Prediction of polymer interface wear amount based on noise emission and machine learning regression

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Abstract

This study explores the complex nonlinear relationship between wear and noise, expanding traditional tribological methods. We conducted friction and wear experiments using two polymers and six metals across a wide temperature range, focusing on the noise generated at the friction interface. The research analyzes the wear mechanisms of polymer-metal tribopairs at low temperatures and establishes a model to clarify the relationship between wear and noise. We employed three machine learning algorithms—LightGBM, AdaBoost, and Extra Trees—to develop a regression model that correlates noise emission with the amount of wear, enhancing feature selection and model robustness through KPCA.

Keywords: Wear;Acoustic;Tree algorithms;Prediction

1.Introduction

Low-temperature valves are critical components in the pressurization and delivery systems of launch vehicles, primarily responsible for controlling the opening and closing, direction switching, flow, and pressure regulation of cryogenic propellants such as liquid hydrogen and liquid oxygen. Their performance and reliability directly impact the safety of the launch vehicle's propulsion system[1-3]. Under conditions of high load, strong vibrations, and multiple openings and closings, wear due to friction between polymer-metal guiding pairs is almost unavoidable. Over time, the accumulated wear between the guiding pairs can lead to frequent sealing leakage issues in the valves. In this context, exploring the wear amount generated from polymer-metal friction is particularly urgent.

Traditional methods for measuring wear amount primarily include mass loss, surface morphology analysis, and functional testing. These methods, based on the principle of "static comparison," require interrupting the friction process at specific time points to perform measurements. While they can provide discrete wear amount data, they fail to capture the transient behavior during dynamic wear processes (such as particle migration and material fatigue accumulation). With the advancements in in-situ detection technologies such as high-speed cameras and micro-force sensors, wear assessment is gradually evolving towards real-time and multi-dimensional approaches.

The behavior of tribological systems is complex and difficult to predict, as the wear process involves intricate relationships among material properties, motion states, and operating conditions, exhibiting high non-linearity[4-9]. Data-driven machine learning methods demonstrate unique advantages in addressing complex tribological problems: they can autonomously extract nonlinear relationships from high-dimensional experimental data, facilitating deep integration of information within friction systems[10-16].Currently, the application of machine learning in friction and wear research primarily follows a "first experiment, then predict" model, wherein various data are collected under predetermined experimental conditions to establish intelligent predictive models for material wear. For instance, Chen et al.[17] compared the wear type classification accuracy of six suitable machine learning algorithms and employed the Lsboost algorithm to regress wear rates; Thomas Bergs et al.[18] used fully convolutional networks (FCN) to monitor wear areas on microscopic tool images; Cheng et al.[19] established a mapping relationship between the time-frequency domain features of friction noise and the friction coefficient using three machine learning algorithms: LightGBM, CatBoost, and XGBoost, achieving monitoring of tribological performance; Liao et al.[20] constructed an extended model for time series prediction using TCN and TCN-GRU algorithms, successfully predicting the friction coefficient of FEP; Zhao et al.[21] combined variational mode decomposition with machine learning algorithms and norm feature selection to build a mapping model for the friction coefficient of polymers, realizing precise monitoring of friction coefficients.Notably, the exploration of physical behavior by machine learning in monitoring tribological behavior is limited, and its application in tribology mainly focuses on predicting tribological performance (such as wear rate and friction coefficient) while lacking attention to the practical engineering value of friction. Wear amount is a quantitative indicator of material loss or geometric morphology changes, directly reflecting the reduction effect of materials after wear. Therefore, this study aims to construct a noise signal regression model for wear amount, striving to fill the gap in previous research regarding the exploration of machine learning and tribology in terms of engineering application value, and to provide new insights for understanding the reliability and wear resistance of materials in friction processes.

In this study, under varying temperature, pressure, and rotational speed conditions, we collected friction noise data from the polymer-metal friction process. We utilized three algorithms—LightGBM, AdaBoost, and Extra Trees—to build a regression model for wear amount based on noise signals. Additionally, we introduced the optimization algorithm KPCA for wear monitoring, further enhancing the accuracy and robustness of the overall model's regression predictions. Thus, this paper proposes an effective method for monitoring wear amount.

2. Noise Generation and Wear Mechanisms of Polymers and Metals at Low Temperatures

The generation mechanism of noise in polymer-metal friction pairs can be attributed to the non-steady-state time-varying characteristics of interfacial contact interactions. When two heterogeneous materials undergo relative motion, the randomness and fluctuations in the microscopic mechanical state at the contact interface disrupt the dynamic equilibrium of the mechanical system, resulting in noise signals with random characteristics. Analyzing from a mesoscopic scale, the friction interface can be viewed as a composite system composed of numerous discrete contact elements, each modeled as a vibrating subsystem with mass, stiffness, and damping characteristics. During the friction process, these vibrating elements are subjected to the coupled effects of normal loads and tangential traction forces, leading to complex adhesive-slip dynamic responses of each subsystem, while the contact area stores potential energy in the form of elastic and plastic deformations. As this energy accumulates and exceeds a critical threshold, surface material begins to wear[22-25]. Meanwhile, this sustained coupling of multiple physical fields can trigger ongoing self-excited vibrations at the interface, converting mechanical vibration energy into acoustic energy.Therefore, the generation of friction noise and the occurrence of wear are fundamentally closely related to energy dissipation, and there is a high degree of nonlinear relationship between the noise signal and the amount of wear.

Temperature is a key factor influencing the performance of thermoplastic polymers and determines the friction characteristics of polymer-metal pairs. Taking FEP and PCTFE, the subjects of this study, as examples, below the glass transition temperature, the polymer chains are in a frozen glassy state, exhibiting minimal segmental motion. This allows the material to maintain a relatively stable structure and performance during temperature variations. In this phase, thermal vibrations and deformations are primarily governed by weak intermolecular forces, such as van der Waals forces. As the temperature decreases, the modulus and hardness of the polymer materials improve, enhancing their wear resistance, while the contact area during friction correspondingly reduces, significantly lowering wear and energy loss. However, as the temperature continues to drop to the material's critical point, the increase in shear force begins to dominate the stiffness effect, surpassing the contributions of hardness and elastic modulus to friction performance, resulting in increased wear and energy dissipation [26-29].As a result, it is evident that more polymers will exhibit more complex wear mechanisms, making it challenging to quantify the relationship between noise and wear between polymers and metals across a wide temperature range. Therefore, we employ machine learning algorithms to explore the nonlinear regression relationship between noise signals and wear amount, as illustrated in

Figure 1.

[Figure 1]

3. Tribological Testing Process at Low Temperatures

In this study, friction and wear tests were conducted using the tribological test module of the Anton Paar MCR301 rheometer, as shown in Figure 2. The instrument applies a normal force to a metal ball fixed between three plates, causing the polymer to rotate and creating a controlled friction and wear environment. The contact mode involves point contact between the three plates and the ball, with dry friction as the friction type. The dimensions of the polymer plates are 14.92 × 5.88 × 3.06 mm, while the steel ball has a diameter of 12.7 mm, a maximum circumference of 0.03990 m, a precision grade of G100, and a hardness of 180 HV.Three different operating conditions were compared: loads and rotational speeds of 5 N at 750 rpm, 10 N at 1000 rpm, and 15 N at 1250 rpm. Five temperature points were established using an external liquid nitrogen tank: 25, 0, -20, -70, and -120 °C. Noise signals were captured using a sound pressure transducer (378C1, PCB Company, USA), positioned 40 mm away from the three-plate ball apparatus, with a sampling frequency of 51,200 data points per second. Each data frame lasted for 40 milliseconds, corresponding to a capture rate of 25 frames per second. Within each frame, a total of 2048 data points were collected, and the tests were conducted for durations of 60 and 900 seconds.

In this experiment, we focused on two low-temperature performing thermoplastic polymers: polychlorotrifluoroethylene (PCTFE) and fluorinated ethylene-propylene copolymer (FEP). The metal ball testing materials included two aluminum alloys (5A06 and 2A12), one aluminum bronze (QAL9-2), and three alloy steels (F151, GH4169, and 304). After the polymers and metals were subjected to friction for a specified duration, the samples were ultrasonically cleaned in water and dried with cold air. The wear amount was determined by measuring the mass difference before and after the experiment using an electronic balance with an accuracy of 0.01 mg.

[Figure 2]

4. Model for Relating Friction Noise Signals to Wear Amount

Noise is characterized by randomness and irregularity, making direct observation of the noise signal waveforms only superficially qualitative in terms of their variation patterns. To establish a deeper quantitative relationship between noise and wear amount, it is essential to first extract features from the noise. The noise signal waveforms can be viewed as more disordered and irregular function graphs, where analysis typically focuses on characteristics such as slope, rate of change, extrema, inflection points, and symmetry. Similarly, when describing a segment of noise signal, one often pays attention to features like extreme values, density, steepness, sharpness, and symmetry.In this study, we extracted time-dependent noise amplitudes in the time domain. Using the following formulas, we computed six key features from the sound pressure amplitude signals to characterize the noise properties over intervals of 900 seconds and 60 seconds: the maximum sound pressure level (Pmax), minimum sound pressure level (Pmin), root mean square value (Prms), crest factor (Pcrest), kurtosis (Pku), and skewness (Psk). These six state feature values are summarized in Table 1. [30-32].

[Table 1]

In the equation, x(n) represents the sound amplitude values at n feature points, where n is defined by the duration of the testing period, specifically 900 seconds and 60 seconds for this test.

The maximum sound pressure level (Pmax) represents the highest sound pressure level measured within a sound wave, indicating the maximum loudness during the friction and wear process at the polymer-metal interface. It can be utilized to monitor changes in noise characteristics associated with equipment wear. The minimum sound pressure level (Pmin) denotes the lowest sound pressure level, providing a background noise level during equipment operation, which serves as baseline data for acoustic monitoring. The root mean square value (Prms) reflects the energy of the noise signal, with an increase in RMS typically indicating an escalation in wear severity. The crest factor (Pcrest), defined as the ratio of the maximum sound pressure level to the root mean square value, illustrates the signal's instantaneous variation and dynamic range, aiding in the identification of sudden events caused by wear. Kurtosis (Pku) measures the concentration of peaks in the noise signal, assisting in the detection of early wear signals. Skewness (Psk) evaluates the symmetry of the noise signal, with variations indicating uneven wear or potential failures.

This study considers specific operating conditions for polymer-metal friction, including temperature, load, speed, and pairing codes, resulting in a total of 11 friction characteristics and the corresponding wear amount. A total of 208 pairs were tested, yielding 2,496 data points. Training and testing sets were established to validate the effectiveness of the algorithms. To ensure the model adequately learns the underlying patterns and characteristics of friction noise rather than noise data, it is crucial that the training set is larger than the testing set. A small training set may lead to unstable evaluation results when assessing unseen data in the testing set, thereby failing to reflect the model's true performance . Consequently, this study establishes appropriate gradient ratios by gradually increasing the proportion of the training set, setting four ratio types: 3:2, 7:3, 4:1, and 9:1, for the evaluation and testing of machine learning algorithms. Additionally, to quantitatively characterize the deviation between predicted and actual values and assess model fitting[33-34], four metrics—MSE, RMSE, MAE, and R^2—are introduced as evaluation indicators, as shown in Table 2.

[Table 2]

Mean Squared Error (MSE) represents the average of the squared differences between predicted values and actual values, making it suitable for evaluating the predictive accuracy of wear models. Root Mean Squared Error (RMSE), which is the square root of MSE, can detect anomalies in wear noise; a value exceeding a specified threshold indicates potential wear or failure. Mean Absolute Error (MAE) represents the average of absolute errors and reflects the overall condition of wear. The coefficient of determination (R^2) is used to measure the model's ability to explain the variability of the predicted results for wear data.

5. Machine learning model

The relationship between the noise generated from metal-polymer friction and the wear rate is highly nonlinear. Therefore, this study introduces three tree-based model algorithms to construct wear amount regression models and extract the underlying relationships.Table 3 summarizes the main parameter settings for the three machine learning algorithms: Random Forest (RF), AdaBoost, and LightGBM.Table 4 compares the characteristics of the three algorithms. Table 5 provides the parameter tuning methods for the three algorithms.

[Table 3.4.5]

5.1 Prediction model based on Boosting algorithm

This study considers the inherent nonlinearity and complexity of the dataset. To reduce the impact of redundant features from small samples on the overall prediction accuracy of the model, we introduce the core idea of Boosting algorithms, which involves iteratively adjusting weights in each round to continuously correct the previous model's prediction bias for specific wear stages, thereby enhancing the global approximation capability for complex wear patterns. Among these, LightGBM and AdaBoost are two typical Boosting algorithms, as illustrated in Figure 3 and the equations. LightGBM employs Gradient-based One-Side Sampling (GOSS)[35], while AdaBoost mitigates the influence of outliers through sample weight decay[36]. Both algorithms continuously adapt to local patterns with abrupt changes while retaining the main wear trends, thereby achieving high prediction accuracy for wear amount.

[Figure 3]

$$\omega_{i1} = \frac{1}{N} \quad (11)$$

$$e_t = \frac{\sum_{i=1}^{N} \omega_i (y_i - h_t(x_i))^2}{\sum_{i=1}^{N} \omega_i} \quad (12)$$

$$\alpha_t = \frac{1}{2}\ln(\frac{1-e_t}{e_t}) \quad (13)$$

$$\omega_{i2} = \exp(-\alpha_t(y_i - h_t(x_i))^2) \quad (14)$$

$$F(x) = \sum_{t=1}^{T}\alpha_t h_t(x) \quad (15)$$

N is the total number of training samples,ht(xi)is the predicted value of sample xi by the t-th base model, y_i is the true value,wi is the weight of sample i in the current iteration,αtht(x) is the weighted predicted value of the t-th base model.

5.2 Prediction model based on Bagging algorithm

In the prediction of industrial wear amount, Bagging algorithms generate differentiated training sets based on Bootstrap resampling. By employing multiple decision trees to learn different combinations of operating conditions in parallel, these algorithms avoid the sensitivity of a single tree to noise. The Extra Trees algorithm is based on the Bagging framework[37], as shown in Figure 4. It achieves efficient modeling through a dual randomness anti-noise mechanism and high-dimensional feature parsing capability, ensuring that the prediction results align with wear mechanisms while also possessing generalization ability across different operating conditions. This provides reliable support for the real-time monitoring of complex systems.

[Figure 4]

6. Feature Engineering Based on KPCA Dimensionality Reduction

In the analysis of wear data, we employ the polynomial kernel KPCA method to address the nonlinear coupling between noise features and wear amount. By adapting the unstandardized features using a polynomial kernel function, we avoid the performance degradation caused by distance distortion in the RBF kernel, while preserving the global associative characteristics among the features. This approach maps the original data to a high-dimensional space, achieving the linear separation of nonlinear noise and effectively extracting key wear principal components. It balances noise resistance and small sample adaptability, significantly reducing the risk of overfitting[38-39].

7. Algorithm Experiment Process

This study conducts a multi-stage experiment on three algorithms: LightGBM, AdaBoost, and Extra Trees. First, a series of preliminary experiments are performed to optimize the parameters. Subsequently, polynomial kernel KPCA is introduced for feature space reconstruction, and a dimension sensitivity analysis is conducted to determine the optimal reduced dimensionality. Finally, under fixed dataset partitions, the differences in predictive performance before and after integrating KPCA are compared to validate its optimization effect against noisy data. The specific process is illustrated in the algorithm experimental framework shown in Figure 5.

[Figure 5]

8. Result analysis

8.1 Analysis of physical experimental results

This study constructed a dataset of 208 wear amount test samples, ranging from -2E-5 mg to 4.5E-4 mg, which comprehensively covers potential wear scenarios. This dataset aids the model in learning the entire process from initial wear to a stable state. Additionally, the data exhibits a decreasing trend within a certain range, a pattern that can be easily captured by the polynomial kernel function of KPCA, thereby achieving nonlinear dimensionality reduction.The statistical results of the actual wear amount are shown in the figure 6.

[Figure 6]

8.2 Analysis of algorithm experimental results

In the construction of the standard model, all three algorithms exhibited goodness-of-fit values exceeding 0.79, indicating that the models can explain 79% of the observed data, demonstrating a good level of fit. Among them, the Extra Trees algorithm performed the best, with an average value of 0.898 and the smallest error, as shown in Figures 7, 8, 9, and 10. This advantage in addressing the wear amount issue stems from the robustness and generalization capability of Extra Trees. In contrast, while AdaBoost also performs well by dynamically adjusting sample weights and combining weak learners, its performance on the noisy wear dataset is not as strong as that of Extra Trees. The histogram-based dimensionality reduction method used by LightGBM may lead to feature loss, especially in small datasets or when feature weights are similar, resulting in lower accuracy compared to the other two algorithms. Overall, the decision tree-based machine learning model architecture is well-suited for addressing this complex nonlinear problem. This framework does not require prior assumptions about the distribution of wear data or the mathematical relationships between wear features. By implementing multi-level nonlinear segmentation and multi-node decision boundary settings within a tree structure, it effectively uncovers the interactions between features and provides visualized decision pathways. This opens up new avenues for utilizing black-box models to explore the deeper mechanisms between noise and wear. Furthermore, the performance of the parallel weak learner model surpasses that of the sequential weak learner model, indicating that the parallel model can better cover different feature subspaces through the parallel learning of multiple decision trees. This result suggests that the nonlinear relationship between wear and noise is composed of multiple independent mechanisms, providing new insights for future exploration of wear amounts using hierarchical composite models.

In the construction of the dimensionality reduction model, the average goodness-of-fit for the AdaBoost algorithm is 0.915, the average goodness-of-fit for the Extra Trees algorithm is 0.899, and the goodness-of-fit for the LightGBM algorithm is 0.874. Notably, the improvement in goodness-of-fit for the LightGBM algorithm with KPCA polynomial kernel dimensionality reduction is the most significant, as shown in Table 6. This enhancement can be attributed to the more compact feature space after KPCA reduction, which reduces the model's reliance on incidental patterns in the training data and lowers the risk of overfitting. The improvement in goodness-of-fit for the Extra Trees algorithm is minimal, and there is even a decline in robustness. This is because Extra Trees, with its random selection of features and split values, inherently possesses strong resistance to high-dimensional noise and the ability to handle nonlinear problems; thus, KPCA's dimensionality reduction did not yield additional benefits. Instead, it may introduce unnecessary noisy features and overfitting information. Overall, the KPCA dimensionality reduction method is suitable for handling nonlinear friction and wear data, as it can simplify the complexity of friction models while retaining the original information. This finding provides an effective feature engineering strategy for tribological modeling.

[Figure 7.8.9.10]

[Table 6]

9. Conclusion

The noise regression model for wear amount is characterized by a high degree of nonlinearity. In this study, the LightGBM, AdaBoost, and Extra Trees algorithms were employed, in conjunction with KPCA for dimensionality reduction, to perform regression predictions of wear amount resulting from friction noise. The main contributions of this research are summarized as follows:

1. A novel wear amount prediction model based on noise has been proposed for regressing the wear amount of polymers and six metals under varying operational conditions across a wide temperature range.

2. A decision tree-based algorithm framework was implemented for the first time in noise regression modeling of wear amount. Comparative evaluation revealed that the LightGBM, AdaBoost, and Extra Trees algorithms exhibited the highest prediction accuracy, with Extra Trees demonstrating superior performance. This systematic study successfully established the feasibility of constructing generalizable wear amount prediction models using a decision tree framework and highlighted the advantages of employing multiple parallel decision trees.

3. The application of KPCA dimensionality reduction to wear amount prediction was conducted for the first time, resulting in significant improvements in feature extraction and prediction accuracy. This approach enhanced the ability of machine learning models to address nonlinear issues and provided an effective feature engineering strategy for tribological modeling.

This study still has the following limitations: both machine learning models and the KPCA dimensionality reduction method are inherently black box models, making it difficult to clearly explain the interaction mechanisms between specific physical quantities. However, experiments have demonstrated that this black box model is suitable for establishing relationships related to friction behavior. Specifically, machine learning algorithms based on a decision tree framework can capture complex combinations of noise and operational parameters while providing interpretable decision pathways, and the KPCA dimensionality reduction method simplifies the complexity of friction models while retaining original information. Achieving the same high level of prediction accuracy for each pair of friction materials under different operating conditions is challenging.In the future, this research is expected to continue developing in the following aspects: Building upon the superiority of the existing decision tree framework, machine learning models that are more tightly integrated with the physical background of tribology could be constructed based on the decision tree structure, thereby enhancing the model's generalization capability and prediction accuracy. Furthermore, by leveraging the interpretable internal structure of decision trees, the potential mechanisms of noise and wear could be further explored, making it possible to predict wear amount under more friction conditions and improving the prediction accuracy for more material pairs.

Declaration of Competing Interest

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

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Data Availability

Data will be made available on request.

[Appendix A. Tables]

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Appendix A. Tables

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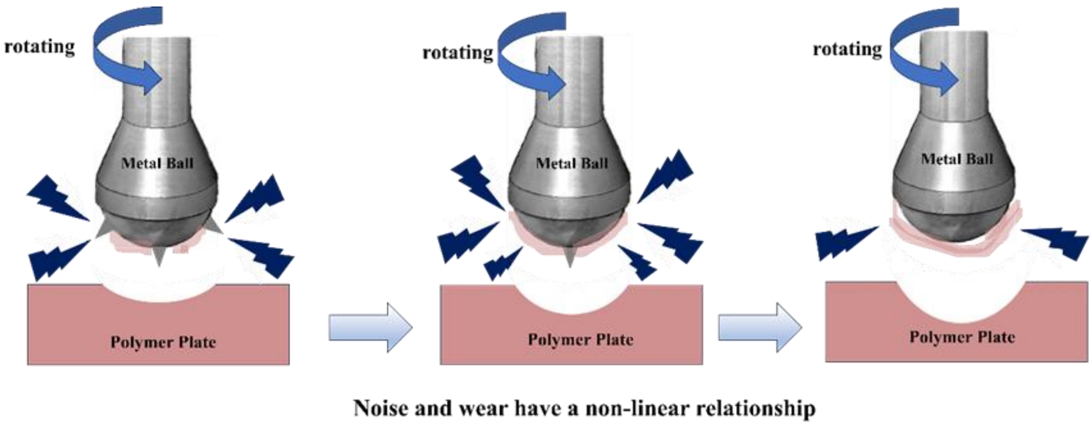

Fig.1. A strong nonlinear relationship between noise and wear

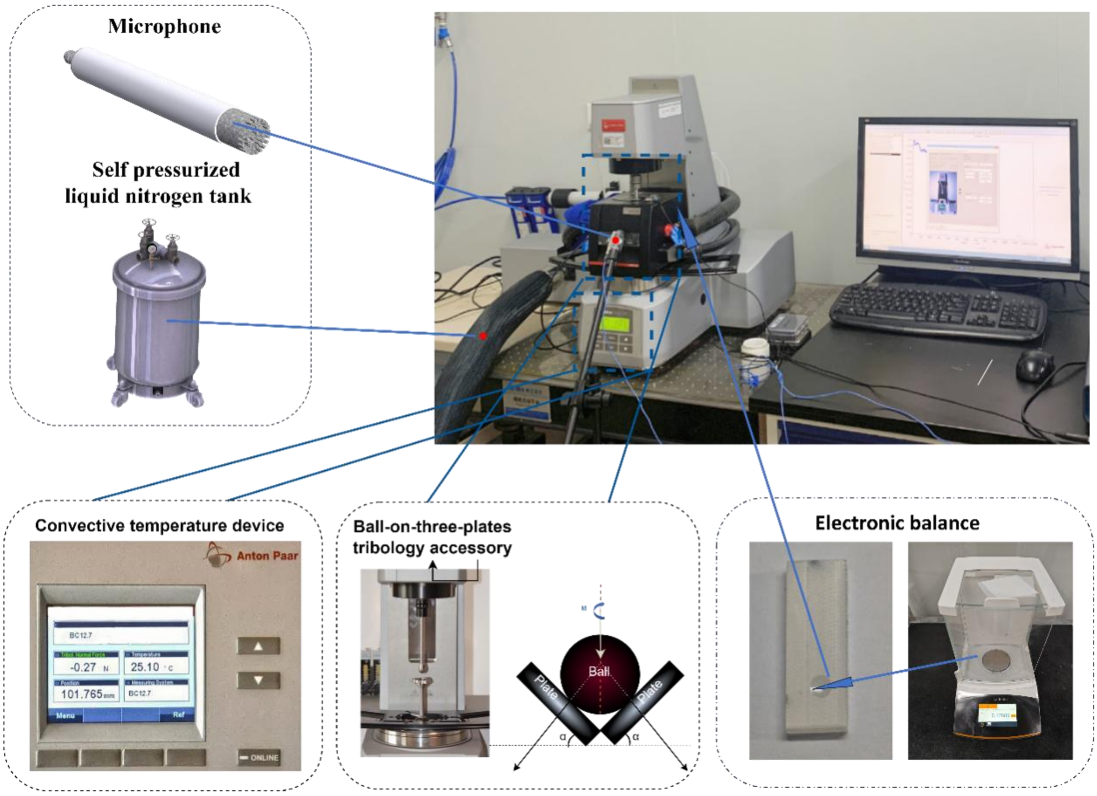

Fig.2. Tribological test equipment for low temperature range and point contact friction

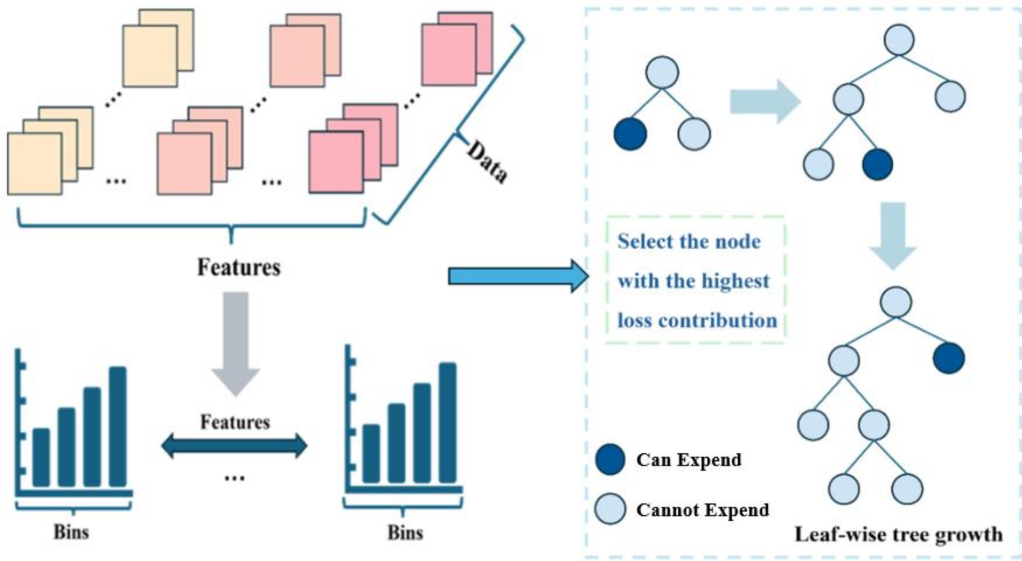

Fig.3. Schematic diagram of LightGBM algorithm principle

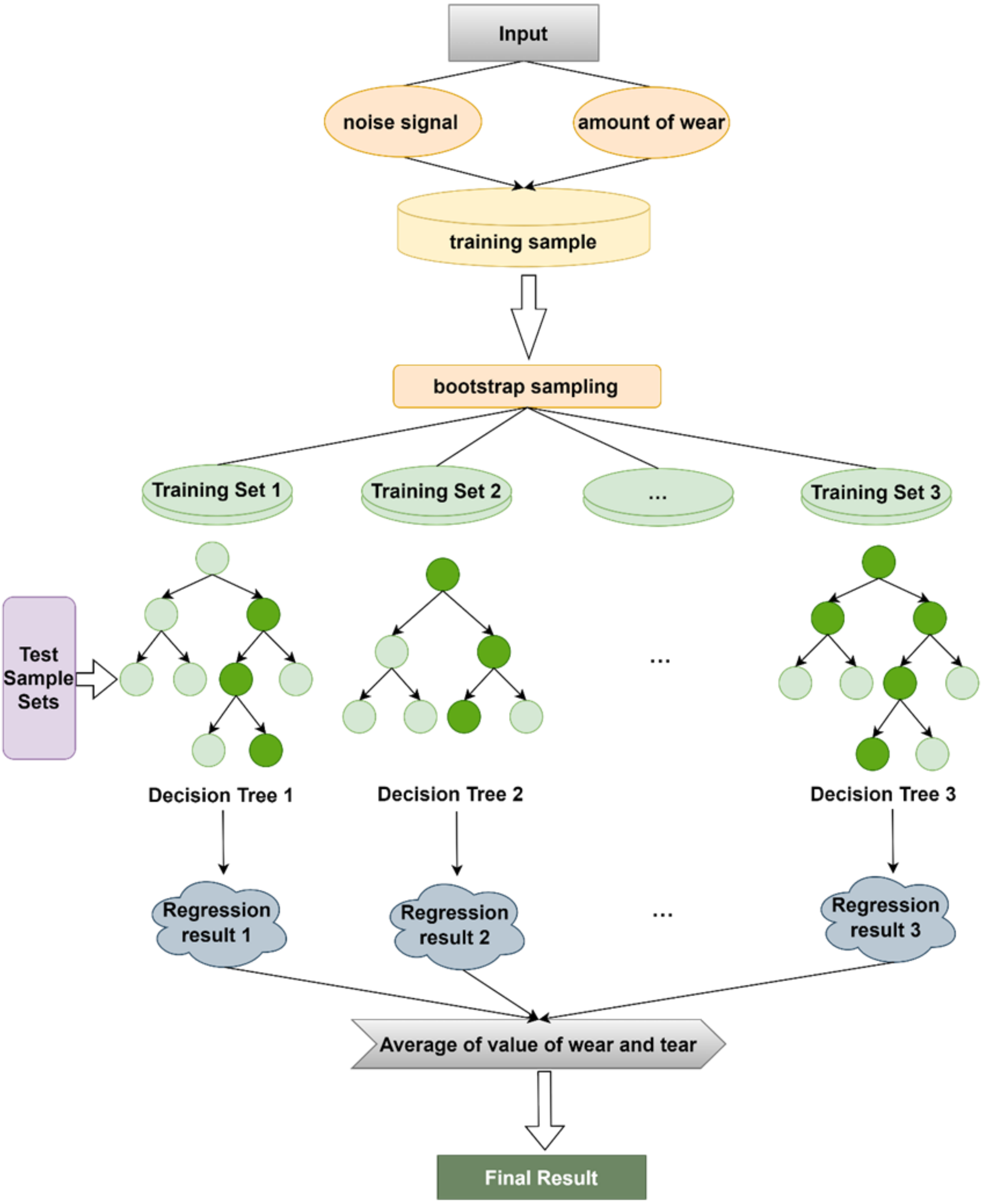

Fig.4. Principles of the Extra Trees algorithm

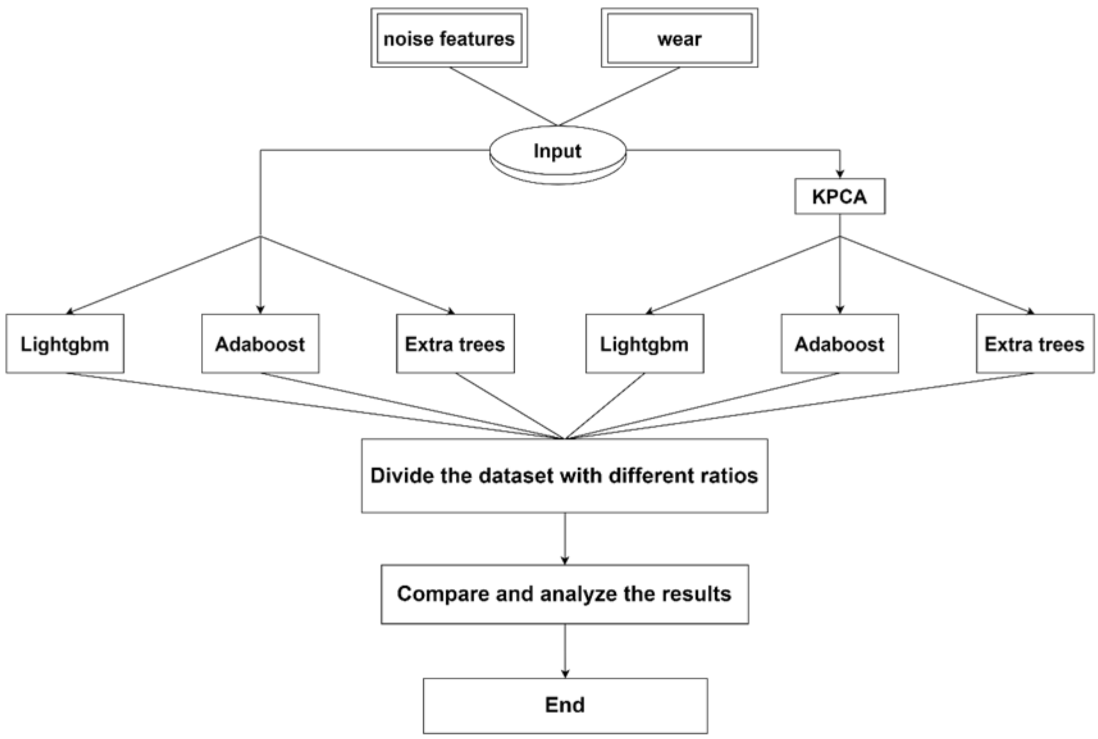

Fig.5. Steps in machine learning for predicting wear amount

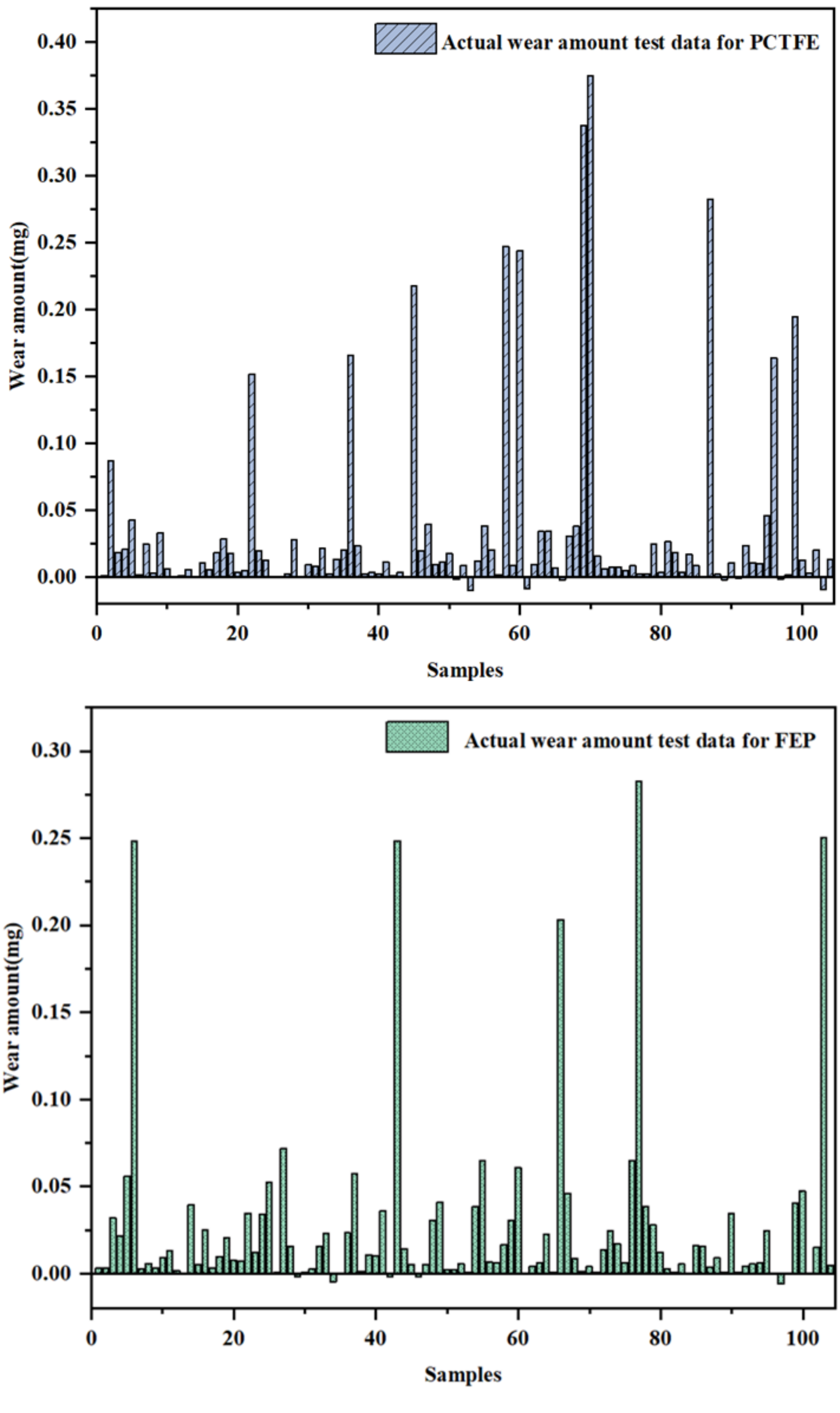

Fig.6. The statistical results of the actual wear amount for PCTFE and FEP

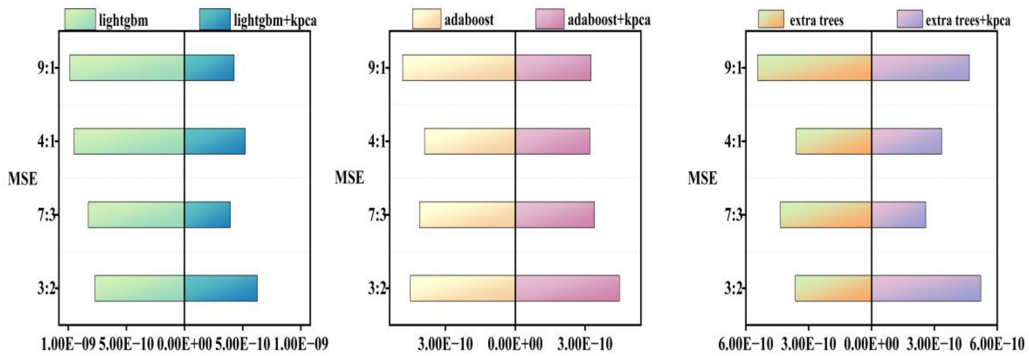

Fig.7. MSE in predicting wear amount

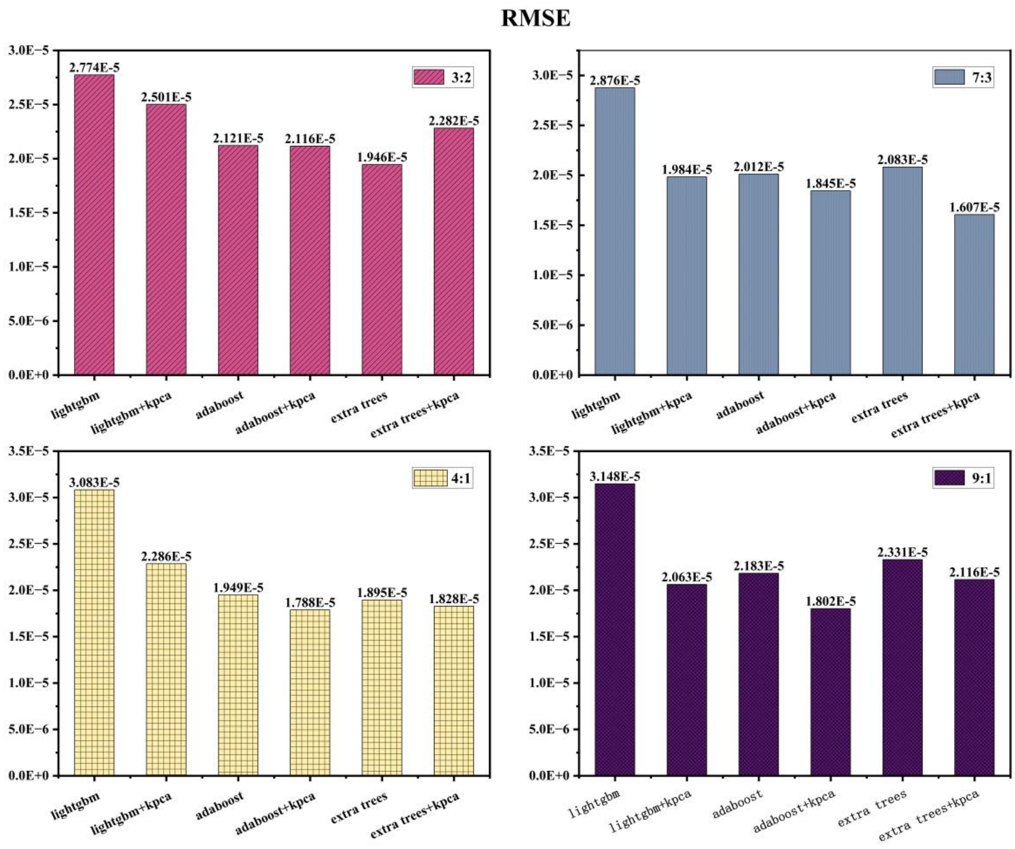

Fig.8. RMSE in predicting wear amount

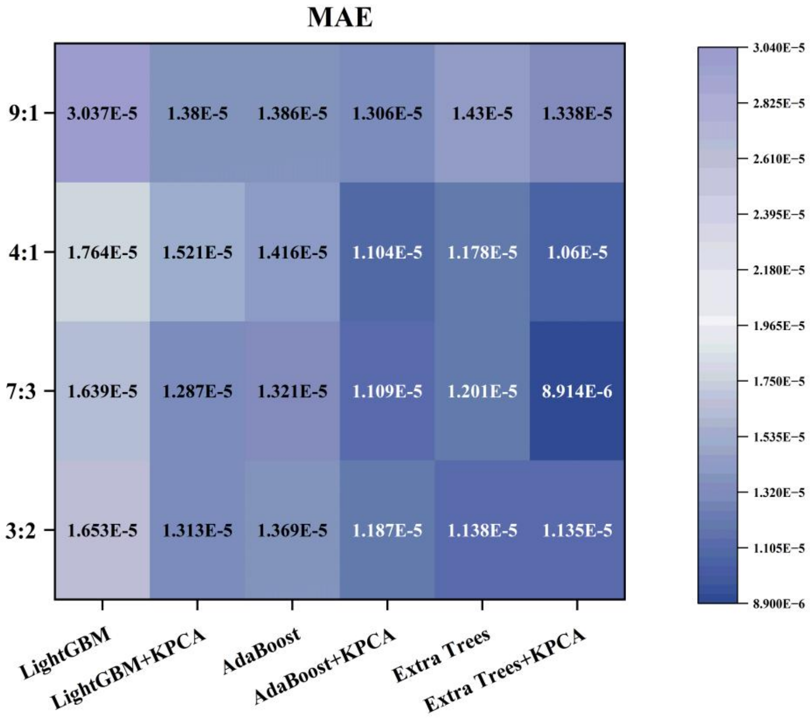

Fig.9. MAE in predicting wear amount

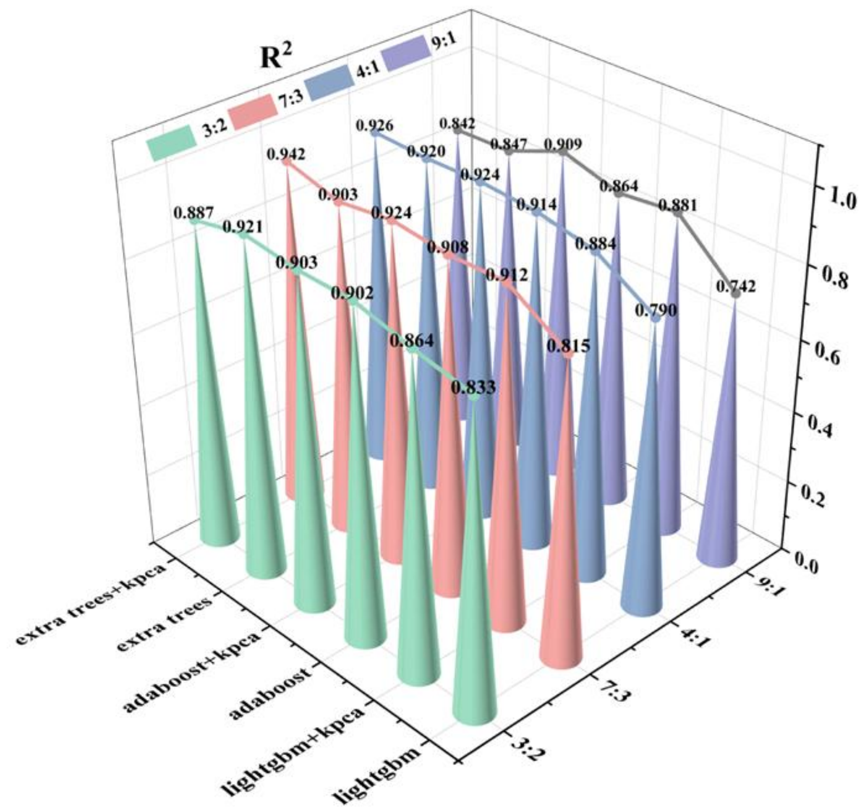

Fig.10.R^2 in predicting wear amount

Table 1. Friction noise time-domain signal characterization

Feature	Formula	Feature	Formula
$P_{\max}$	$\max(x(n))$ (1)	$P_{\min}$	$\min(x(n))$ (2)
P_{rms}	$\sqrt{\frac{1}{N}\sum_{n=1}^{N} x_n^2}$ (3)	P_{crest}	$\frac{\lvert P_{\max} - P_{\min} \rvert}{2P_{rms}}$ (4)
P_{ku}	$\frac{\frac{1}{N}\sum_{i=1}^{N}(\lvert x_n \rvert - \frac{1}{N}\sum_{i=1}^{N} x_n)^4}{P_{rms}^4}$ (5)	P_{sk}	$\frac{\frac{1}{N}\sum_{i=1}^{N}(\lvert x_n \rvert - \frac{1}{N}\sum_{i=1}^{N} x_n)^3}{P_{rms}^3}$ (6)

Table 2. Evaluation indicators for model predictions

Index	Formula	Index	Formula
MSE	$E_{\mathrm{MSE}} = \frac{1}{n}\sum_{i=1}^{n}\left(y_i^{'} - y_i\right)^2$ (7)	*RMSE*	$E_{\mathrm{RMSE}} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(y_i^{'} - y_i\right)^2}$ (8)
MAE	$E_{\mathrm{MAE}} = \frac{1}{n}\sum_{i=1}^{n}\left\|\left(y_i^{'} - y_i\right)\right\|$ (9)	R^2	$R^2 = 1 - \frac{\sum_{i=1}^{n}\left(y_i^{'} - y_i\right)^2}{\sum_{i=1}^{n}\left(\bar{y}_i - y_i\right)^2}$ (10)

Table3. Summary of the main parameter settings of the three machine learning algorithms

Method Parameter	Extra Trees	AdaBoost	LightGBM
learning Mode	bagging	boosting	boosting
base learner	decision trees	decision trees	gbdt
n_estimators	160	300	170
learning rate	-	0.9998	1.008
min_data_in_leaf	2	-	10
max_depth	80	-	10

Table 4. Comparison of three algorithms

Tree Algorithm			
Name	LightGBM	AdaBoost	Extra Trees
Type	Boosting		Bagging
Construction Method	Histogram algorithm	Weighted weak learner	Multiple decision trees
Processing category characteristics	Native support	Solo thermal coding	Solo thermal coding
Hyperparameterization	Complex tuning	Mainly learning rate and number of iterations	Mainly the number and depth of trees
Application	Big Data	Improved Base model	Multi-feature
Support for parallel computing	Support	Not support	Support
Memory Usage	Lower for large-scale data	Higher for multiple weak learners	Higher for storing multiple trees

Table 5.KPCA downgrading steps

1.**Data Centering**:The noise features are centered by subtracting the mean of each feature, resulting in a dataset with a mean of zero.
2. **Kernel Matrix Calculation**:The kernel matrix K is computed using a polynomial kernel function to evaluate the relationships between data points, $Kij = (xi, xj)$ (16)
3.**Centered Kernel Matrix**:The kernel matrix is centered to obtain a new kernel matrix K': $K' = K - \frac{1}{n}1K - K\frac{1}{n}1 + \frac{1}{n^2}1K1$ (17).
4.**Eigenvalue Decomposition**:Eigenvalue decomposition is performed on the centered matrix K' to obtain the eigenvalues and eigenvectors.
5.**Principal Component Selection**:The top k eigenvalues and their corresponding eigenvectors are selected to form the new principal components.
6.**Data Mapping**:The original data points are mapped into the new feature space, resulting in the KPCA outcomes.

Table.6. Analysis of the goodness of fit results for the three algorithms before and after dimensionality reduction

Algorithm	Mean	Variance	Maximum	Minimum
LightGBM	**0.795**	**0.00117**	**0.833**	**0.742**
LightGBM+KPCA	**0.885**	**0.00034**	**0.912**	**0.864**
AdaBoost	**0.897**	**0.00038**	**0.914**	**0.864**
AdaBoost+KPCA	**0.915**	**0.000086**	**0.924**	**0.903**
Extra Trees	**0.898**	**0.000091**	**0.921**	**0.847**
Extra Trees +KPCA	**0.899**	**0.00149**	**0.942**	**0.842**

Appendix A. Tables

Tables A1–A4.

Table A1 Predictive Evaluation Metrics for Noise Regression Wear MSE

MSE				
	3:2	**7:3**	**4:1**	**9:1**
LightGBM	**7.697E-10**	**8.27E-10**	**9.505E-10**	**9.86E-10**
LightGBM+KPCA	**6.258E-10**	**3.938E-10**	**5.224E-10**	**4.256E-10**
AdaBoost	**4.51E-10**	**4.114E-10**	**3.895E-10**	**4.835E-10**
AdaBoost+KPCA	**4.479E-10**	**3.41E-10**	**3.208E-10**	**3.258E-10**
Extra Trees	**3.638E-10**	**4.348E-10**	**3.599E-10**	**5.437E-10**
Extra Trees+KPCA	**5.218E-10**	**2.589E-10**	**3.348E-10**	**4.672E-10**

Table A2 Predictive Evaluation Metrics for Noise Regression Wear RMSE

	RMSE			
	3:2	**7:3**	**4:1**	**9:1**
LightGBM	**2.774E-5**	**2.876E-5**	**3.083E-5**	**3.148E-5**
LightGBM+KPCA	**2.501E-5**	**1.984E-5**	**2.286E-5**	**2.063E-5**
AdaBoost	**2.121E-5**	**2.012E-5**	**1.949E-5**	**2.183E-5**
AdaBoost+KPCA	**2.116E-5**	**1.845E-5**	**1.788E-5**	**1.802E-5**
Extra Trees	**1.946E-5**	**2.083E-5**	**1.895E-5**	**2.331E-5**
Extra Trees+KPCA	**2.282E-5**	**1.607E-5**	**1.828E-5**	**2.116E-5**

Table A3 Predictive Evaluation Metrics for Noise Regression Wear MAE

	MAE			
	3:2	**7:3**	**4:1**	**9:1**
LightGBM	**1.653E-5**	**1.639E-5**	**1.764E-5**	**3.037E-5**
LightGBM+KPCA	**1.313E-5**	**1.287E-5**	**1.521E-5**	**1.38E-5**
AdaBoost	**1.369E-5**	**1.321E-5**	**1.416E-5**	**1.386E-5**
AdaBoost+KPCA	**1.187E-5**	**1.109E-5**	**1.104E-5**	**1.306E-5**
Extra Trees	**1.138E-5**	**1.201E-5**	**1.178E-5**	**1.43E-5**
Extra Trees+KPCA	**1.135E-5**	**8.914E-6**	**1.06E-5**	**1.338E-5**

Table A4 Predictive Evaluation Metrics for Noise Regression Wear R^2

	$\mathbf{R^2}$			
	3:2	**7:3**	**4:1**	**9:1**
LightGBM	**0.833**	**0.815**	**0.790**	**0.742**
LightGBM+KPCA	**0.864**	**0.912**	**0.884**	**0.881**
AdaBoost	**0.902**	**0.908**	**0.914**	**0.864**
AdaBoost+KPCA	**0.903**	**0.924**	**0.924**	**0.909**
Extra Trees	**0.921**	**0.903**	**0.920**	**0.847**
Extra Trees+KPCA	**0.887**	**0.942**	**0.926**	**0.842**