneling processes [135]. Studies on rock burst events and rock failure under extreme dynamic disturbance further demonstrate that acoustic signals can reveal progressive stress redistribution and damage accumulation in rock masses [136], as shown in Fig. 10(c). These investigations extend acoustic monitoring from machinery itself to machine-environment interfaces, where direct ultrasonic interrogation is often impractical under *in situ* conditions.

Overall, existing studies indicate that AI-enabled acoustic monitoring provides a practical and nonintrusive approach for assessing frictional degradation in heavy-duty and off-highway machinery operating under severe conditions [137]. While current industrial implementations are largely dominated by acoustic emission techniques, ultrasonic and guided wave methods offer promising complementary capabilities for future multiscale and multimodal monitoring frameworks as sensor robustness and signal interpretation strategies continue to advance.

4.4 Sealed and inaccessible frictional interfaces requiring *in situ* acoustic-AI monitoring

Many tribological interfaces are sealed or inaccessible during operation, preventing direct measurement of friction and lubrication states and motivating the use of acoustic sensing combined with artificial intelligence for *in situ* condition monitoring.

Sealed lubricated friction interfaces in enclosed components, such as bearings, seals, and confined lubricant films, constitute a primary class of inaccessible tribological systems. Ultrasonic reflectometry has been extensively investigated as an *in situ* characterization technique for such interfaces, enabling the monitoring of lubricant film thickness, viscosity, and contact stiffness through reflected wave responses [138]. In addition, guided ultrasonic wave techniques originally developed for structural health monitoring offer a complementary means to interrogate hidden lubricated interfaces over extended distances without direct access to the contact region [139].

Due to complex wave propagation paths and strong structural coupling, machine learning methods have been increasingly introduced to assist in interpreting ultrasonic and guided wave signals, enabling AI-assisted identification and classification of lubrication states in sealed components [140], as shown in Fig. 11(a).

Enclosed friction joints and sealed contact interfaces represent another major category of inaccessible tribological systems. These interfaces are governed by partial contact, microslip, and stick-slip transitions, leading to pronounced nonlinear frictional behavior. Fundamental studies on frictional contact nonlinearity have demonstrated that ultrasonic shear waves and nonlinear ultrasonic techniques are highly sensitive to changes in contact stiffness and friction state [141, 142]. In practical scenarios, the acoustic signatures generated by enclosed friction joints are indirect and high-dimensional, and their interpretation often relies on data-driven analysis. Machine learning has therefore been employed to distinguish contact states and friction regimes from nonlinear acoustic features, providing robust AI-assisted interpretation for sealed friction joints [143].

Beyond qualitative assessment, many sealed frictional interfaces require quantitative prediction of friction states and parameters during operation. Acoustic emission and friction sound signals acquired from enclosed interfaces have been combined with machine learning techniques to classify operating conditions and capture friction fluctuations [144, 145]. More recently, deep learning models have demonstrated strong capability in predicting coefficients of friction directly from friction sound, enabling real-time parameter estimation for sealed and inaccessible friction interfaces [146], as shown in Fig. 11(b).

Overall, acoustic AI monitoring enables both qualitative assessment and quantitative inference of friction and lubrication

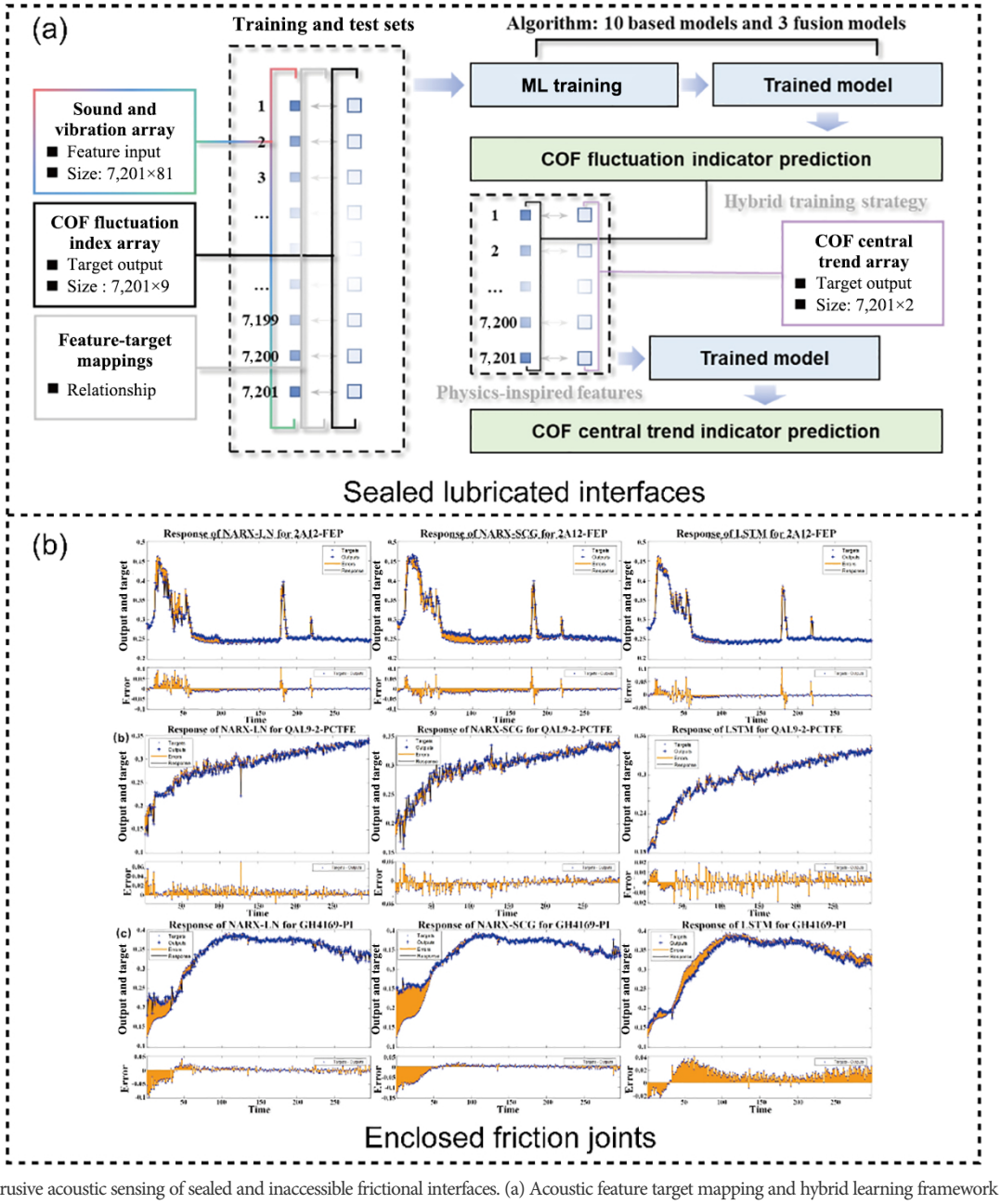


Fig. 11 Nonintrusive acoustic sensing of sealed and inaccessible frictional interfaces. (a) Acoustic feature target mapping and hybrid learning framework for predicting friction indicators from vibration and sound arrays. (b) Learning-based prediction of coefficient of friction evolution under different operating conditions using acoustic sensing. Reproduced with permission from Ref. [140] for (a), © Elsevier Ltd. 2025; from Ref. [146] for (b), © Elsevier Ltd. 2023.

states in sealed and inaccessible interfaces where direct measurement is not feasible.

5 Conclusions and outlook

This review summarizes recent progress in integrating acoustic sensing and artificial intelligence for the tribological monitoring of frictional and lubricated systems. AE, GW, and UR techniques provide nonintrusive access to interfacial dynamics across multiple spatial and temporal scales, enabling quantitative inference of friction evolution, lubricant film thickness, wear progression, and contact-state transitions. By introducing learning-based modeling, complex acoustic responses can be systematically mapped to tribological parameters and states, extending acoustic diagnostics from empirical signal interpretation toward data-informed physical characterization. Applications in engines, gearboxes, bearings, and other sealed frictional systems demonstrate the scalability and engineering relevance of AI-enabled acoustic sensing.

5.1 Challenges and limitations

Despite significant progress, AI-enabled acoustic tribological monitoring still faces several fundamental challenges:

(1) Multiscale and multiphysics coupling

Acoustic responses arise from tightly coupled mechanisms, including asperity contact, lubricant rheology, structural wave propagation, and material evolution. This multiscale complexity limits the transferability of purely data-driven models and complicates the isolation of dominant physical contributors.

(2) Limited labeled data and domain shift

Reliable ground-truth labels representing true lubrication regimes or wear states are scarce. Moreover, substantial domain

shifts exist between controlled laboratory experiments and in-service industrial systems, hindering model generalization across materials, geometries, and operating conditions.

(3) Model interpretability and reliability

Black-box learning frameworks often lack physical transparency, which raises concerns for industrial adoption. Prediction accuracy is strongly dependent on sensor quality, signal-to-noise ratio, and installation consistency, making robustness assessment essential.

(4) Insufficient integration of physical priors

While AE signals are highly sensitive to frictional events, GW and UR techniques are supported by well-established dispersion and reflection theories. Current AI implementations rarely embed these physical constraints systematically, resulting in models that may perform well empirically but lack mechanistic grounding.

5.2 Future perspectives

To advance the field toward scalable and physically grounded intelligent monitoring, future research should emphasize the following directions:

(1) Multimodal sensor fusion

The lubrication state cannot typically be captured by a single sensing modality. AI enables the integration of acoustic, vibration, temperature, chemical, and electrical signals, enhancing robustness against sensor noise and improving cross-condition generalization in engines, gearboxes, bearings, and piston-liner systems.

(2) Physics-informed learning frameworks

Embedding contact mechanics, lubrication theory, and wave–interface interaction principles into model architectures or loss functions can improve interpretability, reduce overfitting, and enhance transferability. GW and UR methods are particularly suitable due to their strong theoretical foundations.

(3) Uncertainty-aware and reliable inference

Industrial deployment requires quantified prediction confidence. Bayesian learning, ensemble methods, and probabilistic modeling should be incorporated to evaluate uncertainty under variable operating regimes and sensor degradation.

(4) Edge deployment and real-time scalability

Lightweight model architectures and on-device inference strategies are necessary for real-time monitoring in harsh environments. Integrating deployable AI with robust sensing hardware will facilitate practical adoption in large-scale engineering systems.

Declaration of competing interest

The authors have no competing interests to declare that are relevant to the content of this article.

References

[1] Holmberg K, Andersson P, Erdemir A. Global energy consumption due to friction in passenger cars. *Tribol Int* **47**: 221–234 (2012)

[2] Holmberg K, Kivikytö-Reponen P, Härkisaari P, Valtonen K, Erdemir A. Global energy consumption due to friction and wear in the mining industry. *Tribol Int* **115**: 116–139 (2017)

[3] Holmberg K, Erdemir A. Influence of tribology on global energy consumption, costs and emissions. *Friction* **5**(3): 263–284 (2017)

[4] Xie Z L, Shen N W, Zhu W D, Tian W C, Hao L. Theoretical and experimental investigation on the influences of misalignment on the lubrication performances and lubrication regimes transition of water lubricated bearing. *Mech Syst Signal Pr* **149**: 107211 (2021)

[5] Wen X L, Gong P, Dong X, Wang A L, Jiang Y Y, Wang X, Yuan N Y, Li L Z, Tian Y, Ding J N. Friction and corrosion properties of water–glycol fire-retardant hydraulic fluids (HFCs) and their modifications. *Friction* **14**(9): 9441199 (2026)

[6] Yin N, Yang P F, Liu S K, Pan S H, Zhang Z N. AI for tribology: Present and future. *Friction* **12**(6): 1060–1097 (2024)

[7] Williams J A, Hyncica A M. Mechanisms of abrasive wear in lubricated contacts. *Wear* **152**(1): 57–74 (1992)

[8] Chang Z, Jia Q, Yuan X, Chen Y L. Main failure mode of oil-air lubricated rolling bearing installed in high speed machining. *Tribol Int* **112**: 68–74 (2017)

[9] Malla C, Panigrahi I. Review of condition monitoring of rolling element bearing using vibration analysis and other techniques. *J Vib Eng Technol* **7**(4): 407–414 (2019)

[10] Jardine A K S, Lin D M, Banjevic D. A review on machinery diagnostics and prognostics implementing condition-based maintenance. *Mech Syst Signal Pr* **20**(7): 1483–1510 (2006)

[11] Vishwakarma M, Purohit R, Harshlata V, Rajput P. Vibration analysis & condition monitoring for rotating machines: A review. *Mater Today Proc* **4**(2): 2659–2664 (2017)

[12] Song L Y, Wang H Q, Chen P. Vibration-based intelligent fault diagnosis for roller bearings in low-speed rotating machinery. *IEEE T Instrum Meas* **67**(8): 1887–1899 (2018)

[13] Rosenkranz A, Martin B, Bettscheider S, Gachot C, Kliem H, Mücklich F. Correlation between solid–solid contact ratios and lubrication regimes measured by a refined electrical resistivity circuit. *Wear* **320**: 51–61 (2014)

[14] Lee P, Zhmud B. Low friction powertrains: Current advances in lubricants and coatings. *Lubricants* **9**(8): 74 (2021)

[15] Tung S C, McMillan M L. Automotive tribology overview of current advances and challenges for the future. *Tribol Int* **37**(7): 517–536 (2004)

[16] Rigas N, Merklein M. Characterization of the tribological behavior of different tool coatings and dry lubricant for high-strength aluminum alloys at elevated temperatures. *Adv Eng Mater* **25**(15): 2201650 (2023)

[17] Volchenko D, Kernytskyy I, Royko Y, Ostashuk M, Fidrovska N, Skrypnyk V, Zhuravlev D, Klochko N, Rys V, Berezovetska O, et al. Optimization of metal polymer friction pair composition for hydrogen wear reduction through thermal stabilization analysis. *Sci Rep* **15**: 3265 (2025)

[18] Peng B, Spikes H, Kadiric A. The development and application of a scuffing test based on contra-rotation. *Tribol Lett* **67**(2): 37 (2019)

[19] Yadav E, Chawla V K. An explicit literature review on bearing materials and their defect detection techniques. *Mater Today Proc* **50**: 1637–1643 (2022)

[20] Dasgupta A, Pecht M. Material failure mechanisms and damage models. *IEEE T Reliab* **40**(5): 531–536 (1991)

[21] Korba P, Huňady R, Hovanec M, Rácek B, Pavelka P. Fatigue life analysis of an aircraft brake component to prevent damage and ensure operational safety. *Eng Fail Anal* **129**: 105653 (2021)

[22] Lampaert V, Al-Bender F, Swevers J. Experimental characterization of dry friction at low velocities on a developed tribometer setup for macroscopic measurements. *Tribol Lett* **16**(1–2): 95–105 (2004)

[23] Yang S, Love T, Dini D, Reddyhoff T, Yu M. Simultaneous measurements of friction and fluid film thickness distribution of reciprocating rubber seals. *Tribol Int* **213**: 110981 (2026)

[24] Vladescu S C, Olver A V, Pegg I G, Reddyhoff T. The effects of surface texture in reciprocating contacts–An experimental study. *Tribol Int* **82**: 28–42 (2015)

[25] Yu M, Zhang J, Joedicke A, Booth J, Reddyhoff T. Using electrical impedance spectroscopy to identify equivalent circuit models of lubricated contacts with complex geometry: *in-situ* application to mini traction machine. *Tribol Int* **192**: 109286 (2024)

[26] Jia Y P, Chang S Y, Xia Y G, Wu T H, Yang P P, Dou P, Yu M. Ultrasonic reflection-based transient temperature gradient inversion for compensating oil film thickness measurement. *Mech Syst Signal Pr* **234**: 112827 (2025)

[27] Rastegaev I, Merson D, Rastegaeva I, Vinogradov A. A time-frequency based approach for acoustic emission assessment of sliding wear. *Lubricants* **8**(5): 52 (2020)

[28] Geng Z, Puhan D, Yu M, Zhang J, Reddyhoff T. Acoustic emission

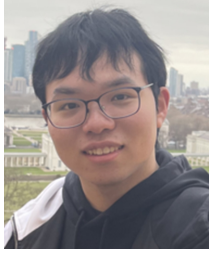
monitoring of lubricant additive behavior in sliding contacts. *Friction* **14**(2): 9441128 (2026)
[29] Geng Z, Puhan D, Reddyhoff T. Using acoustic emission to characterize friction and wear in dry sliding steel contacts. *Tribol Int* **134**: 394–407 (2019)
[30] Hou G, Zhang L C. *In-situ* detection of lubrication status of bearings with acoustic emission monitoring. *Wear* **571**: 205839 (2025)
[31] Miettinen J, Andersson P. Acoustic emission of rolling bearings lubricated with contaminated grease. *Tribol Int* **33**(11): 777–787 (2000)
[32] Dou P, Jia Y P, Zheng P, Wu T H, Yu M, Reddyhoff T, Peng Z X. Review of ultrasonic-based technology for oil film thickness measurement in lubrication. *Tribol Int* **165**: 107290 (2022)
[33] Dou P, Jia Y P, Wu T H, Peng Z X, Yu M, Reddyhoff T. High-accuracy incident signal reconstruction for *in-situ* ultrasonic measurement of oil film thickness. *Mech Syst Signal Pr* **156**: 107669 (2021)
[34] Du F, Li B T, Zhang J, Zhu Q M, Hong J. Ultrasonic measurement of contact stiffness and pressure distribution on spindle–holder taper interfaces. *Int J Mach Tool Manu* **97**: 18–28 (2015)
[35] Taghizadeh S, Ghadbeigi H. A comparative study of *in-situ* wear characterisation in reciprocating tribological contact using ultrasound. *Wear* **570**: 206033 (2025)
[36] Widodo A, Yang B S. Support vector machine in machine condition monitoring and fault diagnosis. *Mech Syst Signal Pr* **21**(6): 2560–2574 (2007)
[37] Cen J, Yang Z H, Liu X, Xiong J B, Chen H H. A review of data-driven machinery fault diagnosis using machine learning algorithms. *J Vib Eng Technol* **10**(7): 2481–2507 (2022)
[38] Tama B A, Vania M, Lee S, Lim S. Recent advances in the application of deep learning for fault diagnosis of rotating machinery using vibration signals. *Artif Intell Rev* **56**(5): 4667–4709 (2023)
[39] Wang H, Xu J W, Sun C, Yan R Q, Chen X F. Intelligent fault diagnosis for planetary gearbox using time-frequency representation and deep reinforcement learning. *IEEE—ASME T Mech* **27**(2): 985–998 (2022)
[40] Sose A T, Joshi S Y, Kunche L K, Wang F X, Deshmukh S A. A review of recent advances and applications of machine learning in tribology. *Phys Chem Chem Phys* **25**(6): 4408–4443 (2023)
[41] Shah R, Jaramillo R, Thomas G, Rayhan T, Hossain N, Kchaou M, Profito F J, Rosenkranz A. Artificial intelligence and machine learning in tribology: Selected case studies and overall potential. *Adv Eng Mater* **27**(23): 2401944 (2025)
[42] Yin N, Xing Z G, He K, Zhang Z N. Tribo-informatics approaches in tribology research: A review. *Friction* **11**(1): 1–22 (2023)
[43] Benabdallah H S, Aguilar D A. Acoustic emission and its relationship with friction and wear for sliding contact. *Tribol T* **51**(6): 738–747 (2008)
[44] Rastegaev I A, Merson D L, Danyuk A V, Afanasyev M A, Vinogradov A. Using acoustic emission signal categorization for reconstruction of wear development timeline in tribosystems: Case studies and application examples. *Wear* **410**: 83–92 (2018)
[45] Schubert F, Schechinger B. Numerical modeling of acoustic emission sources and wave propagation in concrete. *J Nondestruct Test* **7**(9): 1–8 (2002)
[46] Shanbhag V V, Meyer T J J, Caspers L W, Schlanbusch R. Defining acoustic emission-based condition monitoring indicators for monitoring piston rod seal and bearing wear in hydraulic cylinders. *Int J Adv Manuf Tech* **115**(9–10): 2729–2746 (2021)
[47] Ma J J, Zhang H, Shi Z Q, Chu F L, Gu F S, Ball A D. Modelling Acoustic Emissions induced by dynamic fluid-asperity shearing in hydrodynamic lubrication regime. *Tribol Int* **153**: 106590 (2021)
[48] Scheeren B, Kaminski M L, Pahlavan L. Acoustic emission monitoring of naturally developed damage in large-scale low-speed roller bearings. *Struct Health Monit* **23**(1): 360–382 (2024)
[49] Baccar D, Söffker D. Wear detection by means of wavelet-based acoustic emission analysis. *Mech Syst Signal Pr* **60**: 198–207 (2015)
[50] Rahman M Z, Ohba H, Yamamoto T, Yoshioka T. A study on incipient damage monitoring in rolling contact fatigue process using acoustic emission. *Tribol T* **51**(5): 543–551 (2008)
[51] Sadegh H, Mehdi A N, Mehdi A. Classification of acoustic emission signals generated from journal bearing at different lubrication conditions based on wavelet analysis in combination with artificial neural network and genetic algorithm. *Tribol Int* **95**: 426–434 (2016)
[52] Fan Y B, Gu F S, Ball A. Modelling acoustic emissions generated by sliding friction. *Wear* **268**(5–6): 811–815 (2010)
[53] Liu Z P, Wang X F, Zhang L. Fault diagnosis of industrial wind turbine blade bearing using acoustic emission analysis. *IEEE T Instrum Meas* **69**(9): 6630–6639 (2020)
[54] Hutt S, Clarke A, Evans H P. Generation of Acoustic Emission from the running-in and subsequent micropitting of a mixed-elastohydrodynamic contact. *Tribol Int* **119**: 270–280 (2018)
[55] Borghesani P, Smith W A, Zhang X, Feng P, Antoni J, Peng Z. A new statistical model for acoustic emission signals generated from sliding contact in machine elements. *Tribol Int* **127**: 412–419 (2018)
[56] Ferrando Chacon J L, Kappatos V, Balachandran W, Gan T H. A novel approach for incipient defect detection in rolling bearings using acoustic emission technique. *Appl Acoust* **89**: 88–100 (2015)
[57] Sychev S, Batako A D L. A study of sliding friction using an acoustic emission and wavelet-based energy approach. *Machines* **12**(4): 265 (2024)
[58] Tian P Y, Tian Y, Shan L, Meng Y G, Zhang X J. A correlation analysis method for analyzing tribological states using acoustic emission, frictional coefficient, and contact resistance signals. *Friction* **3**(1): 36–46 (2015)
[59] Tan C K, Irving P, Mba D. A comparative experimental study on the diagnostic and prognostic capabilities of acoustics emission, vibration and spectrometric oil analysis for spur gears. *Mech Syst Signal Pr* **21**(1): 208–233 (2007)
[60] König F, Sous C, Ould Chaib A, Jacobs G. Machine learning based anomaly detection and classification of acoustic emission events for wear monitoring in sliding bearing systems. *Tribol Int* **155**: 106811 (2021)
[61] Strablegg C, Summer F, Renhart P, Pusterhofer M, Grün F. In-depth study of direct and derived acoustic emission parameters and their information content for classifying lubricated tribological sliding contacts. *Tribol Int* **190**: 109028 (2023)
[62] Deshpande P, Pandiyan V, Meylan B, Wasmer K. Acoustic emission and machine learning based classification of wear generated using a pin-on-disc tribometer equipped with a digital holographic microscope. *Wear* **476**: 203622 (2021)
[63] Chaix J F, Garnier V, Corneloup G. Ultrasonic wave propagation in heterogeneous solid media: Theoretical analysis and experimental validation. *Ultrasonics* **44**(2): 200–210 (2006)
[64] Ge H, Chua Kim Huat D, Koh C G, Dai G L, Yu Y. Guided wave–based rail flaw detection technologies: State-of-the-art review. *Struct Health Monit* **21**(3): 1287–1308 (2022)
[65] Mitra M, Gopalakrishnan S. Guided wave based structural health monitoring: A review. *Smart Mater Struct* **25**(5): 053001 (2016)
[66] Croxford A J, Moll J, Wilcox P D, Michaels J E. Efficient temperature compensation strategies for guided wave structural health monitoring. *Ultrasonics* **50**(4–5): 517–528 (2010)
[67] Achenbach J D. *Wave Propagation in Elastic Solids*. Amsterdam (the Netherlands): Elsevier, 2012.
[68] Rose J L. *Ultrasonic Guided Waves in Solid Media*. Cambridge (UK): Cambridge University Press, 2014.
[69] Bernard S, Grimal Q, Laugier P. Resonant ultrasound spectroscopy for viscoelastic characterization of anisotropic attenuative solid materials. *J Acoust Soc Am* **135**(5): 2601–2613 (2014)
[70] Castaings M. SH ultrasonic guided waves for the evaluation of interfacial adhesion. *Ultrasonics* **54**(7): 1760–1775 (2014)
[71] Diogo A R, Moreira B, Gouveia C A J, Tavares J M R S. A review of signal processing techniques for ultrasonic guided wave testing. *Metals* **12**(6): 936 (2022)
[72] Mazzotti M, Marzani A, Bartoli I. Dispersion analysis of leaky guided waves in fluid-loaded waveguides of generic shape. *Ultrasonics* **54**(1): 408–418 (2014)
[73] Sueki S, Ladkany S G, O'Toole B J. Wave propagation in layered

cylindrical structures using finite element and wave tracing analysis. *J Solid Mech Mater Eng* **4**(10): 1480–1495 (2010)
[74] Rabe U, Kopycinska M, Hirsekorn S, Arnold W. Evaluation of the contact resonance frequencies in atomic force microscopy as a method for surface characterisation. *Ultrasonics* **40**(1–8): 49–54 (2002)
[75] Chmelar J, Petr K, Mossoczy P, Dynybyl V. Experimental study of lubrication film monitoring in a roller bearing by utilization of surface acoustic waves. *Tribol Int* **141**: 105908 (2020)
[76] Lomazzi L, Giglio M, Cadini F. Towards a deep learning-based unified approach for structural damage detection, localisation and quantification. *Eng Appl Artif Intell* **121**: 106003 (2023)
[77] Tang R L, Zhang S Y, Wu W J, Zhang S H, Han Z C. Explainable deep learning based ultrasonic guided wave pipe crack identification method. *Measurement* **206**: 112277 (2023)
[78] Dwyer-Joyce R S, Drinkwater B W, Donohoe C J. The measurement of lubricant-film thickness using ultrasound. *Proc R Soc A* **459**(2032): 957–976 (2003)
[79] Zhang K, Meng Q F, Geng T, Wang N. Ultrasonic measurement of lubricant film thickness in sliding Bearings with overlapped echoes. *Tribol Int* **88**: 89–94 (2015)
[80] Dwyer-Joyce R S, Harper P, Drinkwater B W. A method for the measurement of hydrodynamic oil films using ultrasonic reflection. *Tribol Lett* **17**(2): 337–348 (2004)
[81] Starzynski G, Buczkowski R. Ultrasonic measurements of contact stiffness between rough surfaces. *J Tribol* **136**(3): 034503 (2014)
[82] Han T, Fan J C. Ultrasonic measurement of contact stress at metal-to-metal interface based on a real rough profile through modeling and experiment. *Measurement* **217**: 113046 (2023)
[83] Dwyer-Joyce R S, Reddyhoff T, Zhu J. Ultrasonic measurement for film thickness and solid contact in elastohydrodynamic lubrication. *J Tribol* **133**(3): 031501 (2011)
[84] He Y B, Wang J Y, Gu L, Zhang C W, Yu H D, Wang L Q, Li Z, Mao Y Z. Ultrasonic measurement for lubricant film thickness with consideration to the effect of the solid materials. *Appl Acoust* **211**: 109563 (2023)
[85] Cao-Romero-Gallegos J A, Taghizadeh S, Aguilar-Rosas O A, Dwyer-Joyce R S, Farfan-Cabrera L I. The effect of electrical current on lubricant film thickness in boundary and mixed lubrication contacts measured with ultrasound. *Friction* **12**(8): 1882–1896 (2024)
[86] Wu Q Z, Dou P, Chang S Y, Wu T H, Yu M, Lei Y G. *In-situ* adaptive calibration of incident signal of ultrasonic lubricant film thickness measurements. *Mech Syst Signal Pr* **224**: 112236 (2025)
[87] Jia Y P, Dou P, Zheng P, Wu T H, Yang P P, Yu M, Reddyhoff T. High-accuracy ultrasonic method for *in-situ* monitoring of oil film thickness in a thrust bearing. *Mech Syst Signal Pr* **180**: 109453 (2022)
[88] Al-Aufi Y A, Hewakandamby B N, Dimitrakis G, Holmes M, Hasan A, Watson N J. Thin film thickness measurements in two phase annular flows using ultrasonic pulse echo techniques. *Flow Meas Instrum* **66**: 67–78 (2019)
[89] Han Z S, Yuan B, Xia Z M, Zhao J H, Ji H, Mu X K, Sun Q C. Interface stiffness measurement of rough surface contact: A novel acoustic method based on robust reflection features. *Meas Sci Technol* **36**(8): 085009 (2025)
[90] Zhang K, Dou P, Wu T H, Feng K, Zhu Y Q. An ultrasonic measurement method for full range of oil film thickness. *P I Mech Eng J—J Eng* **233**(3): 481–489 (2019)
[91] Gutierrez R, Fang T S, Mainwaring R, Reddyhoff T. Predicting the coefficient of friction in a sliding contact by applying machine learning to acoustic emission data. *Friction* **12**(6): 1299–1321 (2024)
[92] Yang S, Gutierrez R, Kirkby T, Bouassida H, Hilbert M, Yu M, Reddyhoff T. Complete Stribeck curve prediction by applying machine learning to acoustic emission data from a lubricated sliding contact. *Mech Syst Signal Pr* **241**: 113544 (2025)
[93] Zhao J, Du H L, Meng F K, Zhang Q F. Application of convolutional neural networks for ultrasonic signal classification in the measurement of oil slick thickness on ocean surface. *J Clean Prod* **508**: 145545 (2025)
[94] König F, Marheineke J, Jacobs G, Sous C, Zuo M J, Tian Z G. Data-driven wear monitoring for sliding bearings using acoustic emission signals and long short-term memory neural networks. *Wear* **476**: 203616 (2021)
[95] Issa J, El Hajj A, Vergne P, Habchi W. Machine learning for film thickness prediction in elastohydrodynamic lubricated elliptical contacts. *Lubricants* **11**(12): 497 (2023)
[96] Haywood-Alexander M, Dervilis N, Worden K, Cross E J, Mills R S, Rogers T J. Structured machine learning tools for modelling characteristics of guided waves. *Mech Syst Signal Pr* **156**: 107628 (2021)
[97] Zhang C X, Zhang K, Wu X Y, Wang Y, Zhu J, Feng K. *In-situ* ultrasonic measurement of the full-range lubricant film thickness in bearings with overlapping echoes. *Measurement* **264**: 120249 (2026)
[98] Li X M, Wang Y, Wan X, Tang B P, Qin Y, Xu C B. Physics-informed deep filtering of ultrasonic guided waves for incipient defect inspection of large-scale square tube structures. *J Sound Vib* **567**: 118066 (2023)
[99] Boris I, Barashok K, Choi Y, Choi Y, Aslam M, Lee J. Machine learning techniques in ultrasonics-based defect detection and material characterization: A comprehensive review. *Adv Mech Eng* **17**(6): 1–41 (2025)
[100] Tervo J, Junttila J, Lämsä V, Savolainen M, Ronkainen H. Hybrid methodology development for lubrication regimes identification based on measurements, simulation, and data clustering.. *Tribol Int* **195**: 109631 (2024)
[101] Zhu Z Y, Ma J J, Xiao D M, Li X J, Gu F S, Ball A D. Acoustic emission diagnosis of lubricant water contamination fault by using adaptive multi-fidelity Bayesian optimization. *Tribol Lett* **74**: 3 (2026)
[102] Saeidi F, Shevchik S A, Wasmer K. Automatic detection of scuffing using acoustic emission. *Tribol Int* **94**: 112–117 (2016)
[103] Bórnea Y P, Vitor A L O, Goedtel A, Castoldi M F, Souza W A, Barbara G V. A novel method for detecting bearing faults in induction motors using acoustic sensors and feature engineering. *Appl Acoust* **234**: 110627 (2025)
[104] Zheng J X, Dong G N. Intelligent wear localization based on friction acoustic signals and machine learning. *Tribol Int* **215**: 111449 (2026)
[105] Khan F, Kamal K, Ratlamwala T A H, Alkahtani M, Almatani M, Mathavan S. Tool health classification in metallic milling process using acoustic emission and long short-term memory networks: A deep learning approach. *IEEE Access* **11**: 126611–126633 (2023)
[106] Fantetti A, Mariani S, Pesaresi L, Nowell D, Cegla F, Schwingshackl C. Ultrasonic monitoring of friction contacts during shear vibration cycles. *Mech Syst Signal Pr* **161**: 107966 (2021)
[107] Yang S, Geng Z, Gutierrez R, Yu M, Reddyhoff T. Data-driven prediction of friction, tribofilm growth, and lubricant composition in sliding contacts using acoustic emission. *Tribol Int* **214**: 111323 (2026)
[108] Olejnik P, Desta Y D. Friction-induced interactions: Acoustic emissions, vibrations, and wear—a multiscale review. *Nonlinear Dynam* **113**(18): 24101–24140 (2025)
[109] He Y, Xiao Y, Su Z Q, Pan Y D, Zhang Z. Contact acoustic nonlinearity effect on the vibro-acoustic modulation of delaminated composite structures. *Mech Syst Signal Pr* **163**: 108161 (2022)
[110] Wu Y D, Sicard B, Gadsden S A. Physics-informed machine learning: A comprehensive review on applications in anomaly detection and condition monitoring. *Expert Syst Appl* **255**: 124678 (2024)
[111] Herwig N, Borghesani P, Smith W, Peng Z. Signal processing- and physics-informed neural network for explainable bearing condition monitoring. *Mech Syst Signal Pr* **235**: 112925 (2025)
[112] Qin Y, Liu H Y, Wang Y, Mao Y F. Inverse physics–informed neural networks for digital twin–based bearing fault diagnosis under imbalanced samples. *Knowl-Based Syst* **292**: 111641 (2024)
[113] Lu H, Pavan Nemani V, Barzegar V, Allen C, Hu C, Laflamme S, Sarkar S, Zimmerman A T. A physics-informed feature weighting method for bearing fault diagnostics. *Mech Syst Signal Pr* **191**: 110171 (2023)

[114] Wu L Q, Palamarciuc I, Bajwa R, Zhang Y, Dwyer-Joyce R. Ultrasonic measurement for surface damage monitoring in coated bearing shells. *Friction* **13**(9): 9441065 (2025)
[115] Jakobsen M O, Herskind E S, Pedersen C F, Knudsen M B. Detecting insufficient lubrication in rolling bearings, using a low cost MEMS microphone to measure vibrations. *Mech Syst Signal Pr* **200**: 110553 (2023)
[116] Mokhtari N, Pelham J G, Nowoisky S, Bote-Garcia J L, Gühmann C. Friction and wear monitoring methods for journal bearings of geared turbofans based on acoustic emission signals and machine learning. *Lubricants* **8**(3): 29 (2020)
[117] Pichika S V V S N, Meganaa G, Geetha Rajasekharan S, Malapati A. Multi-component fault classification of a wind turbine gearbox using integrated condition monitoring and hybrid ensemble method approach.. *Appl Acoust* **195**: 108814 (2022)
[118] Medina R, Sánchez R V, Cabrera D, Cerrada M, Estupiñan E, Ao W G, Vásquez R E. Gearbox faults severity classification using Poincaré plots of acoustic emission signals. *Appl Acoust* **219**: 109918 (2024)
[119] Demetgul M, Lazarova-Molnar S. Data-driven artificial intelligence applications for tyre-road-noise prediction and road condition monitoring: A review and future directions. *Measurement* **264**: 120203 (2026)
[120] Bulatović N, Djukanović S. Mel-spectrogram features for acoustic vehicle detection and speed estimation. In: Proceedings of the 26th International Conference on Information Technology, 2022: 1–4.
[121] Chalançon B, Roda-Buch A, Cornet E, Rapp G, Weisser T, Brambilla L. Acoustic emission monitoring as a non-invasive tool to assist the conservator in the reactivation and maintenance of historical vehicle engines. *Stud Conserv* **69**(2): 102–112 (2024)
[122] Ma J J, Yu J F, Zhou X W, Gu F S, Jiang L L, Li X J. Condition monitoring of journal bearings based on acoustic emissions: A state-of-the-art review. *Friction* **14**(1): 9441080 (2026)
[123] Wang Z L, Li X M, Li N, Shu L L. An AI-driven approach to wind turbine bearing fault diagnosis from acoustic signals. *arXiv preprint* arXiv: 2403.09030 (2024)
[124] Tang J L, Soua S, Mares C, Gan T H. An experimental study of acoustic emission methodology for in service condition monitoring of wind turbine blades. *Renew Energy* **99**: 170–179 (2016)
[125] Shahkar S, Khorasani K. Gas turbine condition monitoring using acoustic emission signals. *J Nondestruct Eval* **2**(3): 031005 (2019)
[126] Nashed M S, Renno J, Mohamed M S, Reuben R L. Gas turbine failure classification using acoustic emissions with wavelet analysis and deep learning. *Expert Syst Appl* **232**: 120684 (2023)
[127] Wang Y F, Xue C, Jia X H, Peng X Y. Fault diagnosis of reciprocating compressor valve with the method integrating acoustic emission signal and simulated valve motion. *Mech Syst Signal Pr* **56**: 197–212 (2015)
[128] Lee G, Kwon D. Acoustic noise-based scroll compressor diagnosis during the manufacturing process. *Comput Model Eng Sci* **144**(3): 3329–3342 (2025)
[129] Surucu O, Gadsden S A, Yawney J. Condition monitoring using machine learning: A review of theory, applications, and recent advances. *Expert Syst Appl* **221**: 119738 (2023)
[130] AlShorman O, Alkahatni F, Masadeh M, Irfan M, Glowacz A, Althobiani F, Kozik J, Glowacz W. Sounds and acoustic emission-based early fault diagnosis of induction motor: A review study. *Adv Mech Eng* **13**(2): 1687814021996915 (2021)
[131] Chen P, Chua P S K, Lim G H. A study of hydraulic seal integrity. *Mech Syst Signal Pr* **21**(2): 1115–1126 (2007)
[132] Zhang G C, Zhang K, Shen W, Xu G Y, Lin Y J. Intelligent fault diagnosis of multi-way directional valves in hydraulic systems using digital twin and deep learning approaches. *Mech Syst Signal Pr* **230**: 112579 (2025)
[133] Akhlaghi M A, Bagherpour R, Hoseinie S H. Real-time monitoring of disc cutter wear in tunnel boring machines: A sound and vibration sensor-based approach with machine learning technique. *J Rock Mech Geotech* **17**(3): 1700–1722 (2025)
[134] Zhang K, Wang J R, Zheng Q, Ding G F, Li Z X, Zhang Z H. Wear anomaly detection method of tunnel boring machine disc cutters based on anomaly-attention improved long short-term memory autoencoder. *Measurement* **253**: 117497 (2025)
[135] Hu M M, Zhou H, Zhang Y H, Zhang C Q, Gao Y, Hu D W, Lu J J. Acoustic emission monitoring on damage evolution of surrounding rock during headrace tunnel excavation by TBM. *Eur J Environ Civ En* **23**(10): 1248–1264 (2019)
[136] Cheng W W, Wang W Y, Huang S Q, Ma P. Acoustic emission monitoring of rockbursts during TBM-excavated headrace tunneling at Jinping II hydropower station. *J Rock Mech Geotech* **5**(6): 486–494 (2013)
[137] Wang B, He B G, Shang J L, Zhu Z H, Yu H J, Lei X Z. Failure mechanism of deep TBM tunnels subjected to dynamic disturbance under true triaxial unloading stress path. *Int J Rock Mech Min* **191**: 106128 (2025)
[138] Schirru M M, Dwyer-Joyce R S. A model for the reflection of shear ultrasonic waves at a thin liquid film and its application to viscometry in a journal bearing.. *P I Mech Eng J—J Eng* **230**(6): 667–679 (2016)
[139] Yang Z Y, Yang H J, Tian T, Deng D S, Hu M T, Ma J T, Gao D Y, Zhang J Q, Ma S Y, Yang L, et al. A review on guided-ultrasonic-wave-based structural health monitoring: From fundamental theory to machine learning techniques. *Ultrasonics* **133**: 107014 (2023)
[140] Wu Z S, Yin N, Wang W Y, Zhou F F, Xu Z H, Zhang Z N. Tribo-informatics approach for monitoring the coefficient of friction and its fluctuation in sliding contact based on sound and vibration multi-signals. *Tribol Int* **214**: 111130 (2026)
[141] Andreades C, Malfense Fierro G P, Meo M. A nonlinear ultrasonic modulation approach for the detection and localisation of contact defects. *Mech Syst Signal Pr* **162**: 108088 (2022)
[142] Pesaresi L, Fantetti A, Cegla F, Salles L, Schwingshackl C W. On the use of ultrasound waves to monitor the local dynamics of friction joints. *Exp Mech* **60**(1): 129–141 (2020)
[143] Liskiewicz T, Sherrington I, Khan T, Liu Y. Advances in sensing for real-time monitoring of tribological parameters. *Tribol Int* **189**: 108965 (2023)
[144] Demmerling A L, Wei X, Söffker D. Extended tapping torque test to differentiate metalworking fluids. *Tribol Int* **175**: 107819 (2022)
[145] Schirru M, Varga M. A review of ultrasonic reflectometry for the physical characterization of lubricated tribological contacts: History, methods, devices, and technological trends. *Tribol Lett* **70**(4): 129 (2022)
[146] Guo F, Cheng G L, Yang Z, Xiang C, Jia X H. Deep learning algorithm to predict friction coefficient of matching pairs at different temperature domains based on friction sound. *Tribol Int* **188**: 108903 (2023)



Song Yang received his B.S. degree (2021) and M.S. degree (2024) in energy and power engineering from Xi'an Jiaotong University, Xi'an, China. He is currently a Ph.D. candidate at the Department of Mechanical Engineering, Imperial College London. His research interests focus on the application of nondestructive testing techniques for monitoring friction and lubrication processes.



Dong Qiang received his M.Eng. degree in mechanical engineering from Imperial College London, London, UK, in 2025. He is currently a Ph.D. student at Imperial College London. His research focuses on the design and control of magnetorheological fluid-based haptic interfaces and the development of sensing strategies for monitoring frictional systems.



Pan Dou received his Ph.D. degree in mechanical engineering from Xi'an Jiaotong University, Xi'an, China, in 2021. He is currently an assistant professor at the School of Mechanical Engineering, Xi'an Jiaotong University. His research interests include ultrasonic measurement of oil film thickness and surface wear.



Tonghai Wu received his Ph.D. degree in mechanical engineering from Xi'an Jiaotong University, Xi'an, China, in 2006. He is currently a professor at the School of Mechanical Engineering, Xi'an Jiaotong University. From 2013 to 2014, he was a visiting scholar at the University of New South Wales, Australia. His current research interests include machinery diagnosis and lubrication status detection.



Tom Reddyhoff is an associate professor in the Department of Mechanical Engineering, Imperial College London, London, UK. His research focuses on improving the performance of sliding contacts and often involves developing novel *in situ* measurement techniques used in combination with numerical modeling.



Min Yu received his Ph.D. degree in control engineering from Imperial College London, London, UK, in 2018. He is currently a research fellow of Imperial College London. His research involved the use of control and sensing techniques to design smart engineering interfaces that improve mechanical performance and enable structural health monitoring.