

Wear modeling and friction-induced noise: A review

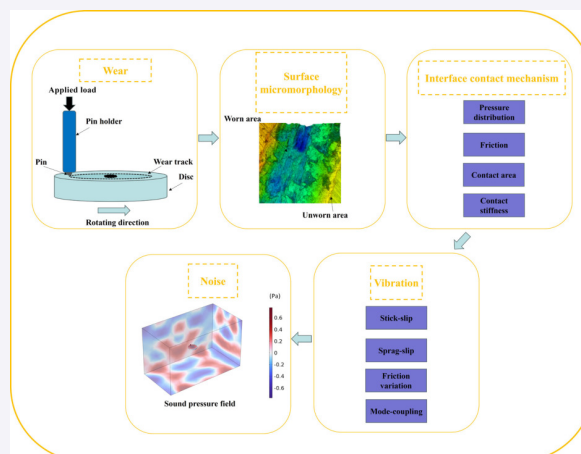
Yang Tian^{1,✉}, Muhammad Khan¹, Hao Yuan², Bohao Zheng³

 **Cite this article:** Tian Y, Khan M, Yuan H, et al. *Friction* 2026, **14**(2): 9441124. <https://doi.org/10.26599/FRICT.2025.9441124>

ABSTRACT: Wear and friction-induced noises are pivotal tribological phenomena that significantly influence the longevity and efficiency of mechanical systems. This review synthesizes current research on wear modeling and friction-induced noises, exploring their mechanisms, influencing factors, and predictive challenges. Wear modeling encompasses a range of approaches, from traditional methods such as the Archard equation to more advanced numerical and machine learning techniques. These models address diverse mechanisms—adhesive, abrasive, and fatigue wear—which are shaped by material properties, surface roughness, and environmental conditions. Friction-induced noise, arising from stick-slip, sprag-slip, and mode-coupling, is influenced by surface states, damping, and operational parameters. Crucially, wear and noise are interlinked. Wear reshapes surfaces and dynamics, thereby modulating noise, while noise can serve as a diagnostic tool for wear progression. Yet, existing models often isolate

these phenomena, neglecting their synergy and impeding accurate system-life predictions. This review highlights this gap and advocates for the development of integrated wear–noise models, harnessing multiscale simulations, advanced computation, and empirical validation. The development of such models has the potential to significantly enhance the accuracy of durability and acoustic performance predictions. They offer a holistic framework that captures the dynamic interplay between surface degradation and noise generation. This framework is essential for advancing non-invasive detection technologies in industries such as automotive, aerospace, and manufacturing. In these sectors, addressing these dual challenges is crucial for enhancing performance, safety, and efficiency.

KEYWORDS: friction; wear modeling; friction-induced noise; interrelationship between wear and noise



1 Introduction

In mechanical systems, the interactions between surfaces in relative motion give rise to two critical phenomena: wear and friction-induced noise. Over the past few decades, researchers have undertaken studies using various analytical, experimental, and computational methods to better understand the intricate interactions between surfaces that are in motion relative to each other [1–3]. Wear, defined as the gradual loss or deformation of materials on a solid surface caused by mechanical forces arising from sliding, rolling, or collision, directly affects the lifespan, reliability, and maintenance costs of components [4]. This intricate phenomenon is affected by various factors including material properties [4], contact mechanisms [5, 6], environmental conditions [1], and the presence of lubricants [7, 8]. Friction-induced noise, such as brake squeals or machining chatter, impacts operational efficiency, user comfort, and system

performance [9, 10]. These investigations explore different aspects, such as the development of models for predicting patterns of wear [11] and friction coefficients [12], examinations of the origins and characteristics of friction-induced noises like brake squeals [9, 10], and the examination of material properties and behaviors under various tribological conditions [13–15].

Both wear and noise stem from friction—the force that resists the motion of two surfaces that are in touch and either sliding or attempting to move against each other [16]. Friction occurs when microscopic asperities on surfaces get interlocked [16] and can be affected by factors such as surface texture [17], material characteristics [18, 19], and the presence of lubricants [7, 8]. Friction has a crucial function in wear mechanisms, as it directly impacts the amount of energy dissipated at contact interfaces, and elevated friction can result in heightened wear [20, 21]. Friction-induced noise arises from the vibrations produced by the stick–slip

¹ Centre of Life-Cycle Engineering and Management, Cranfield University, Milton Keynes MK43 0AL, UK. ² School of Mechanical and Aerospace Engineering, Nanyang Technological University, 50 Nanyang Avenue, Singapore 639798, Singapore. ³ Centre for Digital Engineering and Manufacturing, Cranfield University, Milton Keynes MK43 0AL, UK.

✉ Corresponding author. E-mail: Yang.Tian.593@cranfield.ac.uk

Received: March 4, 2024; Revised: March 23, 2025; Accepted: May 10, 2025

© 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/>).

Nomenclature

ACF	Autocorrelation function	MD	Molecular dynamic model
ANN	Artificial neural networks	MPM	Material point method
ANOVA	Analysis of variance	RCF	Rolling contact fatigue
CA	Cellular automation model	RSM	Response surface methodology
CoF	Friction coefficient	SEM	Scanning electron microscope
DEM	Discrete element method	SVR	Support vector regression
DVAS	Dynamic vibration absorbers	W–M function	Weierstrass–Mandelbrot function
FEM	Finite element method		

motion, mode-coupling, or other dynamic instabilities at the interface of sliding surfaces [9, 10]. The interrelation between wear, friction, and friction-induced noise is apparent, as they all result from the interaction of surfaces in motion relative to each other [22]. As surfaces wear down, their contact behavior changes, resulting in dynamic friction and the production of noise [23, 24]. Conversely, noise often serves as an audible indicator of wear progression, reflecting changes in contact dynamics [25].

Despite their significance across industries like automotive, aerospace, and manufacturing, a critical gap persists in tribological research: the lack of a comprehensive model that integrates wear, friction, and friction-induced noise while accounting for their interdependencies. The foundational principles of these phenomena were established through historical advancements such as Coulomb's law [26], the Archard equation [27], and the stick-slip mechanism [9, 10]. The current state of research has been characterized by sophisticated numerical models, experimental techniques, and interdisciplinary approaches that provide a more profound and nuanced comprehension of these intricate phenomena. This study reviews existing research on these topics and establishes their interconnections, underscoring the need for a comprehensive model that integrates friction, wear, and friction-induced noise. Such a model is crucial for non-invasive detection, enabling the prediction of wear development on surfaces based on friction-induced noise. However, to the best of the authors' knowledge, such an integrated model is currently absent from the field.

This review systematically explores wear modeling and friction-induced noise, weaving together foundational concepts, analytical methods, and their interconnections. Section 2 lays the groundwork by introducing wear and friction, detailing wear mechanisms and key influencing factors. Section 3 examines techniques for modeling rough surfaces, followed by Section 4, which addresses contact mechanisms essential to understanding wear and noise interactions. Section 5 surveys wear modeling approaches, spanning analytical to numerical methods. Shifting focus, Section 6 explores friction-induced noise, including its causes and control strategies. Section 7 synthesizes insights into the interplay between wear and noise, emphasizing their mutual influence. Finally, Section 8 highlights research gaps and proposes a roadmap for integrated modeling, advocating for comprehensive frameworks to tackle these intertwined phenomena in future tribological studies.

2 Background

In the realm of material science and engineering, understanding the principles of wear and friction is pivotal for the development and optimization of materials and mechanical systems. This section delves into the foundational concepts of wear and friction, elucidating their mechanisms, types, and influencing factors.

2.1 Basic principles of wear and friction

2.1.1 Friction mechanisms

Coulomb's law, a fundamental principle for understanding friction, states that the frictional force between contacting surfaces is directly proportional to the normal force and independent of the apparent contact area (Eq. (1)).

$$F_f = \mu \cdot F_n \quad (1)$$

where F_f is the friction force; μ is the coefficient of friction (CoF), a dimensionless quantity; F_n is the normal force perpendicular to the surface in contact. μ is crucial in Coulomb's law because it quantifies the relationship between the normal and frictional forces. Consequently, the study of the CoF and friction has attracted considerable interest from researchers.

(1) Factors influencing the coefficient of friction

The CoF, μ , is influenced by a multitude of factors:

Material properties and surface characteristics. Research indicates that μ varies with different material combinations [18, 19]. Rough surfaces generally exhibit a higher μ due to increased interlocking of surface asperities [16]. Conversely, lubricants are known to reduce μ by forming a protective layer between surfaces, thereby decreasing direct contact and subsequent wear [7, 8].

Contact area and normal force. Empirical studies conducted by Liang et al. [28] have revealed that the linear relationship between friction force and real contact area persists only under loading conditions, breaking down during unloading.

Environmental conditions. Factors such as temperature and humidity also impact μ . For example, sliding converts the work done by friction into heat, affecting material properties and stabilizing μ [29]. Studies by Behera et al. [30] further highlight the role of environmental factors like humidity in altering the CoF.

(2) Dynamic behavior of friction

The classical Coulomb equation does not fully capture the complexities of friction dynamics observed in experiments. These complexities include presliding, friction variations with velocity, frictional lag, transitions between presliding and sliding, and stick-slip behavior. Armstrong-Hélouvy et al. [31] was the first to model these dynamic aspects of friction, introducing a time delay and an additional equation for presliding displacement. However, this approach did not account for the transition from presliding to sliding. In response, more advanced models have emerged, including the Leuven model [32] and the generalized Maxwell-slip friction model [33]. Al-Bender et al. [34] developed a generic model based on both physical principles and empirical data, effectively capturing the aforementioned dynamic friction behaviors and closely matching experimental results. However, the generic model assumes a constant separation between

interacting surfaces, making it unsuitable for scenarios with varying normal forces. Although the generic model can simulate detailed friction force dynamics, its complexity makes it less practical for general simulation and control, especially compared with empirical models.

A physics-informed neural network (PINN) provides an advanced method for accurately modeling frictional behaviors in mechanical systems. It is particularly effective in complex scenarios where dynamic friction phenomena, such as stick-slip motion, are prominent [35]. The PINN method provides a more accurate representation of stick-slip phases and transitions between different friction regimes. Furthermore, the model achieves faster convergence and higher computational efficiency, making it more practical for real-time applications and large-scale simulations.

Xun et al. [36] proposed a new fractional-order friction model that is less complex yet more accurate than the commonly used generalized Maxwell-slip model. Through extensive simulations and experimental validation, the study highlights the model's practical applicability, especially in robotics.

Zhang et al. [37] proposed an analytical tire tread friction model based on brush theory, a widely used approach in tire modeling. Unlike conventional models that use spring elements, this model incorporates modified Kelvin-Voigt elements with inertia components to represent the viscoelastic behavior of tread bristles. This modification allows the model to more precisely capture the dynamic friction response of tread elements, particularly during transitions between sticking and sliding states.

While many models effectively capture friction dynamics, they often overlook the impact of wear-induced changes on surface characteristics.

(3) Impact of wear and surface changes on friction

During sliding, surface asperities detach, forming wear debris, also known as “third bodies”, altering the frictional interaction and, consequently, the μ [38]. The adhesion of third bodies to the surface, combined with plastic deformation, significantly contributes to wear, accounting for over 95% of total wear [39]. Hausberger et al. [40] assessed the relative influence of adhesion and deformation on friction by considering their respective weights on the CoF, based on Eqs. (2) and (3). The results indicate that the ratio between adhesion and deformation in friction is significantly influenced by load, surface texture, and viscoelastic properties of the material. However, it should be noted that they estimate the real contact area A_r using the apparent area; actual surfaces are rough, and the true contact is affected by roughness, material stiffness, and applied pressure.

$$\mu = \mu_{\text{adh}} + \mu_{\text{def}} \quad (2)$$

$$\mu_{\text{adh}} = \frac{\pi}{2} \left(\frac{A_r}{F} \right) \tau_a \tan \delta \quad (3)$$

where A_r is the real contact area; F is the normal load; τ_a is the shear stress, and $\tan \delta$ is the loss factor.

The dynamic behavior of the CoF during frictional sliding, as observed by Ostermeyer and Müller [41], is elucidated by “patch theory”. This theory describes how wear debris patches form, grow, and eventually detach from surfaces, resulting in a dynamic equilibrium of the CoF. Additionally, studies have derived analytical equations for the CoF and wear rate, accounting for boundary layer formation and asperity flattening under mixed lubrication, particularly during the initial running-in phase of rough metallic surfaces [42]. These findings indicate that the CoF

decreases mainly due to the combined effects of boundary layer formation and surface smoothing. Ref. [4] found no direct correlation between friction coefficients and hardness. Instead, wear debris played a more significant role in influencing friction.

In conclusion, accurately determining friction force requires accounting for multiple factors that influence the CoF. These factors include material and surface properties, lubrication, applied force, environmental conditions, and the dynamic behavior of contact surfaces. Integrating these factors is essential for improving the predictive accuracy of the CoF, a fundamental requirement for accurately modeling wear processes and friction-induced noises. Understanding friction dynamics is crucial for system control to prevent undesired phenomena such as stick-slip motion, which can generate noises.

2.1.2 Archard model

Archard wear law, one of the earliest and most widely used wear formulas, developed by John F. Archard, states that wear is proportional to the sliding distance S and the applied normal load F_n but inversely proportional to the hardness H of the softer material in contact, as shown in Eq. (4) [27]:

$$V = \frac{k \cdot F_n \cdot S}{H} \quad (4)$$

where k is the wear coefficient, a dimensionless constant, usually measured via experiment. Its value depends on the material property, surface characteristics, and operating environment.

(4) Limitations of the classical Archard model

However, the Archard model has limitations, particularly in its calculation of wear volume, which relies solely on the applied normal load and sliding distance. This method overlooks surface roughness, which results in variations in contact pressure and relative velocity across different contact regions.

Additionally, the classical Archard model assumes a linear relationship between load and wear volume, which holds only within specific load ranges. However, for lower or higher applied loads, the wear volume-load relationship becomes sublinear or superlinear, respectively [43–47]. Furthermore, the Archard model does not account for different wear regimes (low, moderate, or severe), which are governed by the geometric dimensions of contact asperities and junction sizes, influencing failure modes and wear particle sizes (Fig. 1) [48]. The low wear regime results from shear-driven mechanisms without wear debris formation, while the mild wear regime is associated with tension-driven mechanisms forming small or large wear debris. The severe wear regime is linked to tension-driven mechanisms generating macroparticles.

(5) Modifications and extensions of the Archard model

To address the limitations of the classical Archard model, several modifications have been proposed:

Feng et al. [49] proposed a modified Archard model considering local pressure and velocity, expressed as Eq. (5). This model better accounts for the complexities of real-world wear scenarios.

$$h(x) = \int K_{\text{wear}} P(x, t) v(t) dt \quad (5)$$

where $h(x)$ is the wear depth at contact point x ; K_{wear} is the wear coefficient; $P(x, t)$ is the distribution of contact pressure at time t ; $v(t)$ is the corresponding sliding velocity.

To address the lack of consideration for tribological conditions in the original Archard model, Sarkar [50] extended it to include the CoF, leading to a refined equation (Eq. (6)) for calculating

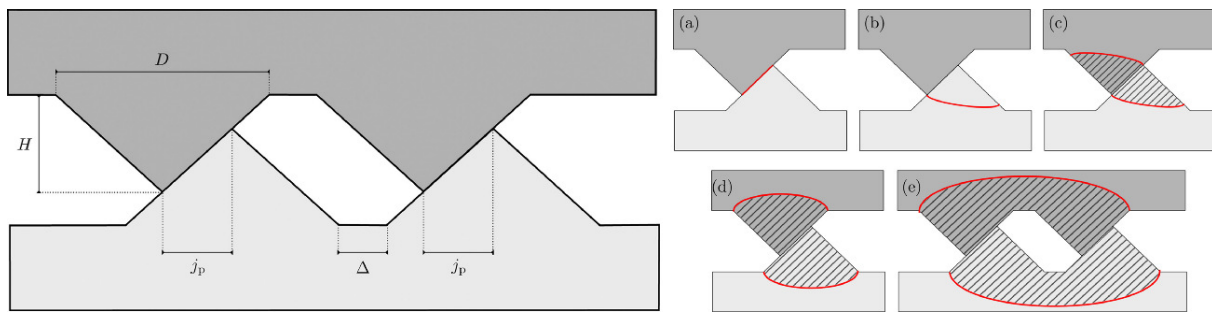


Fig. 1 Transition of wear process: (a, b) low wear regime; (c, d) mild wear regime; (e) severe wear regime. Reproduced with permission from Ref. [48], © Elsevier Ltd. 2020.

wear volume. This expansion proved beneficial in understanding the nanoscale wear behavior of materials like Mo and MoO₃ coatings, as demonstrated in the research by Behrens et al. [51].

$$w = k \cdot [F_n \cdot S \cdot (1 + 3\mu^2)^{0.5}] / H \quad (6)$$

(6) Wear coefficient variability and estimation techniques

Across all variations of the Archard model, the wear coefficient k remains a key parameter. Jendel [52] compiled experimental data under dry conditions to develop a wear map illustrating the variability of k (Fig. 2). This wear map is widely applied in railway research. However, since it is derived from limited data, k is regarded as an uncertain parameter. Liu et al. [53] employed the universal Kriging (uK) technique to offer a more detailed understanding of k 's uncertainty, demonstrating its dependence on material combinations and contact conditions. The uK method provides a continuous distribution of the wear coefficient $k(v, P)$ across varying slipping velocities v and pressures P , enabling its determination within specific upper and lower bounds. This makes it more practical than traditional wear maps. However, the effectiveness and accuracy of the uK method rely on the availability of extensive experimental data across diverse contact conditions.

Further research by Franklin et al. [54] proposed a method to evaluate the k for materials in rolling contact (Eq. (7)), while Zhao et al. [55] employed a Bayesian update procedure to refine the estimation of the wear coefficient using observed mass loss data. As more mass loss data become available, the posterior distribution of the k tightens, and its mean converges to the true wear coefficient value.

$$k = \frac{(\Delta w/a)H}{p_0/2} \quad (7)$$

where Δw is the thickness of material removed per cycle from the surface; a is the semi-contact width; H is the hardness of the wearing material; p_0 is peak pressure.

Kragelskii [56] interpreted the wear coefficient as the inverse of the number of cycles required for wear particle formation, which can be calculated using continuum damage mechanics (CDM). This framework evaluates the accumulation of material damage under cyclic loading by comparing the energy for defect growth to the available system energy. Ghatrehsamani and Akbarzadeh [57] enhanced this approach by integrating surface roughness and friction coefficients into the CDM model, improving the accuracy in predicting wear volume and cycle count for wear particle formation. Their findings show that the wear coefficient increases with the friction coefficient. Additionally, Holm [58] suggested that wear occurred through atomic removal from plastically deformed asperities, while Archard and Hirst [59] proposed that it resulted from fracture and debris formation. Aghababaei et al. [11] later consolidated these theories into a unified model based on

atomistic simulations, see Fig. 3. The model delineates two wear mechanisms regulated by a critical length scale d^* , Eq. (8), predicting asperity smoothing if $d < d^*$ and debris particle formation if $d > d^*$. Although it accurately predicts fracture-induced debris in metals, the model doesn't address smaller-scale wear processes like surface folding and delamination from subsurface dislocation structures or surface oxidation.

$$d^* = \lambda \cdot \frac{\Delta w}{\sigma_j^2 / G} \quad (8)$$

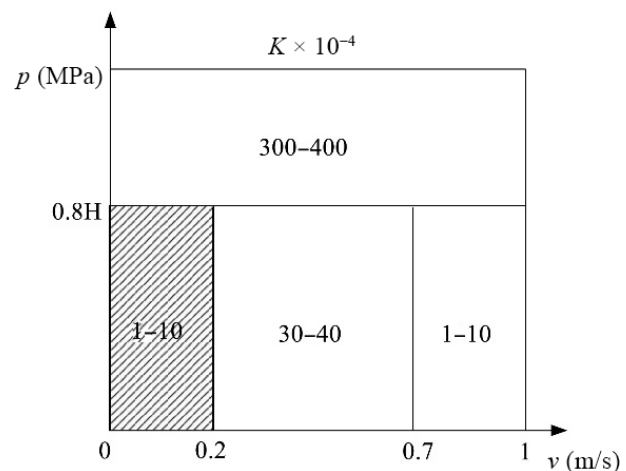


Fig. 2 Jendel's wear map. Reproduced with permission from Ref. [52], © Elsevier Science B.V. 2002.

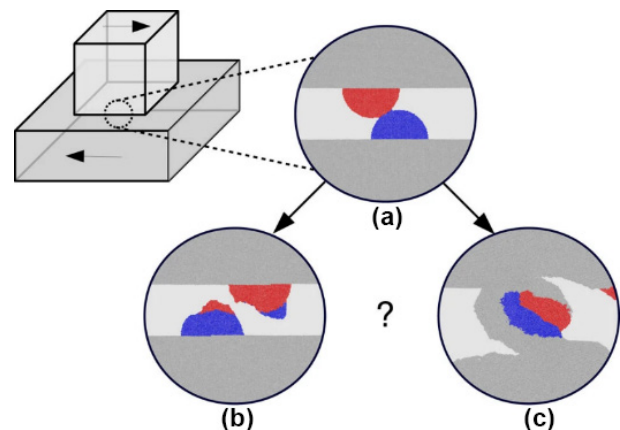


Fig. 3 Diagram illustrates two potential adhesive wear mechanisms at the asperity level. Following (a) an adhesive interaction between surface asperities, the wear process can proceed through (b) a gradual smoothing mechanism facilitated by plastic deformation or (c) a fracture-induced debris formation mechanism. Reproduced with permission from Ref. [11], © The Author(s) 2016.

where λ is a shape factor combining contributions of all geometrical factors; Δw is the energy associated with newly created free surfaces because of a unit area of crack growth in each sliding body; G is the shear modulus; σ_j is the shear strength of the junction.

Based on the critical length scale d^* discovered in Ref. [11], Brink et al. [60] proposed a critical area $A^* = \pi \cdot d^{*2}/4$; based on this, junctions can be categorized into two groups: those that undergo plastic deformation ($A < A^*$) and those that generate wear particles ($A \geq A^*$), depending on their size, which can be used to determine Archard's wear coefficient k , as shown in Eq. (9). Compared with the traditional way of fitting the wear coefficient through experimental data, this method does not require any fit parameter and relies solely on material properties and surface parameters.

$$k = \frac{\sum_i \begin{cases} 0, & A_i < A^* \\ A_i, & A_i \geq A^* \end{cases}}{\sum_i A_i} \quad (9)$$

where A_i is the area of contact junction i and the sum $\sum_i A_i$ is over all junctions.

Despite these advancements, the Archard model, which is primarily effective for metals, encounters challenges when applied to modern materials such as composites, polymers, and advanced alloys [61, 62]. Its assumption of a linear relationship between wear factors and dependence on specific material pairings for experimental data restricts its broader applicability and accuracy. Additionally, the model offers limited insight into the formation, size, and distribution of wear debris, which are crucial for comprehensively understanding wear processes and their implications. These challenges underscore the need for further research and modifications to the Archard model to address contemporary material science and engineering requirements.

2.1.3 Energy-based wear model

The Archard model focuses on load, sliding distance, and material hardness in wear analysis, while the energy-based model ties wear to the energy dissipated at contact surfaces during motion [63]. The dissipated energy refers to the work of friction occurring at the contact interface. The energy-based wear model can be described in a general form as Eq. (10):

$$W = k \cdot E_d \quad (10)$$

where W is the wear volume or wear rate; k is the wear coefficient; E_d is the energy dissipated in the wear process.

Fouvry et al. [64] suggested a method to estimate wear depth from an energy perspective, arguing that only a small part of dissipated energy goes to plasticity, with the rest in heat and debris transfer. Wear begins only after the dissipated energy surpasses a threshold necessary for plastic deformation and tribological transformation. The prediction of wear depth extension can be achieved by utilizing an equivalent energy density wear coefficient, denoted as α_h , as described in Eq. (11).

$$h = \alpha_h \sum E_{d_{h0}} \quad (11)$$

where h is wear depth, $\sum E_{d_{h0}}$ is the accumulated energy density, and $E_{d_{h0}}$ is the maximum dissipated energy density at the contact center, which is obtained by evaluating the maximum shear stress within the Hertzian shear field.

Dreano et al. [65] improved the traditional energy-based model by including temperature and tribo-oxidation effects. Their model

distinguishes between initial fretting, affected by oxidation and abrasion (domain I), and later wear post-glaze layer formation (domain II), as depicted in Fig. 4. They observed that the glaze layer, which expanded with fretting cycles, shifted energy consumption from wear to the glaze's plastic deformation, introducing a critical cycle number, N_{GL} , for glaze formation. However, their model does not consider the effect of contact size, which was examined in the study [66] in relation to debris ejection flow and oxygen accessibility. So, additional factors need to be considered to validate the wear model of glaze layer.

Overall, the energy-based wear model posits that wear occurs when the accumulated dissipated energy exceeds a specific threshold. However, determining this threshold is often complex and typically requires empirical data.

2.1.4 Mechanisms of wear and types of wear

Wear can be classified into various types according to their mechanisms, which are briefly described in this section.

Adhesive wear. This phenomenon occurs when two sliding surfaces form strong adhesive bonds at their asperity contact points, resulting in material transfer, especially under high contact pressure (Fig. 5) [67]. The process initiates at the microscopic level, where asperities on the surfaces establish adhesive junctions. These junctions may fail under tensile or shear stresses, leading to material detachment [48]. Wear occurrence is strongly influenced by the interatomic potential function, where stronger adhesive forces lead to greater wear, particularly in dry contact conditions [68].

In machining processes such as turning, milling, and drilling, adhesive wear is significantly influenced by thermal mechanisms. Chemical interactions between the work material and the cutting tool induce thermal cracks and low-frequency fatigue [69].

In artificial joints, the counterpart material's properties critically affect adhesive wear. For instance, CoCrMo alloys accelerate polyethylene degradation, increasing its susceptibility to adhesive wear. Conversely, although TiN coatings are generally inert, pinholes within them can cause localized abrasion and enhance polyethylene reactivity, leading to substantial material transfer around these defects [70].

Overall, adhesive wear arises from a complex interplay of mechanical, thermal, chemical, and material-specific factors, all of which contribute to the wear process.

Abrasive wear. This phenomenon occurs when hard surfaces or particles physically cut, scratch, or plow through a softer material, leading to material removal in the form of debris. Abrasive wear has three primary modes: cutting, plowing, and wedging [74]. Cutting refers to material removal by a sharp edge, resulting in chip formation. Plowing displaces and deforms the material, creating grooves or furrows on the surface [75, 76]. This mode is particularly common in soft materials subjected to high pressure. Wedging leads to material transfer from the substrate to the contacting surface, resulting in the formation of wedges [73].

Hokkirigawa and Kato [74] correlated experimental findings with existing theoretical models of friction and wear proposed by earlier researchers. Their study employed shear strength at the contact interface and penetration depth to explain the transition between different abrasive wear modes. A major contribution of their study was the development of a wear mode diagram, which defines the conditions under which different wear modes—such as cutting, wedge formation, and plowing—dominate. Mishra et al. [73] demonstrated that these modes were influenced by factors such as the “angle of attack” γ and the “interfacial friction factor” f_{hk} , as shown in Fig. 6. For a spherical asperity, γ represents the

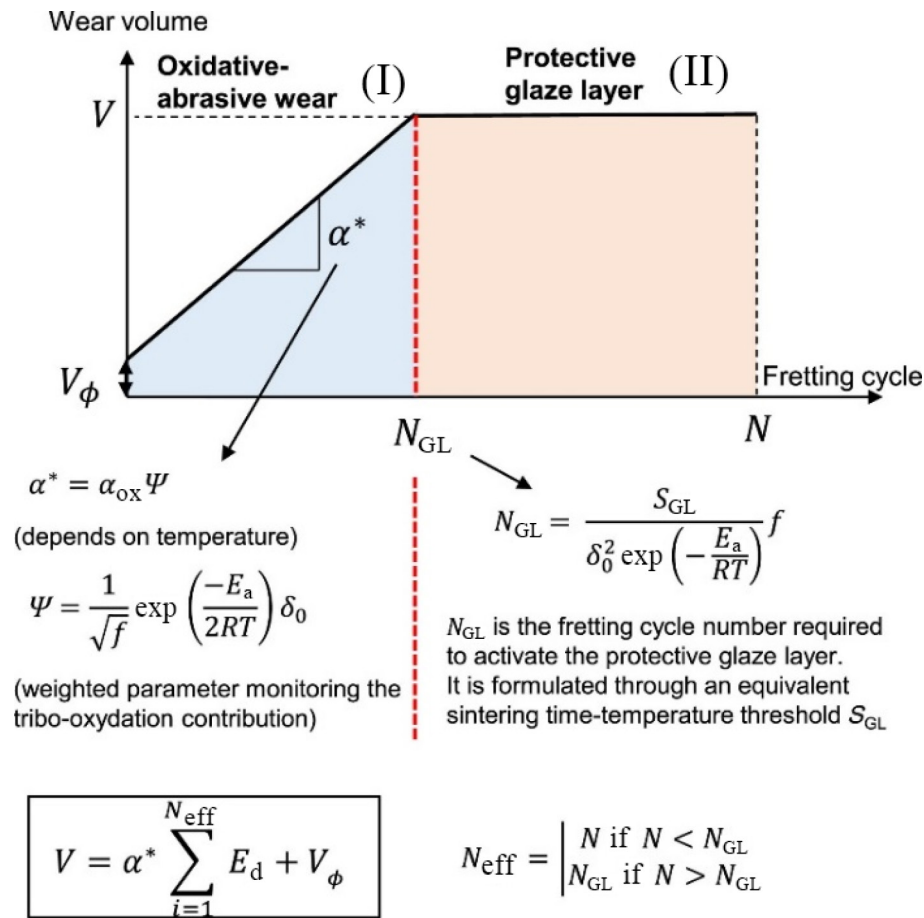


Fig. 4 Illustration of the proposed wear model in schematic form, where f and δ_0 are fretting frequency and sliding amplitude, respectively; E_a is the activation energy for the oxidation process; R is the universal constant; T is the temperature. Reproduced with permission from Ref. [65], © Elsevier B.V. 2019.

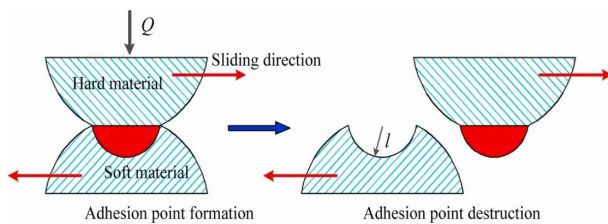


Fig. 5 Mechanism of adhesion wear. Reproduced with permission from Ref. [71], © Elsevier 2021.

angle between the tangent to the sphere at the contact point and the x -direction in the xz plane. f_{hk} represents the ratio of interfacial shear strength to substrate mass shear strength.

Fretting wear. When two surfaces undergo reciprocal motion

and slide against each other with a small amplitude, wear debris forms, leading to surface damage, see Fig. 7(a) [77, 78]. Depending on whether the amplitude is larger or smaller than the initial apparent contact size in the sliding direction, reciprocal motion is classified as partial sliding or gross sliding, each exhibiting distinct wear characteristics.

The wear process is governed by multiple factors, such as oscillation amplitude and frequency, surface roughness, material properties, and environmental conditions. Experiments have demonstrated that the coefficient of friction (CoF) depends on oscillation amplitude and surface finish, exhibiting distinct behaviors in polished and unpolished specimens [79]. Fretting wear is not a single mechanism but a complex interplay of adhesive, abrasive, and fatigue wear, often intensified by corrosive

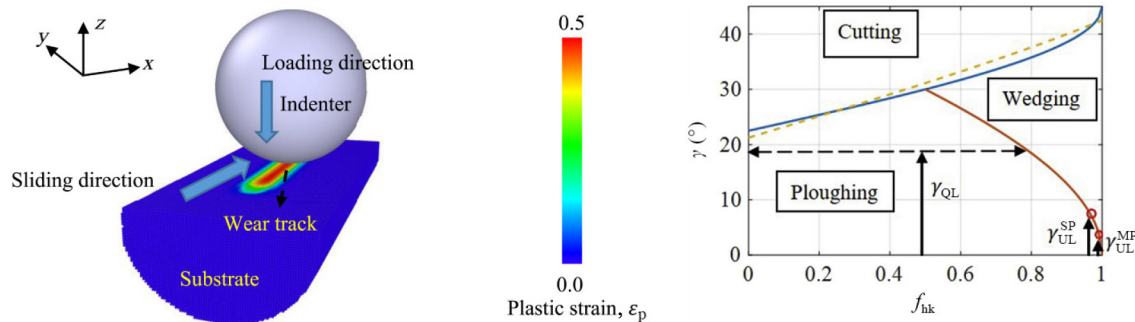


Fig. 6 Diagram illustrating the wear mode observed in ball-on-disc experiments, which were either treated with Quaker lubrication (QL) or left unlubricated (UL) and subjected to two different finishing processes: shine polishing (SP) and mirror polishing (MP). Reproduced with permission from Ref. [73], © The Authors 2020.

elements. Studies on aluminum alloys and coatings have revealed transitions from abrasive wear at low oscillation frequencies to adhesive wear at high oscillation frequencies, along with the formation of protective oxide layers at elevated temperatures and higher frequencies [80].

Fatigue wear. Fatigue wear results from repeated or cyclic loading, leading to material fatigue, cracking, and flaking of the material [81]. In fatigue analysis, multiple methods predict material fatigue life under complex loading conditions. The multi-axial critical plane approaches, like the Ince and Glinka model [82], the Smith–Watson–Topper (SWT) criterion [83, 84], and the Morrow criterion [85–87], each offer unique perspectives but have their limitations, such as overestimating fatigue life or lacking stability in prediction accuracy. In the ratcheting mode, plastic deformation accumulates until the material's ductility is surpassed, resulting in rail rupture. In response to this feature, Kapoor and Johnson [88], Ghanbarzadeh et al. [89], and Holm [58] proposed a model to estimate rail life, which is given by Eqs. (12) and (13):

$$N_f = \frac{\epsilon_c}{\Delta\epsilon_r} \quad (12)$$

$$\Delta\epsilon_r = \sqrt{(\Delta\tilde{\epsilon})^2 + \left(\Delta\tilde{\gamma}/\sqrt{3}\right)^2} \quad (13)$$

where ϵ_c is the critical strain for failure by ratcheting; $\Delta\epsilon_r$ is the equivalent ratcheting plastic strain per cycle; $\Delta\tilde{\epsilon}$ and $\Delta\tilde{\gamma}$ are the average ratcheting axial and shear strain per cycle, respectively.

Corrosive wear. Corrosive wear occurs in environments containing corrosive agents such as chemicals or seawater, where chemical or electrochemical reactions accelerate material degradation, see Fig. 7(b) [89]. Pitting, characterized by the formation of small cavities or pits on a material's surface, arises due to fatigue or corrosion, particularly in gears subjected to cyclic loading [90, 91].

Ghanbarzadeh et al. [89] developed a model to describe surface evolution over time, incorporating both mechanical wear and electrochemical reactions. Their study demonstrated that mechanical wear and electrochemical wear mutually influenced each other, confirming their synergistic relationship. Ghanbarzadeh et al. [92] calculated corrosive wear using Faraday's equation (Eq. (14)) and introduced a modified Archard-type wear model incorporating terms for pure mechanical wear, corrosion-enhanced wear, and wear-enhanced corrosion. This model redefines traditional wear equations to better represent the complex interactions in tribocorrosive environments.

$$V_c = \frac{QM}{nF\rho} \quad (14)$$

where V_c is the volume of metal removed by anodic reactions; Q is the total electric charge passed and is calculated by integrating the current over time when an overpotential is applied; M is the atomic mass of the metal; n is the charge for the oxidation reaction; ρ is the density of the passive metal; F is the Faraday constant.

Erosive wear. When components are exposed to fast-flowing liquids or gases containing entrained particles, surfaces are impacted by fluids or particles, leading to deformation or chipping, see Fig. 7(c) [93, 94].

The study [93] explored the effects of surface roughness of target material and particle rotation on local wear variables. The simulations showed that surface roughness and particle rotation led to more dispersed particle impacts, which changes the wear profile on the surface.

The research [94] distinguished between the energy absorbed by the particle and the surface, considering scenarios where plastic deformation, fragmentation, and surface erosion occur simultaneously. The relationship between the energy absorbed during impact and the resulting erosion rate has been successfully established, highlighting how energy dissipation affects material degradation.

Impact wear. When components are subjected to hammering or pounding, surfaces undergo repeated shocks, leading to deformation or material loss [95, 96].

The study [95] developed a framework to quantify the time-dependent contact parameters of rough surfaces subjected to random shocks. This framework incorporates deformation energy theory and the loading/unloading behavior of contacting asperities, offering insights into how contact surfaces evolve over time in response to random shocks.

The study [96] developed a modular test apparatus specifically designed to simulate and analyze impact wear. This apparatus enables precise control over various test parameters, including impingement angle, contact geometry, impact frequency, and force magnitude. The primary wear mechanisms observed in the study were plastic deformation, surface fatigue, and microcracking. Additionally, the study highlighted the phenomenon of “zero wear volume”, where material underwent plastic deformation without being removed from the surface.

2.2 Factors influencing the wear

2.2.1 Thermal effect

Thermal effects play a crucial role in wear mechanisms, as mechanical work is converted into thermal energy at sliding interfaces. This heat alters material properties, including temperature-dependent softening and surface oxidation, thereby influencing wear processes. Therefore, understanding the distribution of contact temperatures is crucial in wear analysis. However, heat distribution presents challenges, such as heat conduction within materials and heat exchange with external factors, including gases and lubricants. To simplify this, Xia et al. [97] proposed a quasi-static analytical model that approximated high-speed rotation as a static toroidal heat source. However, this approach tends to underestimate contact temperatures, particularly at the frictional interface. The study in Ref. [98] demonstrated that wear and contact temperature increased with surface roughness and friction. Heat transport during sliding wear in an isotropic solid with constant thermal conductivity (k), density (ρ), and specific heat (c_p) is governed by the transient heat conduction equation, as shown in Eq. (15) [99, 100].

$$\frac{\partial(\rho c_p T)}{\partial t} + \vec{V} \cdot \nabla(\rho c_p T) = \nabla \cdot (k \nabla T) \quad (15)$$

where $\vec{V}$ is the relative sliding velocity, and T is the temperature at the interface. The total heat generated per unit contact area is dependent on the contact pressure (P), CoF (μ), efficiency of heat conversion α , and sliding velocity (V), as given by Eqs. (16)–(19) [101]:

$$q_{\text{total}} = \alpha \times \mu \times N \times V \quad (16)$$

$$q_b = \eta q_{\text{total}} \quad (17)$$

$$q_d = (1 - \eta) q_{\text{total}} \quad (18)$$

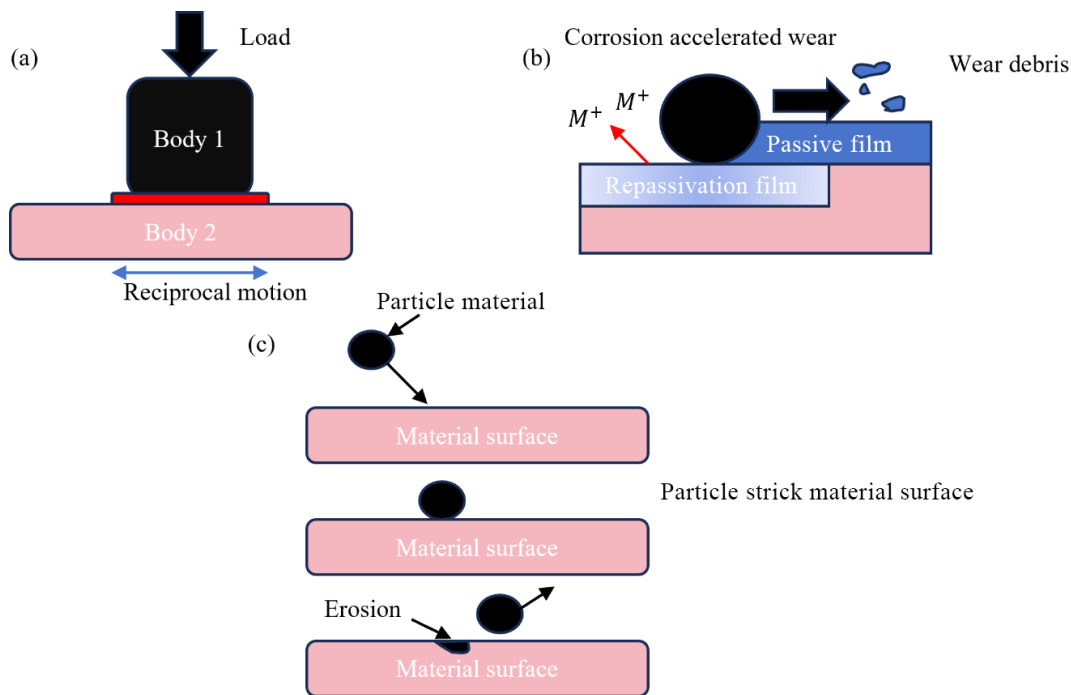


Fig. 7 Illustration of (a) fretting wear, (b) corrosion wear, and (c) erosion wear.

$$\eta = \frac{1}{1 + \frac{\kappa_2}{\kappa_1}(1 + P_e)} \quad (19)$$

A portion of the total heat generated, denoted as q_b , is transferred to the contacting first body. Conversely, the remaining heat, referred to as q_d , is transferred as heat flux to the second body. These respective heat transfer mechanisms are described by Eqs. (17) and (18) [100]. However, it should be noted that the heat flux into the third body and air is not considered here. The symbol η represents the heat partition function [102], which depends on the thermal diffusivities (κ_1 and κ_2) of the two bodies in contact and the dimensionless Peclet number P_e . Yadav et al. [100] found that elevated temperatures promoted oxide layer formation, thereby reducing wear rates. Pu et al. [103] developed a model for the top-ring/liner interface, incorporating factors such as contact geometry and surface roughness. Their findings indicate that the growth rate of anti-wear films is primarily governed by local flash temperatures rather than asperity contact pressure. This model, which accounts for thermal conduction between two bodies and convective heat transfer between a solid and a gas, is simplified by neglecting heat radiation. Overall, thermal effects play a crucial role in understanding wear mechanisms, necessitating models that comprehensively capture the complex interactions among temperature, material properties, and contact dynamics.

2.2.2 Humidity

Increased relative humidity has been shown to reduce debris formation, primarily due to the lubricating effect of water molecules. This effect reduces adhesion and friction between interacting surfaces, consequently lowering debris production [104]. Li et al. [1] reviewed the influence of humidity on friction and wear across various materials, emphasizing its varying effects depending on distinct underlying mechanisms. They found that water interactions at the contact surface were complex and cannot be explained by a single mechanism. Nevertheless, humidity plays a crucial role in friction and wear processes.

2.2.3 Material property

Material properties significantly impact wear progression, as explored in various studies. Nishi [105] analyzed various rubber compositions using a blade-on-disk tribometer and applied the time-temperature superposition principle from polymer science. This principle is used to predict material behavior under varying temperatures and loading rates. The study found that rubber's wear resistance decreased as cracks expanded; however, greater tear resistance at high strain rates can enhance wear resistance. Another study [106] highlighted the improved tribomechanical properties of ultrahigh-molecular weight polyethylene (UHMWPE) when filled, compared to UHMPE without filler.

Additionally, Lin et al. [107] examined the tribological properties of carbon fiber-reinforced polyetheretherketone (PEEK) coatings on PEEK substrates. They found that embedded carbon fibers oriented perpendicular to the sliding direction exhibited the greatest reduction in friction and wear. Furthermore, the inclusion of nano-silica at the interface reduced friction via a rolling effect and adhesion mitigation. The incorporation of nanoparticles into materials can refine grain structure and impede dislocation movement, thereby enhancing wear resistance [13–15]. Nazir et al. [4] utilized “U-shaped” profiles to evaluate energy distribution (Archard factor density) at the interface, as illustrated in Fig. 8. A novel mechano-wear model was developed, integrating energy distribution with mechanical equations to investigate how intrinsic mechanical properties (such as grain size, hardness, porosity, and surface stress) of nanocomposite coatings influenced wear. Experimental data validated the model's predictions, demonstrating that wear rates and friction coefficients of nano-coatings increased with grain size, likely due to elevated eigenstress, porosity, and thermal mismatch in the coatings.

2.2.4 Third body

Particles that do not originally belong to the contacting surfaces but actively contribute to the wear process are referred to as “third bodies”. They play a significant role in wear through various mechanisms:

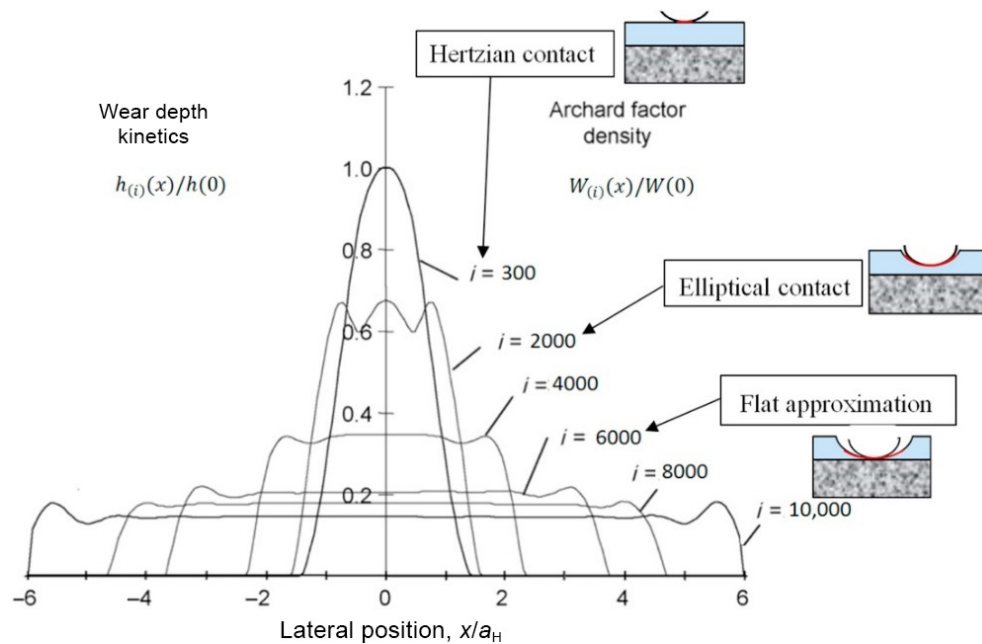


Fig. 8 At various i th fretting cycles, the profile growth of normalized wear depth kinetics and Archard factor density converges to a quasi-flat shape after initially being Hertzian, then elliptical, and finally quasi-flat. Reproduced with permission from Ref. [4], © Elsevier 2018.

Formation of protective layers. Third bodies, such as graphene, can develop a protective layer between contacting surfaces. This minimizes direct surface contact, thereby reducing wear. Graphene, owing to its solid lubricating properties, generates a thin lubricating layer that mitigates metal-to-metal contact and wear loss [108]. Similarly, Lin et al. [107] integrated nano-silica at the interface, reducing friction by minimizing adhesion; however, these particles may also contribute to matrix abrasion.

Modification of contact mechanics. The presence of third bodies alters the actual contact area and stress distribution, thereby influencing wear rates and patterns. For instance, Arnaud and Fouvry [109] observed that a third-body layer concentrated contact pressure, increasing frictional energy dissipation and resulting in greater wear depth.

Characteristics of third-body particles. The size, hardness, and shape of third bodies are crucial in wear processes. Smaller particles tend to increase wear rates by enhancing the particle-matrix interfacial area. In contrast, larger particles reduce the particle's mean free path, increasing hardness and lowering wear rates [110]. The critical length scale d^* , as identified by Brink et al. [60], defines the minimum and typical size for a particle to detach and form wear debris. Materials with larger d^* generate larger wear particles. Harder particles cause more wear on a softer counterface by plowing or indenting the surface. Additionally, sharp-edged particles create localized stress concentrations, resulting in increased contact pressures and wear compared to spherical or rounded particles [111].

2.2.5 Material hardening

The Archard model emphasizes the critical role of material hardness in wear progression, wherein surfaces experience plastic deformation, resulting in material hardening. Accurate prediction of wear evolution necessitates evaluating variations in material hardness throughout the wear process. One approach to achieving this is the Voce hardening law (Eq. (20)), which efficiently characterizes the relationship between stress and plastic strain using fewer parameters than other models [112].

$$\kappa(\gamma) = \frac{\sigma_Y}{\sqrt{3}} + \frac{H}{\sqrt{3}} (1 - e^{-b\gamma}) \quad (20)$$

where $\kappa(\gamma)$ represents the shear strength of the material undergoing γ plastic strain; H is the saturation stress; b is the hardening rate. The factor $\frac{1}{\sqrt{3}}$ relates the values of yield stress σ_Y and saturation stress to their shear counterparts.

Another approach is the power law or Holloman equation, Eq. (21), used for metals with consistent hardening [113].

$$\kappa\sigma = K \cdot \varepsilon^n \quad (21)$$

where σ is true stress; ε is true strain; K is the strength coefficient; n is the strain hardening exponent.

In addition to these two methods, models such as Ludwik's Law [114] and Swift's Law [115] provide alternative approaches for computing hardness variations resulting from material hardening. Each model possesses distinct advantages and should be selected based on the specific material properties and the nature of the applied loading.

2.2.6 Surface roughness

Surface roughness, which quantifies surface texture, plays a crucial role in influencing wear. Rough surfaces with pronounced and sharper asperities induce greater wear damage, particularly during the initial sliding phases [116]. Although smoother surfaces can mitigate friction and wear, their production is often costly [117]. An alternative strategy, surface texturing, improves the tribological performance of mechanical components. Techniques such as three-dimensional (3D) printing facilitate the cost-effective fabrication of complex surface textures with minimal post-processing.

Aziz et al. [118] conducted a pin-on-disc experiment to investigate how texture size and sliding speed influenced the frictional behavior of 3D-printed polylactic acid under various conditions. Under lubricated conditions, they observed that larger textures reduced both the actual contact area and debris entrapment, thereby lowering the CoF. Texture size and sliding

speed impact oil retention; larger textures enhance lubricant retention at moderate speeds, whereas smaller textures achieve this at higher speeds by restricting lubricant flow. Further findings in Ref. [17] indicated that the CoF was influenced by the diameter, aspect ratio, and area density of dimples on contacting surfaces. Samples with dimpled textures exhibit a more substantial reduction in friction and wear compared to non-textured counterparts, highlighting the effectiveness of surface texturing in mitigating wear.

2.2.7 Operating parameters

Operating parameters such as normal load, sliding speed, and sliding distance play a crucial role in influencing the wear process. Studies examining the effects of operating parameters on wear rate and CoF are discussed in Ref. [119]. A high coefficient of friction intensifies shear effects during contact, as observed in brake disc-pad interactions, thereby accelerating surface wear [120]. An increased normal load results in greater deformation of surface asperities and enhanced contact, as illustrated in Fig. 9 [120], thereby promoting material work hardening [14].

Additionally, sliding speed has a significant influence on tribological behavior by modulating the interfacial temperature. A moderate increase in sliding speed can induce oxidation, leading to the formation of a protective oxide layer that reduces wear. However, excessive sliding speeds can soften the material, resulting in greater deformation and stress, thereby accelerating wear [14].

Among these parameters, sliding distance exerts the greatest influence on the weight loss of friction pairs [121]. In braking systems, higher initial speeds generate greater kinetic energy and prolong braking times under the same load. This expansion of the total contact area of the friction pair during braking results in a

substantial accumulation of wear volume. These findings underscore the necessity of carefully evaluating and optimizing operating parameters to effectively control wear.

2.3 How wear contributes to noise generation

Friction-induced noise is widely recognized as an indicator of wear or malfunction [122]. Over time, changes in the morphology of contact surfaces affect interface behavior, thereby altering both noise and friction levels. Therefore, the development of a model integrating wear, friction, and noise can offer critical insights into the condition of machinery and components [22, 123–125]. However, prior to developing such a model, it is crucial to understand how wear contributes to friction noise, as detailed in Table 1.

Based on the previous analysis, an integrated model of wear, friction, and noise necessitates a systematic approach. The first critical consideration is the modeling of the initial surface morphology (Section 3), as it fundamentally influences asperity interactions and the resulting noise generation. Subsequently, defining interfacial contact behavior (Section 4) is essential, as it dictates the evolution of wear, modulates contact stiffness variations, and ultimately impacts system stability and noise characteristics. Lastly, modeling wear evolution (Section 5) is crucial, as it determines the progressive alterations in surface morphology and their subsequent contribution to noise generation.

3 Surface modelling method

The preceding sections have discussed the factors that influence wear. Since wear occurs when two rough surfaces come into contact, the accurate description and generation of these rough

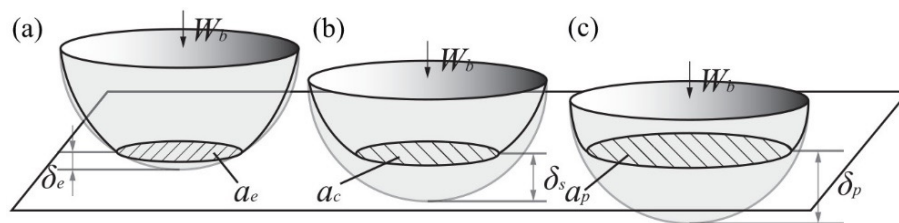


Fig. 9 Illustration of asperity elastoplastic contact mode: (a) elastic contact, (b) critical contact, and (c) plastic contact. Reproduced with permission from Ref. [120], © The Author(s) 2022.

Table 1 How wear contributes to friction noise

Direct mechanisms		
Changes in surface morphology	Wear increases surface roughness and generates debris, leading to stronger asperity impacts, unstable vibrations, and higher noise levels.	[126–131]
Altered frictional behavior	Wear modifies the contact interface, causing stick-slip vibrations and an increased coefficient of friction, which amplifies noise.	[129, 130, 132, 133]
System instability	Progressive wear, such as cracks or eccentric wear, destabilizes the system, enhancing friction-induced noise.	[124, 131–135]
Changes in system dynamics	Wear alters the system's natural frequencies and damping, potentially causing resonance and increased noise.	[136–138]
Indirect factors		
Temperature	Higher temperatures increase wear rates, accelerating surface degradation and debris formation, which indirectly leads to higher noise levels.	[125]
Material properties	Material hardness and wear coefficient influence wear rates; higher hardness and lower wear coefficients reduce wear, thereby lowering noise indirectly.	[134, 135, 139]
Mitigation strategies		
Wear management	Minimizing wear through techniques like lubrication and surface texturing reduces noise by maintaining smoother surfaces and stable frictional behavior, as demonstrated in studies.	[130, 131, 140, 141]

surfaces are a critical aspect of wear modeling. Therefore, this section delves into the methods used to model these surfaces. Rough surfaces play a dual role in tribology: their topology not only drives wear through asperity interactions but also governs the contact dynamics that generate friction noise. Rougher surfaces typically amplify friction noise due to increased asperity collisions and friction forces, though they can sometimes suppress high-frequency squeals by stabilizing contact and reducing stick-slip motion [142, 143]. Since both friction noise and wear stem from the interaction of two rough surfaces, accurately characterizing and generating these surfaces is essential for comprehensive tribological modeling and for predicting and mitigating both phenomena.

3.1 Role of surface topology in friction noise and wear

Surface topology, defined by the height and spatial arrangement of asperities, significantly affects friction, wear, and noise. The real contact area and interaction dynamics during sliding are dictated by surface roughness, influencing wear rates and producing vibrations that manifest as noise [142, 143]. Thus, precise surface modeling is critical for understanding how these features contribute to both wear and friction-induced acoustic emissions.

3.2 Classification of surface characterization methods

A comprehensive review by Li et al. [144] classifies surface characterization methods into two primary approaches: stochastic process theory (STCPSPTs) and fractal theory (STCPFTs). These methods provide frameworks to model rough surfaces, capturing their impact on both wear and noise.

(1) STCPSPTs

STCPSPTs model surface topology using probability distributions, often assuming a Gaussian height distribution. However, real-world surfaces frequently exhibit non-Gaussian traits, such as skewness and kurtosis, which influence friction and wear [145, 146]. These characteristics also affect the acoustic signature of sliding contacts, as deviations in height distribution can alter the intensity and frequency of noises generated during friction [24, 147].

(2) STCPFTs

STCPFTs assume surfaces display self-similarity across scales, where geometric features remain consistent regardless of magnification [148]. This self-affinity, often modeled using the Weierstrass–Mandelbrot (W–M) function [148–150], captures the multiscale nature of roughness. Such properties are key to explaining how surface features at different scales contribute to wear patterns and the frequency spectrum of friction noise [124, 142, 151].

3.3 Key considerations in surface modeling

Effective surface modeling, whether statistical or fractal, relies on two core elements:

(3) Point height distribution

The height distribution, represented using statistical models (Gaussian or non-Gaussian) or the W–M function, shapes contact mechanics. It directly impacts the real contact area and asperity interactions, which drive wear rates and the vibrations that produce noises [126, 127].

(4) Spatial correlations

Spatial relationships between surface points are defined by the auto-correlation function (ACF), which measures the expected correlation between heights separated by a distance l [149, 152]. Although no research has specifically investigated how ACF influences friction-induced noises, it can be inferred from existing

research that ACF affects how asperities engage during sliding, affecting wear patterns and the frequency content of friction-induced sound [24, 142, 153].

3.4 Advances in surface generation techniques

Several techniques have been developed to generate rough surfaces for tribological analysis, balancing accuracy and computational efficiency:

(5) Patir's method

Patir [152] proposed generating Gaussian or non-Gaussian surfaces with a specified ACF by applying linear transformations to random matrices. Solving these nonlinear equations via the Newton–Raphson method, however, is computationally intensive and prone to convergence issues.

(6) Improvements over Patir's model

To address the limitation of Patir's model, Bakolas [154] integrated the nonlinear conjugate gradient method (NCGM) with fast Fourier transforms (FFT) for greater efficiency. Similarly, Liao et al. [155] reframed the problem as nonlinear least squares optimization, introducing an analytical gradient formula for more stable and rapid surface generation.

(7) FFT-based methods

FFT-based approaches, such as those by Newland [156], Hu and Tonder [157], and Wu [158], are widely used for their speed. However, aliasing effects can distort the generated surfaces, reducing accuracy. For further details, see Ref. [159]. These advancements enhance not only wear modeling but also simulations aimed at understanding and controlling friction noise. By generating surfaces that closely mimic real-world topologies, researchers can better predict how surface features contribute to noises under various sliding conditions.

(8) Challenges and implications

While significant progress has been made in generating realistic rough surfaces, the dynamic evolution of surface topology under tribological conditions remains a challenge. Contact forces and kinematics continuously reshape surfaces, altering wear progression and noise characteristics. This interplay underscores the need for models that capture how surface changes affect both wear and acoustic emissions, enabling the design of surfaces that minimize wear and reduce undesirable friction noises in practical applications.

4 Contact mechanisms

Before delving into the methods of wear modeling, it is essential to examine how contact mechanisms between surfaces influence both wear and friction noise, as these mechanisms form the foundational basis for understanding wear behavior and noise generation. Contact mechanisms dictate the interaction between two surfaces, affecting wear rates, wear patterns, and the production of friction-induced vibrations that manifest as noise. Below, we explore these relationships in detail, integrating classical theories, their refinements, and modern models to highlight the critical role of contact mechanisms.

4.1 Classical theories provide a starting point

When two surfaces come into contact, factors such as contact pressure distribution, asperity characteristics, and interface material properties determine the wear rate and patterns, which ultimately influence component durability.

Hertzian contact theory. Hertz [5] introduced a foundational model for elastic contact between smooth surfaces, calculating contact area, stress distribution, and displacement. However, real surfaces are rough, limiting its applicability.

Greenwood (GW) model. Greenwood and Tripp [6] extended Hertz's theory by incorporating Gaussian-distributed asperity heights. This model aligns with Hertz under heavy loads but diverges under lighter ones. It assumes purely elastic deformation, neglecting asperity interactions (e.g., merging) and high-load scenarios (defined by a dimensionless threshold $T = 200$), which restricts its accuracy for wear prediction under complex conditions. Moreover, these simplifications limit its ability to capture dynamic asperity interactions that drive friction-induced vibrations and noises [160].

4.2 Refinements reveal further limitations

Nayak's contribution. Nayak [161] distinguished between surface and profile statistics, showing that profile data underestimates peak heights, summit curvature, and gradients compared to surface-level observations [162, 163]. This impacts the analysis of rough surface contact and wear.

Greenwood's extension. Greenwood [164] later introduced joint probability distributions for asperity heights and curvatures, revealing that most summits are elliptical, not spherical as assumed in earlier models. This variability in asperity geometry improves estimates of contact area and load, refining wear predictions.

4.3 Modern models address complex contact scenarios

Multivariate model. Tomota et al. [165] proposed a shift from Gaussian to multivariate distributions for asperity heights, accommodating non-Gaussian surfaces. However, it assumes isotropy, limiting its suitability for anisotropic surfaces common in wear scenarios.

Elastic-plastic models. Traditional models focused on elastic [5, 6] or plastic [166] deformations separately. Newer asperity-based models [167] integrate both, conserving volume during plastic deformation and treating GW (elastic) and PW (plastic) models as lower and upper bounds. Yet, these struggle with high-load conditions due to unmodeled asperity interactions like merging. Johnson et al. [168] proposed that the elastoplastic contact solution of two rough surfaces was approximated by solving the problem of the contact between a rigid surface (whose geometry equals the gap between the two original surfaces) and a flat elastic-perfectly plastic half-space. Nevertheless, this simplification is adequate for simulations of stationary contact but fails in the context of sliding-contact friction dynamics due to its omission of asperity interactions of the original surfaces. Therefore, these models still fall short, as their focus on elastic

deformation neglects plastic effects and dynamic asperity interactions—key contributors to wear development and friction-induced vibrations under real-world conditions [160].

Dynamic models. To overcome the limitations of earlier models in dynamic conditions, De Moerloose et al. [169] developed a sliding contact model, as shown in Fig. 10. This model simulates asperity interactions using a mass-spring system with nonlinear elastic-plastic behavior, specifically the Maxwell-slip model, and incorporates adhesion laws. This approach effectively captures the variations in dynamic friction forces that are responsible for noise generation [170]. However, Moerloose's model does not account for the fact that wear-induced changes in surface morphology alter contact behavior and asperity interactions, which in turn influence subsequent stick-slip behavior and noise levels [170].

Contact mechanisms between surfaces are fundamental to understanding how wear occurs and why friction produces noise. Early theories, like the Hertzian contact theory and the Greenwood model, provided a starting point by explaining how smooth and rough surfaces interact, but they oversimplified real-world conditions. Over time, refinements such as Nayak's surface statistics and Greenwood's elliptical asperity insights improved accuracy by better capturing the complexity of surface roughness. Modern models, including multivariate and elastic-plastic approaches, have tackled more realistic scenarios like non-Gaussian surfaces and mixed deformations, while dynamic models like Moerloose's simulate friction dynamics. However, challenges persist, particularly in modeling friction dynamics while accounting for wear progression. Continued research into these contact mechanisms is essential for integrating wear predictions with friction noise in practical applications.

5 Wear modelling methods

5.1 Historical perspective

The understanding of wear originally derived from empirical observations conducted by artisans and engineers, who noted its effects on tools and machinery. Following advancements in scientific methods, researchers such as Ragnar Holm [58] and John F. Archard [59] commenced the development of theoretical models to elucidate wear mechanisms. The Archard model has emerged as pivotal for wear prediction. Subsequent advancements resulted in the development of more complex models that account for material properties, environmental factors, and mechanical parameters. However, these sophisticated models frequently

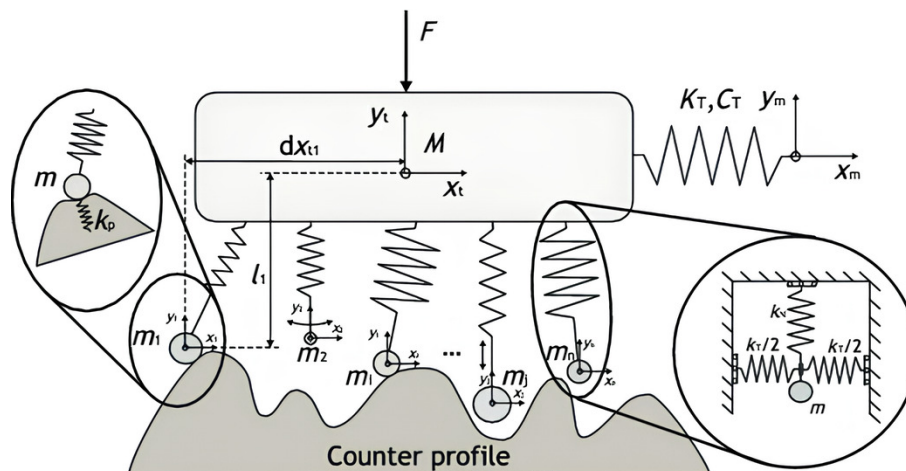


Fig. 10 The contact scenario. Reproduced with permission from Ref. [167], © Springer Science Business Media, LLC 2010.

present challenges in deriving analytical solutions, occasionally making such derivations infeasible. Consequently, numerical methods, such as finite element analysis (FEA), have attained prominence in the simulation and prediction of wear in complex systems. More recently, machine learning and artificial intelligence have increasingly been utilized in predictive wear modeling, representing a significant evolution in the field. The following sections will explore various wear modeling approaches.

5.2 Different approaches of wear modelling

5.2.1 Analytical wear models

Analytical wear models are essential tools for predicting material degradation under frictional sliding, offering insights into the complex interplay of mechanical, thermal, and material factors. This text examines three significant approaches: the patch theory by Ostermeyer and Müller [41], the dissipation wear model by Li et al. [1], and recent improvements to the Archard model [1, 12, 66]. These models address different aspects of wear dynamics, from microscale patch formation to entropy-based wear predictions and refined contact mechanics, with friction noises emerging as a recurring experimental observable.

(1) Patch theory by Ostermeyer and Müller

Ostermeyer and Müller [41] developed the “patch theory” to elucidate the dynamic behavior of the CoF during frictional sliding. This theory posits that wear debris, arising from temperature increases in the pad-disc system, disintegrates to form patches on the contact surface. These patches eventually attain a state of instability, resulting in cracking and detachment, as illustrated in Fig. 11. This cycle of patch formation and destruction establishes a dynamic equilibrium, characterized by the dynamic friction coefficient $\mu(t)$, expressed in Eq. (22) from an energy perspective:

$$\dot{\mu} = f_1 - f_2 = -a \times nv(t) \times \mu + bT_{\text{eff}} \quad (22)$$

where $\dot{\mu}$ denotes the time derivative of μ ; f_1 represents patch growth processes; f_2 represents patch destruction processes. The coefficients a and b quantify the impact of these processes on the friction coefficient, determinable through experimental or theoretical analysis. The dimensionless parameter $(nv(t))$ represents the product of the instantaneous normal load and tangential velocity, while T_{eff} denotes the effective temperature

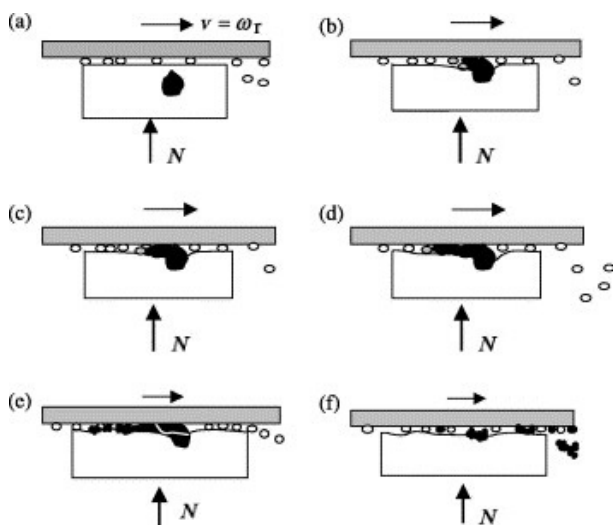


Fig. 11 Patch formation mechanism at the sliding interface. Reproduced with permission from Ref. [41], © Elsevier Ltd. 2005.

influencing patch growth and size. The formation and destruction of patches, driven by temperature increases and mechanical instability, can induce localized vibrations at the contact interface, potentially contributing to friction noises—a phenomenon explored further in subsequent sections.

1) Dissipation wear model

Building on thermodynamic principles, Li et al. [1] developed a dissipation wear model that establishes a linear relationship between wear and entropy increase. This model suggests that wear tests yielding identical entropy increments, despite varying parameters, are equivalent. The rate of entropy increase depends on factors such as sliding velocity, normal load, and temperature; consequently, adjusting these factors can accelerate wear tests. By accounting for key wear-influencing factors like temperature and friction coefficient, this entropy-based approach more accurately reflects experimental outcomes compared to the Archard model. Due to advancements in abrasive resistance technologies—such as structural modifications and novel materials—the prolonged duration required for traditional wear tests has become impractical, necessitating accelerated methods to reduce lifespan evaluation time. As energy dissipates through wear processes, a fraction transforms into vibrational energy, potentially manifesting as friction noise, which aligns with the model's focus on entropy and energy dissipation [172].

2) Improvements to the Archard model

To address the Archard model's limitations, particularly its neglect of contact geometries and third-body effects, recent advancements offer refined formulations. Reference [66] developed novel formulations predicting fretting wear volume and rate as functions of contact geometries and wear scar width. The wear rate is inversely proportional to wear scar width, where widening scars restricts metal oxidation and may result in metal-metal transfer, forming a lubricating film that reduces wear. Similarly, a study [12] investigated the interplay between friction, wear, and material transfer in aluminum adhesive wear, presenting a friction model that predicts variations in the CoF and transfer area from the running-in phase to a stable state, as shown in Fig. 12. These variations depend on sliding distance and contact load, with higher loads reducing the running-in duration, increasing the saturated transfer amount, and elevating the steady-state wear rate. Furthermore, Guilbault and Lalonde [171] formulated a statistical model to depict asperity shape evolution due to wear and plastic deformations under mixed lubrication, incorporating asperity strain hardening and a methodology for predicting contact crack initiation using multiaxial criteria and damage accumulation based on load history. These enhancements introduce factors that may influence friction noises, such as changing contact geometries and third-body interactions.

3) Potential role of friction noise across analytical wear models

Friction noise, manifested as acoustic emissions during frictional sliding, is established as a valuable indicator of wear processes and can be integrated with these analytical wear models. In the patch theory [41], the detachment of unstable patches generates transient vibrational events audible as noises, with frequency and intensity reflecting patch dynamics (e.g., f_1 and f_2). This suggests that noise analysis could non-invasively validate parameters like a , b , and T_{eff} . Similarly, in the model of Li et al. [1], friction noise correlates with entropy increase, driven by sliding velocity, normal load, and temperature, offering real-time feedback for accelerated wear testing and enhancing predictive accuracy. For the Archard model improvements [12, 66, 171], variations in wear scar width and third-body particles (e.g., wear debris) modify vibrational modes, amplifying or attenuating noise, while asperity evolution and crack initiation in the formulation of

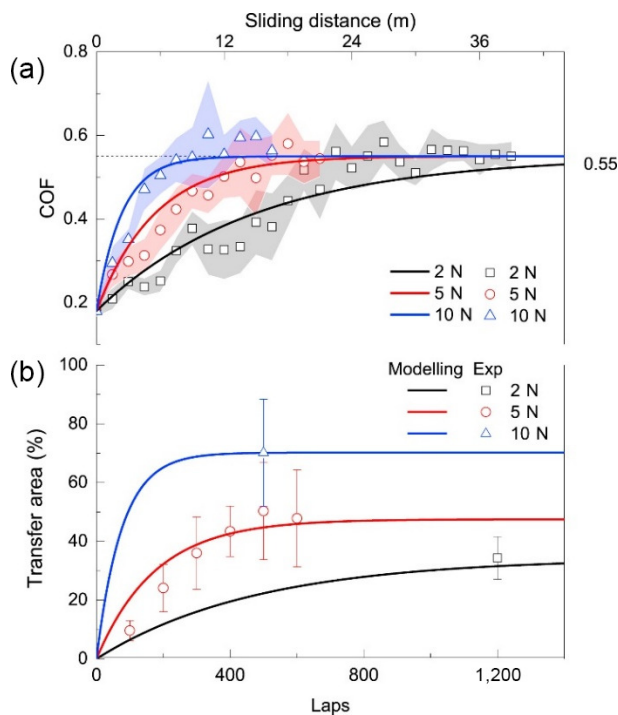


Fig. 12 Comparing the outcomes of modeling with experimental results in terms of (a) the changes in COF and (b) variation in the transfer area across different contact loads. Reproduced with permission from Ref. [12], © Elsevier Ltd. 2018.

Guilbault and Lalonde [171] further contribute to noise generation. Integrating friction noise analysis into these models could improve their capacity to depict the dynamic interplay of wear mechanisms, bridging theoretical predictions with empirical observations.

5.2.2 Empirical wear models

Wear prediction relies on diverse modeling approaches, each balancing physical insight, data-driven analysis, and statistical rigor. This section explores three key types: semi-empirical models, which integrate physical phenomena with empirical data; AI-based models, leveraging machine learning for complex pattern recognition; and regression models, offering interpretable statistical relationships. Across these approaches, friction noise—acoustic emissions from sliding interfaces—emerges as a valuable observable, potentially enhancing model development and validation.

(1) Semi-empirical models

Semi-empirical models bridge empirical observations with physical theories, deriving parameters through experimental data regression to capture specific wear processes. Unlike purely data-driven AI models, they incorporate mechanistic understanding, making them particularly suited to targeted applications.

Al-Maliki et al. [2] proposed a semi-empirical formula, Eq. (23), for wheel–rail contact wear, accounting for variables such as material combinations, load, slip, and lubrication:

$$\text{Wear rate} = k_1 z_0 + k_2 \tau^{k_3} \quad (23)$$

where z_0 represents the damaged layer depth; τ is the peak shear stress; k_1 , k_2 , and k_3 —specific to material pairs—are optimized by minimizing squared errors between experimental and predicted outcomes. This model effectively captures both mild (linear) and severe (superlinear) wear regimes, with shear stress and damage layer dynamics potentially generating friction noise through surface disruptions.

Similarly, researchers [173] introduced a dimensionless severity parameter, Sc , based on dry rolling tests of brittle materials like silicon nitride and alumina, incorporated into Eq. (24):

$$\text{Wear rate} = \alpha \cdot Sc^n \quad (24)$$

where $\alpha = 1.56 \times 10^{-5}$ and $n = 5.46$, $Sc = P_m \sqrt{\bar{R}_{\max}} / K_{IC} \cdot P_m$ denotes average Hertzian pressure; $\bar{R}_{\max}$ is the average maximum roughness of the worn surface; K_{IC} is fracture toughness. This model focuses on brittle fracture-dominated wear, where cracking and spalling could produce distinct acoustic signatures tied to Sc .

(2) AI-based models

AI-based models, including artificial neural networks (ANN), support vector regression (SVR), and deep learning, excel in predicting wear across diverse conditions by identifying nonlinear patterns in large datasets, though they often lack physical interpretability.

A study [174] demonstrated ANN's ability to estimate fretting wear volume in low-alloyed steel, outperforming traditional friction energy approaches by accurately predicting wear kinetics for unseen test conditions. Friction noise, arising from fretting vibrations, could enhance such models as an input feature reflecting surface interactions. Similarly, Wang et al. [175] applied SVR to predict rail steel wear, leveraging its robustness and efficiency, and noise signals might correlate with wear progression.

For wear mechanism classification, traditionally reliant on time-intensive SEM image analysis [176, 177], AI methods—ANN [176] and deep learning [177]—utilize worn surface images, reducing expert dependency. Cavaleri et al. [178] developed an ANN to predict tribological behavior in heat-treated tool steels, while Mahanta et al. [179] used a multi-response ANN for Al7075/B4C/fly ash nanocomposites, achieving high accuracy. Integrating friction noise data (e.g., frequency spectra) into these training sets could improve sensitivity to dynamic wear processes, such as material transfer or surface degradation.

(3) Regression models

Regression models, particularly linear regression, provide transparent statistical frameworks for modeling wear, contrasting with the “black box” nature of AI methods. They excel with smaller datasets and linear relationships, offering clear coefficients for interpretability.

In wear studies, techniques like analysis of variance (ANOVA), response surface methodology (RSM), and Taguchi design enhance regression models. ANOVA evaluates variables like load and velocity on wear rate and CoF [119, 121, 180], while RSM optimizes variable combinations for desired responses [180–182]. Taguchi design, using orthogonal arrays, minimizes experimental runs to study variable interactions [119, 121, 183, 184], paired with signal-to-noise (S/N) ratios to rank influences. For wear and CoF—responses to be minimized—a “smaller-is-better” S/N approach identifies optimal conditions with low variability [121, 184, 185]. Friction noise, as a measurable outcome of surface dynamics, can be incorporated as a response variable or noise factor, revealing how load or velocity alters acoustic emissions alongside wear.

(4) The potential role of friction noise across empirical wear models

Friction noise serves as a pivotal element in enhancing the predictive capabilities of various wear modeling approaches by providing insights into the underlying physical processes. This subsection summarizes the role of friction noise across semi-empirical, AI-based, and regression models, highlighting its contribution to improving wear predictions.

Semi-empirical models. In semi-empirical models, friction

noise is strongly correlated with physical events such as shear stress and fracture. This correlation enables researchers to associate distinct noise patterns with physical phenomena, thereby predicting shear stress, fracture, and wear processes.

AI-based models. For AI-based models, friction noise can enrich training datasets, enabling machine learning and deep learning algorithms to capture complex, nonlinear wear kinetics. By incorporating noise as an additional feature, these models gain the ability to discern intricate patterns that traditional methods might miss, improving their robustness and predictive power across diverse and previously unseen conditions.

Regression models. In regression models, friction noise can be integrated into S/N analysis to quantitatively assess variability in the wear process. This approach enables researchers to evaluate the interdependence of friction noise with other factors (such as load and velocity), thereby optimizing experimental conditions to reduce the noise level.

5.2.3 Numerical wear models

(1) Finite element models (FEMs)

Gear systems and vibrational dynamics. In helical gear machines, wear alters tooth profiles, amplifying vibrational energy and noise. Zhao and Vacca [186] developed a three-dimensional FEM to predict wear patterns, gear vibrations, and axial rotor shaft dynamics. Their approach simulates sliding and rolling contacts, capturing how wear-induced surface degradation increases vibrational energy at the gear interface. This vibrational energy is directly correlated with friction noise, as worn surfaces alter asperity interactions, resulting in dynamic instability. Although the quantitative relationship between wear and noise has not been established, by linking wear to vibrations, the model of Zhao and Vacca [186] paves a path for predicting noise escalation in geared systems, offering insights into how wear progression can be monitored through noise signatures.

Multi-scale modeling and thermal influences. Wear and noise are influenced by phenomena spanning multiple scales, necessitating integrated modeling approaches. Waddad et al. [23] created a micro-macro scale FEM model for thermal and wear analysis in sliding contacts (Fig. 13), incorporating micro-scale surface roughness evolution into a macro-scale framework to

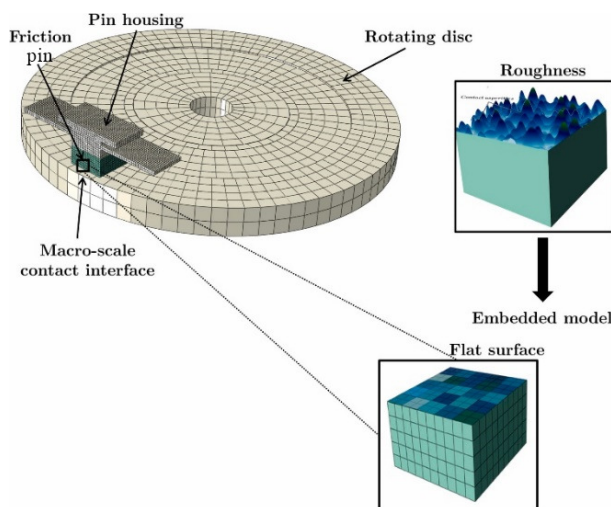


Fig. 13 Schematic illustration of a sliding contact application employing the multiscale strategy. The actual contact area is influenced by surface roughness and its development during movement. At the macroscopic scale, the surface is flat, but its roughness is incorporated in the interface behavior. Reproduced with permission from Ref. [23], © Elsevier B.V. 2018.

reduce computational demands. This model simulates heat generation from friction, which can alter material properties like stiffness and damping, influencing wear rates and vibrational energy. However, it assumes all wear volume exists in the contact zone, neglecting debris retention that could affect vibration and noises. Although no direct relationship between wear and noise has been identified, the work of Waddad et al. [23] presents a multiscale modeling framework that could be expanded to elucidate how microscale contact influences macroscale vibration and noise.

Turbomachinery and feedback loops. In turbomachinery, wear and noise exhibit a complex interplay. Berthoul et al. [187] investigated wear interactions between casing coatings and blades, identifying four mechanisms—machining, plasticity at junctions, plowing, and micro-rupture—synthesized into a 3D FEM model (Fig. 14). They found that the vibrational energy from blade contact accelerated wear, increasing friction noise as surface degradation intensifies. However, wear-induced operational clearance growth reduces subsequent contacts, decreasing vibrational energy transmission and, consequently, noises. This feedback loop suggests that friction noise reflects the system's dynamic state: An initial noise increase signals active wear, while a subsequent decrease indicates stabilized clearance. The findings of Berthoul et al. [187] underscore noise's potential as a non-invasive diagnostic tool for wear progression in turbomachinery, where vibrational energy is a significant driver.

Fretting wear and dynamic responses. Fretting wear, involving small-amplitude oscillatory motion, generates distinct vibrational signatures that manifest as noises. Armand et al. [3] combined nonlinear dynamics and contact mechanics in a multi-scale FEM approach to study fretting wear's impact on structural responses. Their model, assuming negligible wear depth, captures transitions between partial and gross slip regimes, which alter contact stiffness and energy dissipation—key factors in noise generation. By extending this framework with acoustic simulations, the model could predict friction noise patterns, such as frequency shifts reflecting wear severity. This enhancement would deepen our understanding of noise in precision machinery, where reducing acoustic emissions is critical. Zhang et al. [188] advanced fretting wear modeling for Ti-6Al-4V alloy, tracking debris layer evolution and ratcheting deformation. Debris accumulation dampens vibrational energy by altering contact dynamics, potentially reducing noise intensity. However, their assumption of identical properties between debris and bulk

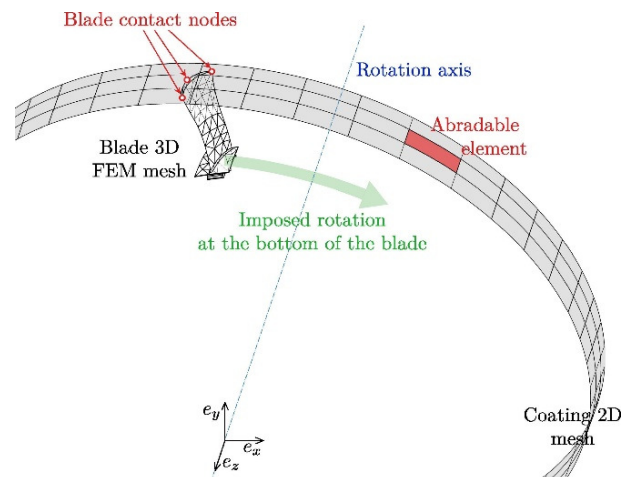


Fig. 14 Simulation representation between a blade and a coated casing. Reproduced with permission from Ref. [187], © Elsevier Ltd. 2017.

materials overlooks the unique characteristics of oxidized, compressed debris, which may further modulate noises. Cross et al. [189] modeled fretting wear in cobalt–chromium alloys using the Franklin–Kapoor model [190], tracking plastic shear strain accumulation (Eq. (25)). This strain induces material hardening and stress evolution, thereby altering contact behavior, which subsequently affects vibrational energy and noise.

$$\Delta\gamma_{i+1} = \begin{cases} c \frac{\tau_{xy}}{\kappa(\gamma_i)}, & \text{if } \tau_{xy} > k \\ 0, & \text{otherwise} \end{cases} \quad (25)$$

where $\kappa(\gamma_i)$ represents the shear strength of the i th loading cycle and is a function of the accumulated shear strain γ_i at a given location within the material. This relationship is utilized to model material hardening (Voce hardening law [112]); c is the strain-accumulation per cycle, to be determined experimentally, and τ_{xy} is the shear stress distribution under the point of contact.

Fatigue and stress redistribution. Wear influences fatigue life and noise through stress redistribution. Zhang et al. [78] integrated an energy-based wear model [64] with multiaxial damage accumulation [82] to simulate fretting fracture initiation in press-fitted shafts (Fig. 15). Severe wear alleviates stress concentrations at contact edges, reducing crack initiation and potentially noise, but induces deeper cracks within the contact zone, altering vibrational patterns. Similarly, Pinto et al. [191] assessed fretting fatigue under variable amplitude loading, using Miner's rule (Eq. (26)) for damage accumulation. Wear introduces nonlinearity, complicating noise predictions, as changing contact conditions affects vibrational energy. An FEM study [192] further explored fretting fatigue endurance, considering debris as a third body (Fig. 16). Trapped debris reduces peak stresses and cyclic loading, enhancing endurance while possibly dampening noise, suggesting that noise variations could indicate debris dynamics and wear progression.

$$D_m(x) = \sum_{i=1}^m \frac{\Delta N}{N_{fi}(x)} \quad (26)$$

where D_m is the total cumulated damage at the m th simulated fretting cycle, ΔN is the jumping factor considered in the wear computations, and $N_{fi}(x)$ is the estimated life by using any multiaxial fatigue criterion for a given material point with coordinates x .

Third-body effects and contact dynamics. Debris as a third body significantly affects wear and noise. A study [109] on Ti–6Al–4V cylinder/plane interfaces integrated a third-body layer

into an FEM model (Fig. 17), revealing its critical role in wear depth prediction. Omitting this layer underestimates wear by 300%, as debris alters friction and vibrational energy transmission, influencing noise. Another FEM model for press-fitted shafts [193] shows that exceeding a critical stress ratio creates an open zone, changing contact dynamics and potentially noise characteristics. These findings highlight how third-body effects modulate noise by altering the tribological interface.

Thermal and material property changes. Thermal effects link wear and noise through material property changes. Bochkareva et al. [98] used FEM to study polymer composites, identifying friction as the primary driver of contact temperature, which affects stiffness and damping, thus influencing noise. Yadav et al. [100] simulated temperature elevation in ball–disc sliding wear (Fig. 18), observing peak temperatures that could lead to thermal softening, altering wear rates and noise patterns. These studies demonstrate how temperature mediates the wear–noise relationship, a critical consideration for high-friction environments.

Although the aforementioned FEM studies have not explicitly examined the correlation between wear and noise, by analyzing this research, noise can be integrated into these models to enhance our understanding of how wear generates vibrational energy and friction noise. However, limitations persist: Assumptions about debris properties, neglect of material changes, and simplified fatigue models can constrain wear prediction accuracy. Future research should integrate acoustic simulations into FEM frameworks, coupling structural and acoustic analyses to capture noise frequency and intensity alongside wear. For example, in gear systems, noise shifts could signal wear severity, while in turbomachinery, they could indicate clearance stabilization. Enhanced models incorporating realistic debris dynamics and temperature-dependent properties would improve predictive power, supporting the design of quieter, more durable systems.

(2) Cellular automaton (CA) models

The CA method, first introduced in Ref. [141], is a versatile numerical technique widely applied in tribology to model complex frictional and wear processes. This approach discretizes a continuous system into a grid of cells, each assigned attributes such as debris count, temperature, or state (e.g., “patch” or “non-patch”). These attributes evolve over time based on simple rules influenced only by neighboring cells, as illustrated in Fig. 19. This localized interaction enables CA to simulate emergent behaviors in multi-physics systems, making it particularly valuable for studying the dynamic interactions at contact interfaces.

One significant application of the CA method is in analyzing wear and thermal effects in brake systems. Mueller and Ostermeyer [194] employed a CA model to compute wear particle density and temperature fields within the boundary layer between a pad and disc. Their work highlights how CA can capture boundary layer dynamics, offering insights into wear evolution. While focused on brake systems, this model's adaptability suggests potential for other frictional contexts.

Expanding on this foundation, Yan et al. [195] adapted the CA framework into a spring-block-conveyor system to explore the role of third-body particles (TBPs) in friction dynamics, as depicted in Fig. 20. They divided the block's interface into units matching the size of TBPs, using a prescribed particle flow function to predict distribution changes. Friction in each cell is calculated and aggregated to determine the total friction force, which feeds into a dynamic model to compute the block's displacement, velocity, and acceleration. Their results revealed a positive friction force–velocity correlation without TBPs, shifting to a negative correlation when TBPs were present. Discrepancies between simulations and experiments were linked to unmodeled

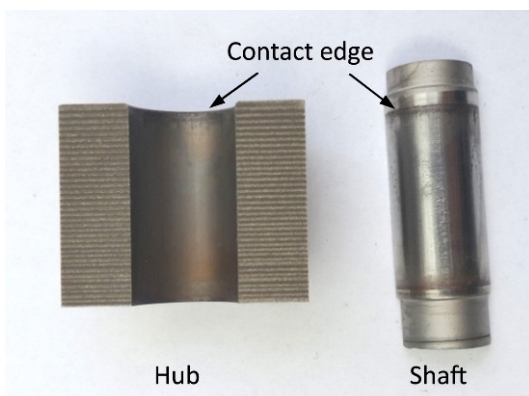


Fig. 15 The specimen of the press-fitted shaft. Reproduced with permission from Ref. [78], © Elsevier B.V. 2018.

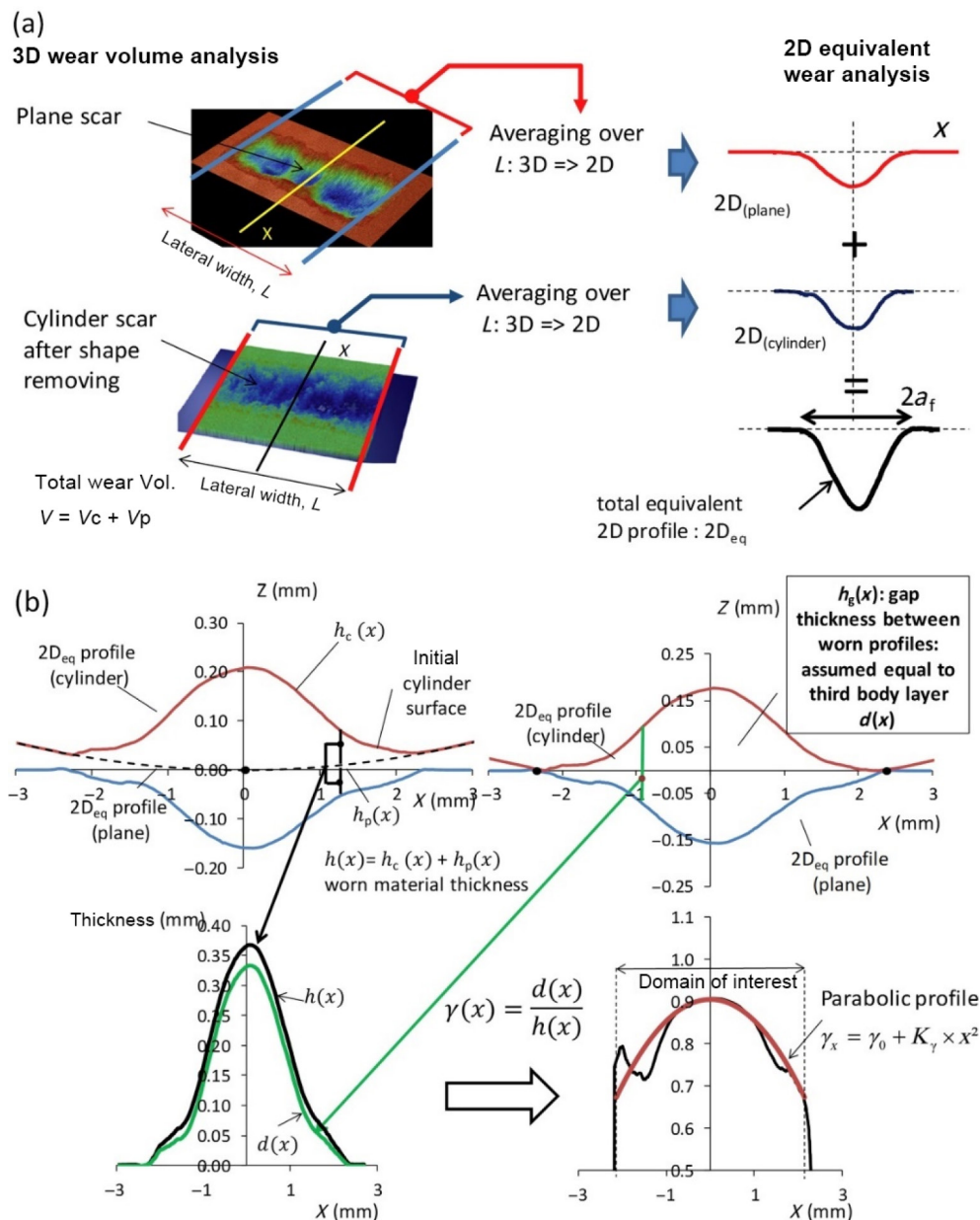


Fig. 16 Methodology employed to quantify fretting scar after ultrasonic cleaning: (a) utilization of an averaging strategy to extract representative 2D equivalent wear profiles from 3D surface analysis; (b) comparison of plane and cylinder worn 2D equivalent surface profiles to ascertain wear thickness profile ($h(x)$) and debris thickness profile ($d(x)$), where K_f and γ_0 depend on the wear volume extension and therefore may be expressed as a function of the accumulated friction energy. Reproduced with permission from Ref. [192], © Elsevier Ltd. 2020.

factors, such as particle rolling, temperature variations, and material deformation.

The CA method excels at modeling dynamic behaviors at contact interfaces, such as temperature fluctuations and transient debris distributions. By discretizing the system and updating cell states based on local rules, CA integrates seamlessly with contact mechanics and dynamic models. This capability enables the simulation of wear evolution in complex tribological systems, bridging microscopic interactions with macroscopic outcomes. Beyond wear and friction, the CA method shows promise for simulating friction noise, a critical concern in applications like automotive braking. The model's ability to track transient changes—such as the formation and destruction of “patches” or the movement of TBPs—can induce localized vibrations that contribute to noise phenomena like squeal or chatter. For example, the findings by Mueller and Ostermeyer [194] on

evolving wear particle density and temperature fields in brake systems suggest a link to noise characteristics. As debris redistributes or temperatures fluctuate, interactions between neighboring cells may generate vibrational energy. By incorporating rules to quantify vibrational energy or acoustic emissions based on these changes, the CA model could predict how wear processes influence friction noise. Such enhancements would provide valuable insights into noise mitigation alongside wear prediction, particularly for performance-critical systems.

(3) Particle-based models

Particle-based numerical methods, such as the material point method (MPM) and the discrete element method (DEM), excel at simulating large deformations and strains—phenomena that pose significant challenges for traditional finite element methods. In tribology, these methods are critical for modeling complex processes like wear, contact mechanics, and frictional interactions

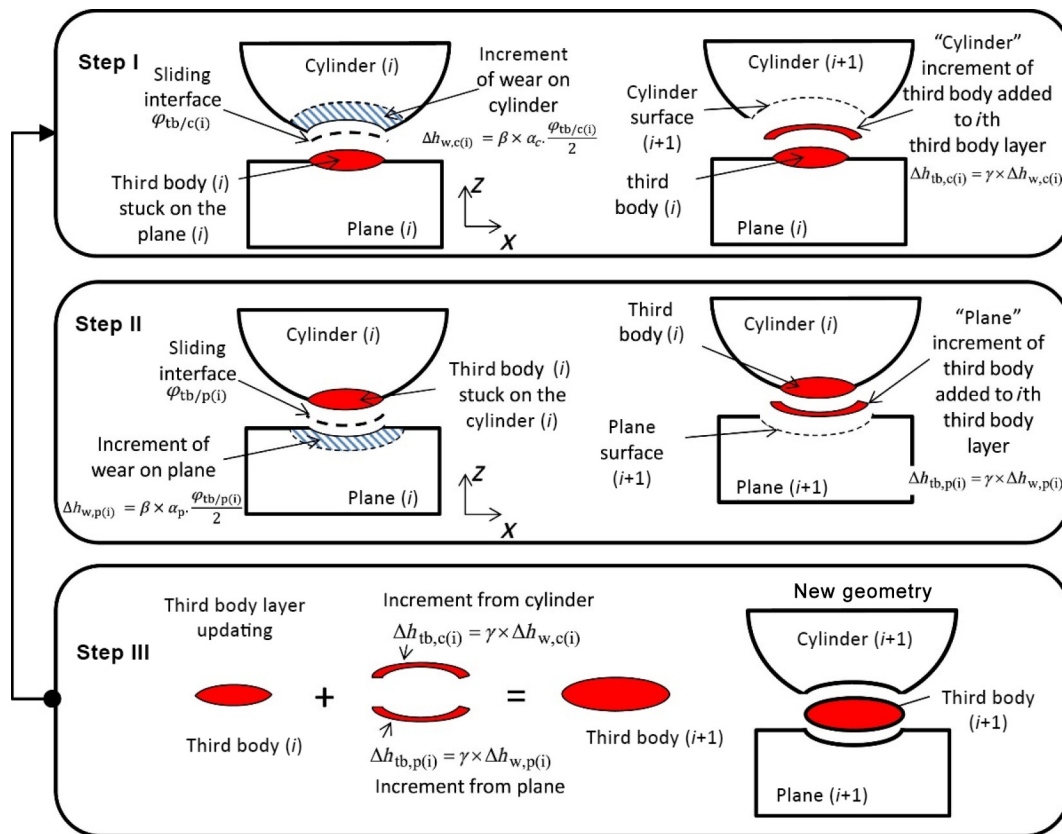


Fig. 17 Illustration of the algorithm used to simulate the surface wear of a plane and its cylinder counterpart, taking a dynamic third-body layer into consideration, where the friction energy density dissipated at the interface, φ_i , causes wear, but only a portion is consumed in the wear process, depending on the upper and lower bodies' energy wear factors, α_c and α_p . A “numerical jump”, β , allows for the simulation of several experimental cycles within a single numerical cycle, saving simulation time. A parabolic function $\gamma(x)$ is defined to determine the fraction of wear and the proportion of worn material converted to the third body. Reproduced with permission from Ref. [109], © Elsevier B.V. 2018.

under extreme conditions. This section introduces MPM and DEM, followed by detailed discussion on their applications, limitations, and their potential in understanding friction noise.

MPM in tribology. MPM is a hybrid numerical technique that combines particle-based and grid-based approaches to simulate the behavior of solids and fluids, particularly in scenarios involving plastic flow and large deformations [73, 76]. In tribological applications, MPM represents the indenter using rigid triangular meshes, while the substrate is modeled with elastic cubic particles—typically sized at twice their radius—carrying predefined material properties. These particles interact with a background computational grid via an interpolation function, enabling the exchange of information such as position and momentum. Contact between the indenter and substrate is detected by calculating the minimum distance; contact occurs when this distance is less than the particle or cell diameter, and the contact point lies within the triangle's projected area [76]. This approach, illustrated in Fig. 21, allows for the computation of nominal and tangential (frictional) forces and the total contact area.

Mishra et al. [75] applied MPM to study plowing forces and profiles when a rigid elliptical asperity slid across a rigid-plastic substrate, assuming negligible elastic deformation. Their results demonstrate that the asperity's size and orientation relative to the sliding direction significantly influence plowing behavior. However, MPM faces challenges in accurately modeling complex surface geometries and wear processes such as material transfer (e.g., in wedging wear). Studies [75, 76] note that discrepancies between MPM simulations and experimental results arise partly

because MPM struggles to capture intricate surface topographies. To address this, researchers limited sliding distances to 2 mm in experiments, as longer distances amplified errors due to evolving surface geometry and wear that MPM cannot fully replicate.

DEM in tribology. Unlike MPM, DEM models materials as assemblies of discrete particles that interact based on physical laws, making it well-suited for simulating granular flows and wear in particulate systems. Capozza and Hanley [196] developed a DEM-based failure model to analyze wear in impact and scratching scenarios, as depicted in Fig. 22. In their model, an irrotational particle (projectile) is assigned an initial velocity for impact simulations, while an indenter with both horizontal velocity and normal load is used for scratching. Their findings reveal that the wear volume in impact scenarios increases with incident velocity, peaking at a 90° angle, while in scratching, wear follows Archard's law (proportional to normal load) up to a threshold, beyond which it transitions to a nonlinear regime. DEM's strength lies in its ability to capture microscale particle interactions, but like MPM, it struggles with complex surface topographies due to its reliance on simplified particle shapes (e.g., small spheres).

Friction noise and particle-based models. Friction noise, resulting from particle interactions and surface deformations, is a phenomenon that particle-based methods like MPM and DEM are naturally equipped to explore. In MPM, vibrations generated during plowing—due to interactions between the indenter's mesh and substrate particles—contribute to noises, as observed by Mishra et al. [75]. Similarly, in DEM, the discrete particle collisions and movements modeled by Capozza and Hanley [196] directly influence noises, particularly in high-velocity impact or

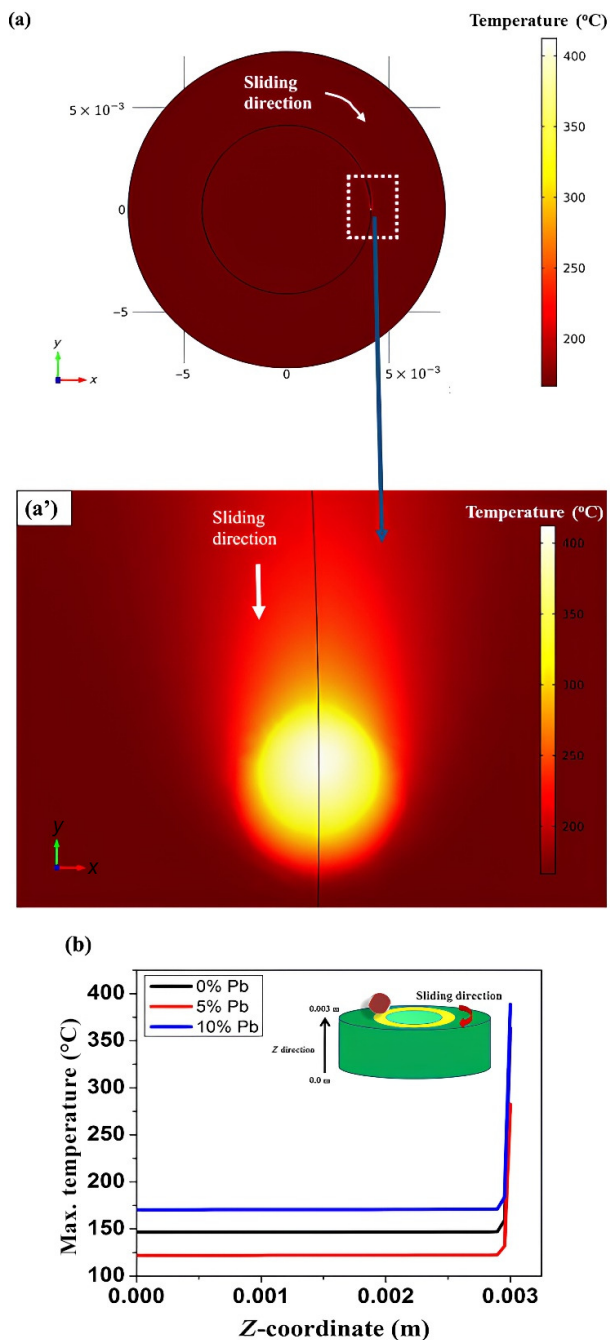


Fig. 18 (a) Result of COMSOL Multiphysics analysis of the maximum surface temperature at contact point between a rotating (CuCrFeTiZn)90Pb10 HEA disc and a stationary steel ball. The maximum surface temperature within contact zone is 388.6 °C. (b) variation of surface temperature along z-direction (0.003 m represents the surface) for different Pb concentrations. Reproduced with permission from Ref. [100], © Elsevier B.V. 2018.

scratching scenarios. For example, the observed increase in wear volume with incident velocity likely correlates with heightened noises from more energetic collisions.

To enhance their utility, MPM and DEM simulations could be coupled with acoustic models. By linking particle velocities or collision rates to vibrational frequencies, researchers could predict noise characteristics alongside wear outcomes. This integration would be particularly valuable in high-wear, high-noise environments—such as manufacturing tools or granular flows—where reducing noise is as critical as managing wear.

(4) Brick wall model

The “brick” wear model, developed by Franklin et al. [54], is a computational framework designed to simulate crack initiation and surface wear in rolling contact fatigue. The model conceptualizes a material as a layered structure of discrete “bricks”, analogous to a brick wall, where each brick represents a small volume of material subjected to cyclic loading. This “brick wall” metaphor reflects the progressive deterioration of the material under stress, much like bricks crumbling in a wall. The model’s core mechanism is based on ductility exhaustion, a process where repeated plastic deformation depletes a material’s ability to withstand further strain, ultimately leading to failure [197, 198].

In this framework, material failure begins when the maximum shear stress exceeds the shear yield stress, causing shear strain to accumulate within individual brick elements. As illustrated in Fig. 23—showing the material state after n wheel passes—failure occurs when the accumulated shear strain surpasses a critical threshold. This triggers crack initiation, which propagates and eventually results in surface wear through material removal. By modeling these subsurface processes, the Brick model excels at predicting material failure beneath the surface, a key factor in wear analysis for rolling contact systems like gears or bearings.

Despite its strengths, applying the model presents a significant challenge: selecting an appropriate size for the brick elements. Smaller elements capture finer details of stress and strain distributions, improving the accuracy of wear predictions. However, they significantly increase computational demands, making simulations time-consuming and resource-intensive for large-scale systems. Larger elements, while computationally efficient, may oversimplify the material’s behavior, reducing prediction accuracy. Striking a balance between precision and practicality is thus critical for effective use of the model.

The brick model also offers insights into friction noise, the acoustic emissions generated during material failure. Each brick failure—when accumulated shear strain exceeds the critical threshold—releases stored strain energy, producing vibrational waves that manifest as noises. In rolling contact fatigue, as explored by Franklin et al. [54], the sequential collapse of brick elements could generate a series of microscale noise events, collectively contributing to the audible friction noise in mechanical systems. This connection suggests that the model’s predictions extend beyond wear to include noise generation, a byproduct of crack initiation and propagation.

(5) Molecular dynamics (MD) models

MD modeling is a computational technique that simulates the physical motions of atoms and molecules, offering atomic-level insights into tribological phenomena such as wear, friction, and material behavior. In MD simulations, atoms and molecules are treated as particles interacting through forces defined by potential energy functions, which depend on their relative positions [199, 200]. The motion of these particles follows Newton’s laws, enabling the capture of atomic trajectories over time. This capability makes MD a powerful tool for predicting wear mechanisms, optimizing material properties, and exploring microscopic interactions in tribological systems.

MD’s role in wear prediction. A key strength of MD modeling is its ability to simulate how materials degrade under frictional forces. For example, Sharma et al. [201] used MD to study wear during diamond turn machining of CuBe alloys. They assessed the thermodynamic temperature of the bulk material by relating temperature to kinetic energy through Eq. (27):

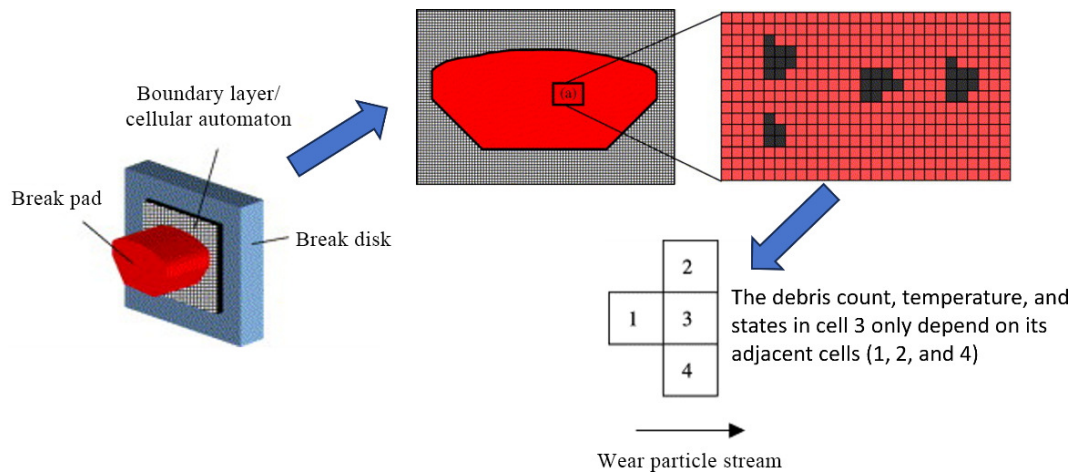


Fig. 19 Illustration for CA model of a pad-disc braking system. Reproduced with permission from Ref. [41], © Elsevier Ltd. 2005.

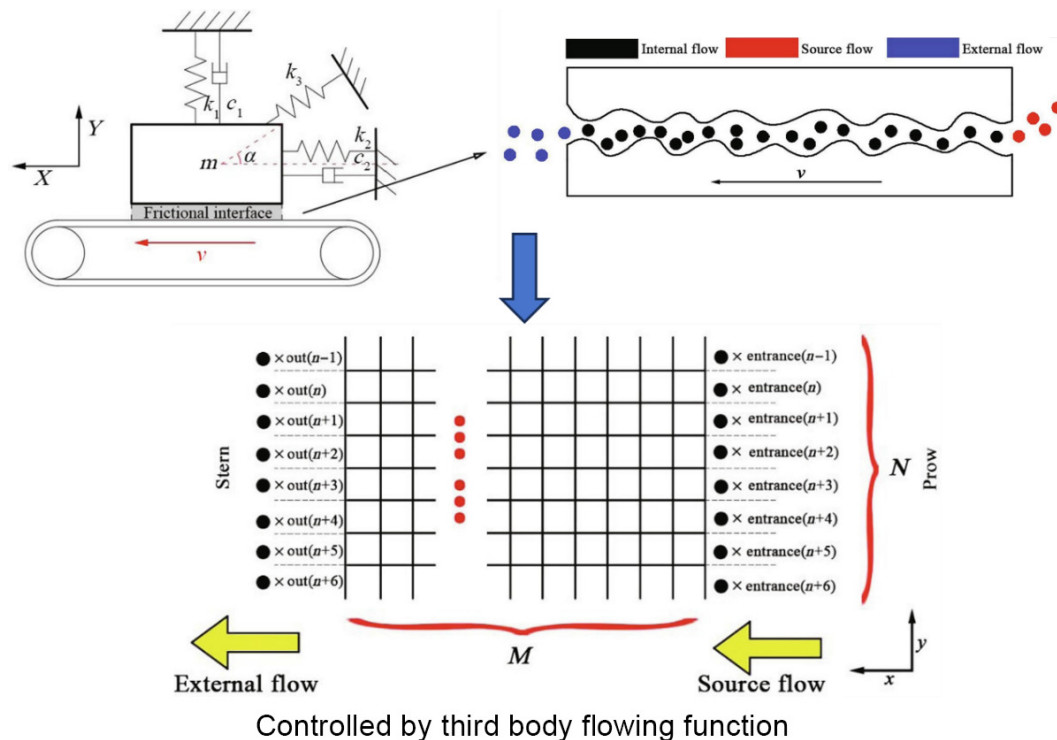


Fig. 20 Illustration of the spring-block-conveyor system to reveal the impact of TBPs on friction force-velocity relationships. Reproduced with permission from Ref. [195], © Elsevier Ltd. 2021.

$$\frac{1}{2} \sum_i m_i v_i^2 = \frac{3}{2} N k_B T \quad (27)$$

where N is the number of atoms; v_i represents the resultant velocity of the i th atom; k_B is the Boltzmann constant; T represents the temperature of the atoms. Their results showed that both stress and temperature significantly increased tool wear rates, illustrating how MD connects microscopic events to macroscopic wear outcomes.

Optimizing material properties with MD. Beyond wear prediction, MD enables the design of materials with improved tribological performance by adjusting atomic compositions and structures. Kong et al. [202] investigated the effect of Cr-rich precipitate volume fractions on the friction behavior of FeCrNi alloys using MD simulations. They found that lower precipitation volumes reduced wear volume and rate during scratching, while higher fractions elevated the average friction coefficient. This

demonstrates MD's potential to tailor material properties for specific tribological applications. Insights from specific studies: MD simulations also provide detailed insights into wear mechanisms under varying conditions. Sun et al. [200] explored how sliding velocity and depth affected surface morphology, temperature, mechanical forces, and subsurface damage in stainless steel. Their findings highlight the microscopic origins of wear, offering a complement to experimental data. Similarly, Hakala et al. [203] adopted a multiscale approach to study diamond-like carbon (DLC) coatings. Their MD simulations revealed that covalent bond formation at the interface increased the CoF, as depicted in Fig. 24. These atomic-scale insights were integrated into a finite element (FE) model to simulate DLC fracture, showcasing MD's ability to bridge scales.

Limitations of MD simulations. Despite its advantages, MD modeling faces limitations due to high computational demands, restricting simulations to small spatial and temporal scales [204].

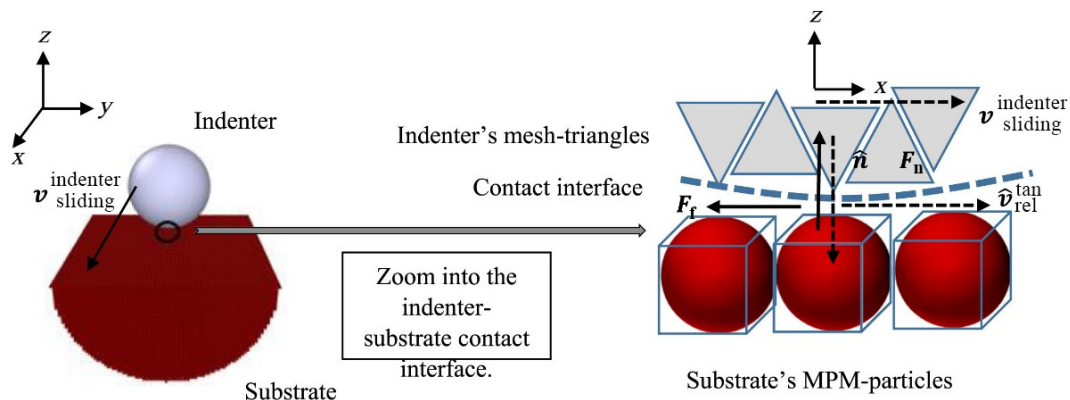


Fig. 21 (a) Visualization of plowing of MPM. (b) Schematics of contact forces between the indenter's mesh triangle and the substrate's MPM particles. Reproduced with permission from Ref. [72], © Elsevier B.V. 2019.

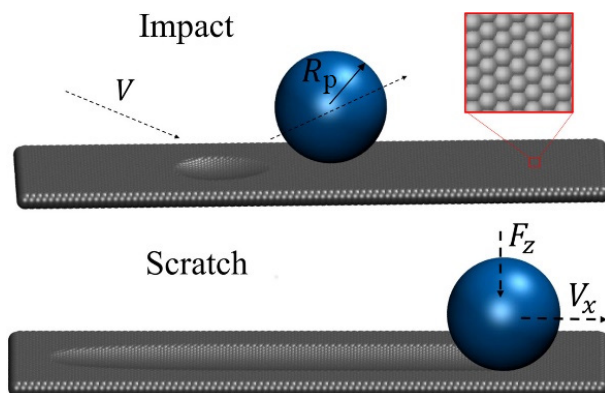


Fig. 22 Simulating the impact (top) and scratching (bottom) wear on a flat surface. As a projectile, the irrotational particle is assigned an initial velocity; as an indenter, both a horizontal velocity and a normal load are assigned. Reproduced with permission from Ref. [196], © The Author(s) 2022.

This constraint limits its ability to capture long-term wear processes or large-scale system behavior, often requiring a combination with other methods for a complete analysis.

Exploring friction noise with MD. MD also holds promise for understanding friction noise, a phenomenon arising from atomic-scale vibrations and interactions. The atomic trajectories and energy fluctuations captured in MD simulations—such as those by Sharma et al. [201] and Kong et al. [202]—reveal events like bond breaking and thermal fluctuations that generate high-frequency vibrations. For instance, Hakala et al. [203] noted that covalent bond formation in DLC coatings increases friction, likely producing vibrational signatures that contribute to noise. By extending MD to compute vibrational spectra or phonon dissipation, researchers could link these microscale mechanisms to

macroscopic friction noise, enhancing our understanding of noise generation in tribological systems.

(6) Other numerical models

In addition to traditional wear models, several innovative numerical approaches have been developed to study corrosive, impact, and erosive wear. These models illuminate the complex interactions between mechanical, chemical, and dynamic factors in tribological systems, offering valuable insights for material design and system performance.

Tribocorrosive wear modeling. Ghanbarzadeh et al. [89] developed numerical models to explore the relationships among surface topography, wear, and corrosion. Their work reveals the intricate interplay between mechanical and corrosive wear, demonstrating synergistic effects that accelerate material degradation. Similarly, research [92] establishes a linear relationship between applied load and tribocorrosive wear components, adapting Archard's wear model to account for these complex interactions. This relationship is expressed in Eq. (28):

$$W_T = (\alpha_m + \alpha_c + \alpha_{mc} + \alpha_{cm}) \frac{L}{H} s \quad (28)$$

where W_T is the total tribocorrosive wear; α_m is the pure mechanical wear coefficient; α_c is the pure corrosive wear coefficient; α_{mc} is the wear enhanced corrosion wear coefficient; α_{cm} is the corrosion-enhanced wear coefficient; L is the applied load; H is the material hardness; s is the sliding distance. This equation highlights how tribocorrosive wear integrates multiple wear mechanisms into a single wear coefficient. Future models should incorporate additional phenomena—such as work hardening, flash temperature, and lubricant properties—to enhance predictive accuracy.

Friction noise in tribocorrosive systems may exhibit distinct

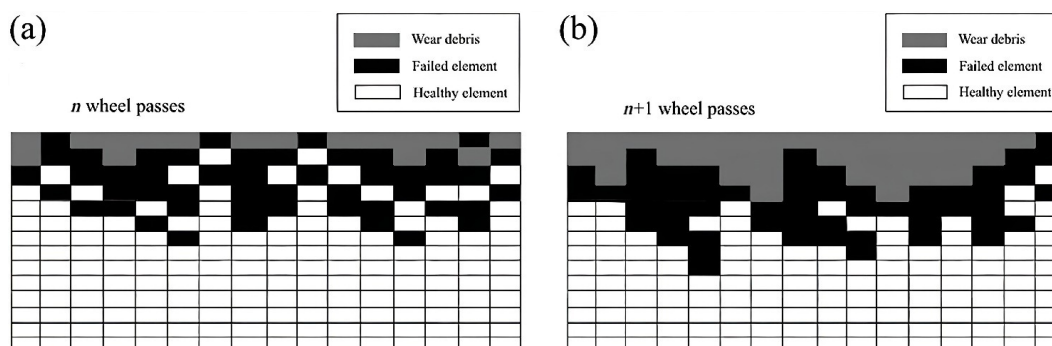


Fig. 23 Representation of the "brick" model: (a) after n wheel passes; (b) after $n+1$ wheel passes. Reproduced with permission from Ref. [72], © Elsevier Ltd. 2020.

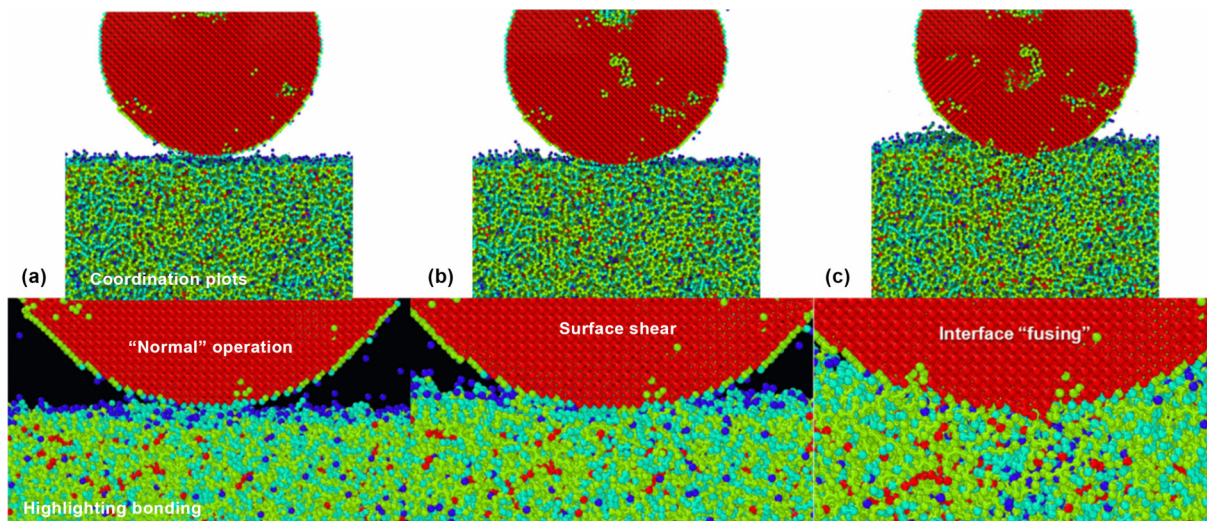


Fig. 24 Various interactions between a diamond tip and a DLC surface under progressive loads: (a) initial surface sliding with close to zero friction force; (b) surface graphitization and formation of a shear layer; (c) surface chemistry and formation of covalent bonds in conjunction with increased contact stresses. Reproduced with permission from Ref. [203], © the authors 2021.

characteristics due to the combined effects of mechanical wear and corrosion. For instance, corrosion products can increase surface roughness or form new interfacial layers, altering the frequency or intensity of noises during sliding contact.

Impact wear modeling. In the study [95], researchers quantitatively assessed time-dependent contact parameters of rough surfaces under random shocks. They assume that shock energy follows a normal distribution and shock intervals follow an exponential distribution. The energy from these shocks transforms into elastic or elastic-plastic strain in surface asperities. A key insight is the trade-off between material hardening, which enhances resistance to plastic deformation, and reduces elasticity, which limits the surface's ability to adapt to changing contact conditions. Time-dependent contact parameters under random shocks likely influence friction noises significantly. Each shock event could produce a noise burst, with its frequency and amplitude tied to material properties. For example, a hardened surface might emit higher-frequency noise due to reduced damping, while a more elastic surface could absorb energy, resulting in quieter operation. Integrating acoustic emission modeling into this framework could predict noise patterns linked to shock-induced wear, aiding noise-reduction strategies in applications like automotive suspensions or industrial machinery.

Erosive wear modeling. Research [93] proposed erosion wear models using computational fluid dynamics and experimental data but neglected particle size distribution and inter-particle interactions, potentially reducing accuracy. In contrast, Zhang et al. [205] introduced a standardized approach for simulating particle impact-rebound in solid particle erosion. Their findings indicate that combining a softball model with a rough wall aligns better with experimental results than alternative methods. However, the model's empirical basis and focus on specific materials (e.g., aluminum alloy, stainless steel) limit its generalizability. Although not explicitly studied, friction noise in erosive wear could stem from particle impacts and surface damage. The dynamics of collisions might produce unique acoustic signatures tied to particle size, velocity, and impact angle. Future models could incorporate acoustic analysis to correlate these parameters with noise characteristics, providing deeper insights into wear severity.

Wear modeling has evolved significantly from its origins in empirical observations by artisans and engineers to a sophisticated

field encompassing a diverse range of predictive approaches. Historically, foundational models like the Archard model laid the groundwork by linking wear to mechanical parameters, while subsequent advancements incorporated material properties, environmental factors, and complex system dynamics. Today, analytical models, such as the patch theory and dissipation wear model, provide deep insights into specific wear mechanisms, while empirical models, including semi-empirical and AI-based techniques, excel at predicting wear in intricate systems where analytical solutions falter. Numerical methods, notably finite element analysis, have become essential for simulating wear in complex geometries, with additional techniques like cellular automaton, particle-based, brick wall, and molecular dynamics models offering specialized perspectives on wear processes. Friction noise can be integrated into these approaches to characterize real-time wear dynamics. Looking forward, the integration of these diverse wear modeling strategies, when combined with friction noise, provides the potential to establish a non-invasive wear prediction tool, thereby facilitating advancements in system health monitoring and maintenance efficiency.

6 Friction-induced noise

Transitioning from the intricate domain of wear modeling, which primarily examines the physical and chemical interactions affecting material surfaces, we now direct our attention to another critical aspect of tribology: the generation of noise resulting from friction. This phenomenon is intrinsically linked to wear processes, as both are governed by interactions at surfaces undergoing relative motion.

6.1 Mechanisms leading to friction-induced noise

6.1.1 Stick-slip mechanism

The stick-slip mechanism, a phenomenon in which components in contact alternate between sticking and slipping, results in energy release and noise emission [170]. This mechanism originates from the difference between static and kinetic friction coefficients [9, 34, 206], as depicted in Fig. 25(a). During the stick phase, the friction force increases with the applied external force, maintaining surface immobility. Once this force exceeds the static

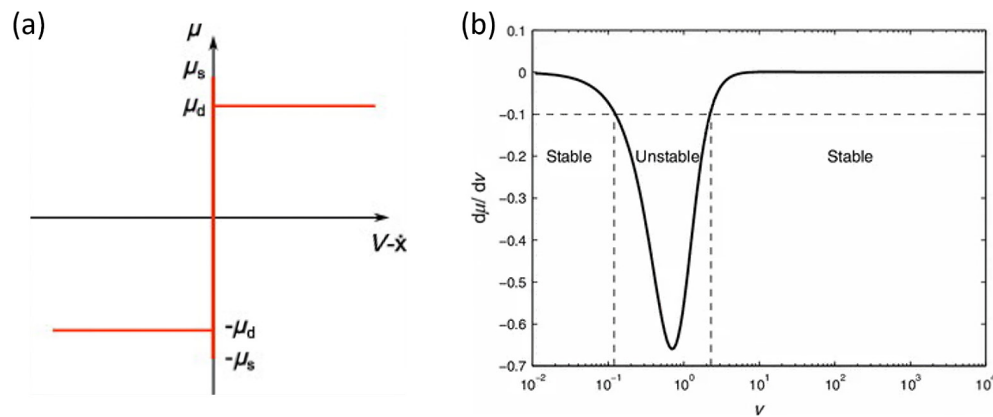


Fig. 25 (a) Coefficient of kinetic friction, which remains constant regardless of the sliding speed between surfaces, is lower than that of static friction; (b) first derivative $d\mu/dv$ of the Stribeck master curve. Reproduced with permission from Ref. [9] for (a), © Elsevier Ltd. 2013; from Ref. [210] for (b), © Springer Nature 2013.

friction threshold, sliding commences due to the typically lower kinetic friction coefficient. This produces a non-smooth, abrupt movement, termed slipping, during which accumulated potential energy from asperities's elastic deformation in the stick phase is converted into vibration and noise [207]. Research by Currier et al. [208] on ceramic-on-ceramic hip implants attributes squeaking to a rolling/sliding mechanism, characterized by a position-dependent CoF. The alternation between kinetic and static sliding in this mechanism generates an audible squeal. Graf and Ostermeyer [209] observed that, during braking, displacement waves at the pad-disc interface induced partial slipping and sticking, thereby producing noise. Studies [170, 210] demonstrated that a negative gradient in the friction-velocity curve, characteristic of the stick-slip mechanism, was associated with noise generation, as illustrated in Fig. 25(b). However, Chen and Zhou [211] demonstrated that both negative and positive friction-velocity slopes can trigger vibrations and squeals. In regions where the friction-velocity slope is negative, vibration may not always be initiated. Chen et al. [212] noted that a negative slope did not invariably result in vibration and squeal; the occurrence of noise was attributed to friction force fluctuations stemming from surface interactions, such as asperity deformation, plowing, and adhesion.

6.1.2 Sprag-slip mechanism

The sprag-slip phenomenon, a variant of the stick-slip mechanism, involves an infinite spragging force stemming from specific positional relationships between contacting pairs, thereby impeding relative motion across sliding surfaces [213]. Research [214] demonstrates that this infinite force is generated when the angle θ remains constant in the linear sprag model, as illustrated in Fig. 26. However, when this angle fluctuates, the spragging force is constrained, resulting in material elasticity and deformation. Slip occurs when the shear force induced by strain exceeds the critical frictional force, thereby releasing stored energy and resetting the mass for cyclic repetition [213]. The occurrence of sprag-slip, which generates vibration and noise, is primarily determined by the angle θ , CoF, and factors from contact models, such as spring stiffness and curvature radii [215]. Hoffmann and Gaul [216] established a sufficient criterion for the onset of sprag-slip, associating it with parameter combinations, such as the CoF and the beam's inclination angle. Notably, when a system's motion equation lacks a static solution, increasing damping does not substantially enhance vibration characteristics, as there is no stable static state toward which the more damped system can converge.

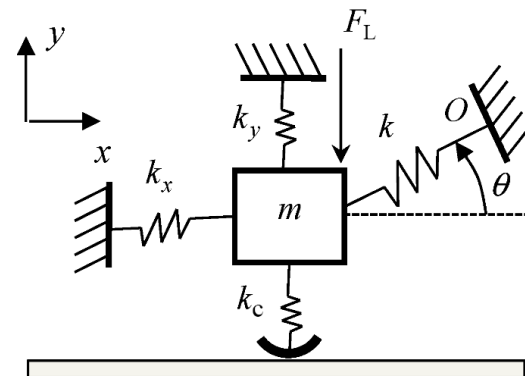


Fig. 26 Explanation of the spring-mass model: the variable is the inclined angle θ . Reproduced with permission from Ref. [214], © the authors 2020.

6.1.3 Friction variation mechanism

Certain researchers attribute the generation of noises to variations in friction. Kinkaid et al. [217] attributed brake squeal to a sudden change in velocity direction occurring at low slip velocities in the braking direction. During braking, the circumferential velocity nears zero, while the radial velocity gains prominence. Consequently, there is an abrupt shift in both the overall velocity direction and the friction force direction. These variations in friction can induce vibrations in the braking system, which may manifest as noise. Weiss et al. [10] proposed that squealing noise resulted from friction-induced whirl vibration. This occurs when components of a system with similar natural frequencies are mutually excited by oscillatory variations in friction forces resulting from deformation within the contact zone.

6.1.4 Mode-coupling mechanism

A system with multiple natural frequencies displays distinct vibration patterns, commonly referred to as modes. Mode-coupling occurs when a system is subjected to an external force, and the natural frequencies of its modes are closely aligned, causing these modes to activate, interact, and amplify vibration and noise [218]. Rhee et al. [219] proposed that noise arose from impacts between peaks and valleys on the rough contact surfaces during sliding. A stochastic rough surface serves as an excitation source in friction-induced vibration and noise systems, amplifying vibration peaks as the frequencies of two modes converge, even in stable systems [128]. Chen et al. [220] introduced a mechanism in which reciprocating sliding motion induces periodic contact loss, resulting in detachment-reattachment cycles at the contact interface. This process generates periodic impulsive excitation,

regarded as the primary cause of friction-induced vibration and brake squeal, rather than mode-coupling. Furthermore, Elmaian et al. [9] determined that the three mechanisms (stick-slip, sprag-slip, and mode-coupling) and three noise categories (creak, squeal, and squeak) can coexist within the same dynamic system. Creaking is attributed to the stick-slip phenomenon; squealing is primarily attributed to the mode-coupling phenomenon; squeaking can result from either the mode-coupling or stick-slip phenomena, as illustrated in Fig. 27.

Friction-induced noise arises from several mechanisms, as outlined in Ref. [218]:

(1) Vibrations and waves: Friction between sliding surfaces generates vibrations and waves within the material, which propagate and radiate as sound waves, causing noise.

(2) Instabilities: Excessive energy from friction-induced vibrations can surpass the system's dissipative capacity, leading to oscillations and sound radiation.

(3) Surface motion interaction: The interplay between friction forces and surface waves amplifies motion, increasing noise.

(4) Feedback mechanism: A cycle where friction affects surface motion, which in turn influences friction, amplifies vibrations, and contributes to noise.

(5) Overall, friction causes noise by generating vibrations and waves within solids, leading to instabilities, and amplifying surface motion, which eventually radiates as sound waves.

6.2 Factors affecting noises

The generation of noise in mechanical systems, particularly within

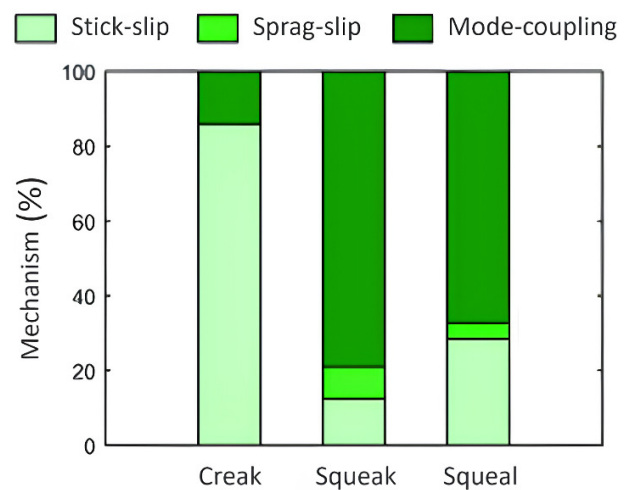


Fig. 27 Correlation between friction-induced sounds and mechanisms. Reproduced with permission from Ref. [9], © Elsevier Ltd. 2013.

the context of friction and braking mechanisms, is a multifaceted phenomenon shaped by the intricate interplay of numerous factors. Recent studies have explored the diverse factors contributing to noise generation, encompassing surface characteristics and textures, as well as the intricacies of internal damping, thermal effects, and the dynamics of friction and wear, as detailed in Table 2.

In summary, the generation of noise in friction-based systems

Table 2 Factors influencing noise and vibration in mechanical systems

Factors	Mechanism of affecting noise/vibration	Ref.
Surface characteristics and textures	In dry sliding contact, squeal arises from the dynamic behavior of the third-body layer. Particle compaction and redistribution modify interface stiffness and adaptability, resulting in unstable vibrations and noise.	[221]
	Surface textures, such as M-shaped grooves on brake disks or micro-dimples filled with solid lubricant, mitigate noise and vibration by enhancing modal damping, distributing contact pressure evenly, and managing surface temperature effectively. These alterations reduce friction and improve tribological performance.	[222, 223]
Load and thermal effects	In pin-on-disc systems, wear and roughness influence contact pressure and temperature distributions, inducing vibrations and noise. Microscale surface changes, driven by thermal conditions, amplify macroscale vibrational responses.	[23]
	Increased load elevates contact pressure, intensifying friction force fluctuations that trigger vibrations. These vibrations, amplified by the system's dynamic response, propagate as noise through the air.	[224]
Damping	Higher internal damping dissipates vibrational energy, reducing both vibration and noise levels. As noise is proportional to the square of vibration velocity, increased damping lowers both, governed by the power balance equation.	[225]
	Damping influences mode coupling instability: optimal application stabilizes energy transfer between modes to reduce noise, while improper control can exacerbate instability and increase noise.	[226, 227]
Friction and wear dynamics	High-frequency friction force fluctuations couple with the system's natural frequencies, causing self-excited vibrations (squeal). Smoother surfaces with adhesion and debris amplify these fluctuations, whereas rougher surfaces disperse contact and reduce them.	[24]
	Contact localization affects squeal: macroscopic contact areas determine squeal frequencies, while mesoscopic distributions influence occurrence probability. Mode-coupling instabilities from friction promote high-frequency squeals in centralized zones.	[228]
	In railway curve squeal, a negative friction-velocity slope induces negative damping, leading to self-excited vibrations. Mode-coupling between wheel dynamics and falling friction characteristics amplifies squeal.	[226]
Lubrication conditions	MoS ₂ nanoparticles in a polyimide matrix form a tribofilm, stabilizing frictional forces and minimizing fluctuations and surface deformations. This suppresses noise and vibration in low-velocity friction conditions.	[229]
Contact area and surface roughness	Surface topographies, such as pit-like detachments and small projections, generate fluctuating friction forces during reciprocating sliding, triggering vibrations and squeal noise.	[212]
	Larger high-pressure contact plateaus, formed by wear debris compaction near steel fibers, enhance friction instability at low sliding velocities by increasing static friction and stick-slip amplitudes, resulting in noise and vibrations.	[230]
Structural factors and mode coupling	In brake systems, mode coupling arises from structural design (e.g., stiffness, mass distribution), causing vibration modes to interact and transfer energy under load, amplifying vibrations and generating noise.	[140]
	Higher structural stiffness increases contact stress and unstable vibration modes, intensifying noise. Moderate stiffness minimizes these effects through uniform stress distribution.	[231]

arises from the convergence of multiple critical factors. Comprehending the intricate interactions among these factors is crucial for the effective design and optimization of mechanical systems, aimed at minimizing noise, improving performance, and ensuring operational efficiency.

6.3 Modelling approaches to predict or characterize friction-induced noise

Based on the preceding discussion, it is evident that the occurrence of friction-induced noises is closely tied to the vibrational dynamics of the mechanical system and the resultant forces that initiate oscillations. The mass–spring–damper system, a fundamental model in classical mechanics, effectively captures these two aspects. This model is commonly utilized in the analytical investigation of friction-induced noise phenomena [214, 224]. The motion equation of the mass–spring–damper system is represented by a second-order linear differential equation, as expressed below [217, 220, 227, 228]:

$$m\ddot{x} + c\dot{x} + kx = F(t) \quad (29)$$

Here, x , $\dot{x}$, and $\ddot{x}$ represent the displacement of the mass from its equilibrium position, the velocity of the mass, and the acceleration of the mass, respectively. $F(t)$ denotes the external force acting on the system, while m , c , and k signify the mass, damping coefficient, and spring stiffness, respectively. Solving this equation, which is often complex, benefits from the application of the Laplace transform, which converts functions from the time domain to the complex frequency domain, thereby facilitating analysis. Subsequently, complex eigenvalue analysis (CEA) is conducted to derive the eigenvalues and eigenvectors of the system [220, 228, 232]. The resulting eigenvalues may be complex, as expressed in Eq. (30), offering insights into the system's behavior [128].

$$\lambda_i = \sigma_i \pm \omega_i j \quad (30)$$

where σ_i is the real part indicating damping; if $\sigma_i < 0$, the system is stable and the oscillations decay over time, and otherwise, self-excited magnified vibrations will occur [128]. $\omega_i j$ is the imaginary part representing the oscillation frequency of the system, where j is imaginary unit and $|\omega_i|$ is the natural frequency of the system's i th mode.

CEA facilitates the investigation of the effects of factors such as stochastic rough surface perturbations [128], CoF [228], and

stiffness [231] on friction-induced vibrations and noise. However, this approach assumes linear system behavior, which may be inadequate for systems displaying nonlinear characteristics, such as non-linear contact stiffness, non-smooth behaviors (stick, slip, and separation between surfaces), and geometrical non-linearity. Liu and Ouyang [233] emphasized that, while CEA was computationally efficient and capable of identifying unstable eigenvalues, it cannot detect self-excited vibrations in bi-stable systems where stable and unstable solutions coexist. In such cases, transient dynamic analysis (TDA) is indispensable. TDA has been employed to examine friction-induced noise, uncovering periodic time-varying patterns in pressure distribution at the contact interface during sliding [220]. However, the computational cost of TDA can vary considerably depending on the degrees of freedom in a finite element model. Consequently, despite TDA offering greater reliability than CEA, the industry predominantly employs CEA [232].

In conclusion, while the mass-spring-damper system and methods such as CEA and the Laplace transform provide valuable insights into friction-induced noise, their limitations in addressing nonlinear and bistable systems underscore the necessity of TDA, highlighting its critical role in advanced mechanical system design and analysis.

6.4 Approaches to control and evaluate friction-induced vibrations and noise

In the realm of mechanical engineering, addressing the challenges posed by friction-induced vibrations and noises is crucial for the stability and efficiency of various systems. Table 3 briefs the techniques employed to mitigate these issues.

In addition to controlling vibration and noise, it is also crucial to assess the level and propagation of noise. Soobarayen et al. [134] utilized the boundary element method (BEM) to assess acoustic radiation in terms of levels and directivity. However, conventional BEM approaches face high computational demands when calculating noise pressure. To address this limitation, researchers [135] proposed selecting only those harmonic components that significantly contribute to the mean square surface normal velocity, thereby simplifying the estimation of acoustic directivity and power levels and circumventing the need for extensive BEM calculations.

These innovative approaches not only offer effective vibration suppression but also pave the way for efficient and accurate noise assessment and control.

Table 3 Methodologies in mechanical engineering for analyzing and mitigating friction-induced vibrations and noises

Method	Mechanism	Limitation	Ref.
Dynamic vibration absorbers (DVAs)	Used in dry conditions to reduce friction-induced vibrations, this method involves connecting a mass to the host structure and adjusting its natural frequency to align with the desired damping frequency, effectively dissipating vibrational energy, see Fig. 28.	DVAs are designed to target specific frequencies, so they may not be as effective in suppressing broadband vibrations that cover a wide range of frequencies.	[234]
Active vibration control	Uses external energy sources or control systems to mitigate system vibrations by applying counteracting forces or displacements.	This may be challenging in practical applications.	[235]
Passive vibration control	Utilizes passive elements like dampers, isolators, or tuned mass dampers to absorb or dissipate vibrational energy without external energy or control systems.	While often simpler and more cost-effective, passive control may not suffice in scenarios demanding precise vibration management.	[235]
Alignment of relative velocity and input energy	Proposes strategies to align relative velocity and input energy in antiphase, reducing vibration amplitudes and preventing stick-slip motion.	This method requires precise control and synchronization of the relative velocity and input energy in antiphase, which may be challenging in complex systems with multiple sources of vibration.	[236]

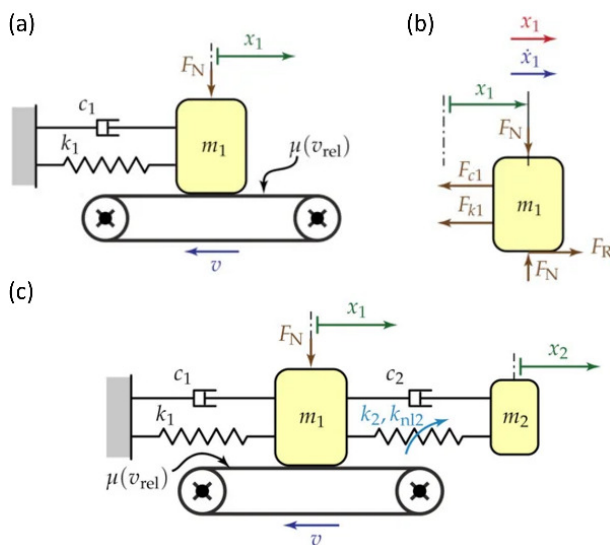


Fig. 28 (a) The host system devoid of the absorber; (b) A diagram of the host system's free body; and (c) The host system with the DVA affixed. Reproduced with permission from Ref. [234], © the authors 2020.

7 Interrelationship and combined modeling of wear and noise

7.1 Interrelations between wear and friction-induced noise

In mechanical systems, the phenomena of wear, friction, and friction-induced noise are deeply intertwined, forming a complex interaction that shapes the behavior and longevity of moving components. At the core of this relationship is friction, acting as the primary driver of both wear and noise. As frictional energy dissipates, it erodes or deforms materials, leading to wear, while simultaneously generating vibrations that manifest as audible noise, such as the squeal of brakes or the chatter of a machining tool. Beyond these direct effects, wear feeds back into the system by altering surface characteristics like roughness and hardness, which in turn influence friction and noise in a dynamic cycle. This interplay is not just a theoretical curiosity; it plays out in practical scenarios—think of a car's brake system or a cutting tool in action—where noise often signals underlying wear. Viewed through an energy lens, these connections reveal how frictional dissipation splits into material degradation and sound, offering a unified framework to understand and manage these critical phenomena in engineering applications.

7.1.1 Direct connections

(1) Friction as the primary driver

Friction serves as the fundamental mechanism initiating both wear and friction-induced noise. When two surfaces undergo relative motion, the frictional force dissipates energy. Part of this energy contributes to material removal or deformation (wear), while another portion generates vibrational energy (noise) [237]. Friction, defined as the resistance opposing motion, directly leads to surface degradation over time. Additionally, mechanisms such as stick-slip motion, involving alternating static and kinetic friction phases, release vibrational energy that manifests as audible noise.

(2) Friction to wear

Wear arises from the mechanical action of friction, which detaches material through adhesive wear or deforms it via abrasive wear. This relationship is quantitatively captured by the Archard

wear model, which states that wear volume is proportional to the normal load and sliding distance, driven by frictional energy dissipation. Thus, friction acts as the primary driver of surface material loss.

(3) Friction to noise

Friction generates noise through vibrational mechanisms. Stick-slip motion produces vibrations due to periodic sticking and slipping, while mode-coupling induces dynamic instabilities that amplify a system's natural modes, both radiating as sound. A practical example is brake squeal in automotive systems, where such frictional dynamics result in audible noise.

7.1.2 Feedback loop: Wear's influence on friction and noise

(1) Wear alters surface properties

As wear progresses, it modifies surface characteristics, including roughness, hardness, and the introduction of third bodies such as wear debris. These alterations influence the interactive dynamics between surfaces, establishing a feedback loop that affects both friction and noise generation.

(2) Impact on friction

Wear can either increase or decrease friction depending on surface changes. Abrasive wear may roughen surfaces, elevating the friction coefficient through enhanced asperity interlocking [238]. Conversely, adhesive wear can smooth surfaces, or wear debris may act as a lubricant, reducing friction. Protective layers formed by third bodies can further lower frictional forces [239].

(3) Impact on noise

Surface modifications due to wear alter vibration characteristics. Increased roughness intensifies asperity impacts, leading to louder, higher-frequency noise, as wear debris and rougher surfaces generate unstable vibrations [240]. In contrast, smoothed surfaces or debris-induced damping may reduce noise intensity.

(4) System dynamics

Wear also influences system dynamics by shifting natural frequencies and damping properties [241, 242]. Progressive wear can modify resonance conditions, potentially amplifying noise when frequencies align or reducing it if contact stabilizes.

7.1.3 Practical examples

The interplay of friction, wear, and noise is evident in real-world applications:

Automotive brakes: Friction between brake pads and rotors causes wear, altering surface texture. Uneven wear may enhance stick-slip motion, producing squealing, whereas uniform wear can stabilize contact and reduce noise.

Machining processes: Friction between a tool and workpiece induces tool wear, with resulting noise (e.g., chatter) reflecting the wear state, aiding in process monitoring.

7.1.4 Energy perspective

Friction dissipates energy, which is partitioned into wear (material degradation) and noise (vibrational energy) [237]. Energy-based wear models and noise analyses highlight this common mechanism, where the distribution of frictional energy determines the extent of wear and noise generation.

The interrelationship between friction, wear, and friction-induced noise constitutes a dynamic interplay:

(1) Friction drives wear and noise through energy dissipation.

(2) Wear modifies surface properties, subsequently influencing friction and noise levels, either amplifying or mitigating them based on conditions.

(3) Noise serves as a diagnostic tool for wear, with unusual sounds often indicating surface degradation.

(4) This feedback loop underscores the need for integrated models to predict and manage these phenomena effectively in mechanical systems.

7.2 Combined models that consider both wear and noise

Contemporary research primarily focuses on either noise or wear independently; however, investigations that concurrently examine both phenomena remain limited. In a study [243], researchers identified a notable correlation between the root mean square (RMS) variation of “weak” friction-induced vibration—stemming from asperity interactions on the friction surface—and the associated sound pressure, relative to changes in CoF. This relationship suggests potential applications for monitoring variations in friction and wear states of friction pairs. Nevertheless, the model’s precision is compromised by its dependence on correlation assumptions, arbitrary frequency selection, and susceptibility to periodic noise. Furthermore, its applicability is restricted by specific experimental conditions and the exclusion of tangential vibrations.

Basit et al. [224] proposed a vibrational analysis model to forecast incremental wear and the resultant noise. This model integrates the geometrical indentation wear model (GIWM), which assumes an elliptical evolution of indentation geometry, with the Archard and Hertz models. Through this integration, the model derives the pin’s displacement equation, enabling the formulation of equations for wear depth and sound pressure, as depicted in Fig. 29. However, the model oversimplifies the system by assuming that the pin’s vibration constitutes the sole noise source, an assumption inconsistent with real-world scenarios where multiple noise contributors exist.

Lontin and Khan [160] posited that vibration and noise arise from the purely elastic deformation of asperities on contact surfaces, whereas wear results from fully plastic asperity deformation. Leveraging this framework, they constructed an analytical model to quantify the interplay between wear and sound emission in a pin-on-disc configuration. For simplicity, the model presupposes a single asperity on the pin surface interacting with a linear array of asperities on the disc—an assumption that fails to capture the complexity of actual contact interfaces.

Despite their contributions, these models exhibit excessive simplification and overlook several pivotal factors. These include the decreasing disparity between static and kinetic friction coefficients, which drives the transition from stick-slip to continuous sliding motion [206], the influence of wear on the system’s modal parameters [136], and the frequency characteristics of friction-induced vibration signals [244].

8 Challenges and future research directions

This section outlines the primary challenges in wear modeling and friction-induced noise analysis, as identified through the comprehensive review presented in this paper. It addresses gaps in current research and proposes a roadmap for future investigations to advance the understanding and prediction of these interconnected phenomena. The challenges are categorized into wear modeling, noise analysis, and integrated modeling, reflecting their distinct yet overlapping natures. Future research directions are suggested to bridge these gaps, with an emphasis on developing unified models that enhance the durability and quietness of mechanical systems.

8.1 Wear modeling challenges

Complex interactions in wear processes. Wear in real-world scenarios involves intricate interactions among factors such as debris layers, lubrication, surface roughness, and temperature. For instance, the review highlights how third bodies (e.g., wear debris) modify contact mechanics (Section “Third body”), yet many models, like the classical Archard model, oversimplify these dynamics by assuming constant conditions (Section “Archard model”). This simplification reduces predictive accuracy, particularly in complex systems like automotive brakes or machining tools.

Multiple wear mechanisms. Industrial applications often exhibit multiple wear types—adhesive, abrasive, erosive, fretting, impact, and fatigue (Section “Mechanisms of wear and types of wear”). Integrating these into a single model remains challenging. For example, the Archard model excels for adhesive wear in metals but struggles with composites or polymers, limiting its applicability (Section “Limitations of the classical Archard model”).

Material and surface property changes. The insufficient consideration of wear-induced changes in material and surface properties, including alterations in surface roughness, hardness, and the development of tribological layers, is a common issue. Models frequently use the assumption of constant material properties or surface characteristics, which might result in inaccuracies.

Predictive accuracy and generalizability. Empirical models, while effective under specific conditions, often lack generalizability across materials or wear mechanisms (Section “Empirical wear models”). The Archard model’s reliance on experimentally determined wear coefficients exemplifies this issue, as its accuracy diminishes outside tested scenarios (Section “Wear coefficient variability and estimation techniques”).

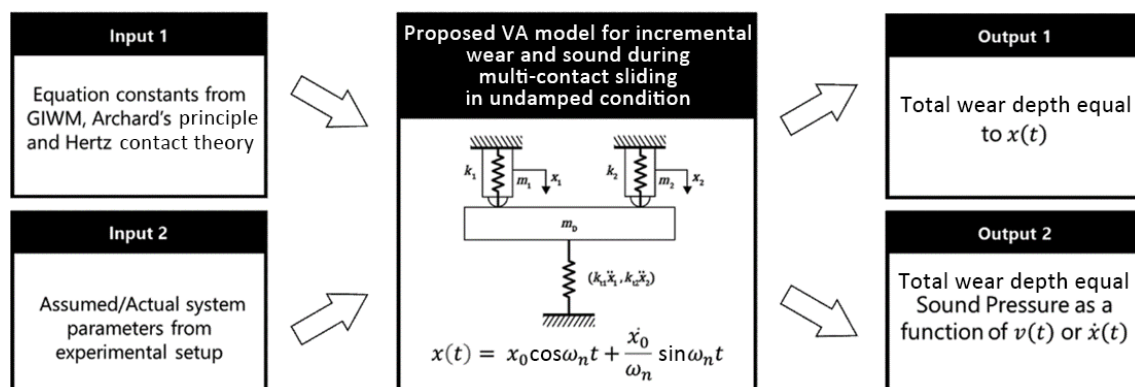


Fig. 29 Vibrational analysis model flowchart for incremental wear and sound generation during multi-contact sliding in an undamped situation. Reproduced with permission from Ref. [224], © The American Society of Mechanical Engineers 2023.

Influence of environmental and operational conditions. Factors like temperature, humidity, and load profoundly influence wear but are not fully integrated into existing models (Section “Factors influencing the wear”). The review underscores how thermal effects and humidity alter wear rates, yet these variables are often treated as constant or ignored.

Data-driven and machine learning approaches. Machine learning shows promise for wear prediction (Section “AI-based models”), but challenges persist in data collection, model training, and interpretability. Ensuring these models generalize across diverse systems remains a significant hurdle.

8.2 Noise analysis challenges

In the realm of noise analysis, the following challenges are encountered:

Understanding of underlying mechanisms. Despite progress, the mechanisms driving friction-induced noise—stick-slip, sprag-slip, mode-coupling, and friction variation (Section “Mechanisms leading to friction-induced noise”)—are not fully understood, especially in complex systems like brakes. The review notes conflicting findings, such as the variable role of friction-velocity slopes in noise generation, highlighting gaps in mechanistic insight.

Modeling and prediction accuracy. Simplified models, such as those using CEA, fail to capture transient dynamics or mode-coupling instabilities accurately (Section “Modeling approaches to predict or characterize friction-induced noise”). The review indicates that while TDA offers more details, its computational cost limits widespread use.

Influence of system parameters. Parameters like damping, contact area, surface roughness, and environmental conditions affect noise, but their interactions are poorly elucidated (Section “Factors affecting noise”). For example, higher damping reduces noise, yet improper application can exacerbate instability, a nuance that current models struggle to address.

Multi-scale phenomena. Friction-induced noise spans microscale asperity interactions to macroscale system vibrations (Section “Surface modeling method”). Integrating these scales into predictive models is challenging, as most approaches focus on a single scale, missing the full spectrum of noise generation.

Coupling with wear processes. Wear alters contact conditions and system dynamics, influencing noise over time (Section “Interrelations between wear and friction-induced noise”), yet this dynamic relationship is underexplored. The review highlights how wear-induced surface changes amplify or mitigate noise, but models rarely account for this interplay.

8.3 Integrated modeling challenges

Lack of unified models. Current research typically separates wear and noise (Section “Combined models that consider both wear and noise”), missing their interdependencies. The review emphasizes that friction drives both phenomena, yet no comprehensive model integrates them effectively.

Advanced contact models. Existing contact models (Section “Contact mechanisms”) do not adequately account for wear-induced changes in surface morphology and their effects on noise. This gap hinders the ability to predict how evolving interfaces influence system behavior.

8.4 Future research roadmap

To address these challenges, the following research directions are proposed:

Unified wear and noise models. Create models that

simultaneously account for wear mechanisms (e.g., adhesive, abrasive) and noise generation factors (e.g., stick-slip, mode-coupling). These should leverage the energy perspective highlighted in the review, where frictional dissipation splits into wear and vibrational energy (Section “Energy perspective”).

Multiscale modeling. Employ multiscale approaches to bridge microscale asperity interactions and macroscale system responses, improving predictions of wear patterns and noise spectra.

Advanced contact models. Develop contact models that incorporate wear-induced changes in surface properties (e.g., roughness and hardness) and their impacts on pressure, friction, and stiffness. Analytical methods integrating contact models with system motion equations, adjusted for wear, could offer a breakthrough over computationally intensive numerical methods like FEM (Section “Numerical wear models”).

Coupling multiple physical fields. Future models should integrate mechanical, thermal, and chemical fields to capture the full spectrum of wear and noise influences. For example, thermal effects on material properties and debris formation (Section “Thermal effect”) should be coupled with mechanical vibrations driving noise.

Machine learning integration. Enhance data-driven models with physics-informed approaches to improve generalizability and interpretability.

Experimental validation. Conduct comprehensive experiments to validate integrated models, focusing on real-world applications like automotive brakes or machining tools. These should measure wear progression and noise characteristics under varying conditions (e.g., load and temperature) to refine model accuracy.

8.5 Impact of addressing these challenges

Overcoming these challenges will facilitate the development of a unified model that integrates friction-induced noise and wear, primarily utilized in predictive maintenance strategies. This model provides several key applications, as detailed below:

Fault detection. The model is highly effective in identifying early-stage faults, such as bearing wear, by analyzing acoustic emissions and thermal wear indicators. This proactive approach minimizes the risk of sudden machinery failures [245].

Condition monitoring. It continuously monitors the operational state of machinery using noise and wear data, enabling maintenance to be performed only when necessary, rather than adhering to a fixed schedule [246].

Remaining useful life prediction. The model estimates the remaining service life of components, such as gearboxes, facilitating strategic maintenance planning that conserves both financial and time resources [247].

Implementing this model results in significant cost savings by reducing unexpected operational interruptions. Additionally, it enhances safety by preventing critical equipment failures and supports environmental sustainability by extending the lifespan of machinery. Its significance is particularly pronounced in industries such as manufacturing, where machinery represents a substantial capital investment and downtime leads to considerable financial losses.

9 Conclusions

This review comprehensively explores the current state of research on wear modeling and friction-induced noises, two pivotal phenomena in tribology. These phenomena significantly influence the durability, efficiency, and operational smoothness of mechanical systems. The analysis elucidates the foundational principles governing these processes, such as Coulomb’s law and

the Archard model, and traces their evolution through subsequent refinements aimed at addressing their inherent limitations. It details a spectrum of wear mechanisms, including adhesive, abrasive, erosive, fretting, impact, and fatigue, alongside various factors affecting wear, such as thermal effects, humidity, material properties, and surface roughness. Similarly, the review dissects the mechanisms driving friction-induced noise, such as stick-slip, sprag-slip, and mode-coupling, and identifies key influencing factors, including surface conditions, damping, and operating parameters.

Key findings highlight the challenges in wear modeling, which arise from the complexity of wear processes, the simultaneous occurrence of multiple wear mechanisms, and the dynamic changes in material and surface properties during sliding interactions. Regarding friction-induced noise, the review emphasizes the intricate interplay of various mechanisms and system factors, including material properties, surface characteristics, damping, and operating conditions, which collectively govern its generation and propagation. A critical insight is the complex interrelationship between wear and noise. Wear alters surface interactions, characteristics, and system dynamics, thereby influencing noise generation. Conversely, noise often serves as an audible indicator of wear progression. This dynamic interplay is essential for assessing component lifespan, optimizing system performance, and mitigating issues related to wear and noise disturbances. Significant advancements have been made in modeling approaches, ranging from analytical and empirical methods to sophisticated numerical techniques such as finite element analysis, cellular automaton, particle-based simulations, and molecular dynamics. However, developing integrated models that simultaneously address wear and friction-induced noise remains a formidable challenge. Current research predominantly addresses these phenomena separately, thereby overlooking their interdependence. The lack of unified frameworks that capture the dynamic feedback between wear-induced surface changes and noise generation hinders the ability to predict and manage these effects holistically.

Future research should prioritize the development of comprehensive models that integrate wear and noise. These models should leverage advancements in computational tools, such as multiscale modeling and machine learning, alongside refined experimental techniques. Such models should account for the multifaceted interactions among mechanical, thermal, and chemical factors, as well as the evolving contact dynamics influenced by wear. By addressing these gaps, integrated approaches will facilitate the design of mechanical systems that are more durable, efficient, and quieter. This will advance the field of tribology and enhance its practical applications across industries such as automotive, aerospace, and manufacturing. This review not only consolidates the current knowledge base but also lays a robust foundation for future investigations aimed at unraveling and harnessing the intricate relationship between wear and friction-induced noise.

Acknowledgements

We express our gratitude to Yang Tian for his primary role in drafting and editing this review. Additionally, our thanks go to Hao Yuan and Bohao Zheng for their significant involvement in writing and supplying resources. Special thanks to Dr. Muhammad Khan for his guidance, editorial expertise, and supervision. Each of these individuals has played a crucial role in the development of this work.

Declaration of competing interest

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

References

- [1] Li H J, Liu Y, Liao H R, Liang Z R. Accelerated wear test design based on dissipation wear model entropy analysis under mixed lubrication. *Lubricants* **10**(4): 71 (2022)
- [2] Al-Maliki H, Meierhofer A, Trummer G, Lewis R, Six K. A new approach for modelling mild and severe wear in wheel–rail contacts. *Wear* **476**: 203761 (2021)
- [3] Armand J, Pesaresi L, Salles L, Wong C, Schwingshackl C W. A modelling approach for the nonlinear dynamics of assembled structures undergoing fretting wear. *Proc R Soc A* **475**(2223): 20180731 (2019)
- [4] Nazir M H, Ahmad Khan Z, Saeed A, Bakolas V, Braun W, Bajwa R. Experimental analysis and modelling for reciprocating wear behaviour of nanocomposite coatings. *Wear* **416–417**: 89–102 (2018)
- [5] Hertz H. On the Contact of Elastic Solids. *crll* **1882**(92): 156–171 (1882) (in Germany)
- [6] Greenwood J A, Tripp J H. The elastic contact of rough spheres. *J Appl Mech* **34**(1): 153–159 (1967)
- [7] García I, Guerra S, de Damborenea J, Conde A. Reduction of the coefficient of friction of steel-steel tribological contacts by novel graphene–deep eutectic solvents (DESS) lubricants. *Lubricants* **7**(4): 37 (2019)
- [8] Ng K P, Liew K W, Lim E. Role of eco-friendly bio-based graphene-oil nanofluids on friction reduction for wind turbine application. *IOP C Ser Earth Env* **943**(1): 012012 (2021)
- [9] Elmaian A, Gautier F, Pezerat C, Duffal J M. How can automotive friction-induced noises be related to physical mechanisms. *Appl Acoust* **76**: 391–401 (2014)
- [10] Weiss C, Hothan A, Huber G, Morlock M M, Hoffmann N P. Friction-induced whirl vibration: Root cause of squeaking in total hip arthroplasty. *J Biomech* **45**(2): 297–303 (2012)
- [11] Aghababaei R, Warner D H, Molinari J F. Critical length scale controls adhesive wear mechanisms. *Nat Commun* **7**: 11816 (2016)
- [12] Hu Y, Zheng Y, Politis D J, Masen M A, Cui J, Wang L. Development of an interactive friction model to predict aluminum transfer in a pin-on-disc sliding system. *Tribol Int* **130**: 216–228 (2019)
- [13] Jiang J F, Xiao G F, Che C J, Wang Y. Microstructure, mechanical properties and wear behavior of the rheoformed 2024 aluminum matrix composite component reinforced by Al₂O₃ nanoparticles. *Metals* **8**(6): 460 (2018)
- [14] Yadav S, Aggarwal A, Kumar A, Biswas K. Effect of TiB₂ addition on wear behavior of (AlCrFeMnV)₉₀Bi₁₀ high entropy alloy composite. *Tribol Int* **132**: 62–74 (2019)
- [15] Radhika N, Raghu R. Prediction of mechanical properties and modeling on sliding wear behavior of LM25/TiC composite using response surface methodology. *Part Sci Technol* **36**(1): 104–111 (2018)
- [16] De Chiffre L, Küçükildiz Ö C, Bay N. A simple model linking surface roughness with friction coefficient and manufacturing cost. *Key Eng Mater* **767**: 275–282 (2018)
- [17] Ezhilmaran V, Vasa N J, Vijayaraghavan L. Investigation on generation of laser assisted dimples on piston ring surface and influence of dimple parameters on friction. *Surf Coat Tech* **335**: 314–326 (2018)
- [18] Sathickbasha K, Selvakumar A S, Balachandran S R, Hariharasakthisudhan P. Multi-metal sulfide pre-blend combination on the tribological performance of the brake friction material. *Ind Lubr Tribol* **73**(2): 235–334 (2021)
- [19] Rewolińska A, Perz K, Kinal G. Experimental tests of static friction coefficient for selected material combinations of expanded graphite-steel used in sealing nodes. *Mechanics* **26**(2): 103–107 (2020)

- [20] Gou R Y, Luo X. Friction behavior and wear mechanism of the PDC-CR in comparison with different friction pairs at high temperatures. *Ceram Int* **50**(5): 8132–8140 (2024)
- [21] Dmitrievskiy A, Komarov V, Karelin R, Andreev V, Stolyarov V. Friction and wear resistance of nanostructured TiNi shape memory alloy. *Metals* **14**(11): 1248 (2024)
- [22] Lontin K, Khan M. Interdependence of friction, wear, and noise: A review. *Friction* **9**(6): 1319–1345 (2021)
- [23] Waddad Y, Magnier V, Dufrénoy P, De Saxcé G. Multiscale thermomechanical modeling of frictional contact problems considering wear—Application to a pin-on-disc system. *Wear* **426–427**: 1399–1409 (2019)
- [24] Wang A Y, Mo J L, Wang X C, Zhu M H, Zhou Z R. Effect of surface roughness on friction-induced noise: Exploring the generation of squeal at sliding friction interface. *Wear* **402–403**: 80–90 (2018)
- [25] Ding C, Zhu H, Sun G D, Jiang Y, Wei C L. Dynamic states recognition of friction noise in the wear process based on moving cut data-approximate entropy. *J Tribol* **140**(5): 051604 (2018)
- [26] Lynch K M, Mason M T. Pulling by pushing, slip with infinite friction, and perfectly rough surfaces. *Int J Robot Res* **14**(2): 174–183 (1995)
- [27] Archard J F. Contact and rubbing of flat surfaces. *J Appl Phys* **24**(8): 981–988 (1953)
- [28] Liang X M, Xing Y Z, Li L T, Yuan W K, Wang G F. An experimental study on the relation between friction force and real contact area. *Sci Rep* **11**: 20366 (2021)
- [29] Aloisio A, Contento A, Boggian F, Tomasi R. Probabilistic friction model for aluminium–steel Asymmetric Friction Connections (AFC) *Eng Struct* **274**: 115159 (2023)
- [30] Behera P, Lee L, Rajagopalan S K, Chromik R R, Yue S. Friction transitions and connections to third bodies for a Cd coating on steel substrate. *Friction* **8**(4): 784–801 (2020)
- [31] Armstrong-Hélouvy B, Dupont P, De Wit C C. A survey of models, analysis tools and compensation methods for the control of machines with friction. *Automatica* **30**(7): 1083–1138 (1994)
- [32] Lampaert V, Swevers J, Al-Bender F. Modification of the Leuven integrated friction model structure. *IEEE Trans Automat Contr* **47** (4): 683–687 (2002)
- [33] Lampaert V, Al-Bender F, Swevers J. A generalized Maxwell-slip friction model appropriate for control purposes. In: Proceedings of the IEEE International Workshop on Workload Characterization, Saint Petersburg, Russia, 2003: 1170–1177.
- [34] Al-Bender F, Lampaert V, Swevers J. Modeling of dry sliding friction dynamics: From heuristic models to physically motivated models and back. *Chaos* **14**(2): 446–460 (2004)
- [35] Olejnik P, Ayankoso S. Friction modelling and the use of a physics-informed neural network for estimating frictional torque characteristics. *Meccanica* **58**(10): 1885–1908 (2023)
- [36] Xun T Z, Chen P C, Wang S H, Pi Y G, Luo Y. A fractional order friction model. *ISA Trans* **142**: 550–561 (2023)
- [37] Zhang M, Unrau H J, Gießler M, Gauterin F. A detailed tire tread friction model considering dynamic friction states. *Tribol Int* **193**: 109342 (2024)
- [38] Garcia-Suarez J, Brink T, Molinari J F. Roughness evolution induced by third-body wear. *Tribol Lett* **72**(2): 37 (2024)
- [39] Gong W J, Chen Y X, Li M W, Kang R. Coupling fractal model for adhesive and three-body abrasive wear of AISI 1045 carbon steel spool valves. *Wear* **418–419**: 75–85 (2019)
- [40] Hausberger A, Major Z, Theiler G, Gradt T. Observation of the adhesive- and deformation- contribution to the friction and wear behaviour of thermoplastic polyurethanes. *Wear* **412–413**: 14–22 (2018)
- [41] Ostermeyer G P, Müller M. Dynamic interaction of friction and surface topography in brake systems. *Tribol Int* **39**(5): 370–380 (2006)
- [42] Zhang Y Z, Kovalev A, Meng Y G. Combined effect of boundary layer formation and surface smoothing on friction and wear rate of lubricated point contacts during normal running-in processes. *Friction* **6**(3): 274–288 (2018)
- [43] Hsu S M, Shen M. Wear prediction of ceramics. *Wear* **256**(9–10): 867–878 (2004)
- [44] Hokkirigawa K. Wear mode map of ceramics. *Wear* **151**(2): 219–228 (1991)
- [45] Kitsunai H, Kato K, Hokkirigawa K, Inoue H. The transitions between microscopic wear modes during repeated sliding friction observed by a scanning electron microscope tribosystem. *Wear* **135**(2): 237–249 (1990)
- [46] Kato K, Adachi K. Wear of advanced ceramics. *Wear* **253**(11–12): 1097–1104 (2002)
- [47] Wang Y S, Hsu S M. Wear and wear transition modeling of ceramics. *Wear* **195**(1–2): 35–46 (1996)
- [48] Collet S, Molinari J F, Brach S. Variational phase-field continuum model uncovers adhesive wear mechanisms in asperity junctions. *J Mech Phys Solids* **145**: 104130 (2020)
- [49] Feng K, Smith W A, Peng Z X. Use of an improved vibration-based updating methodology for gear wear prediction. *Eng Fail Anal* **120**: 105066 (2021)
- [50] Sarkar A D. *Friction and Wear*. London (UK): Academic Press, 1980.
- [51] Behrens B A, Poll G, Möhwald K, Schöler S, Pape F, Konopka D, Brunotte K, Wester H, Richter S, Heimes N. Characterization and modeling of nano wear for molybdenum-based lubrication layer systems. *Nanomaterials* **11**(6): 1363 (2021)
- [52] Jendel T. Prediction of wheel profile wear: Comparisons with field measurements. *Wear* **253**(1–2): 89–99 (2002)
- [53] Liu B B, Bruni S, Lewis R. Numerical calculation of wear in rolling contact based on the Archard equation: Effect of contact parameters and consideration of uncertainties. *Wear* **490–491**: 204188 (2022)
- [54] Franklin F J, Widiyarta I, Kapoor A. Computer simulation of wear and rolling contact fatigue. *Wear* **251**(1–12): 949–955 (2001)
- [55] Zhao F Q, Tian Z G, Liang X H, Xie M J. An integrated prognostics method for failure time prediction of gears subject to the surface wear failure mode. *IEEE Trans Rel* **67**(1): 316–327 (2018)
- [56] Kragelskii I V. *Friction and Wear: Calculation Methods*. London (UK): Pergamon Press, 1982.
- [57] Ghatrehsamani S, Akbarzadeh S. Predicting the wear coefficient and friction coefficient in dry point contact using continuum damage mechanics. *P I Mech Eng J—J Eng* **233**(3): 447–455 (2019)
- [58] Holm R. *Electric Contacts*. Berlin (Germany): Springer, 1967.
- [59] Archard J F, Hirst W. The wear of metals under unlubricated conditions. *Proc R Soc Lond Ser A Math Phys Sci* **236**(1206): 397–410 (1956)
- [60] Brink T, Frérot L, Molinari J F. A parameter-free mechanistic model of the adhesive wear process of rough surfaces in sliding contact. *J Mech Phys Solids* **147**: 104238 (2021)
- [61] Bang J, Kim M, Bae G, Kim H G, Lee M G, Song J. Efficient wear simulation methodology for predicting nonlinear wear behavior of tools in sheet metal forming. *Materials* **15**(13): 4509 (2022)
- [62] Singhal V, Shelly D, Babbar A, Lee S Y, Park S J. Review of wear and mechanical characteristics of Al–Si alloy matrix composites reinforced with natural minerals. *Lubricants* **12**(10): 350–350 (2024)
- [63] Mohrbacher H, Blanpain B, Celis J P, Roos J R, Stals L, Van Stappen M. Oxidational wear of TiN coatings on tool steel and nitrided tool steel in unlubricated fretting. *Wear* **188**(1–2): 130–137 (1995)
- [64] Fouvry S, Liskiewicz T, Kapsa P, Hannel S, Sauger E. An energy description of wear mechanisms and its applications to oscillating sliding contacts. *Wear* **255**(1–6): 287–298 (2003)
- [65] Dreano A, Fouvry S, Guillonnet G. A combined friction energy and tribo-oxidation formulation to describe the high temperature fretting wear response of a cobalt-based alloy. *Wear* **426–427**: 712–724 (2019)
- [66] Zhu T, Shipway P H, Sun W. The dependence of wear rate on wear scar size in fretting: the role of debris (third body) expulsion from the contact. *Wear* **440–441**: 203081 (2019)

- [67] Cao H, Tian Y, Meng Y G. A fracture-induced adhesive wear criterion and its application to the simulation of wear process of the point contacts under mixed lubrication condition. *FU Mech Eng* **19**(1): 23 (2021)
- [68] Aramfard M, Avanzi L, Nicola L. On the adhesive interaction between metals in atomistic simulations of friction and wear. *Tribol Lett* **72**(3): 80 (2024)
- [69] Svenningsson I, Tatar K. Exploring the mechanics of adhesion in metal cutting. *Int J Adv Manuf Technol* **127**(7): 3337–3356 (2023)
- [70] Galetz M C, Seifert S H, Theile B, Glatzel U. Potential for adhesive wear in friction couples of UHMWPE running against oxidized zirconium, titanium nitride coatings, and cobalt–chromium alloys. *J Biomed Mater Res* **93B**(2): 468–475 (2010)
- [71] Zhao J J, Lin M X, Song X C, Wei N. A modeling method for predicting the precision loss of the preload double-nut ball screw induced by raceway wear based on fractal theory. *Wear* **486–487**: 204065 (2021)
- [72] Lian Q L, Deng G Y, Tieu A K, Li H J, Liu Z M, Wang X, Zhu H T. Thermo-mechanical coupled finite element analysis of rolling contact fatigue and wear properties of a rail steel under different slip ratios. *Tribol Int* **141**: 105943 (2020)
- [73] Mishra T, de Rooij M, Shisode M, Hazrati J, Schipper D J. Characterization of interfacial shear strength and its effect on ploughing behaviour in single-asperity sliding. *Wear* **436–437**: 203042 (2019)
- [74] Hokkirigawa K, Kato K. An experimental and theoretical investigation of ploughing, cutting and wedge formation during abrasive wear. *Tribol Int* **21**(1): 51–57 (1988)
- [75] Mishra T, de Rooij M, Shisode M, Hazrati J, Schipper D J. A material point method based ploughing model to study the effect of asperity geometry on the ploughing behaviour of an elliptical asperity. *Tribol Int* **142**: 106017 (2020)
- [76] Mishra T, Ganzenmüller G C, de Rooij M, Shisode M, Hazrati J, Schipper D J. Modelling of ploughing in a single-asperity sliding contact using material point method. *Wear* **418–419**: 180–190 (2019)
- [77] Yang H D, Green I. Fretting wear modeling of cylindrical line contact in plane-strain borne by the finite element method. *J Appl Mech* **86**(6): 061012 (2019)
- [78] Zhang Y B, Lu L T, Zou L, Zeng D F, Zhang J W. Finite element simulation of the influence of fretting wear on fretting crack initiation in press-fitted shaft under rotating bending. *Wear* **400–401**: 177–183 (2018)
- [79] Ramaswamy J, Lokesh N H, Swamy D. Experimental study and analysis of fretting wear and its influence on functionality of mechanical components. *ASEP* **16**(3): 6816 (2023)
- [80] Paul D. Fretting wear behavior of aluminum coatings. *Exp Theor Nanotechnol*: 257–267 (2023)
- [81] Butini E, Marini L, Meacci M, Meli E, Rindi A, Zhao X J, Wang W J. An innovative model for the prediction of wheel–rail wear and rolling contact fatigue. *Wear* **436–437**: 203025 (2019)
- [82] Ince A, Glinka G. A modification of Morrow and Smith–Watson–Topper mean stress correction models: A modification of morrow and Smith–Watson–Topper mean stress correction models. *Fatigue Fract Eng Mater Struct* **34**(11): 854–867 (2011)
- [83] Lu S, Su Y L, Yang M, Li Y. A modified walker model dealing with mean stress effect in fatigue life prediction for aeroengine disks. *Math Probl Eng* **2018**: 5148278 (2018)
- [84] Pinto A L, Cardoso R A, Talemi R, Araújo J A. Fretting fatigue under variable amplitude loading considering partial and gross slip regimes: Numerical analysis. *Tribol Int* **146**: 106199 (2020)
- [85] Gu X J, Moumni Z, Zaki W, Zhang W H. Shakedown based model for high-cycle fatigue of shape memory alloys. *Smart Mater Struct* **25**(11): 115012 (2016)
- [86] Szusta J, Seweryn A. Fatigue damage accumulation modeling of metals alloys under high amplitude loading at elevated temperatures. *Metals* **8**(12): 1030 (2018)
- [87] Morrow J. *Fatigue Design Handbook*. Warrendale, Pennsylvania (USA): Society of Automotive Engineers, 1968.
- [88] Kapoor A, Johnson K L. Plastic ratchetting as a mechanism of metallic wear. *P Roy Soc Lond A Mat* **445**(1924): 367–384 (1994)
- [89] Ghanbarzadeh A, Motamen Salehi F, Bryant M, Neville A. Modelling the evolution of electrochemical current in potentiostatic condition using an asperity-scale model of tribocorrosion. *Biotribology* **17**: 19–29 (2019)
- [90] Feng K, Smith W A, Randall R B, Wu H K, Peng Z X. Vibration-based monitoring and prediction of surface profile change and pitting density in a spur gear wear process. *Mech Syst Signal Process* **165**: 108319 (2022)
- [91] Huangfu Y F, Dong X J, Chen K K, Tu G W, Long X H, Peng Z K. A tribo-dynamic based pitting evolution model of planetary gear sets: A topographical updating approach. *Int J Mech Sci* **220**: 107157 (2022)
- [92] Ghanbarzadeh A, Salehi F M, Bryant M, Neville A. A new asperity-scale mechanistic model of tribocorrosive wear: Synergistic effects of mechanical wear and corrosion. *J Tribol* **141**(2): 021601 (2019)
- [93] Adedjeji O E, Yu W C, Sanders R S. Analysis of local wear variables for high-precision erosion modelling in complex geometries. *Wear* **426–427**: 562–569 (2019)
- [94] Uzi A, Levy A. On the relationship between erosion, energy dissipation and particle size. *Wear* **428–429**: 404–416 (2010)
- [95] Zhang W B, Chen Y X. Modeling and analysis of the time-dependent contact behavior of multiscale rough surfaces subjected to random shocks. *Tribol Trans* **63**(4): 597–609 (2020)
- [96] Slatter T, Zalzal M, Lewis R. Analysis of reciprocating hammer type impact wear apparatus. *Wear* **523**: 204816 (2023)
- [97] Xia Q F, Gillespie D R H, Owen A K, Franceschini G. Quasi-static thermal modeling of multiscale sliding contact for unlubricated brush seal materials. *J Eng Gas Turbines Power* **141**(7): 071016 (2019)
- [98] Bochkareva S A, Panin S V, Lyukshin B A, Lyukshin P A, Grishaeva N Y, Matolygina N Y, Aleksenko V O. Simulation of frictional wear with account of temperature for polymer composites. *Phys Mesomech* **23**(2): 147–159 (2020)
- [99] Carslaw H, Jaeger J. *Conduction of Heat in Solids*, 2nd Ed. Oxford (UK): Oxford University Press, 1959.
- [100] Yadav S, Sarkar S, Aggarwal A, Kumar A, Biswas K. Wear and mechanical properties of novel (CuCrFeTiZn)_{100-x}Pb_x high entropy alloy composite via mechanical alloying and spark plasma sintering. *Wear* **410–411**: 93–109 (2018)
- [101] Kennedy F E, Lu Y, Baker I. Contact temperatures and their influence on wear during pin-on-disk tribotesting. *Tribol Int* **82**: 534–542 (2015)
- [102] Blok H. The flash temperature concept. *Wear* **6**(6): 483–494 (1963)
- [103] Pu W, Zhang Q, Zhang W, Ren S, Chen Z, Tian T. Flash temperature and anti-wear tribofilm growth mechanisms by asperity contact in top-ring/liner conjunction of IC engines. *Tribol Int* **146**: 106186 (2020)
- [104] Liu X L, Li Z H, He J F, Xiao Q, Yang W B, Chen D Y. Influence of humidity on endurance of electrical contact during fretting wear. *J Mater Eng Perform* **31**(2): 933–943 (2022)
- [105] Nishi T. Rubber wear mechanism discussion based on the relationship between the wear resistance and the tear resistance with consideration of the strain rate effect. *Wear* **426–427**: 37–48 (2019)
- [106] Bochkareva S A, Grishaeva N Y, Buslovich D G, Kornienko L A, Lyukshin B A, Panin S V, Panov I L, Dontsov Y V. Development of a wear-resistant extrudable composite material based on an ultrahigh-molecular polyethylene with predetermined properties. *Mech Compos Mater* **56**(1): 15–26 (2020)
- [107] Lin L Y, Ecke N, Huang M Z, Pei X Q, Schlarb A K. Impact of nanosilica on the friction and wear of a PEEK/CF composite coating manufactured by fused deposition modeling (FDM) *Compos Part B—Eng* **177**: 107428 (2019)

- [108] Arif S, Jamil B, Naim Shaikh M B, Aziz T, Ansari A H, Khan M. Characterization of surface morphology, wear performance and modelling of graphite reinforced aluminium hybrid composites. *Eng Sci Technol Int J* **23**(3): 674–690 (2020)
- [109] Arnaud P, Fouvry S. A dynamical FEA fretting wear modeling taking into account the evolution of debris layer. *Wear* **412–413**: 92–108 (2018)
- [110] Yilmaz O. Abrasive wear of FeCr (M_7C_3 – $M_{23}C_6$) reinforced iron based metal matrix composites. *Mater Sci Technol* **17**(10): 1285–1292 (2001)
- [111] Gee M G, Gant A, Hutchings I M. Rotating wheel abrasive wear testing. In: *Measurement Good Practice Guide*. 55, 2002.
- [112] Watanabe T. Numerical analysis for stress wave propagation of a cylindrical bar with material nonlinearity by cellular automaton. *Trans Jpn Soc Mech Eng Ser A* **76**(766): 761–769 (2010)
- [113] Hollomon J H. Tensile deformation. *AIME Trans* **162**: 268–290 (1945)
- [114] Ludwik P. *Elemente der Technologischen Mechanik*. Berlin (Germany): Springer, 1909.
- [115] Swift H W. Plastic instability under plane stress. *J Mech Phys Solids* **1**(1): 0022509652900021 (1952)
- [116] Jiang J R, Arnell R D. The effect of substrate surface roughness on the wear of DLC coatings. *Wear* **239**(1): 1–9 (2000)
- [117] Zhang Y P, Liang F, Lin Y, Chen X, Zhu Y T. Mitigating friction and wear by pre-designed or tribo-induced heterostructures: An overview. *Mater Res Lett* **12**(8): 535–550 (2024)
- [118] Aziz R, Ul Haq M I, Raina A. Effect of surface texturing on friction behaviour of 3D printed polylactic acid (PLA) *Polym Test* **85**: 106434 (2020)
- [119] Milojević S, Stojanović B. Determination of tribological properties of aluminum cylinder by application of Taguchi method and ANN-based model. *J Braz Soc Mech Sci* **40**(12): 571 (2018)
- [120] Sha Z H, Hao Q, Yin J, Ma F J, Liu Y, Zhang S F. Wear calculation and life prediction model of disc brake based on elastoplastic contact mechanics. *Adv Mech Eng* **14**(4): 168781322210931 (2022)
- [121] Meher A, Mahapatra M M, Samal P, Vundavilli P R. Modeling the abrasive wear behavior of *in-situ* synthesized magnesium RZ5/TiB₂ metal matrix composites. *P I Mech Eng E—J Pro* **236**(4): 1500–1510 (2022)
- [122] Feng P P, Borghesani P, Smith W A, Randall R B, Peng Z X. A review on the relationships between acoustic emission, friction and wear in mechanical systems. *Appl Mech Rev* **72**(2): 020801 (2020)
- [123] Khan M A, Basit K, Khan S Z, Khan K A, Starr A G. Experimental assessment of multiple contact wear using airborne noise under dry and lubricated conditions. *P I Mech Eng J—J Eng* **231**(12): 1503–1516 (2017)
- [124] Albuquerque de Freitas T V, do Nascimento Rodrigues R, Santos Costa C A, de Araujo Bezerra R, Vieira Gonçalves V, Cardoso Maciel M H. Parametric analysis of the relationship between squeal and friction wear in motorcycle disc brakes. *P I Mech Eng J—J Eng* **238**(11): 1433–1448 (2024)
- [125] Lontin K, Khan M, Alharbi B. Investigation of the effect of temperature on the wear rate and airborne noise in sliding wear. *Materials* **15**(3): 812 (2022)
- [126] Ben Abdelounis H, Zahouani H, Le Bot A, Perret-Liaudet J, Ben Tkaya M. Numerical simulation of friction noise. *Wear* **271**(3–4): 621–624 (2011)
- [127] Le Bot A. Noise of sliding rough contact. *J Phys: Conf Ser* **797**: 012006 (2017)
- [128] Lin C G, Zou M S, Can S M, Liu S X, Jiang L W. Friction-induced vibration and noise of marine stern tube bearings considering perturbations of the stochastic rough surface. *Tribol Int* **131**: 661–671 (2019)
- [129] Xu J Y, Mo J L, Huang B, Wang X C, Zhang X, Zhou Z R. Reducing friction-induced vibration and noise by clearing wear debris from contact surface by blowing air and adding magnetic field. *Wear* **408–409**: 238–247 (2018)
- [130] Lu G C, Shi X L, Liu X Y, Zhou H Y, Chen Y. Effects of wear characteristics of Ni₃Al metal matrix self-lubrication composites on friction-induced vibration and noise properties. *Mater Res Express* **6**(5): 056539 (2019)
- [131] Ma B, Lu W C, Yu L, Xiong C B, Dang G Q, Chen X B. Friction-wear and noise characteristics of friction disks with circular texture. *Materials* **17**(10): 2337 (2024)
- [132] Abdallah O, Sassi S. Contribution of friction-induced vibration to the realistic failure analysis of spur gear cracked teeth. *Eng Fail Anal* **158**: 107956 (2024)
- [133] Zhou H Y, Shi X L, Ibrahim A M M, Liu X Y, Lu G C, Chen Y. Tribological and friction-induced vibration and noise performance of Ti₆Al₄V-multilayer graphene self-lubricating composites. *Mater Res Express* **5**(9): 096511 (2018)
- [134] Soobbarayen K, Besset S, Sinou J J. Noise and vibration for a self-excited mechanical system with friction. *Appl Acoust* **74**(10): 1191–1204 (2013)
- [135] Soobbarayen K, Besset S, Sinou J J. A simplified approach for the calculation of acoustic emission in the case of friction-induced noise and vibration. *Mech Syst Signal Process* **50–51**: 732–756 (2015)
- [136] Fantetti A, Tamatam L R, Volvert M, Lawal I, Liu L, Salles L, Brake M R W, Schwingshackl C W, Nowell D. The impact of fretting wear on structural dynamics: Experiment and Simulation. *Tribol Int* **138**: 111–124 (2019)
- [137] Liu Y Q, Chen Z G, Wang K Y, Zhai W M. Surface wear evolution of traction motor bearings in vibration environment of a locomotive during operation. *Sci China Technol Sci* **65**(4): 920–931 (2022)
- [138] Qian H H, Mo J L, Xiang Z Y, Fan Z Y, Wu Y K, Zhou Z R. The effect of the macroscopic surface morphology caused by the uneven wear on friction induced vibration. *Tribol Int* **154**: 106672 (2021)
- [139] Tian Y, Khan M, Deng H X, Omar I. Quantifying the interrelationship between friction, wear, and noise: A comparative study on aluminum, brass, and steel. *Tribol Int* **203**: 110403 (2025)
- [140] Chowdhary H V, Bajaj A K, Krousgrill C M. An analytical approach to model disc brake system for squeal prediction. In: *Proceedings of ASME 2001 International Design Engineering Technical Conferences and Computers and Information in Engineering Conference*, Pittsburgh, Pennsylvania, USA, 2001.
- [141] Nam J, Baek J, Do H, Kang J. Experimental investigation of friction noise on lubricated contact. *J Mech Sci Technol* **31**(12): 5751–5760 (2017)
- [142] Stoimenov B L, Maruyama S, Adachi K, Kato K. The roughness effect on the frequency of frictional sound. *Tribol Int* **40**(4): 659–664 (2007)
- [143] Ben Abdelounis H, Le Bot A, Perret-Liaudet J, Zahouani H. An experimental study on roughness noise of dry rough flat surfaces. *Wear* **268**(1–2): 335–345 (2010)
- [144] Li W B, Zhang L J, Zhang C M, Meng D J, He P F. The influence of surface topography on friction squeal—a review. *P I Mech Eng J—J Eng* **236**(11): 2067–2086 (2022)
- [145] Wang W Z, Chen H, Hu Y Z, Wang H. Effect of surface roughness parameters on mixed lubrication characteristics. *Tribol Int* **39**(6): 522–527 (2006)
- [146] Sedlaček M, Podgornik B, Vižintin J. Influence of surface preparation on roughness parameters, friction and wear. *Wear* **266** (3–4): 482–487 (2009)
- [147] Tayebi N, Polycarpou A A. Modeling the effect of skewness and kurtosis on the static friction coefficient of rough surfaces. *Tribol Int* **37**(6): 491–505 (2004)
- [148] Majumdar A, Bhushan B. Role of fractal geometry in roughness characterization and contact mechanics of surfaces. *J Tribol* **112**(2): 205–216 (1990)
- [149] Majumdar A, Tien C L. Fractal characterization and simulation of rough surfaces. *Wear* **136**(2): 313–327 (1990)
- [150] Mandelbrot B. How long is the coast of Britain? statistical self-similarity and fractional dimension. *Science* **156**(3775): 636–638 (1967)

- [151] Ge S R, Chen G A. Fractal prediction models of sliding wear during the running-in process. *Wear* **231**(2): 249–255 (1999)
- [152] Patir N. A numerical procedure for random generation of rough surfaces. *Wear* **47**(2): 263–277 (1978)
- [153] John M M, Hanief M. Frictional noise mitigation using synergetic approach of laser surface texturing and bio-lubrication. *Tribol Int* **178**: 108056 (2023)
- [154] Bakolas V. Numerical generation of arbitrarily oriented non-Gaussian three-dimensional rough surfaces. *Wear* **254**(5–6): 546–554 (2003)
- [155] Liao D R, Shao W, Tang J Y, Li J P. An improved rough surface modeling method based on linear transformation technique. *Tribol Int* **119**: 786–794 (2018)
- [156] Newland D E. *An Introduction to Random Vibration Spectral and Wavelet Analysis*. London (UK): Longman, 1984.
- [157] Hu Y Z, Tonder K. Simulation of 3-D random rough surface by 2-D digital filter and Fourier analysis. *Int J Mach Tools Manuf* **32**(1–2): 83–90 (1992)
- [158] Wu J J. Simulation of rough surfaces with FFT. *Tribol Int* **33**(1): 47–58 (2000)
- [159] Pawlus P, Reizer R, Wiczorowski M. A review of methods of random surface topography modeling. *Tribol Int* **152**: 106530 (2020)
- [160] Lontin K, Khan M A. Wear and airborne noise interdependency at asperitical level: Analytical modelling and experimental validation. *Materials* **14**(23): 7308 (2021)
- [161] Nayak P R. Random process model of rough surfaces. *J Lubr Technol* **93**(3): 398–407 (1971)
- [162] Tallian T E, Chiu Y P, Huttenlocher D F, Kamenshine J A, Sibley L B, Sindlinger N E. Lubricant films in rolling contact of rough surfaces. *ASLE Trans* **7**(2): 109–126 (1964)
- [163] Cooper M G, Mikic B B, Yovanovich M M. Thermal contact conductance. *Int J Heat Mass Transf* **12**(3): 279–300 (1969)
- [164] Greenwood J A. A simplified elliptic model of rough surface contact. *Wear* **261**(2): 191–200 (2006)
- [165] Tomota T, Kondoh Y, Ohmori T. Modeling solid contact between smooth and rough surfaces with non-Gaussian distributions. *Tribol Trans* **62**(4): 580–591 (2019)
- [166] Pullen J, Williamson J B P. On the plastic contact of rough surfaces. *P Roy Soc Lond A Mat* **327**(1569): 159–173 (1972)
- [167] Chang W R, Etsion I, Bogy D B. An elastic-plastic model for the contact of rough surfaces. *J Tribol* **109**(2): 257–263 (1987)
- [168] Johnson K L, Greenwood J A, Higginson J G. The contact of elastic regular wavy surfaces. *Int J Mech Sci* **27**(6): 383–396 (1985)
- [169] De Moerloose K, Al-Bender F, Van Brussel H. A generalised asperity-based friction model. *Tribol Lett* **40**(1): 113–130 (2010)
- [170] Sakamoto T. Normal displacement and dynamic friction characteristics in a stick-slip process. *Tribol Int* **20**(1): 25–31 (1987)
- [171] Guilbault R, Lalonde S. A stochastic prediction of roughness evolution in dynamic contact modelling applied to gear mild wear and contact fatigue. *Tribol Int* **140**: 105854 (2019)
- [172] Zhang L J, Wang H, Liu D H, Zhang Q, Guo W J, Yang N, Xu J Y, Fu S L, Yang B H, Liu S B, et al. Research on wear detection mechanism of cylinder liner-piston ring based on energy dissipation and AE. *Wear* **508–509**: 204472 (2022)
- [173] Kim S S, Kato K, Hokkirigawa K, Abe H. Wear mechanism of ceramic materials in dry rolling friction. *J Tribol* **108**(4): 522–526 (1986)
- [174] Baydoun S, Fartas M, Fouvry S. Comparison between physical and machine learning modeling to predict fretting wear volume. *Tribol Int* **177**: 107936 (2023)
- [175] Wang J L, Su Y, Subramaniam N A, Pang J H L. Archard model guided feature engineering improved support vector regression for rail wear analysis. *Eng Fail Anal* **137**: 106248 (2022)
- [176] Sieberg P M, Kurtulan D, Hanke S. Wear mechanism classification using artificial intelligence. *Materials* **15**(7): 2358 (2022)
- [177] Viáfara C C, Valenzuela B, Martínez F, Penagos J J. A method to analyze wear mechanisms on worn chute lining surfaces using computer vision tools. *Tribol Int* **186**: 108586 (2023)
- [178] Cavaleri L, Asteris P G, Psyllaki P P, Douvika M G, Skentou A D, Vaxevanidis N M. Prediction of surface treatment effects on the tribological performance of tool steels using artificial neural networks. *Appl Sci* **9**(14): 2788 (2019)
- [179] Mahanta S, Chandrasekaran M, Samanta S, Arunachalam R. Multi-response ANN modelling and analysis on sliding wear behavior of Al7075/B₄C/fly ash hybrid nanocomposites. *Mater Res Express* **6**(8): 0850h4 (2019)
- [180] Sarkar D, Borah P, Samanta S, Teyi N, Chetia P, Borah R. Tribop-performance of saw dust filled natural fiber–Glass fiber reinforced epoxy composites: Modelling and optimization. *Mater Today Proc* **80**: 904–910 (2023)
- [181] Das S, Madheshiya A, Das S, Gautam S S, Gautam C. Mechanical, surface morphological and multi-objective optimization of tribological properties of V₂O₅ doped lead calcium titanate borosilicate glass ceramics. *Ceram Int* **46**(11): 19170–19180 (2020)
- [182] Sahu M K, Sahu R K. Experimental investigation, modeling, and optimization of wear parameters of B₄C and fly-ash reinforced aluminum hybrid composite. *Front Phys* **8**: 219 (2020)
- [183] Rajesh Kanna S K, Sundar G N, Ganesan R, Mallireddy N, Shingadia H, Anandaram H, De Poures M V, Paramasivam P. Artificial intelligence investigation on (Al–Si–Fe) alloy reinforced with nanoceramic particles by RSM. *J Nanomater* **2022**: 2892738 (2022)
- [184] Kurapati V B, Kommineni R, Sundarrajan S. Statistical analysis and mathematical modeling of dry sliding wear parameters of 2024 aluminium hybrid composites reinforced with fly ash and SiC particles. *Trans Indian Inst Met* **71**(7): 1809–1825 (2018)
- [185] John M M, Hanief M. Effect of lubrication on frictional noise and coefficient of friction in sliding tribo-pair using Taguchi's integrated TOPSIS method. *Biomass Convers Biorefin* **14**(13): 14175–14188 (2024)
- [186] Zhao X R, Vacca A. Multi-domain simulation and dynamic analysis of the 3D loading and micromotion of continuous-contact helical gear pumps. *Mech Syst Signal Process* **163**: 108116 (2022)
- [187] Berthoulet B, Batailly A, Stainier L, Legrand M, Cartraud P. Phenomenological modeling of abrasible wear in turbomachines. *Mech Syst Signal Process* **98**: 770–785 (2018)
- [188] Zhang L, Ma S Y, Liu D X, Zhou B, Markert B. Fretting wear modelling incorporating cyclic ratcheting deformations and the debris evolution for Ti–6Al–4V. *Tribol Int* **136**: 317–331 (2019)
- [189] Cross P S G, Limbert G, Stewart D, Wood R J K. A multiscale finite element model of sliding wear for cobalt-chromium undergoing ratcheting wear. *Wear* **462–463**: 203482 (2020)
- [190] Kapoor A, Franklin F J. Tribological layers and the wear of ductile materials. *Wear* **245**(1–2): 204–215 (2000)
- [191] Pinto A L, Araújo J A, Talemi R. Effects of fretting wear process on fatigue crack propagation and life assessment. *Tribol Int* **156**: 106787 (2021)
- [192] Arnaud P, Fouvry S. Modeling the fretting fatigue endurance from partial to gross slip: The effect of debris layer. *Tribol Int* **143**: 106069 (2020)
- [193] Zhang Y B, Lu L T, Gong Y B, Zhang J W, Zeng D F. Finite element modeling and experimental validation of fretting wear scars in a press-fitted shaft with an open zone. *Tribol T* **61**(4): 585–595 (2018)
- [194] Mueller M, Ostermeyer G P. Cellular automata method for macroscopic surface and friction dynamics in brake systems. *Tribol Int* **40**(6): 942–952 (2007)
- [195] Yan X Y, Fan C L, Wang W, Liu X J, Chen B S. Experimental and simulation study of the dynamic characteristics of friction force under third-body intrusion behaviour. *Mech Syst Signal Process* **168**: 108726 (2022)
- [196] Capozza R, Hanley K J. A comprehensive model of plastic wear based on the discrete element method. *Powder Technol* **410**: 117864 (2022)
- [197] Fletcher D I, Franklin F J, Kapoor A. Image analysis to reveal crack development using a computer simulation of wear and rolling contact fatigue. *Fatigue Fract Eng M* **26**(10): 957–967 (2003)

- [198] Eden H C, Garnham J E, Davis C L. Influential microstructural changes on rolling contact fatigue crack initiation in pearlitic rail steels. *Mater Sci Technol* **21**(6): 623–629 (2005)
- [199] Foiles S M, Baskes M I, Daw M S. Embedded-atom-method functions for the FCC metals Cu, Ag, Au, Ni, Pd, Pt, and their alloys. *Phys Rev B* **33**(12): 7983–7991 (1986)
- [200] Sun J T, Yuan Z W, Zheng P, Tang M L, Wang Y, Sun X H, He Y. Study on the microscopic wear mechanism of nanoparticles sliding stainless steel. *Model Simul Mater Sc* **31**(6): 065010 (2023)
- [201] Sharma A, Datta D, Balasubramaniam R. Prediction of tool wear constants for diamond turn machining of CuBe. *J Micromanuf* **4**(1): 18–26 (2021)
- [202] Kong J Y, Fang Q H, Li J. Optimizing the friction behavior of medium entropy alloy via controllable coherent nanoprecipitation. *Model Simul Mater Sc* **31**(8): 085019 (2023)
- [203] Hakala T J, Holmberg K, Laukkanen A. Coupling molecular dynamics and micromechanics for the assessment of friction and damage accumulation in diamond-like carbon thin films under lubricated sliding contacts. *Lubricants* **9**(3): 30 (2021)
- [204] Badisch E, Varga M, Eder S J. A brief review of abrasive wear modelling using a numerical-experimental approach. *Key Eng Mater* **799**: 83–88 (2019)
- [205] Zhang R, Zhu D, Liu H X, Liu Y. Random process of particle-wall collision and its application in numerical simulation of solid particle erosion. *Wear* **452–453**: 203288 (2020)
- [206] Gao H, Zhao L J, Li L, Wu S Y, Lin Z Q, Wang Q. Effect of wear-induced surface deformation on stick-slip friction of galvanized automotive steels. *Langmuir* **38**(37): 11459–11467 (2022)
- [207] Ibrahim R A. Friction-induced vibration, chatter, squeal, and chaos: Part I: Mechanics of contact and friction. *Appl Mech Rev* **47**(7): 209–226 (1994)
- [208] Currier J H, Anderson D E, Van Citters D W. A proposed mechanism for squeaking of ceramic-on-ceramic hips. *Wear* **269**(11–12): 782–789 (2010)
- [209] Graf M, Ostermeyer G P. Instabilities in the sliding of continua with surface inertias: An initiation mechanism for brake noise. *J Sound Vib* **330**(22): 5269–5279 (2011)
- [210] Le Rouzic J, Le Bot A, Perret-Liaudet J, Guibert M, Rusanov A, Douminge L, Bretagnol F, Mazuyer D. Friction-induced vibration by stribeck's law: Application to wiper blade squeal noise. *Tribol Lett* **49**(3): 563–572 (2013)
- [211] Chen G X, Zhou Z R. Correlation of a negative friction-velocity slope with squeal generation under reciprocating sliding conditions. *Wear* **255**(1–6): 376–384 (2003)
- [212] Chen G X, Zhou Z R, Kapsa P, Vincent L. Effect of surface topography on formation of squeal under reciprocating sliding. *Wear* **253**(3–4): 411–423 (2002)
- [213] Choi H, Lee S H, Lee C. Research on stick & sprag-slip phenomenon of door waist belts. *SAE Tech Pap Ser* **1**: 2018–1-0674 (2018)
- [214] Kang J, Nam J. Minimal model for sprag-slip oscillation as catastrophe-type behavior. *Appl Sci* **10**(8): 2748 (2020)
- [215] Keitzel H, Hoffmann N. Influence of the contact model on the onset of sprag-slip. *PAMM* **6**(1): 311–312 (2006)
- [216] Hoffmann N, Gaul L. A sufficient criterion for the onset of sprag-slip oscillations. *Arch Appl Mech* **73**(9): 650–660 (2004)
- [217] Kinkaid N M, O'Reilly O M, Papadopoulos P. On the transient dynamics of a multi-degree-of-freedom friction oscillator: A new mechanism for disc brake noise. *J Sound Vib* **287**(4–5): 901–917 (2005)
- [218] Akay A. Acoustics of friction. *J Acoust Soc Am* **111**(4): 1525–1548 (2002)
- [219] Rhee S K, Tsang P H S, Wang Y S. Friction-induced noise and vibration of disc brakes. *Wear* **133**(1): 39–45 (1989)
- [220] Chen F, Ouyang H J, Wang X C. A new mechanism for friction-induced vibration and noise. *Friction* **11**(2): 302–315 (2023)
- [221] Singla N, Brunel J F, Mège-Revil A, Kasem H, Desplanques Y. Experiment to investigate the relationship between the third-body layer and the occurrence of squeals in dry sliding contact. *Tribol Lett* **68**(1): 4 (2019)
- [222] Zhang D Y, Gao F, Wei X, Liu G L, Hua M, Li P Y. Fabrication of textured composite surface and its tribological properties under starved lubrication and dry sliding conditions. *Surf Coat Technol* **350**: 313–322 (2018)
- [223] Zhu D P, Yu X K, Sai Q Y, Wang S W, Barton D, Fieldhouse J, Kosarieh S. Noise and vibration performance of automotive disk brakes with laser-machined M-shaped grooves. *P I Mech Eng D—J Aut* **237**(5): 978–990 (2023)
- [224] Basit K, Shams H, Ali Khan M, Mansoor A. Vibration analysis approach to model incremental wear and associated sound in multi-contact sliding friction mechanisms. *J Tribol* **145**(9): 091109 (2023)
- [225] Le Bot A, Bou Chakra E. Measurement of friction noise versus contact area of rough surfaces weakly loaded. *Tribol Lett* **37**(2): 273–281 (2010)
- [226] Ding B, Squicciarini G, Thompson D, Corradi R. An assessment of mode-coupling and falling-friction mechanisms in railway curve squeal through a simplified approach. *J Sound Vib* **423**: 126–140 (2018)
- [227] Sinou J J, Jézéquel L. Mode coupling instability in friction-induced vibrations and its dependency on system parameters including damping. *Eur J Mech A* **26**(1): 106–122 (2007)
- [228] Lai V V, Paszkiewicz I, Brunel J F, Dufrénoy P. Multi-scale contact localization and dynamic instability related to brake squeal. *Lubricants* **8**(4): 43 (2020)
- [229] Liu S T, Dong C L, Yuan C Q, Bai X Q, Tian Y, Zhang G L. A new polyimide matrix composite to improve friction-induced chatter performance through reducing fluctuation in friction force. *Compos Part B—Eng* **217**: 108887 (2021)
- [230] Kim J W, Joo B S, Jang H. The effect of contact area on velocity weakening of the friction coefficient and friction instability: A case study on brake friction materials. *Tribol Int* **135**: 38–45 (2019)
- [231] Liu Q A, Xiang Z Y, Mo J L, Zhang Q X, Zhu Y G. The effects of the structural stiffness of vibration transfer path on friction-induced vibration and noise. *Tribol Int* **173**: 107687 (2022)
- [232] Nobari A, Ouyang H J, Bannister P. Statistics of complex eigenvalues in friction-induced vibration. *J Sound Vib* **338**: 169–183 (2015)
- [233] Liu N Y, Ouyang H J. Friction-induced vibration considering multiple types of nonlinearities. *Nonlinear Dyn* **102**(4): 2057–2075 (2020)
- [234] Hu J L, Habib G. Friction-induced vibration suppression via the tuned mass damper: Optimal tuning strategy. *Lubricants* **8**(11): 100 (2020)
- [235] Popp K. Modelling and control of friction-induced vibrations. *Math Comp Model Dyn* **11**(3): 345–369 (2005)
- [236] Popp K, Rudolph M. Vibration control to avoid stick-slip motion. *J Vib Control* **10**(11): 1585–1600 (2004)
- [237] Liu H, Yang B M, Wang C, Han Y S, Liu D M. The mechanisms and applications of friction energy dissipation. *Friction* **11**(6): 839–864 (2023)
- [238] Wei T, Zhou Z Y, Ling X, Lv M H, Di Y F, Qin K, Zhou Q. A study of the effect of roughness on the three-body wear mechanism from a microscopic point of view: Asperity peak removal. *Metals* **14**(12): 1385 (2024)
- [239] Zhao F, Zhu Z, Yu J X, Luo Z Q, Qi H M. Contrast role of third body layer and hard abrasives in the wear process of a TiAlSiN hardness-modulated multilayer coating: A case study on the effect of normal load and velocity. *Coatings* **14**(7): 821 (2024)
- [240] Onu P, Stella I M. An overview on impact of surface roughness on tribological behaviour. In: Proceedings of the International Conference on Science, Engineering and Business for Driving Sustainable Development Goals, 2024.
- [241] Tamatam L R, Botto D, Zucca S. A novel test rig to study the effect of fretting wear on the forced response dynamics with a friction contact. *Nonlinear Dyn* **105**(2): 1405–1426 (2021)
- [242] Chen J, Dong N, Min J H. Study on the coupling relationship

- between wear and dynamics in planetary gear systems. *Machines* **11**(11): 986 (2023)
- [243] Xing P F, Zhu Y C, Li G B, Liu T, Gao H L, Song Y C, Zhang H P. A detecting method for “weak” friction-induced vibration based on cross-correlation analysis between vibration and sound signals. *Appl Sci* **13**(13): 7468 (2023)
- [244] Li G B, Lin Y H, Wang H Z, Wei H J, Wang G Y. Harmonic wavelet packet analysis of friction-induced vibration. *Tribol Trans* **54**(6): 895–901 (2011)
- [245] Zhang Z, Ouyang W, Liang X X, Yan X P, Yuan C Q, Zhou X C, Guo Z W, Dong C L, Liu Z L, Jin Y, et al. Review of the evolution and prevention of friction, wear, and noise for water-lubricated bearings used in ships. *Friction* **12**(1): 707 (2024)
- [246] Sayyad S, Kumar S, Bongale A, Kamat P, Patil S, Kotecha K. Data-driven remaining useful life estimation for milling process: Sensors, algorithms, datasets, and future directions. *IEEE Access* **9**: 110255–110286 (2021)
- [247] Sikorska J Z, Hodkiewicz M, Ma L. Prognostic modelling options for remaining useful life estimation by industry. *Mech Syst Signal Process* **25**(5): 1803–1836 (2011)



Muhammad Khan. Upon receiving his bachelors in mechanical engineering from NEDUET Karachi in 2002, he joined Technology Promotion Internationals (Head Quarter: Maryland, USA) for more than 3 years in the capacity of a research engineer. In these years, he was involved in fault diagnosis of defense applications mainly funded by General Dynamics including US Marines Expeditionary Fighting Vehicle (EFV) and Medium Tactical Vehicle Replacement (MTVR). In 2006, he went to The University of Manchester for his master degree leading to doctoral studies and completed his Ph.D. degree in 2008 with more than 12 publications in the area of fatigue of gear assemblies. Later, he joined University of Hertfordshire as a post-doctoral research associate in 2009 for two years. Where he worked on a UK MOD project related to aerospace transmission fatigue diagnosis partnered with the University of Manchester, University of Warwick and QinetiQ. He briefly taught mechanical engineering at Universiti Teknologi Petronas (Malaysia) as a lecturer in 2011 and in the same year he then joined National University of Sciences and Technology (NUST) Pakistan as an assistant professor. At

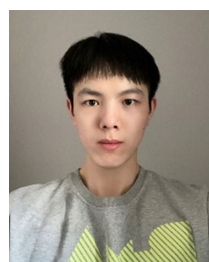
NUST, he established a Root Cause Failure Analysis (RCFA) center and being the Head of Postgraduate Programme started a new master in the area of computational mechanics. He is involved in the industrial and the academic research for the last 15 years. His current areas of interest are: Fatigue of metallic structures and machine components, experimental evaluation of damage and prediction of useful life, non-destructive testing methodologies, and tribological phenomenon in mechanical contacts. He is a Chartered Engineer (CEng) and a full member of Institute of Mechanical Engineers (IMechE) UK.



Yang Tian earned his bachelor degree in aircraft manufacturing engineering in 2021 from Northwestern Polytechnical University, China. Subsequently, he obtained his master of science degree in aerospace manufacturing engineering from the University of Cranfield, UK, in 2022. Presently, he is pursuing his doctor of philosophy degree at the University of Cranfield. His research primarily focuses on the study of friction and material wear.



Hao Yuan is a master student in mechanical engineering in Nanyang Technological University, Singapore. He is a member of Le Ferrand research group, School of Mechanical and Aerospace Engineering, Nanyang Technological University. His research areas cover 3D printing, composite mechanics, and bioinspired structures.



Bohao Zheng received his bachelor degree in mechanical engineering from Hebei University of Technology, China, his master degree in robotics from the University of Sheffield, UK, and is currently pursuing a Ph.D. degree at the Center for Digital Engineering and Manufacturing at Cranfield University, UK. His research involves using multimodal data to sense and understand the surrounding environment.



DSPACE

<https://dspace.org/>

Wear modeling and friction-induced noise: a review

Tian, Yang; Khan, Muhammad; Yuan, Hao; Zheng, Bohao

2026-02

Tsinghua University Press

<https://doi.org/10.26599/frict.2025.9441124>

Tian Y, Khan M, Yuan H, Zheng B. (2026) Wear modeling and friction-induced noise: a review. Friction, Volume 14, Issue 2 February 2026, Article number 9441124