

Quantifying the interrelationship between friction, wear, and noise: A comparative study on aluminum, brass, and steel

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ABSTRACT

Friction-induced wear and noise affect the performance and lifespan of industrial components, yet models often address them separately. This study proposes a model linking wear volume, coefficient of friction (COF), and noise. Ball-on-disc tribometer tests on 6082 aluminum, UNS C38500 brass, and 304 stainless steel were conducted under various loads and speeds. Key findings reveal thermal expansion affects wear in aluminum but minimally impacts brass and steel. The aluminum-based equation also predicts noise for brass and steel, with errors under 10 % within 5–15 N loads and 0.21–0.63 m/s speeds, suggesting broader applicability. This model provides a simplified approach to linking friction, wear, and noise, offering potential improvements in wear monitoring and noise control for mechanical systems.

1. Introduction

Research on friction-induced wear in industrial applications has gained significant attention due to its effects on machine efficiency and lifespan. Wear mechanisms, particularly in unlubricated contacts, are key factors in material degradation, affecting performance across industries [1,2]. Friction-induced noise is also recognized as an indicator of wear or malfunction [3,4]. As wear progresses, changes in contact surface morphology affect interface behavior, altering both friction and noise. Therefore, developing a model that links wear, friction, and noise can provide valuable insights into machinery and component conditions [5–8].

Previous studies have developed several models linking friction and noise. Abdelounis et al. [9] used 2D explicit dynamic finite element software ABAQUS to simulate friction noise from two rough, dry surfaces. Their findings show that surface roughness significantly influences noise levels, which increase with both roughness and sliding speed.

Qian et al. [10] developed observer-based methods to estimate friction force in brake systems under low-frequency vibration, focusing on the stick-slip phenomenon. Le et al. [11] examined the mechanical origin of friction noise on rough surfaces, demonstrating that noise arises from impacts between surface asperities. They also explored the relationship between the number of noise sources and sound levels

caused by vibration dissipation. In friction-induced vibration and noise systems, a stochastic rough surface acts as an excitation source, amplifying vibration peaks as two-mode frequencies converge, even in stable systems [12].

Chen et al. [13] introduced a mechanism in which reciprocating sliding motion causes periodic contact loss, leading to detachment and reattachment cycles at the contact interface. This process generates periodic impulsive excitation, identified as the primary cause of friction-induced vibration and brake squeal, rather than mode-coupling.

However, these models do not account for wear-induced changes in surface morphology, limiting their applicability in scenarios where wear is a key factor.

Although some studies have unified friction, noise, and wear into a single model, they have not provided a clear quantitative relationship between these factors. Zhang et al. [14] investigated how interfacial wear characteristics affect stick-slip vibration under different normal loads using both experimental and numerical methods. However, their study only demonstrates when the friction system becomes unstable and vibrates due to uneven wear on the friction block. Li et al. [15] analyzed the nonlinear characteristics of frictional vibration signals during the running-in wear process using the Multifractal Detrended Fluctuation Analysis (MFDFA) algorithm. They applied Ensemble Empirical Mode Decomposition to denoise signals from friction tests and used MFDFA to derive the q-order Hurst exponent and multifractal spectrum. The results

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show that this method effectively tracks wear progression, providing a basis for real-time monitoring, though it is limited to specific test conditions and the running-in wear phase. Seong [16] developed a method for monitoring adhesive and abrasive wear in metal systems by analyzing acoustic signals using Haar wavelet coefficients and Peak Signal-to-Noise Ratio. Experiments on metal friction demonstrated that wavelet analysis effectively distinguished between adhesive and abrasive wear based on contact pressure variations. The method shows promise for real-time wear monitoring but is limited by its specific experimental setup and may need refinement for more complex environments. Albuquerque de Freitas et al. [17] analyzed how operational and material parameters, such as brake pressure and friction coefficient, influence friction wear and brake squeal in motorcycle disc brakes using finite element simulations. They used static and modal analyses with and without wear models to assess instability and squeal, finding that wear and high friction coefficients significantly increase system instability. While the study provides valuable insights for reducing brake squeal, it is based solely on simulations and lacks experimental validation. Abdallah et al. [18] explored the relationship between wear, specifically cracks in gear teeth, and noise in gear systems. Their findings showed that as cracks develop and grow, they alter meshing stiffness, increasing friction-induced vibrations and noise levels. This study highlights the importance of considering both wear and noise in diagnosing and maintaining gear systems. Further illustrating the wear-noise connection, Xiang et al. [19] examined the wear patterns of brake pads in high-speed trains. They found that taller brake pads, which experience greater eccentric wear, lead to higher friction-induced noise and vibration. Reducing brake pad height mitigates this wear, lowering noise levels. This underscores the importance of managing wear to control noise in braking systems. Wen et al. [20] classified different types of polymer interface wear using machine learning algorithms based on friction noise signals. They explored using algorithms like Random Forest (RF), Deep Forest (DF), and XGBoost (XGB) to identify various wear types in real-time. The addition of MLG to Ti6Al4V significantly improved tribological performance, reducing friction and wear while also suppressing friction-induced vibration and squeal noise. The formation of an anti-friction film on the TMC surface protected the material and reduced noise emissions, making it suitable for high-performance applications requiring low friction and noise [21]. The authors of the study [22] observed a significant correlation between the root mean square variation in "weak" friction-induced vibration, caused by asperity interactions on the friction surface, and corresponding sound pressure, with changes in CoF. This finding holds the potential for monitoring changes in the friction and wear conditions of friction pairs.

Few studies have provided qualitative relationships between wear, friction, and noise, but these models also have significant limitations. Lontin et al. [23] assumed that surface asperities behave like beams, and the vibration of these beams generates noise after impact. However, their model considers only the tangential force on the beam to determine wear and vibration, excluding the normal force. This assumption contradicts the widely used Archard model, where wear volume depends on normal load, which alters surface morphology. Ignoring the effect of normal force on noise is therefore unreasonable. Basit et al. [24] proposed an analytical ball-on-disc model to examine the relationship between friction noise and wear evolution. However, their model is oversimplified, attributing friction noise solely to the ball's vibration and ignoring noise from the disc. Both Lontin and Basit's models require numerical iteration to update inter-surface contact behavior, making them inconvenient to apply.

In general, existing studies either ignore the effect of wear-induced changes in surface morphology on noise, or, if they consider wear, fail to provide a quantitative relationship between wear, friction, and noise. Even the few that do offer a quantitative relationship are hindered by cumbersome numerical iterations, making them difficult to use.

Therefore, a simple model that quantitatively describes the

relationship between friction, wear volume, and noise is needed for practical application. This study aims to fill this gap by developing a model that incorporates these relationships quantitatively. We used symbolic regression to derive an equation relating friction, wear volume, and noise, based on 6082 aluminum. The derived equation has been validated for UNS C38500 brass and 304 stainless steel, showing potential for practical applications in maintenance and diagnostics, allowing wear checks and real-time inspection without disassembling machinery.

2. Methodology

2.1. Wear experiment setup

Wear tests were conducted under dry conditions using an Anton Paar TRB3 tribometer (Anton Paar, Graz, Austria). The experimental setup and simulation boundary conditions are illustrated in Fig. 1. Ball-on-disc experiments were performed on 6082 aluminum, UNS C38500 brass, and 304 stainless steel discs at sliding speeds of 100–0.63 m/s (0.21–0.63 m/s) and loads of 5–15 N. The ball material used was 440C steel. The material properties of 6082 aluminum are listed in Table 1. The properties of UNS C38500 brass, 304 stainless steel, and 440C steel were obtained from the COMSOL Multiphysics software material database (version 6.2.0.339). Notably, due to the high wear resistance of 304 stainless steel, its wear test was conducted for 4 min to obtain a visible wear scar, while the tests for the other two materials were conducted for only 2 min.

The maximum temperature in the contact area was measured with an infrared thermometer, accurate to $\pm 2^\circ\text{C}$. Temperature measurements were taken under a laboratory temperature range of 20–23 $^\circ\text{C}$.

2.2. Simulation setup

Wear problems usually involve multiple physical phenomena (e.g. mechanics, heat, material wear, etc.), and solid-thermal coupled simulation requires the coupling of multiple physical fields such as mechanical stress, frictional heat generation, temperature distribution, material deformation, and wear. COMSOL Multiphysics allows users to easily couple different physical field models, making it easy to model complex coupled problems. Therefore, the wear simulation was conducted using COMSOL Multiphysics software. The framework of the simulation is presented in Fig. 2. The simulation geometry included a sphere pin and a disc surface as Fig. 1. A ball with a diameter of 6 mm slid against a disc at a point 20 mm away from the disc's center, while the disc had a radius of 50 mm and a thickness of 5 mm. The mesh was created using a tetrahedral mesh configuration. To obtain accurate outcomes and optimize computational efficiency, the contact region between the disc and ball was locally refined. This resulted in the disc being divided into 5162 elements and the ball into 15,034 elements.

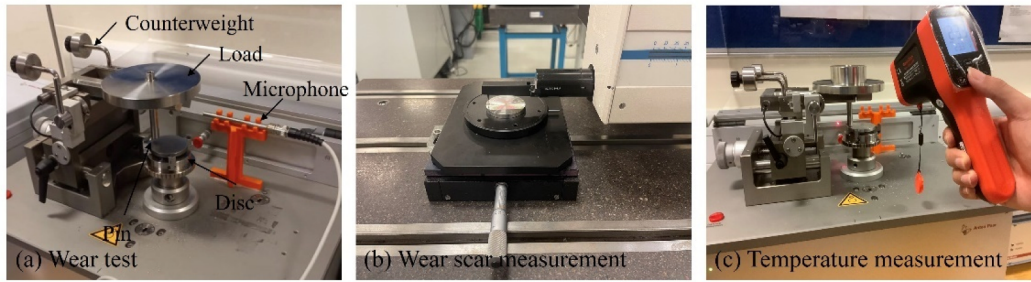
The contact behavior between the ball and disc was modeled using the Augmented Lagrangian Method, as it provides more accurate results compared to the Penalty Method [26]. The traditional Archard model neglects the effect of contact between two rough surfaces, leading to inaccurate wear rate predictions [27]. In this study, we applied the wear model proposed by Sarkar, which incorporates the coefficient of friction into the Archard model to account for contact effects on the wear process, as shown in Eq. (1) [28].

$$w = k \cdot \left(\frac{F_n \cdot V \cdot \sqrt{1 + 3\mu^2}}{H} \right) \quad (1)$$

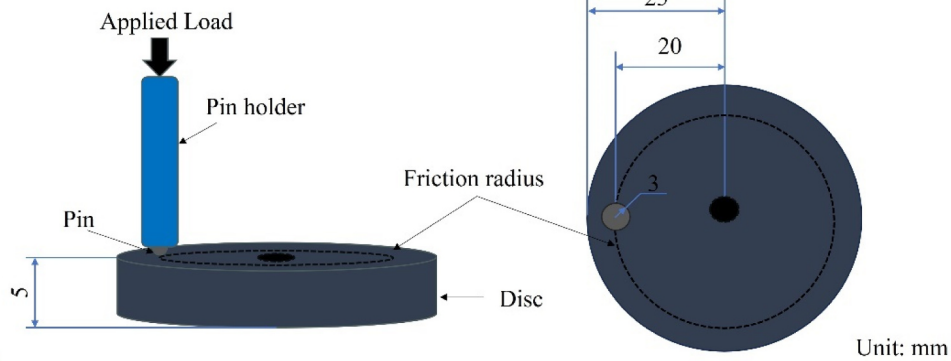
This equation shows that the wear rate w depends on the wear coefficient k , which is calculated from experimental measurements (1×10^{-4} for aluminum, 6.5×10^{-5} for brass, and 1.02×10^{-5} for 304 stainless steel); the normal force F_n ; the sliding velocity V ; the coefficient of friction μ , which varies over time and is averaged to 0.66 (aluminum),

Wear Experiment and Simulation Setup

Experiment setup



Dimension of specimen



Boundary condition of FEM

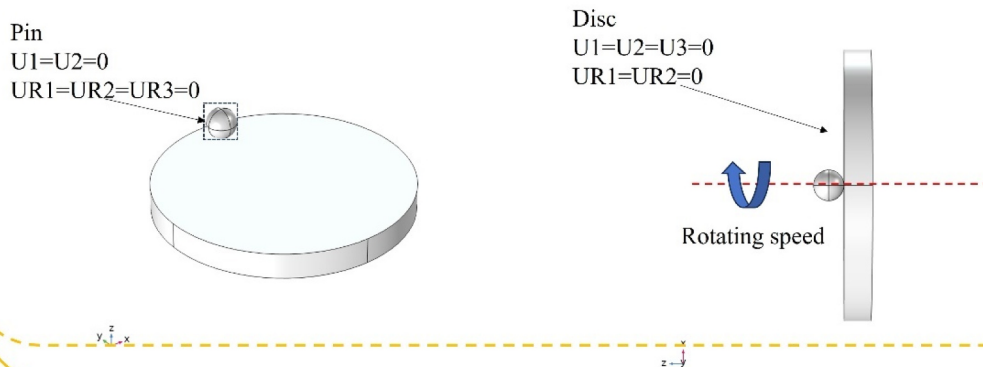


Fig. 1. Wear experiment and simulation setup.

0.22 (brass), and 0.45 (stainless steel) to enhance model convergence; and the hardness of the softer material H .

Then the contact behavior in the solid mechanism model was exported to the heat transfer model to determine the heat source by frictional dissipation, in which heat transfer, heat convection, and heat radiation were considered to ensure the accuracy of the simulation. The thermal partition coefficient between the ball and disc was determined by the Charon relationship built-in COMSOL Multiphysics.

Since the wear coefficient is derived from the material loss volume after the wear test, a finite element method (FEM) model was developed using COMSOL Multiphysics to ensure that this coefficient accurately

captured the wear depth progression. The model was then compared with the measured wear scar profile.

2.3. Noise model derived from symbolic regression

Fig. 3 illustrates the relationship between wear and friction-induced noise. Wear initiates at the interface when two surfaces contact and move relative to each other. As wear progresses, it significantly alters the surface micromorphology, affecting the contact behavior at the interface. These changes impact key factors such as pressure distribution, friction, contact area, and stiffness. Modifications at the contact

Table 1
Material properties of 6082 aluminum.

Symbol	Property	Value	Unit
ρ_1	Density	2700	kg/m ³
$E_1(T)$	Young's Modulus	$E_1(T) = E_{10} \left(1 - \frac{T}{T_m} \exp \left(\theta_g \left(1 - \frac{T_m}{T} \right) \right) \right)$ [25]	Pa
E_{10}	Young's modulus at 0 K	$7.20E + 09$	Pa
T	Temperature	Input from solid heat transfer model	K
T_m	Melting Temperature	828.15	K
θ_g	Material Constant	2.295	K
ν_1	Poisson's Ratio	0.33	1
C_{p1}	Heat Capacity	897	J/(kg·K)
k_1	Thermal Conductivity	195	W/(m·K)
α	Thermal Expansion Coefficient	$2.30E - 05$	1/K
σ_{y50}	Initial Yield Stress	$2.71E + 08$	Pa
H	Hardness	90	MPa

interface serve as excitation sources, propagating vibrations throughout the system. These vibrations produce acoustic energy, resulting in noise. The noise characteristics and intensity closely correlate with the type and extent of wear at the interface.

The wear-noise relationship is highly complex, complicating the development of an analytical model linking the two phenomena. Using FEM methods to solve this problem is challenging, as integrating wear and noise into a single model requires consideration of multiple factors. These factors include surface roughness, COF transitions from static to kinetic during sliding, and the need to incorporate inertial terms to

simulate vibration. Moreover, coupling at least two physical fields—solid mechanics and pressure acoustics—increases computational costs and complicates FEM simulation accuracy. Noise generation mechanisms, such as stick-slip [29,30], sprag-slip [31], friction variation [32], and mode-coupling [12], are closely linked to changes in COF and wear that affect surface morphology. Recent studies [33–37] have explored the relationships between noise, wear volume, and COF, identifying a positive correlation among these factors. Based on these findings, wear volume and COF from experiments serve as input variables, while cumulative average sound pressure, recorded by a microphone, acts as the output in a symbolic regression algorithm. Unlike traditional regression methods, which rely on predefined models (e.g., linear or polynomial), symbolic regression does not require specifying the model form in advance. Instead, it searches for the best-fitting equation by exploring combinations of mathematical functions (e.g., addition, subtraction, multiplication, division, and other operations) to identify the relationship between input and target variables, and the obtained symbolic regression model was compared with the friction noise model proposed by Lontin [23] (see Fig. 4).

In this study, the overall noise signal was segmented into one-second intervals, with the root-mean-square (RMS) noise value for each interval calculated, as shown in Eq. (2). Subsequently, the cumulative average noise was determined using Eq. (3).

$$P_{\text{expAverageValues}}(i) = \sqrt{\frac{1}{\text{SplitSize}} \sum_{k=\text{startIndex}}^{\text{endIndex}} P_{\text{exp}}(k)^2} \quad (2)$$

Where $P_{\text{expAverageValues}}(i)$ represents the root-mean-square (RMS) value of the i -th segment (second) of the experimental data, $P_{\text{exp}}(k)$ represents the value of the experimental data at index k . SplitSize is the size of each segment (the number of data elements in each split), startIndex is the

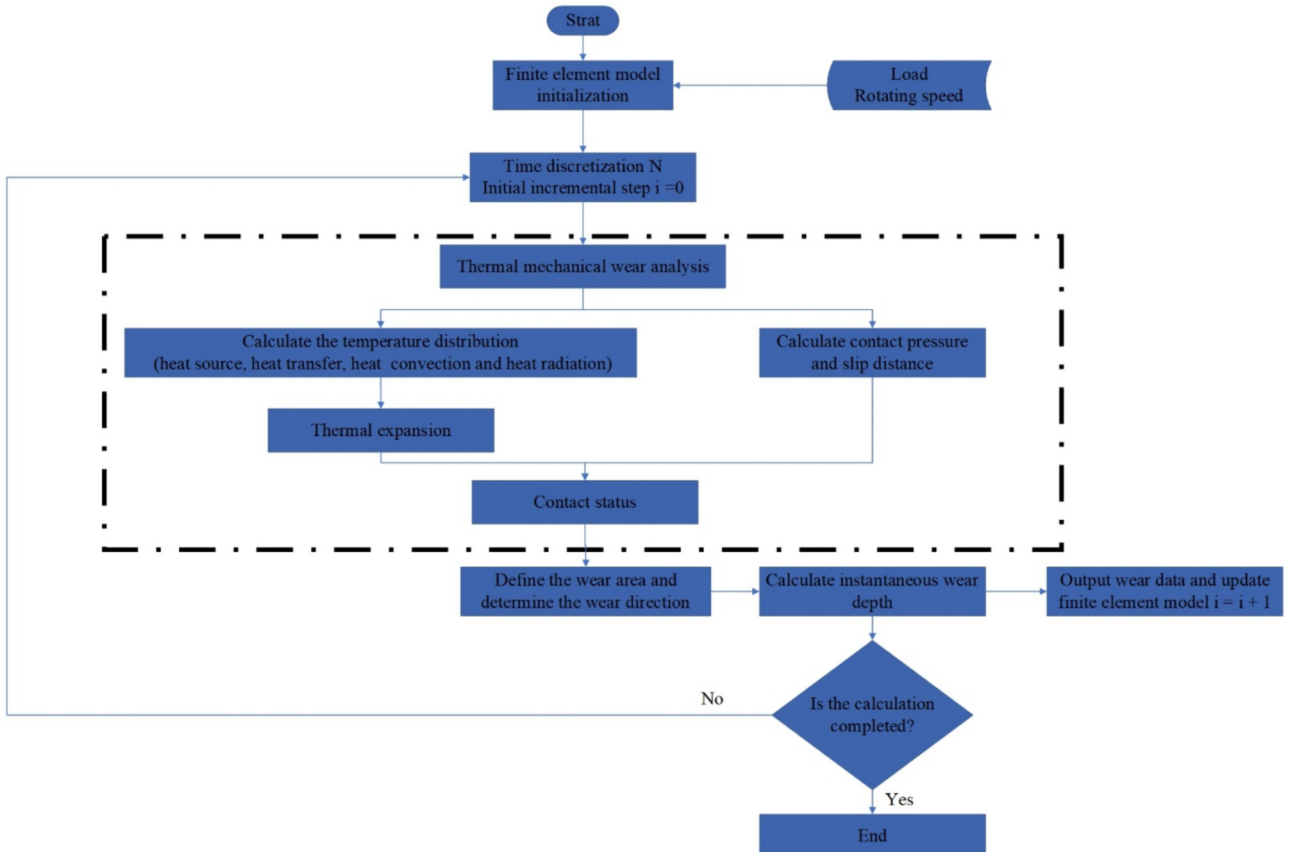


Fig. 2. FEM simulation framework.

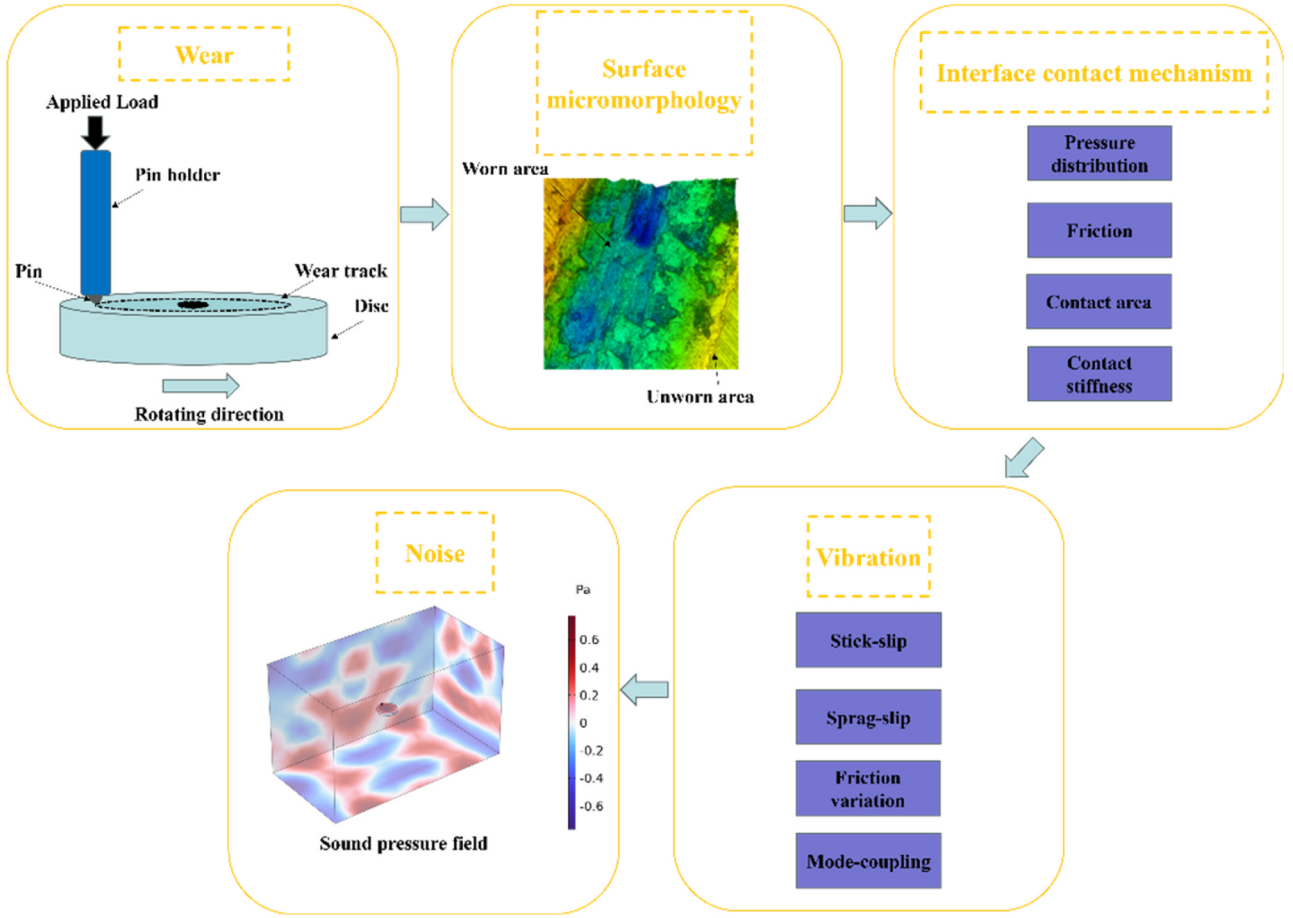


Fig. 3. Interrelationship between wear and noise.

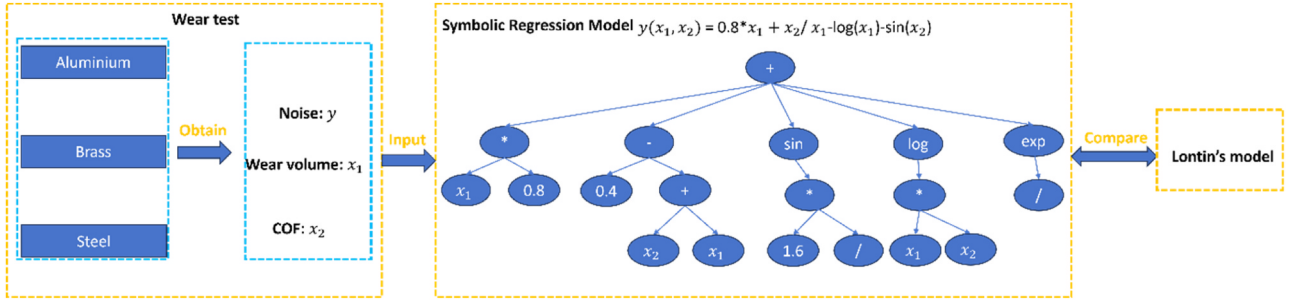


Fig. 4. Illustration of symbolic regression mode.

starting index of the current segment, endIndex is the ending index of the current segment.

$$P_{\text{cumulative}}(i) = \frac{1}{i} \sum_{j=1}^i P_{\text{exp averageValues}}(j) \quad (3)$$

Where $P_{\text{cumulative}}(i)$ represents the cumulative average value of $P_{\text{exp averageValues}}(j)$ up to the i -th segment, $P_{\text{exp averageValues}}(j)$ represents the root-mean-square (RMS) value of the j -th segment of the experimental data. $1/i$ represents the average over i segments, and $\sum_{j=1}^i$ indicates summation from the first segment $j = 1$ to the i -th segment.

3. Result and discussion

3.1. Wear scar profile

Fig. 5 shows aluminum wear scar profiles under various operating parameters, comparing simulation and experimental results. Under a 5 N load, 0.63 m/s, and a 1-min duration, the experimental wear scar profile closely aligns with simulation results that include thermal expansion. However, when the load increases to 10 N, the wear center shifts slightly, and two distinct wear scar valleys appear. As the load increases further to 15 N, these valleys become more pronounced. In contrast, simulations without thermal effects display wear limited to the nominal contact center. However, simulations that incorporate thermal expansion better reflect experimental observations by showing two wear valleys. Compared to the other two materials, aluminum tends to have

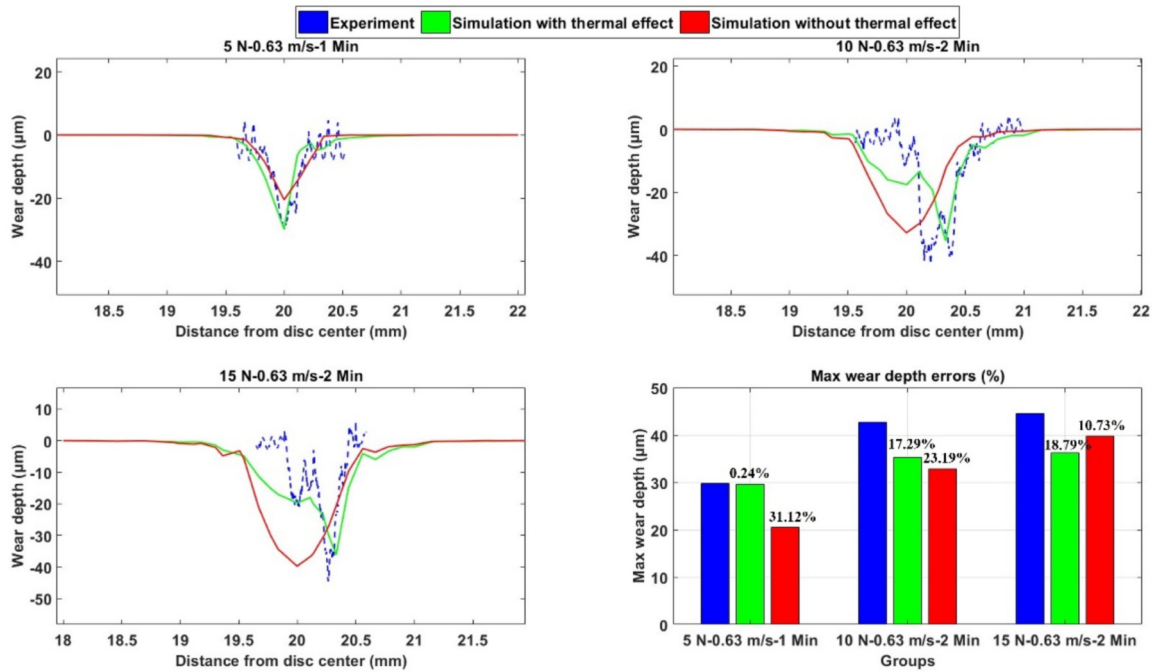


Fig. 5. Wear scar profile of aluminum.

greater thermal expansion, so the higher thermal expansion at the outer contact area, where speed is greater, causes greater squeeze and accelerates wear in this region. Although alignment improves, discrepancies remain between the experimental profiles and those predicted by the thermal expansion model. These differences may result from the inherent randomness of wear or slight temperature variations between experimental and simulation conditions.

Fig. 6 compares brass wear scar profiles under different operating conditions. Unlike aluminum, brass shows no observable shift in the wear center, with wear concentrated primarily at the contact center. At 5 N, 0.21 m/s, and 2 min, the experimental wear scar profile deviates

significantly from both simulation results, whether thermal expansion is included or not. This discrepancy results from unaccounted surface roughness, which plays a critical role in the initial wear stages. As the load and speed increase to 10 N-0.42 m/s and 15 N-0.63 m/s, surface roughness becomes less influential, and both simulations, regardless of thermal expansion, align well with the experimental data.

Fig. 7 illustrates the wear scar profiles of stainless steel under various conditions. Unlike aluminum and brass, the FEM overestimates the wear scar width for stainless steel under varying conditions. This over-estimation can be explained due to the constant wear coefficient used in the model [38]. Moreover, the FEM model may not fully capture

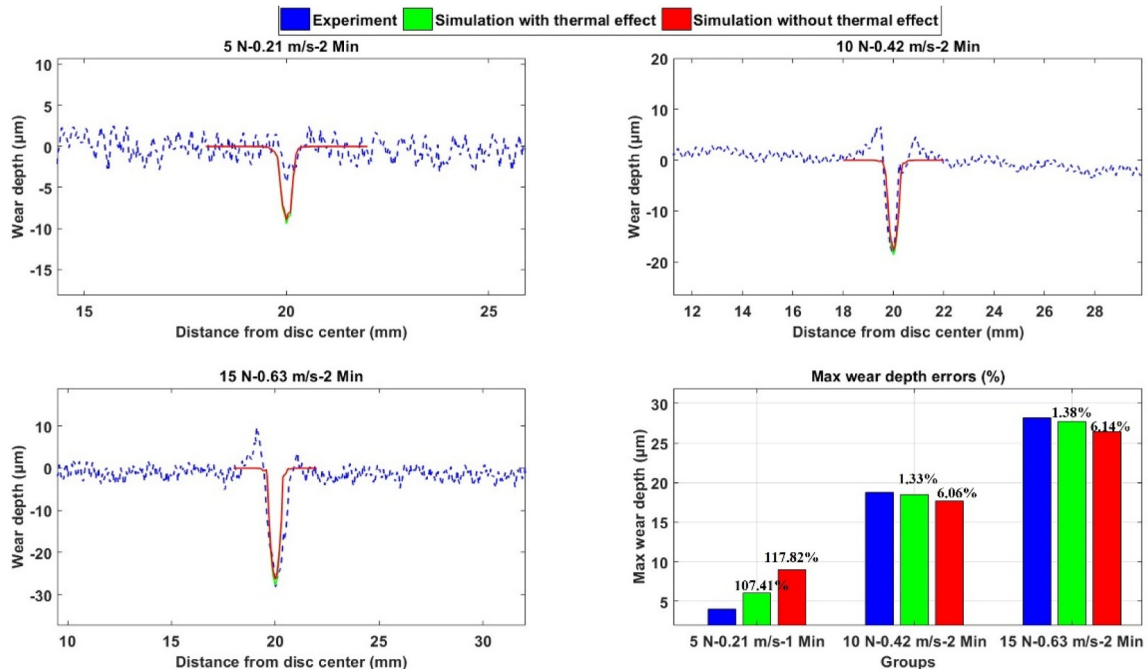


Fig. 6. Wear scar profile of brass.

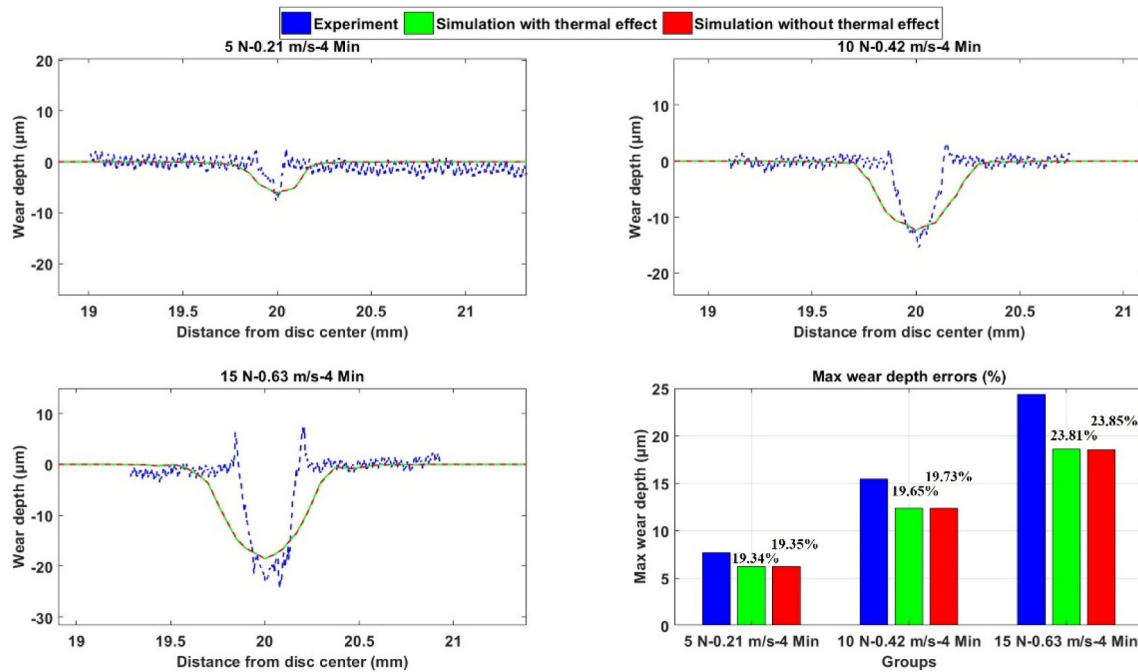


Fig. 7. Wear scar profile of steel.

complex wear mechanisms, such as material transfer and changes in surface roughness, which also contribute to overestimation [39]. Furthermore, thermal expansion has minimal impact on the wear progression of stainless steel.

In summary, aluminum demonstrates high sensitivity to thermal expansion, as wear simulation with thermal expansion aligns more closely with experimental results. In contrast, thermal expansion consideration shows no noticeable effect on wear progression for brass and stainless steel.

3.2. Temperature

At low speed and load, the temperature increase from frictional sliding is minimal. Therefore, to examine wear's impact on temperature rise, we focus on high-speed and high-load conditions (15 N and 0.63 m/s). Fig. 8 shows the temperature distribution on the disc, comparing scenarios with and without wear. Importantly, thermal expansion is included even in the scenario without wear.

As the ball slides over the disc, heat generated at the contact center dissipates radially, forming a comet-shaped temperature pattern along the sliding direction [40], consistent with previous studies [41,42].

The maximum temperature increase differs between wear and non-wear simulations. In the non-wear simulation, temperature increases steadily throughout sliding. In contrast, the wear-inclusive simulation shows temperature fluctuations, reflecting the complex contact interactions. This occurs because the ball gradually penetrates the disc, increasing the contact area, which reduces maximum contact pressure and, consequently, maximum temperature. Thus, ignoring wear in simulation leads to an overestimation of maximum temperature. Experimental temperature measurements align more closely with simulations that include wear. However, some discrepancies remain, likely due to initial temperature differences between simulation and laboratory conditions.

The maximum temperature discrepancy between the simulation and experiment is larger for stainless steel than for aluminum or brass. This occurs because the thermal gun only measures exposed areas, not the contact area with the highest temperature. Due to stainless steel's high hardness, it has a smaller contact area with higher contact pressure. As a

result, a more noticeable maximum temperature difference is observed between the simulation and experiment for stainless steel.

3.3. Friction coefficient

The coefficient of friction (COF) for aluminum, brass, and steel is shown in Figs. 9–11, respectively. For each material, COF initially increases with wear progression and then gradually stabilizes. This COF variation with sliding speed is attributed to changes in wear mechanisms [43] and plastic deformation [44]. The rise in COF occurs as the ball penetrates deeper into the disc, enlarging the contact area and increasing surface adhesion. As contact area expansion slows, COF stabilizes.

For aluminum, a constant load with increasing sliding speed leads to a reduction in COF. This occurs because higher sliding speeds promote the formation of protective layers, such as lubricating films generated from wear debris, which help reduce COF [45]. Under constant sliding speed and increasing load, the COF tends to increase. This increase can be attributed to intensified interactions between the sliding surfaces as the load increases. Higher loads accelerate wear, expand the contact area, and increase surface adhesion, all contributing to an increase in COF.

For brass and stainless steel, increasing sliding speed and load simultaneously results in higher COF. This is because higher loads and speeds accelerate wear, enlarge the contact area, and enhance surface adhesion, leading to a COF increase [46].

3.4. Noise signal

Fig. 12 presents the cumulative average sound pressure measured in the experiments. For aluminum, under a constant 5 N load, noise increases as the rotational speed rises from 0.21 m/s to 0.42 m/s, but decreases slightly with a further increase to 0.63 m/s. According to reference [9], without accounting for wear, an increase in sliding speed causes more intense shocks at the asperity scale, leading to greater vibratory power dissipation and thus a higher radiated noise level. However, when wear is considered, changes in the COF cannot be ignored. As noted by [47], the mechanism of noise variation with COF

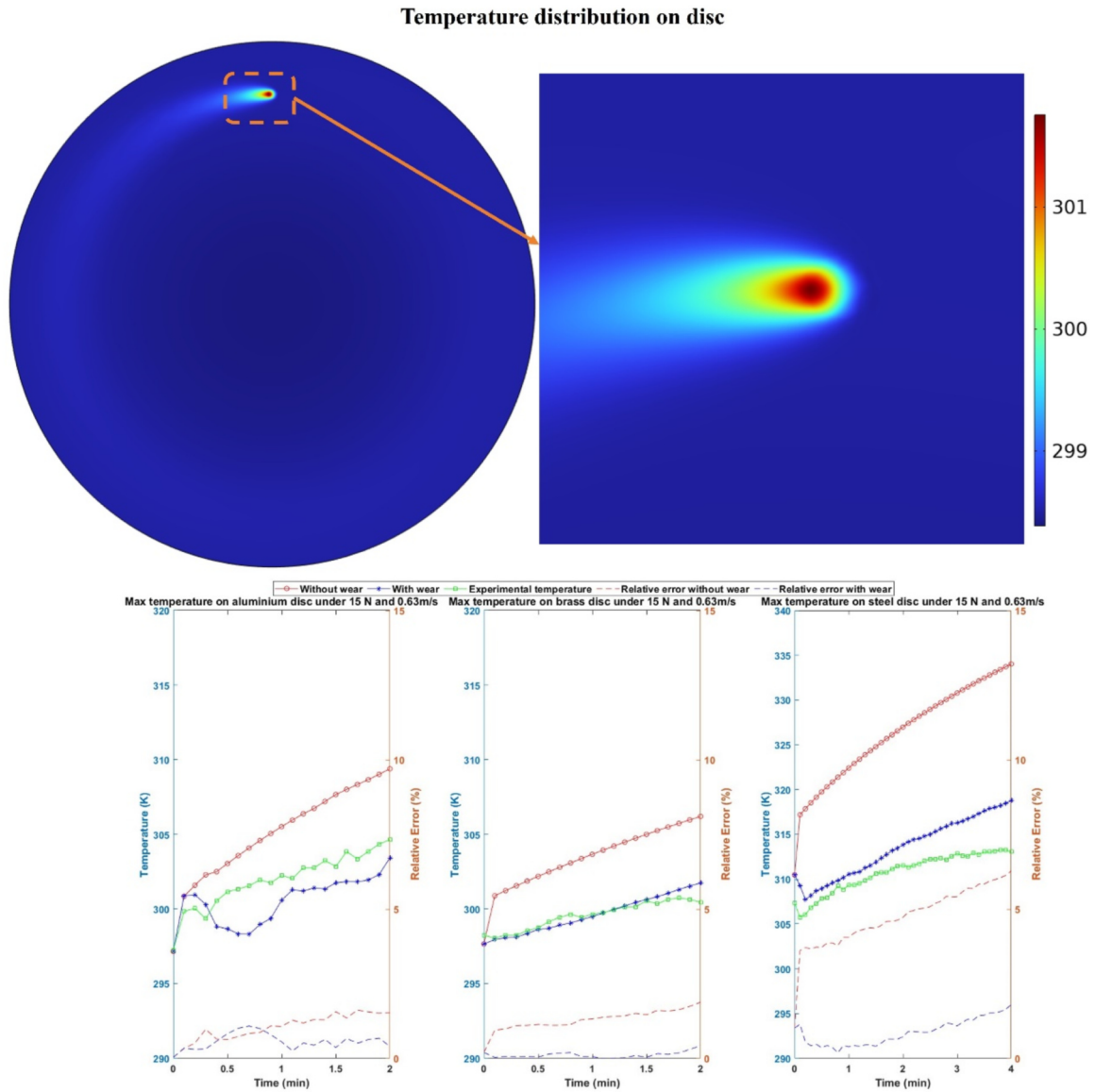


Fig. 8. Temperature on disc.

involves the vibration modes of the sliding ball. Specifically, vibration modes with dominant deflection in the sliding direction are major contributors to friction noise. This suggests that as COF increases, these vibration modes become more active, amplifying the noise. As shown in Fig. 9, COF decreases as sliding speed increases, suggesting that both noise-intensifying effects of increased sliding speed and noise-dampening effects of decreased COF occur simultaneously. Initially, the effect of increased sliding speed is dominant, causing the noise level to rise from 5 N-0.21 m/s to 5 N-0.42 m/s. When sliding speed further increases to 0.63 m/s, the opposing effects of COF reduction and sliding speed increase become comparable, resulting in minimal change in noise level. When speed is held constant at 0.63 m/s and load increases from 5 N to 10 N and 15 N, sound pressure consistently rises due to the increased COF and larger contact area.

For brass and stainless steel, the lowest sound pressure is recorded at 5 N-0.21 m/s. At 10 N-0.42 m/s, sound pressure exceeds that at 5 N-0.21 m/s, reaching its highest level at 15 N-0.63 m/s. Increases in both COF and sliding speed amplify the noise level.

Overall, cumulative sound pressure shows a similar pattern to COF during the wear process, indicating a possible correlation between these two factors.

3.5. Symbolic regression model

The COF and wear volume were scaled to the range [0,1] to normalize feature values, preventing any feature from disproportionately affecting model training due to magnitude differences. The scaled COF and wear volume data were then input into the PySRRegressor in Python to derive an equation relating COF, wear volume, and cumulative average sound pressure. Each experiment was repeated three times under the same parameters: two trials were used for fitting, and the third for validation.

Only data from the aluminum tests were used to fit the symbolic regression model, as the goal was to derive a general equation linking wear, COF, and noise. Brass and steel data were excluded to focus on aluminum; however, if the equation proves applicable to brass and steel, it will indicate some generalizability. Therefore, only aluminum data was used for model fitting.

The derived equations are shown in Table 2 and evaluated by complexity and loss. Complexity refers to the structural intricacy of the equation, while loss measures the goodness of fit to the data. Generally, equations with higher complexity exhibit lower loss, indicating a better data fit but often at the cost of interpretability. After balancing

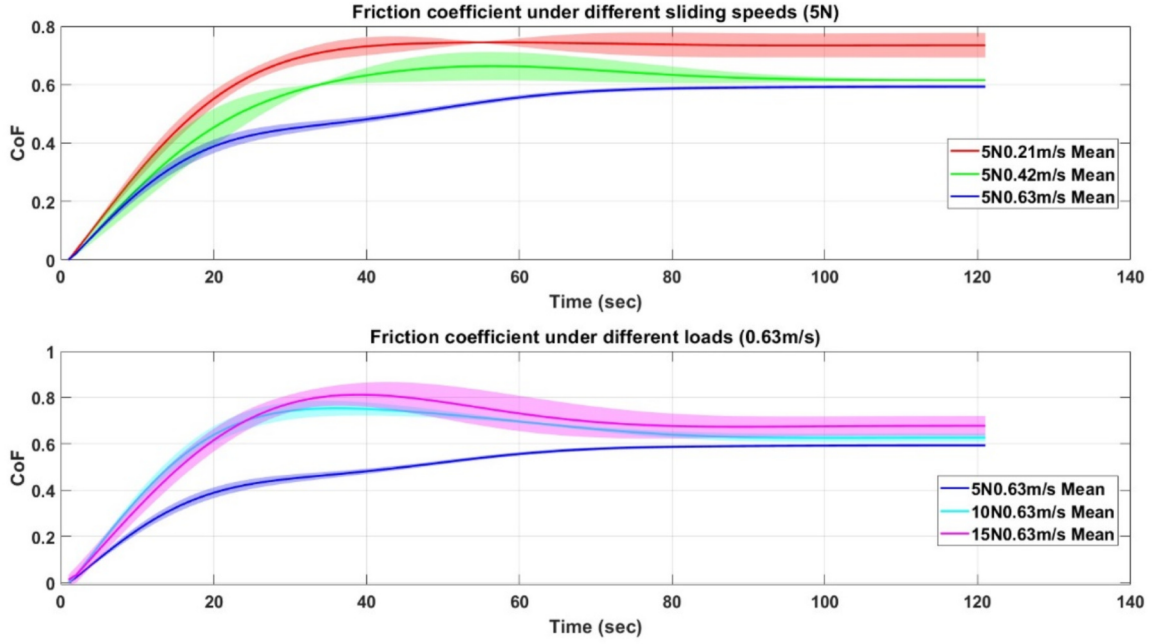


Fig. 9. COF of 6082 aluminum under different conditions.

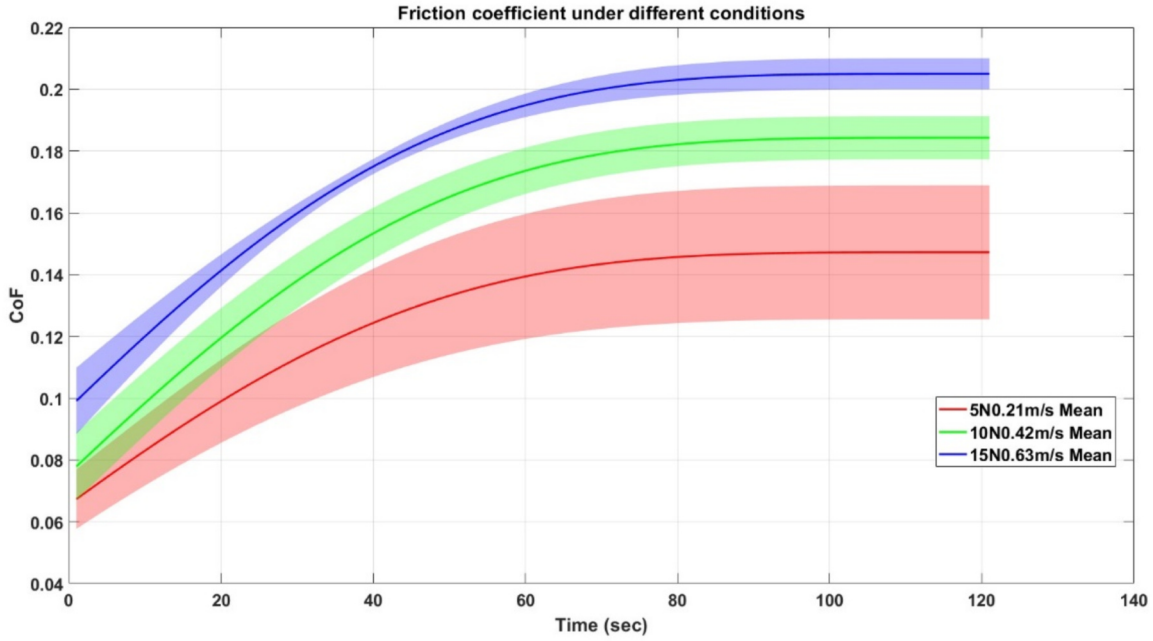


Fig. 10. COF of UNS C38500 brass under different conditions.

complexity and loss, the following equation was chosen:

$$P = \sqrt{x_0 \cdot 16.752525 \cdot 1.05 \cdot x_1} \quad (4)$$

here, P represents the cumulative average noise pressure (Pa), x_0 is the normalized wear volume, and x_1 is normalized the coefficient of friction.

The validation of the equation using the validation dataset is shown in Fig. 13. Initially, the error between the prediction and experimental data is relatively large. This occurs because the initial pressure values are small, and even minor fluctuations in the data can result in significant relative errors. However, as the wear process progresses, the relative errors between the prediction and experiment gradually decrease to below 10 %. Except for the 5 N-0.21 m/s condition, the predictions

align well with the experimental results under other conditions, which are analyzed late.

Based on the preceding discussion, we propose that the relationship between the cumulative average sound pressure P , wear volume V_m , and coefficient of friction μ takes the form in Eq. (5).

$$P = A \cdot \sqrt{V_m} \cdot \mu \quad (5)$$

In the previous analysis, the constant A (unit: $\text{kg} \cdot \text{m}^{-4} \cdot \text{s}^{-2}$) in Eq. (5) was derived by fitting data from various experimental conditions using symbolic regression. This approach may cause deviations between predicted and experimental values, particularly if A is influenced by applied load and rotational speed. Thus, in the subsequent analysis, A was fitted

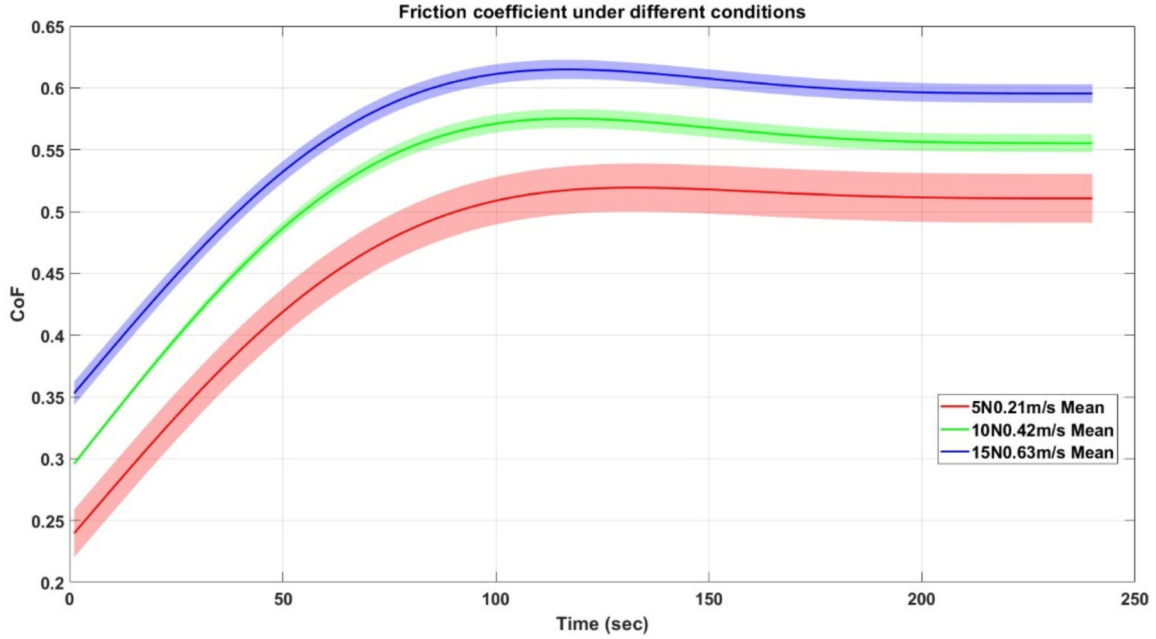


Fig. 11. COF of 304 stainless steel under different conditions.

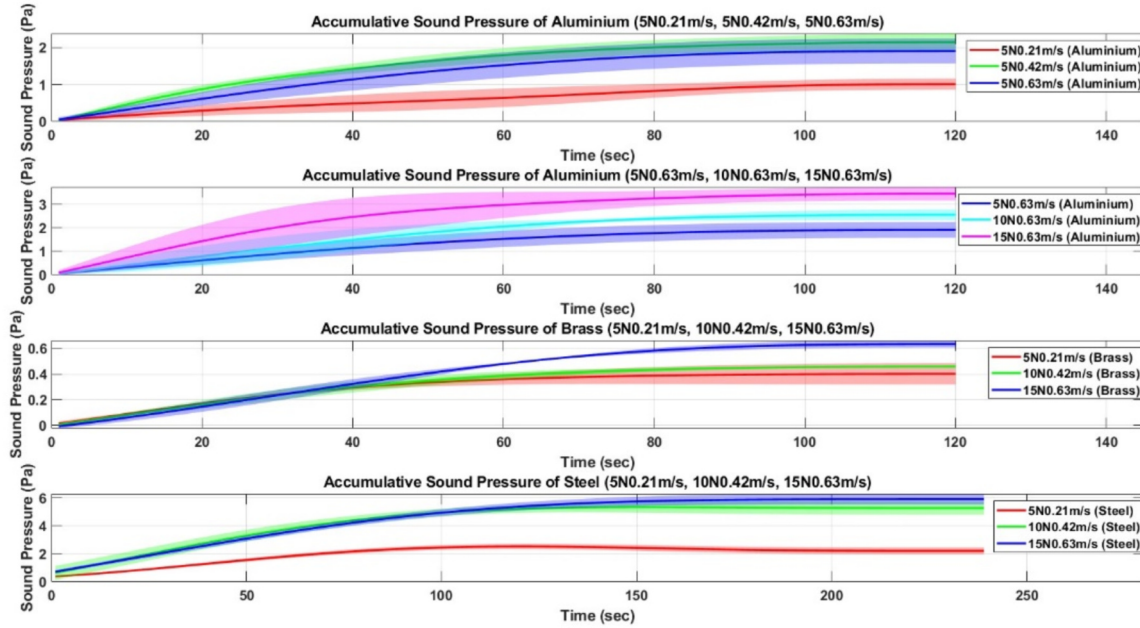


Fig. 12. Accumulative sound noise of aluminum, brass, and steel discs under different conditions.

individually for each set of operating parameters using the least squares method, following the form of Eq. (5). Mean values of COF and wear volume from wear tests conducted under different conditions were used.

Notably, wear volume and the coefficient of friction (COF) were not normalized, which explains the significantly larger values of A in this analysis. The results, along with A values for each group, are shown in Fig. 14. The constant A is related to the applied load and sliding speed, as its values vary under different conditions. However, no clear monotonic relationship was observed; A does not consistently increase or decrease with changes in load and sliding speed.

Compared to Fig. 13, where A was fitted across all tests with varying parameters, individually fitted A values align more closely with experimental data (see Fig. 14), particularly for 5 N-0.21 m/s. The relative

error between predicted and experimental values significantly decreased to less than 10 %.

In Fig. 14, Lontin's model [23] was compared with the symbolic regression model, which generally aligns better with experimental results. Lontin's model assumes that noise results from the vibration and break-off of asperities on the disc surface. However, to simplify, his model is developed in two dimensions rather than three, making it unable to capture real-world contact behavior changes due to wear. This also explains why Lontin's model aligns well with experimental results at the initial stage under low load and speed, where wear-induced surface morphology changes are minimal. However, as sliding distance, load (up to 10 N), or speed (up to 0.63 m/s) increase, surface morphology changes quickly, leading to a large discrepancy between his

Table 2
Equations and losses by complexity.

Complexity	Loss	Equation
1	0.945513	1.5146831
2	0.622748	$\exp(x_0)$
3	0.481538	$4.6112285 \cdot x_0$
4	0.366046	$\sqrt{9.8527155 \cdot x_0}$
5	0.34089	$(2.8841968 \cdot x_0) + x_1$
6	0.296663	$\sqrt{x_0 \cdot 16.752525 \cdot 1.05 \cdot x_1}$
7	0.275954	$(x_0^{0.66206867}) \cdot (5.312876^{x_1})$
8	0.275125	$\sqrt{(x_0 \cdot 38.15414)^{x_1}} + -0.86139137$
9	0.261439	$x_0 \cdot ((19.058714 \cdot (x_1^{x_0})) + -11.762121)$
10	0.261427	$x_0 \cdot (-28.181612 + (35.40806 \cdot \sqrt{x_1^{x_0}}))$
11	0.259378	$0.19220752 + ((7.310067 \cdot (x_1^{3.7207565^{x_0}})) \cdot x_0)$
12	0.258686	$0.17377272 + (((x_1^{\exp(x_0)}) \cdot 7.631451) - x_0) \cdot x_0$
13	0.250379	$(x_1^{18.063734}) + (((-12.405976 / (x_1^{x_0})) + 19.0364) \cdot x_0)$
14	0.247822	$\sqrt{16.67468 \cdot x_0} + \left(\frac{x_0 \cdot 0.030315889}{x_1 - 0.69649905} \right) \cdot x_1$
15	0.22866	$(4.617171 \cdot (x_0^{0.6403947})) + \left(\frac{x_0 \cdot 0.030704815}{x_1 - 0.69649905} \right) \cdot x_1$
17	0.226699	$(4.617171 \cdot (x_0^{0.6403947})) + \left(\frac{(x_0 + -0.05837795) \cdot 0.036241785}{x_1 - 0.69649905} \right) \cdot x_1$
19	0.226235	$\left(\frac{x_1 - 0.017 \cdot (x_0^{0.5984224})}{x_1 - 0.69649905} \right) + ((4.6617517 \cdot (x_0^{0.5984224})) + -0.116826266) \cdot x_1$

Note: x_0 represents wear volume, x_1 represents COF (Coefficient of Friction).

model and experimental results.

3.6. Validate the model on brass

To assess the applicability of Eq. (5) to brass, wear tests were conducted under various conditions, with each configuration repeated three times. One dataset from each group was used to determine the constant A in Eq. (5), while the remaining two datasets evaluated the equation's accuracy and were compared with Lontin's model. The results in Fig. 15

show that the predictions align well with experimental data, confirming that Eq. (5) is also applicable to brass. As analyzed previously, Lontin's model only aligns with the experiment in the initial stages.

Notably, as load and sliding speed increase, A shows a decreasing trend. Additionally, a comparison of A values for aluminum and brass under identical conditions reveals substantial differences. For example, under 5 N-100 m/s, aluminum has an A value of 113,416.5330, while brass has a much higher value of 371,084.1516. Conversely, under 15 N-300 m/s, aluminum's A is 292,936.2364, whereas, for brass, it is much lower at 124,063.4691.

3.7. Validate the model on stainless steel

The applicability of Eq. (5) was also assessed for steel. Wear tests were conducted under various conditions, with each configuration repeated three times. One dataset from each group was used to determine the constant A in Eq. (5), while the remaining two datasets were used to evaluate the equation's accuracy and to compare with Lontin's model. The results in Fig. 16 show that the predictions align well with experimental data, confirming that Eq. (5) is applicable to steel, while Lontin's model only aligns with the experiment at the initial stage under 5 N and 0.21 m/s.

As load and sliding speed increase from 5 N and 0.21 m/s ($A = 1,215,112.2788$) to 10 N and 0.42 m/s ($A = 1,243,418.0305$), A does not show a decrease. However, at 15 N and 0.63 m/s, A decreases to 846,285.2274. Compared with aluminum and brass, steel shows a higher A value, indicating that A is influenced not only by operating parameters but also by material properties.

3.8. Limitation of the model

Although the symbolic regression model fits the experiment better than Lontin's model, it still shows relatively high errors compared to the experimental values at the initial stage (see Fig. 13). This discrepancy arises because certain factors affecting noise have not been accounted for in the current model.

Firstly, the transition from static to kinetic friction at the beginning

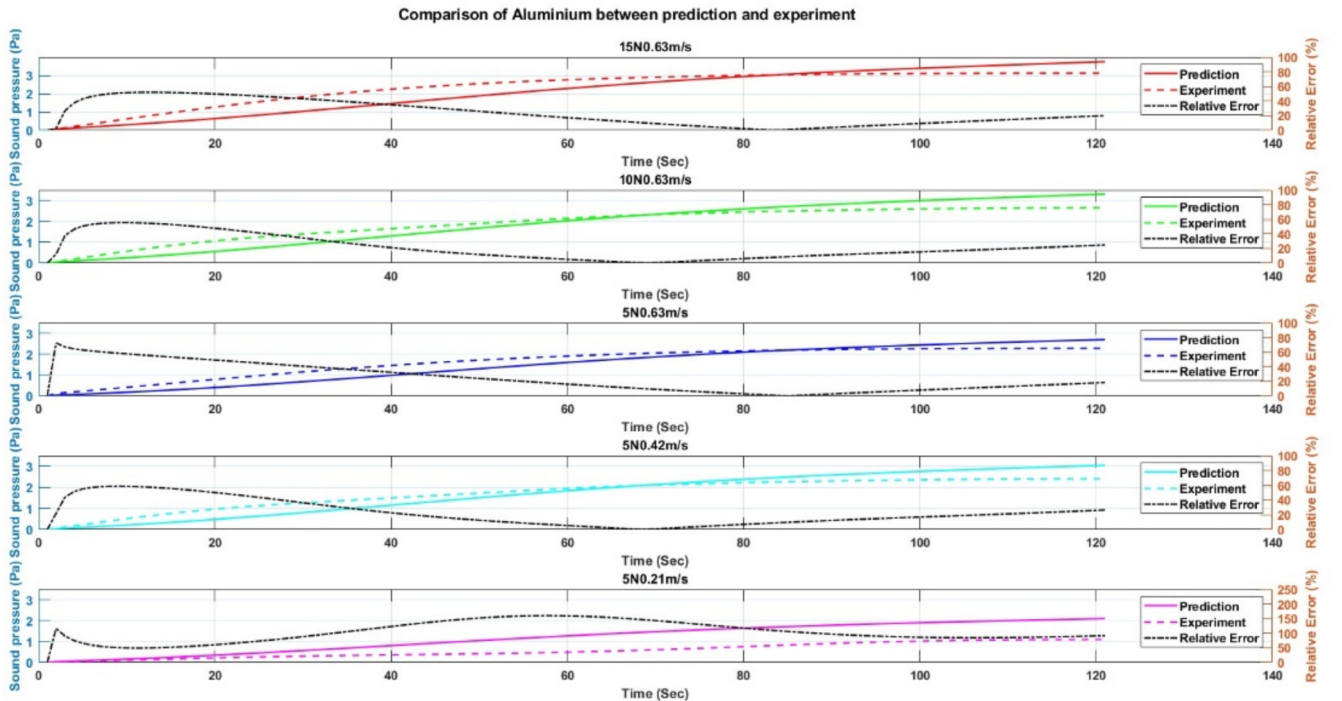


Fig. 13. Comparison of cumulative average noise of aluminum between prediction and experiment.

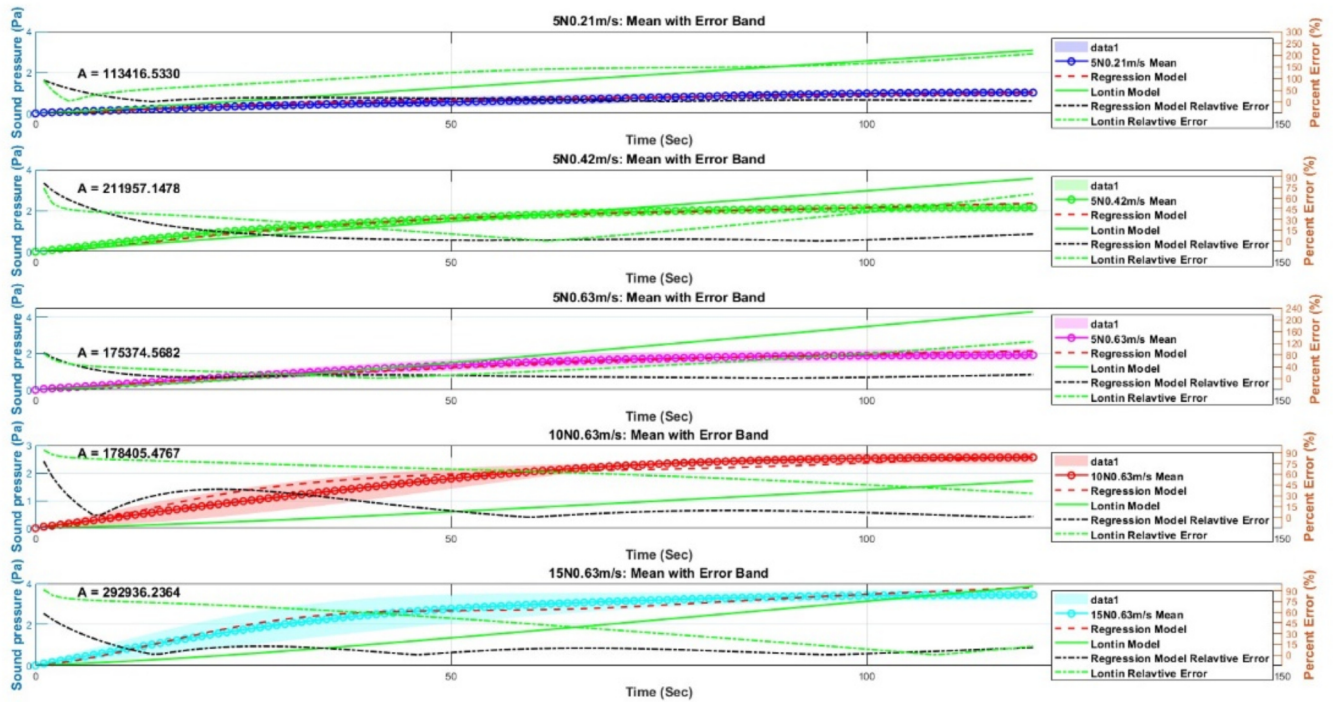


Fig. 14. Comparison of aluminum cumulative average noise between prediction from the least squares method, Lontion's model, and experiment.

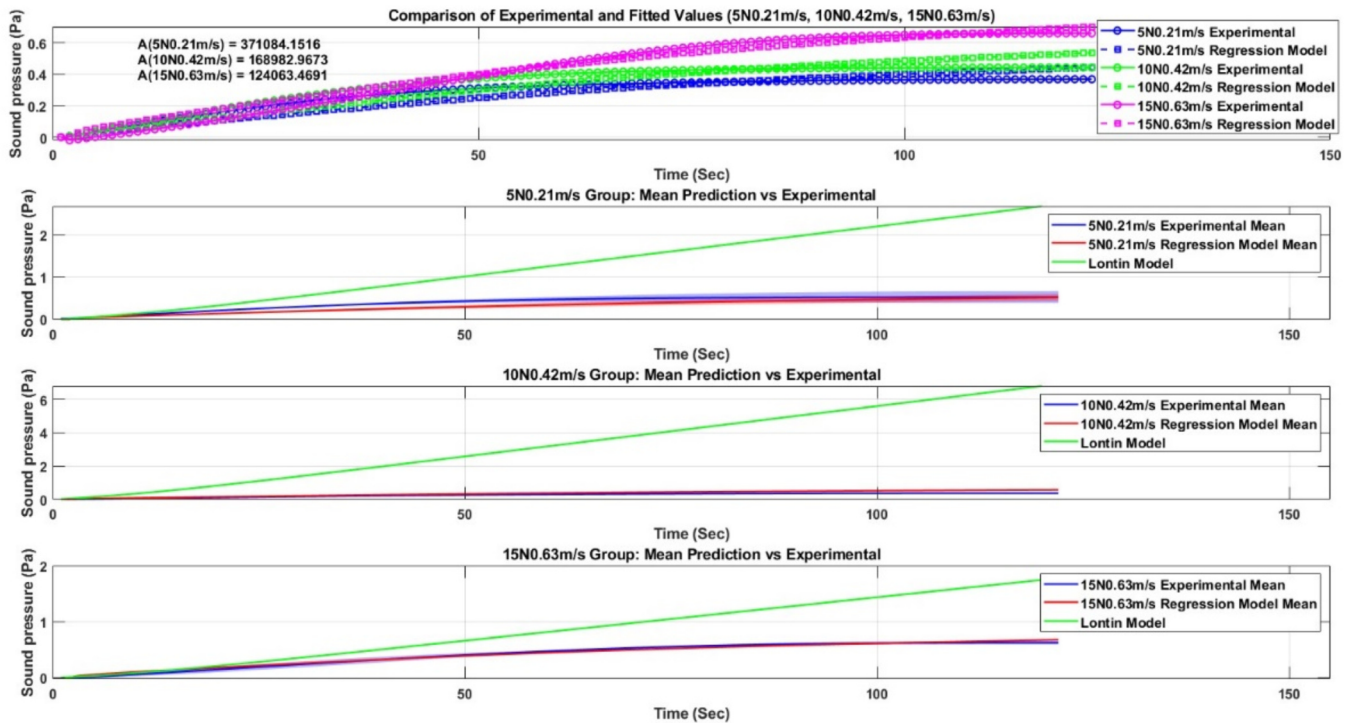


Fig. 15. Compare the regression model and Lontion's model on brass.

of sliding was not considered. Generally, static COF is higher than kinetic COF due to the "stick-slip" phenomenon at the atomic level. When two surfaces come into contact, they interlock at microscopic asperities, requiring greater force to initiate than to maintain sliding [48]. The strain released during the transition from static to kinetic friction is emitted as acoustic energy. However, this process was not considered in the current model, which is why the symbolic regression model shows

significant relative errors compared to experimental noise across different configurations.

Furthermore, in this research, the main noise source is frictional sliding between the ball and disc, which was the only noise source considered in developing the symbolic regression model. However, other noise sources exist, such as the tribometer motor and vibrations induced by contact pairs. Although these noise sources are less intense

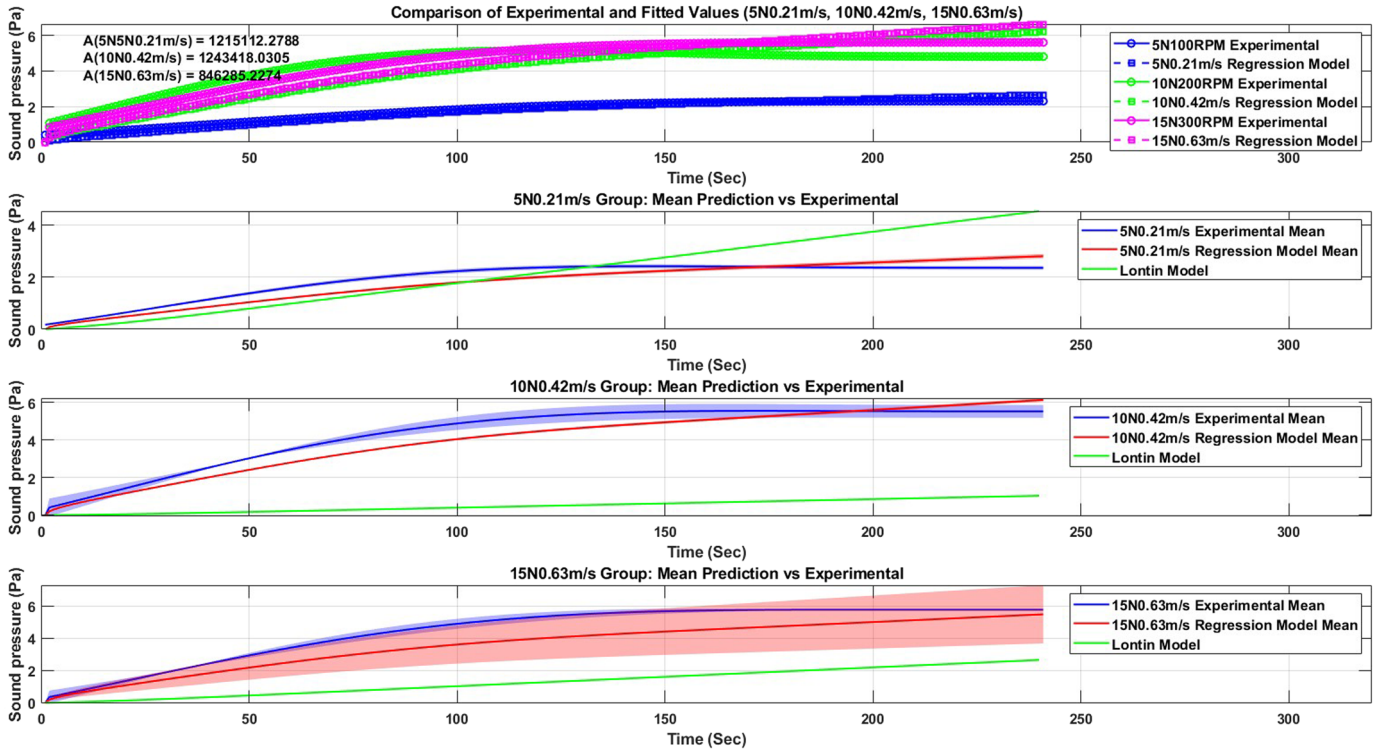


Fig. 16. Compare the regression model and Lontin's model on stainless steel.

than the ball-on-disc frictional sliding noise, they initially contribute significantly. As wear progresses, the ball-on-disc noise quickly dominates, leading to a reduction in relative error.

3.9. Explanation of the model

By substituting the Archard model or the Sarkar model into Eq. (5), replacing the wear volume, the resulting equation can be derived, Eq. (6). For the sake of simplification, the Archard model has been employed in this analysis.

$$P_t = A \cdot \sqrt{\frac{K \cdot F_n \cdot V \cdot t}{H}} \cdot \mu_t \quad (6)$$

Where P_t is the cumulative average sound pressure of time duration (0, t), and μ_t is the coefficient of friction at time t.

From Eq. (6), it can be seen that increasing material hardness facilitates a reduction in friction-induced noise, which aligns with the findings in [49,50]. In the context of ship propeller bearings, materials with higher hardness demonstrated improved frictional properties and reduced noise, meeting the requirements for low-noise design [50]. Similarly, in friction connections using steel shims, harder materials exhibited more stable frictional behavior and generated less noise compared to materials with lower hardness [49]. This can be explained by the fact that harder materials tend to have lower friction coefficients due to stronger interatomic bonds, which reduce adhesion and frictional resistance at the contact interface. The reduction in friction can lead to less vibration and noise during sliding contact, as lower friction (represented by the term F_n) typically correlates with smoother interactions between surfaces [51].

Moreover, a lower wear coefficient is associated with reduced noise levels. This relationship can be explained through the physical interpretation of the wear coefficient. The wear coefficient.

K represents the likelihood of wear particle formation during sliding contact between surfaces [52]. A higher value of K indicates a greater probability of wear particle generation, during which crack propagation

occurs, leading to the release of stored elastic energy. This energy release manifests as vibrations and the emission of acoustic energy.

The term V represents the rate of impacts occurring between asperities on two surfaces per unit time. A higher sliding speed increases the frequency of these impacts between asperities, which, in turn, leads to an increase in noise pressure.

The constant A (unit: $kg \cdot m^{-4} \cdot s^{-2}$) is influenced by the applied load, sliding speed, and material properties. However, its precise physical interpretation remains to be further investigated.

4. Conclusion

This study investigated the wear behavior of 6082 aluminum, UNS C38500 brass, and 304 stainless steel under various conditions by combining experimental ball-on-disc wear tests with finite element method (FEM) simulations. Incorporating thermal expansion effects into the FEM model improved wear scar profile prediction accuracy, especially at higher loads and rotational speeds, where thermal effects become more pronounced. For aluminum, wear scar profiles aligned more closely with experimental results when thermal expansion was included, whereas brass and steel were less sensitive to these thermal effects. Without accounting for wear, the model may overestimate the maximum temperature on the disc.

Additionally, symbolic regression was used to analyze the complex relationship between wear and noise. The resulting noise model, Eq. (6), based on wear volume and the coefficient of friction (COF), effectively predicted the cumulative average noise pressure for aluminum. Validation tests on brass and steel confirmed the equation's applicability to other materials, though the constant A varied significantly, depending on material properties and operating conditions. Although the proposed model did not account for the static-to-kinetic friction transition or other noise sources, leading to high initial relative errors, these errors decreased to 10 % as the wear process progressed.

The proposed model establishes a quantitative relationship between wear volume, COF, and cumulative average noise pressure, enabling COF prediction and wear volume evaluation through noise signals.

Findings further demonstrated that increased material hardness, lower sliding velocity, and reduced wear and friction coefficients help mitigate friction-induced noise, corroborating previous studies.

Since the model was originally derived from metal materials and sphere-flat contact conditions, its applicability should be validated across a broader range of materials, including non-metallic materials like ceramics and rubber. Further testing is also required under different conditions—such as planar contact, ball-cylinder, cylinder-planar, and other contact types to ensure the model's generalizability.

CRedit authorship contribution statement

Intisar Omar: Writing – review & editing, Methodology. **Yang Tian:** Writing – original draft, Visualization, Methodology, Formal analysis, Data curation, Conceptualization. **Muhammad Khan:** Supervision, Methodology, Conceptualization. **Haoxuan Deng:** Methodology.

Statement of Originality

We, the authors of the manuscript titled "Quantifying the Interrelationship Between Friction, Wear, and Noise: A Comparative Study on Aluminum and Brass," hereby confirm the following:

- The content of this manuscript is original and has not been previously published, either in full or in part, in any other journal, conference proceeding, or book.
- The manuscript is not currently under consideration for publication elsewhere, and will not be submitted to another journal while it is under review by Tribology International.
- The research presented in this manuscript, including all experiments, analyses, and findings, is the result of original work carried out by the authors. All data sources, references, and relevant prior work have been properly cited and acknowledged.
- Should this manuscript be accepted for publication, it will not be published elsewhere in the same form or any other language, without the written consent of the publisher.

We confirm that the above statements are true and accurate to the best of our knowledge.

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Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have influenced the work reported in this paper.

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Data availability

Data will be made available on request.

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Quantifying the interrelationship between friction, wear, and noise: a comparative study on aluminum, brass, and steel

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