



Research article

Predicting wear damage in moving mechanical contacts: Comparative analysis of regression algorithms and feature selection techniques

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ABSTRACT

+Accurate wear prediction is essential for industries such as manufacturing, transportation, and power generation, as it helps reduce operational risks, minimise downtime, and extend the lifespan of critical components. This study presents a machine learning-based predictive model for estimating wear volume in pin-on-disc systems. The methodology comprises four key stages: feature selection, sample size determination, regression model selection, and model evaluation. The experimental data include parameters such as friction coefficient, tangential force, penetration depth, sliding distance, sound pressure, and load. Feature selection is employed to identify the most relevant parameters for wear prediction, utilising two methods—wrapping and embedding—to refine the feature subset and enhance accuracy. To optimise model performance, the sample size is determined to balance underfitting and overfitting. Initially, linear regression is applied, followed by adjustments to the sample size. Where necessary, more complex algorithms, such as support vector machines (SVMs) and random forests (RFs), are explored to enhance accuracy. Model evaluation employs metrics including mean absolute error (MAE), mean bias error (MBE), root mean square error (RMSE), and the coefficient of determination (R^2) to assess predictive performance. This research offers a systematic approach to wear volume estimation and presents a comparative analysis of regression algorithms, providing valuable insights for researchers and practitioners in wear prediction applications.

1. Introduction

Wear is a common phenomenon in industrial production, defined by the OECD in 1968 as the gradual loss of material from the surface of an object due to relative motion [1]. Over time, wear can lead to mechanical failures, causing operational breakdowns and significant economic losses. Therefore, the ability to monitor and predict wear is essential. However, wear detection and prediction remain complex challenges.

Traditional wear detection methods have included wear particle analysis [2–5], vibration analysis [6–8], radioactive detection [9–15], and acoustic testing [16,17]. In the past, predictions were often based on an operator's experience following these observations [18–20], with limited use of quantitative analysis or predictive modelling.

The advent of machine learning (ML) has transformed the field of wear prediction. Researchers now collect experimental data on machine wear and use it to build predictive models. For example, Wu and Jennings used data from 315 milling tests to train random forest (RF), artificial neural network (ANN), and support vector regression (SVR)

models, concluding that RF outperformed the others in predicting tool wear [21]. Hasan et al. applied five ML algorithms to predict the friction coefficient and wear rate of aluminium alloys, finding that k-nearest neighbours (KNN) best predicted friction, while RF was most effective for predicting wear rate [22]. Similarly, Khan et al. successfully used random forest regression and genetic expression programming to predict wear depth in environmentally friendly fly ash concrete [23].

Other studies have demonstrated the importance of selecting suitable algorithms and parameters. Rajput and Das developed an ANN model using features such as composition, microstructure, hardness, load, and temperature to predict steel wear, achieving strong agreement with experimental results [24]. Altay et al. compared linear regression, support vector machines, and Gaussian process regression for wear prediction in AISI 1020 steel, finding that SVM and Gaussian process regression performed better than linear models [25]. Omar et al. emphasised that selecting the right features and model complexity is critical to achieving accurate predictions, recommending a staged modelling approach [26]. Recent studies show that both model accuracy and interpretability are crucial in wear prediction [27–34]. Material

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properties such as hardness and ductility also significantly affect prediction outcomes, highlighting the importance of careful feature selection and data preprocessing. More recently, Sayyad et al. utilised long short-term memory (LSTM) variants and hybrid feature selection techniques to improve tool wear prediction, demonstrating that deep learning approaches can further enhance predictive accuracy [34].

In addition to mechanical measurements, acoustic signals have been investigated as indicators of wear progression. Lontin and Khan proposed a model linking friction, wear, and noise, suggesting that machine noise could be analysed to predict wear behaviour. However, accurately correlating these signals to wear volume remains challenging. Machine learning offers a promising approach by uncovering hidden patterns in noisy data and linking them to wear progression.

Despite this progress, several research gaps persist. Many previous studies focus on a single algorithm without systematically comparing model performance under different sample sizes or material conditions [34–36]. Moreover, limited work has explored the impact of feature selection on predictive accuracy [37]. The novelty of this study lies in its comprehensive analysis of different ML algorithms, integrated with advanced feature selection techniques, and applied across different material types.

The predictive framework developed in this study provides a foundation that can be adapted for such AI-driven applications. Recent research on machine learning applications for wear prediction is summarised in Table 1. These studies span diverse materials, algorithms, and experimental configurations.

Building on previous pin-on-disc experiments [28], this study uses experimental data, specifically sound pressure and friction coefficients, to develop predictive models for wear volume. By applying systematic feature selection, determining optimal sample sizes, and evaluating different regression models, this work aims to improve the reliability and accuracy of wear predictions under varied loading conditions.

The key contributions of this study are summarised as follows:

1. Comparative analysis of regression algorithms (Linear Regression, Support Vector Machine (SVM), and Random Forest) for wear volume prediction.
2. Evaluation of two advanced feature selection methods—wrapping and embedding—to identify the most relevant features.
3. Investigation of model performance under varying dataset sizes to optimise predictive accuracy.
4. Experimental validation of the proposed models across three material types: mild steel, aluminium, and iron.

2. Methodology

2.1. Proposed strategy

In order to achieve the goal of the research, the work can be divided into the following parts: screening of features, determination of the sample size of the data set, selection of the regression model based on machine learning, and evaluation of the results of the prediction model. The flow chart of the work content of this research is shown in Fig. 1.

2.2. Acquisition of experimental data

The experimental data for this research were sourced from prior studies [28]. Pin-on-disc experiments were conducted on three materials, iron, mild steel, and aluminium T351, under dry, unlubricated conditions. These materials were specifically selected due to their distinct mechanical properties and their relevance to practical applications where wear prediction plays a critical role.

- **Iron** is a well-established material with high hardness and wear resistance, commonly used in industrial applications such as automotive and machinery components. Its wear behaviour is expected to show moderate wear rates, which can provide valuable data on the relationship between hardness and wear.

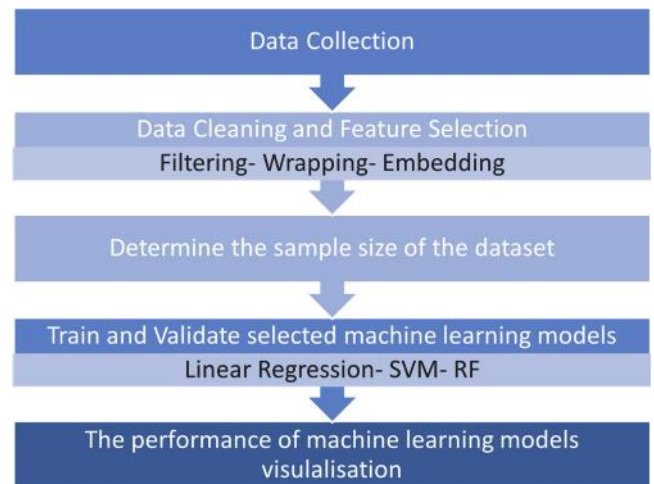


Fig. 1. Methodology overview.

Table 1

Recent Research on Wear Prediction Using Machine Learning.

Author(s)	Year	Material / Application	ML Algorithm(s)	Input Features	Key Findings / Outcome
Kalifa et al. (Review)	2025	General tribology	Review of ML models	Multimodal, system-level	Identified gaps in data integration and interpretability
Shah et al.	2024	Multi-material tools	Ensemble ML	Wear depth, tool type, time	Ensemble models outperformed single models
Kim et al.	2023	Titanium alloys	Bayesian ANN	Force, tool geometry, temperature	Included uncertainty-aware predictions
Rajput & Das	2023	Steels	ANN	Composition, hardness, microstructure	Strong experimental correlation
Xu et al.	2023	Cutting tools	LSTM (time-series)	Force, sound, torque	LSTM outperformed static models
Abdelhamid et al. [38]	2022	Tool-workpiece interface	CNN	Acoustic emission, force	CNN effectively captured wear patterns
Omar et al.	2022	Structural materials	Dynamic ML framework	Crack propagation signals	Proposed dynamic modelling approach
Sayyad et al.	2022	Tool steel	LSTM + hybrid FS	Acoustic emission, vibration, force	Deep learning outperformed traditional models
Singh et al. [39]	2022	Mixed materials	Hybrid ensemble	Microstructure, load, environment	Ensemble learning is effective across material types
Hasan et al.	2021	Aluminium alloys	KNN, RF	Friction coefficient, wear rate	RF predicted wear rate best; KNN better for friction
Wang et al.	2021	Engine components	Gradient Boosted Trees	Oil temp, RPM, pressure	Prediction error under 10 %
Zhang et al. [40]	2020	Tribo-systems	Deep Neural Network (DNN)	Load, time, speed	DNNs outperformed linear regression

- **Mild steel** was chosen for its relative softness compared to iron, which allows for a more noticeable wear process under the same testing conditions. This material is widely used in manufacturing due to its strength and versatility. The wear performance of mild steel will likely differ significantly from that of iron, offering insights into how softer materials behave under sliding friction.
- **Aluminium T351**, an alloy known for its light weight and excellent corrosion resistance, was selected to evaluate wear in softer, more ductile materials. It is commonly used in aerospace and automotive industries where weight reduction is a priority. The wear behaviour of aluminium T351 is expected to differ from both iron and mild steel due to its unique combination of mechanical properties, including lower hardness and greater susceptibility to wear under specific loading conditions.

The materials’ properties—such as hardness, tensile strength, and ductility—directly influence wear characteristics as shown in Table 2, including the formation of wear debris and the rate at which the materials degrade during frictional contact. This diversity in material properties provides a comprehensive foundation for understanding how different metals behave under similar tribological conditions. The inclusion of these materials allows for a thorough exploration of the influence of hardness and other mechanical properties on wear behaviour, with implications for predictive modelling of wear in engineering applications.

The tests were performed at a constant sliding speed of 300 RPM and under two load conditions, 10 N and 20 N, with each test lasting 10 min. To ensure consistency, each test was repeated three times, and average values were calculated for both wear and sound data.

The setup, shown in Fig. 2, includes a stationary stainless-steel pin (440 C) with a 3 mm radius, positioned against a rotating disc. A single pin was used for all tests. To monitor noise generated by friction, a GRAS pressure microphone capable of measuring up to 20 kHz was positioned approximately 10 cm from the pin and disc. The microphone was connected to an NI 9350 DAQ card, which was linked to a computer for data acquisition. The DAQ card was configured with an acquisition rate of 25.6 kHz, and the microphone’s sensitivity was calibrated to 47.46 mV/Pa, with an accuracy of ± 0.003 Pa for sound pressure measurements.

Wear was measured using a penetration depth sensor on the tribometer, which sampled at 100 Hz. This sensor tracked the pin’s penetration depth, which was then multiplied by the distance travelled by the pin to calculate wear volume.

The accuracy of the wear measurements was $\pm 1 \times 10^{-5}$ mm³. For ease of data analysis, sound pressure data were down-sampled by a factor of 50. Throughout the experiments, additional parameters such as friction coefficient, tangential force, and number of rotations were recorded, providing comprehensive insights into the wear process.

2.3. Feature selection

2.3.1. Initial analysis of the features

In previous research, it has been established that wear volume is influenced by various parameters such as temperature, load, and noise [28,41]. Given the extensive range of parameters collected during the

Table 2
Summary of Material Characteristics and Expected Wear Behaviour.

Material	Hardness (HV)	Tensile Strength (MPa)	Expected Wear behaviour
Iron	180–250	370–550	Moderate wear resistance due to higher hardness and strength.
Mild Steel	130–180	350–550	Higher wear rates due to lower hardness and softer nature.
Aluminum T351	120–150	250–350	Higher wear rates, especially under load, due to low hardness.

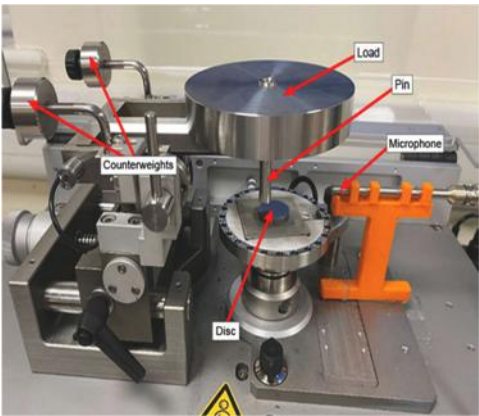


Fig. 2. Wear test equipment [28].

experiments, it is essential to pre-process the data before performing feature selection. Feature selection is a crucial step in identifying the variables that are most strongly correlated with the dependent variable (wear volume), while filtering out those with little or no meaningful relationship. This process helps streamline the data and ensures that only the most relevant features are used in predictive modelling.

The features considered for selection in this study are listed in Table 3 and include the coefficient of friction, tangential force, penetration depth, sliding distance, sound pressure, and load. These particular features were chosen based on their known or hypothesised influence on wear volume, as they directly or indirectly reflect the wear process.

Rationale for feature selection:

- **Coefficient of Friction:** This is a key parameter that represents the resistance between the pin and disc surfaces. A higher coefficient of friction typically correlates with increased wear due to greater resistance to sliding motion.
- **Tangential Force:** The tangential force, which is related to the applied load and friction, can directly impact wear rate. Higher tangential forces often result in higher wear volumes due to increased contact stress.
- **Penetration Depth:** This measures how deeply the pin indents the surface of the disc, providing a direct indication of the material wear and deformation that occurs during the experiment.
- **Sliding Distance:** This parameter is important because wear volume is proportional to the distance over which two surfaces slide against each other. Longer sliding distances generally result in more wear, making this feature critical for assessing wear behaviour.
- **Sound Pressure:** As wear occurs, frictional forces generate sound, which can be an indicator of the wear rate. Monitoring sound pressure provides an indirect but useful measure of wear. The correlation between sound pressure and wear volume has been demonstrated in

Table 3
Possible Features and Their Expected Influence on Wear Volume.

Suggest possible features	Expected Impact on Wear Volume	Predictive value
M Coefficient of friction	Higher friction correlates with increased wear	Wear volume
Ft Tangential force	Higher forces lead to higher wear rates	
Pd Penetration depth	Greater penetration suggests more material wear	
Sd Sliding distance	A longer distance increases the total wear	
Sp Sound pressure	Higher sound pressure often correlates with higher wear rates	
L Load	Higher loads increase contact pressure, leading to higher wear volumes	

previous studies, particularly under varying load and speed conditions.

- **Load:** The applied load directly affects the contact pressure and, consequently, the wear rate. Different loads can cause varying levels of material deformation and wear.

First of all, starting from the actual situation of this research, a preprocessing analysis of each variable is carried out. Regarding the applied load, the experimental data were acquired while subjecting the material to load conditions of 10 N and 20 N. However, due to the relatively minor variation in the rate of load change, its influence on the alteration of wear quantity is deemed insubstantial. Consequently, using the load as a predictive indicator for wear within the context of fitting a regression model is considered inappropriate.

For sound pressure, the noise emitted by the pin-to-disc contact differs under different wear conditions, and the microphone device records a large amount of sound data at different times, providing a sufficient data set for wear prediction. Therefore, sound pressure can be used as a pre-selected feature in preparation for subsequent feature screening analysis.

For friction coefficient and tangential force, they have a linear relationship; that is, the value of tangential force is the product of friction coefficient and load. Since the load remains constant in the experiment, it is only necessary to select one of them as a feature. This research selects the friction coefficient as a pre-selected feature, awaiting the subsequent feature screening process.

The penetration depth is related not only to the wear process but also to factors such as the material of the disc and the degree of surface unevenness, and it gradually deepens as wear progresses. It can be used as a pre-selected feature for subsequent feature selection.

For sliding distance, since the pin rotates around the disc at a constant speed, the sliding distance increases with time and is positively correlated with wear volume. Therefore, it can be used as a pre-selected feature for subsequent analysis. Therefore, after preliminary analysis, friction coefficient, penetration depth, sound pressure, and sliding distance are used as preprocessing features to prepare for the next feature screening.

2.3.2. Final feature selection

After the features are pre-processed, these features need to be further screened. This requires the ‘importance analysis’ method to screen out the final features and prepare for the subsequent training of the regression model.

Common feature selection methods are divided into three categories, namely filtering method, wrapping method, and embedding method [29]. Filtering is to use the correlation between features to score each feature, commonly used variance selection method and the Pearson coefficient method. Since the logic of this method is not rigorous and is usually only applicable to linearly related cases, crossover is often used together with other methods. Therefore, this study does not consider the use of filtering methods. The wrapping method continuously selects subsets from the initial feature set recursively and evaluates them through training to obtain the optimal subset as features. This method needs to select training algorithms in advance, such as RF, SVM, KNN, etc. Its reliability is strong, but the amount of calculation is large when there are many features. Different from the previous two methods, the embedding method performs feature selection in the process of training the regression model, and it is usually combined with decision tree-related algorithms, such as RF and XGBOOST [30–34]. This method calculates the number of splits for the tree model to measure feature importance.

In this research, the wrapping method and the embedding method are used to screen the features, and the final features are determined according to the results. The wrapping and embedding methods were selected for feature selection due to their proven effectiveness in machine learning applications involving small to medium-sized datasets.

The wrapping method offers strong predictive accuracy by recursively selecting feature subsets and evaluating their performance using a specific algorithm (e.g., SVM). However, it is computationally expensive. In contrast, the embedding method integrates feature selection during model training (e.g., through tree-based models like Random Forest), making it more efficient while still retaining interpretability. Using both approaches allowed us to cross-validate the importance of selected features and ensure robustness in the model’s predictive performance.

2.4. Determination of the sample size of the data set

The selection of the sample size for the dataset was determined through a careful balance between ensuring model accuracy and avoiding overfitting. For linear regression models, a general rule of thumb is to have a sample size that is at least 20 times the number of features. This ensures that the model has enough data to learn the underlying patterns without the risk of poor fit due to a small sample size. Initially, the sample size was set to 20 times the number of features, and further evaluations were conducted by incrementally increasing the sample size. The fitting results were then compared to assess whether the linear relationship was adequately captured. For nonlinear models such as SVM and RF, the sample size was adjusted based on model performance. Since these models are less prone to overfitting with larger datasets, the sample size was increased beyond the initial estimate, and cross-validation techniques were employed to evaluate the effect of sample size on model performance. Specifically, k-fold cross-validation was used to assess how different sample sizes influenced the accuracy and generalisation of the models. The performance metrics obtained from cross-validation provided an objective basis for determining the optimal sample size, ensuring that the model was neither underfitted nor overfitted. This approach, combining initial sample size guidelines with empirical testing and cross-validation, allowed for the selection of an optimal sample size that maximised model accuracy and robustness while maintaining the efficiency of computational resources.

2.5. Regression algorithm selection based on machine learning

Regarding the choice of regression model, this research follows the principle of first easy and then difficult. The dataset is first trained using the linear regression algorithm. If the prediction results obtained are not good enough, consider changing the sample size and verifying again. If the results still do not meet the requirements, it means that the linear regression model has a general predictive ability for wear, so the SVM and RF algorithms are used instead. Then compare the prediction results of the SVM and RF algorithms and choose a better prediction model.

2.6. Evaluation of predictive models

The selection of evaluation metrics is crucial for assessing the quality and performance of the regression model. The following metrics were chosen for their ability to provide a comprehensive understanding of model accuracy and predictive performance:

- **Mean Absolute Error (MAE):** This metric measures the average size of the errors in the model’s predictions, without considering whether they are positive or negative. It provides a simple and clear way to understand how far off the model’s predictions are on average. MAE is useful for giving an overall idea of prediction accuracy, especially when the magnitude of errors is important.
- **Mean Bias Error (MBE):** MBE helps to identify if the model has any consistent bias, such as overestimating or underestimating wear. A positive MBE means the model tends to overestimate, while a negative MBE means it underestimates. This metric is important in wear prediction because even small, consistent biases can impact long-term predictions.

- **Root Mean Square Error (RMSE):** RMSE gives more weight to larger errors by squaring the differences before averaging. This means that if the model makes large errors, they will be penalised more than smaller ones. RMSE is valuable when larger errors are more critical to the application, such as in wear prediction, where extreme wear could cause significant damage.
- **R² (Coefficient of Determination):** R² measures how well the model explains the variation in the wear data. An R² value close to 1 indicates that the model explains most of the data's variability, while a value close to 0 suggests that the model is not effective in capturing the patterns in the data. R² is a common metric for understanding the overall quality of the regression model.

These four metrics were chosen because they offer complementary perspectives on model performance. MAE provides a simple measure of accuracy, while RMSE emphasises the importance of reducing large errors. MBE reveals any systematic bias in the model, and R² shows how well the model fits the data as a whole. Together, these metrics align with the research goal of developing a reliable model for predicting wear behaviour under different conditions.

3. Results and discussion

3.1. Insights into crack propagation behaviour in ABS materials

3.1.1. Wrapping method

This research applies the concept of recursive feature elimination from the wrapping method, combining the four features μ , Pd, Sp, and Sd, in various ways to generate multiple feature subsets. These subsets are then trained using the SVM algorithm, and the training results are compared. The subset with the smallest error among the combined features is selected as the final feature set for subsequent training. The error results obtained after training are presented in Table 4.

Through the comparative analysis of the results, it can be concluded that the fitting result is the best when the friction coefficient, sound pressure and sliding distance are used as the features, followed by the sound pressure and sliding distance as the features.

3.1.2. Embedded method

The abscissas 1, 2, 3, and 4 in Fig. 3 respectively represent the four parameters of penetration depth, sound pressure, friction coefficient, and sliding distance, while the ordinates show their importance indicators. Initially, the importance threshold is set at 0.2. It can be seen from the figure that only the two parameters, sound pressure and sliding distance, meet this threshold. The importance index for penetration depth was negative, indicating that this parameter has an inhibitory effect on the regression model as a feature. Although the friction coefficient is related to wear volume, its importance value is low, so this feature can be ignored in subsequent training tasks. Combining the results obtained from the two feature screening methods, this research finally decided to use sliding distance and sound pressure as features and

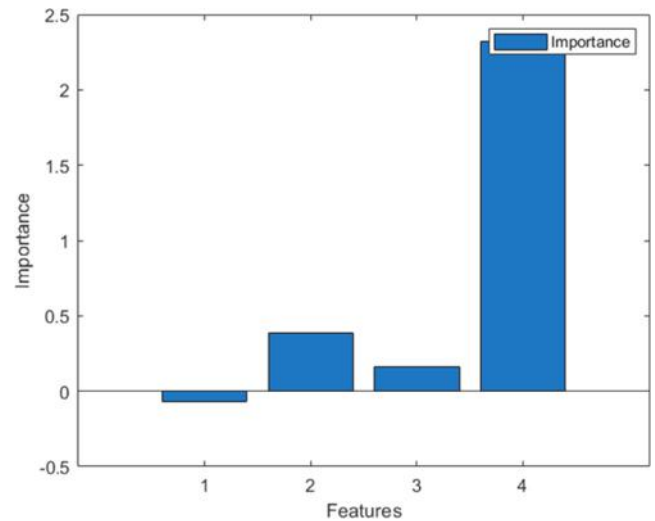


Fig. 3. Feature importance histogram.

to study their regression relationship with wear volume.

3.2. Regression model result

3.2.1. Linear regression result

After determining the features, start to select the regression model to train the data set. First, a linear regression model is selected to fit, and the results are shown in Fig. 4. Since two features are finally selected for regression fitting, based on experience, the sample size is not less than 20 times the number of features, so 40 sets of data are first selected as the data set, and the results are shown in Fig. 4 [a]. The sample size should be carefully chosen to avoid the risk of overfitting. In Fig. 4 [a], [b], [c], [d], and [e], the linear regression results are presented for sample sizes of 40, 100, 200, 600, and 1000, respectively.

It can be seen from the figure that the first three fitting results are not linear, and the R² values are 0.22, 0.39, and 0.65, respectively. Although the result of the fourth fitting has been greatly improved, the R² value is 0.72, still less than 0.8, and the fitting effect becomes worse as the number of samples continues to increase. When the data set is 1000, the R² value after training is 0.27. In general, if the R² value is less than 0.8, the fit is considered poor. Therefore, SVM and RF algorithms were used instead for regression analysis of the data.

3.2.2. SVM regression result

First, make sure that the ratio of the training set to the test set is 4:1, and the total sample size of the data set is set to 100. The SVM regression results are shown in Fig. 5. The RMSE values of the training set and validation set are 0.12299 and 0.14716, respectively; the R² value is 0.52733, the MAE value is 0.071117, and the MBE value is 0.052641. Next, expand the sample size of the dataset to 200, and the results are shown in Fig. 6. The RMSE values of the training set and validation set are 0.093297 and 0.11625, respectively. It can be found that the RMSE of the validation set is reduced by an order of magnitude compared to before, indicating that the regression effect has been significantly improved. The R² also exceeded 0.8, reaching 0.81611. Compared with before, the MAE value was basically the same as before at 0.063026, and the MBE value is 0.002484.

In order to maintain consistency with linear regression, continue to increase the sample size to 600, of which the training set size is 480, and the test set is 120. The regression results after training are shown in Fig. 7.

After increasing the training set to 600, the RMSE values of the training set and validation set are 0.014575 and 0.016629, respectively. The R² value increases to 0.86465, the MAE value is 0.013143, and the

Table 4

Feature subset regression model analysis.

Feature subset	Mean square error of the test set
Sp, Pd	0.02362
Sp, Sd	0.00668
Sp, μ	0.04952
Pd, Sd	0.07557
Pd, μ	0.06840
Sd, μ	0.01406
Sp, Pd, Sd	0.06278
Sp, Pd, μ	0.05239
Sp, Sd, μ	0.00388
Pd, Sd, μ	0.01759
Sp, Pd, Sd, μ	0.02247

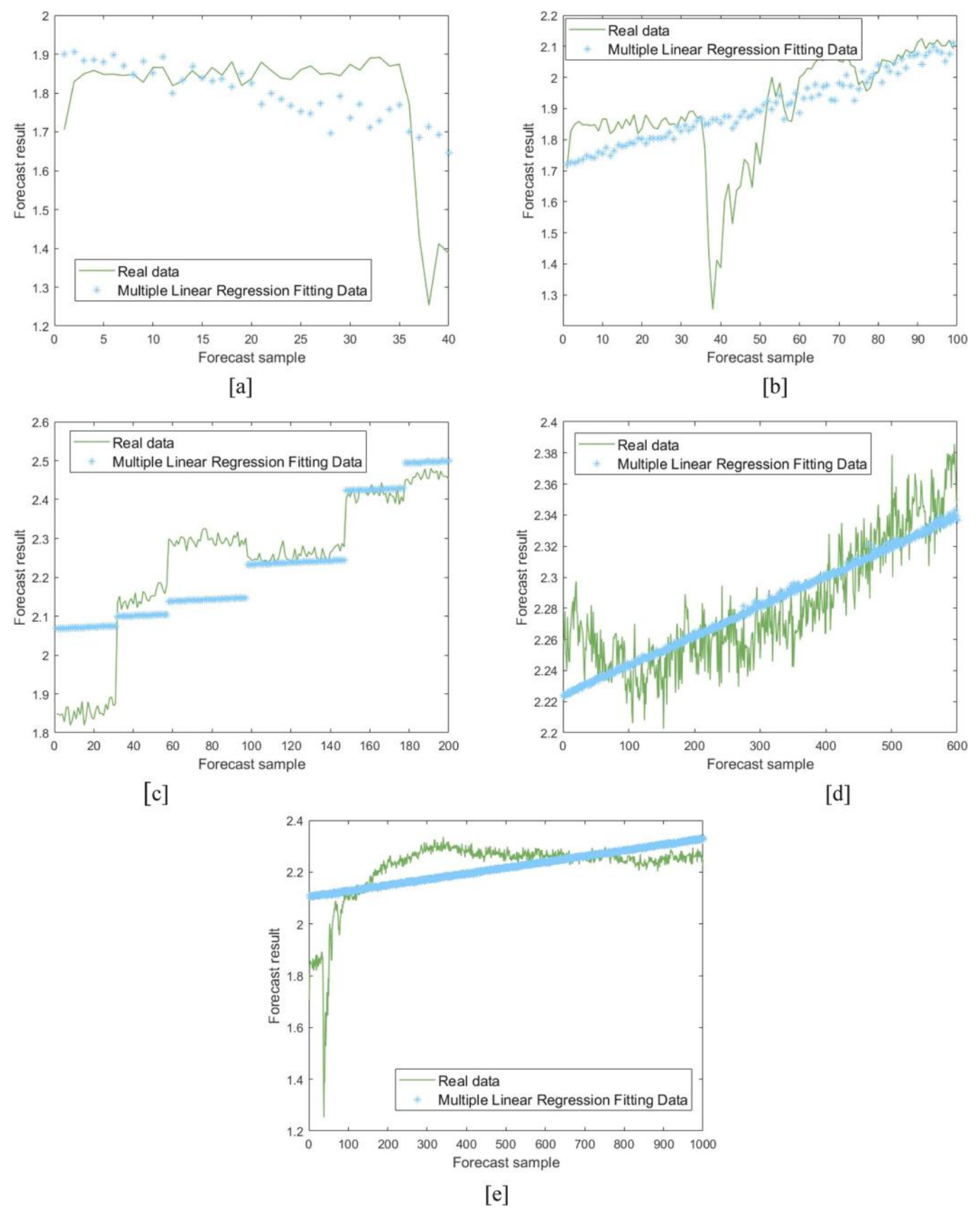


Fig. 4. Linear Regression Model Results.

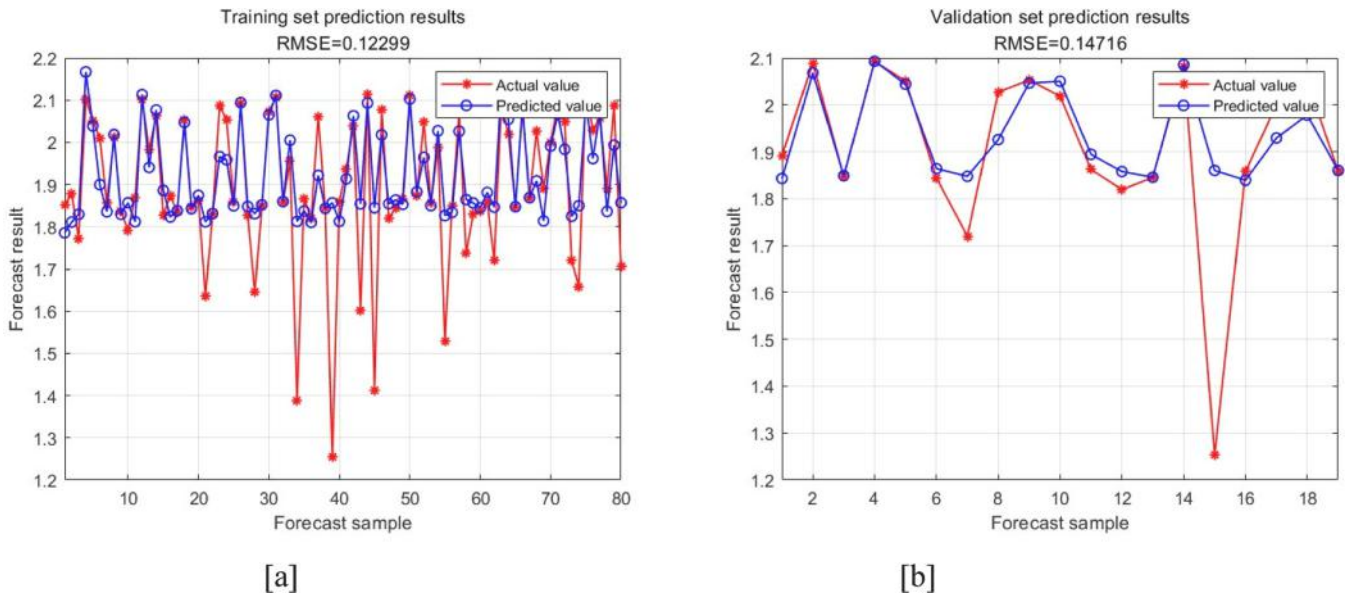


Fig. 5. SVM regression results for 100 data set.

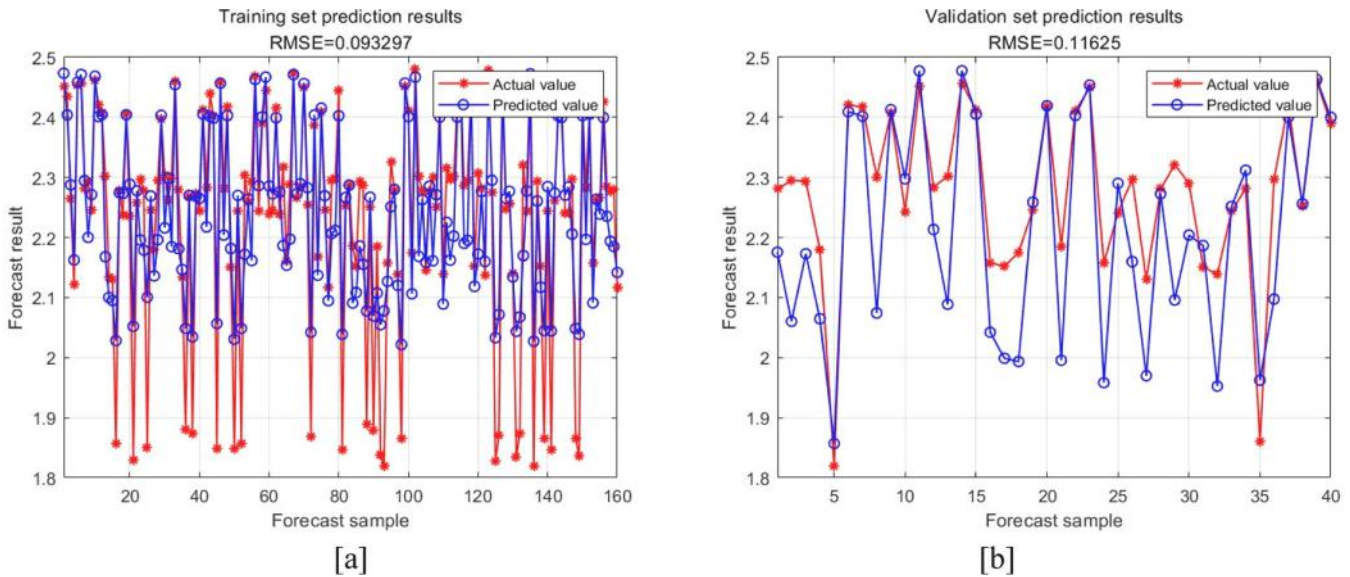


Fig. 6. SVM regression results for the 200 data sets.

MBE value is -0.0015924 . Compared with the training results of 100 and 200 samples, the fitting results are better this time.

Since it is not known whether the optimal sample size has been reached at this time, and in order to have a comparison with the previous linear regression, the sample size is increased to 1000, and the regression result is shown in Fig. 8.

From the results, when the data set is increased to 1000, the RMSE values of the training set and validation set are 0.053441 and 0.059661, respectively. R2, MAE and MBE are not as good as the results when the data set is 600. Their values are 0.073712, 0.72618, 0.027116 and 0.01188, respectively.

3.2.3. RF regression result

In order to maintain the consistency of the comparison experiment, the sample size of the random forest is the same as that of the previous two algorithms, and the data set is also divided 4–1 between the training set and the test set. At the same time, set the number of decision trees to 100 and the minimum number of leaves to 5. The regression results with

a training set of 100 are shown in Fig. 9. The results show that the RMSE values of the training set and validation set are 0.0676 and 0.078169, respectively; the R2 value is 0.86985, the MAE value is 0.049638, and the MBE value is -0.0068208 . When the sample size of the training set is 200, the fitting results are shown in Fig. 10.

It can be seen that the RMSE value of the training set and validation set are 0.02318 and 0.03691, respectively, and the R2 value is very close to 1, which is 0.96378, indicating that when the sample size of this data set is 200, the fitting result obtained by using the random forest regression model is very good. Meanwhile, its MAE and MBE values are 0.016198 and 0.0039336, respectively. Then, continue to expand the data set to 600, and the fitting results are shown in Fig. 11.

At this time, although the R2 value dropped to 0.91026, the RMSE value of the training set and validation set and MAE, MBE values were better than the previous two fitting results, they were 0.01025, 0.015003, 0.011446 and 0.00044142, respectively. Finally, increase the data set to 1000, and the results are shown in Fig. 12. Although the R2 value increased slightly to 0.93931, the RMSE values of the training set

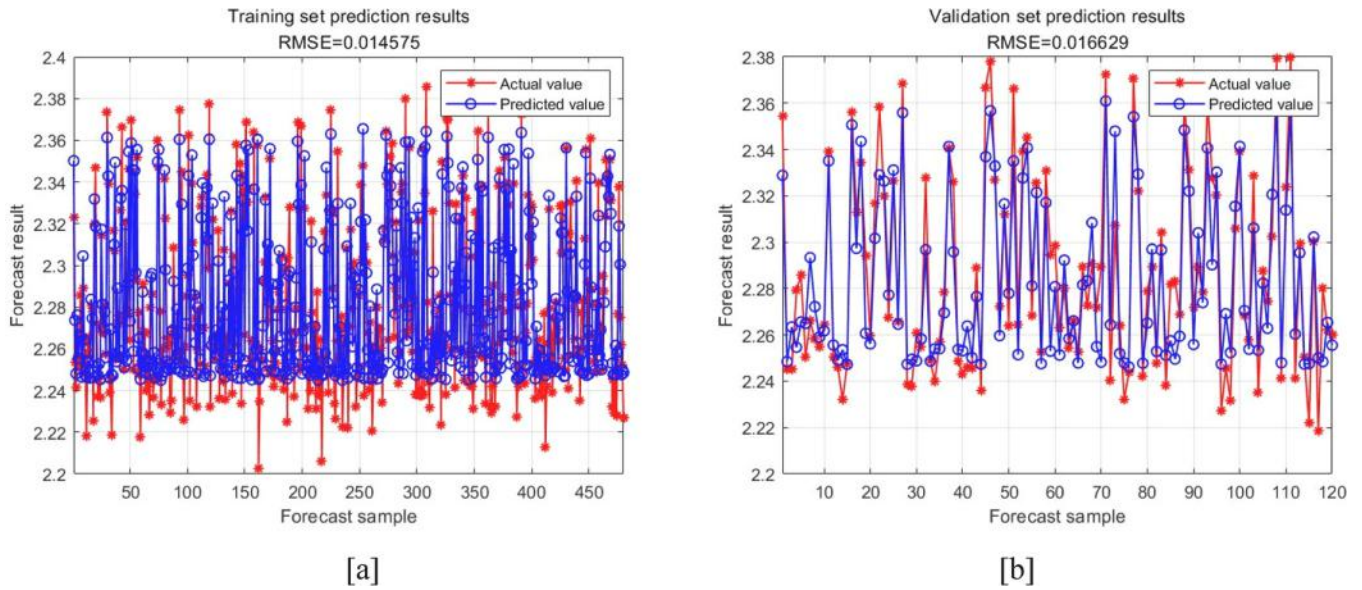


Fig. 7. SVM regression results for the 600 data sets.

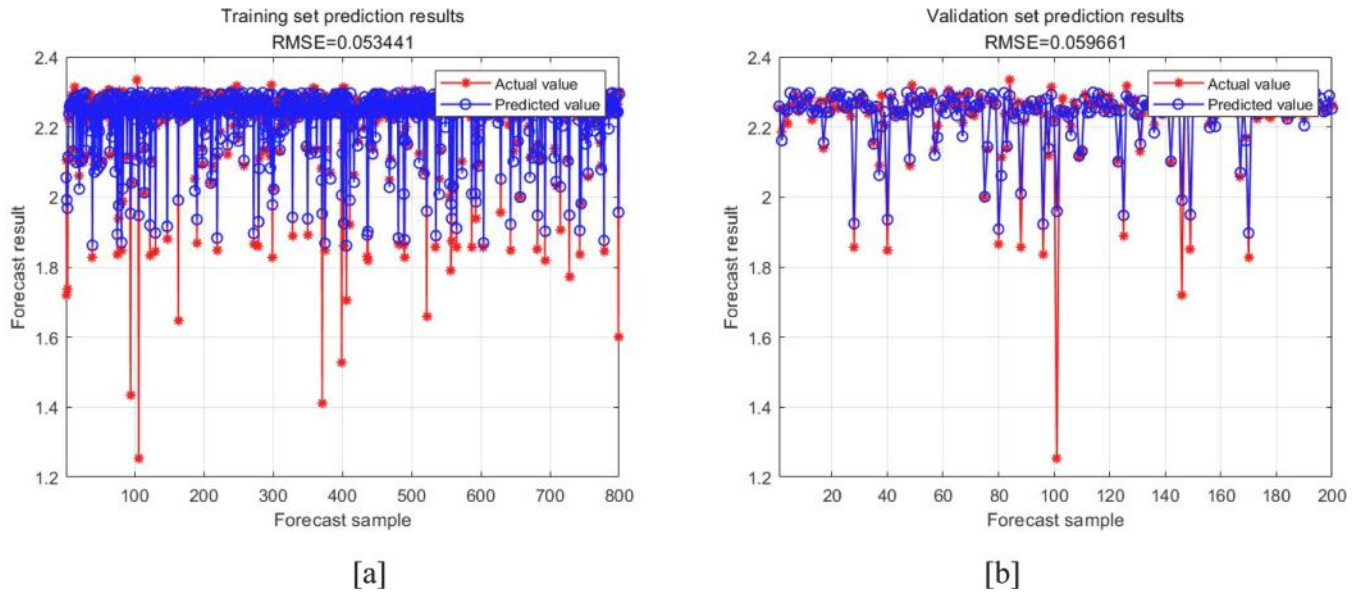


Fig. 8. SVM regression results for the 1000 data sets.

and validation set are 0.025789 and 0.02894, respectively. The MAE value and MBE value were 0.019123 and 0.001875 respectively, and the fitting results were not as good as the fitting results with a sample size of 600.

3.3. Comparative analysis of three methods

For the three regression models, it can be seen that the linear regression cannot fully explain the variation in wear volume. For both SVM and RF algorithms, the fitting results can explain the wear condition very well, and the RF algorithm is better. In addition, four sample sizes were selected for regression fitting, and when the sample size was 600, the fitting results were better. The RMSE value of the random forest regression result is 0.015003, the R^2 value is 0.91026, and the MAE and MBE values are 0.011446 and 0.00044142 respectively, which are higher than the training results of the SVM algorithm when the same sample set is 600. (RMSE, R^2 , MAE, MBE values are 0.016629, 0.86465,

0.013143 and -0.0015924 respectively).

3.4. Analysing regression results for a mid-steel material dataset

In order to avoid the chance of collecting data in one experiment, the correlation between sliding distance, sound pressure, and wear volume under different materials will continue to be discussed. Due to the different wear resistance of different materials, the generated data, such as temperature and noise, are not the same, so the experimental data under different materials are regressed and discussed according to the results. The data results mentioned above are collected and verified under the mid steel material, and the following data sets are experimentally obtained under the two materials of aluminium and iron.

The previous regression results show that the results obtained using the random forest regression algorithm are better than the support vector machine regression algorithm, and the regression model obtains better results when the data set is 200 or 600. Therefore, we only try the

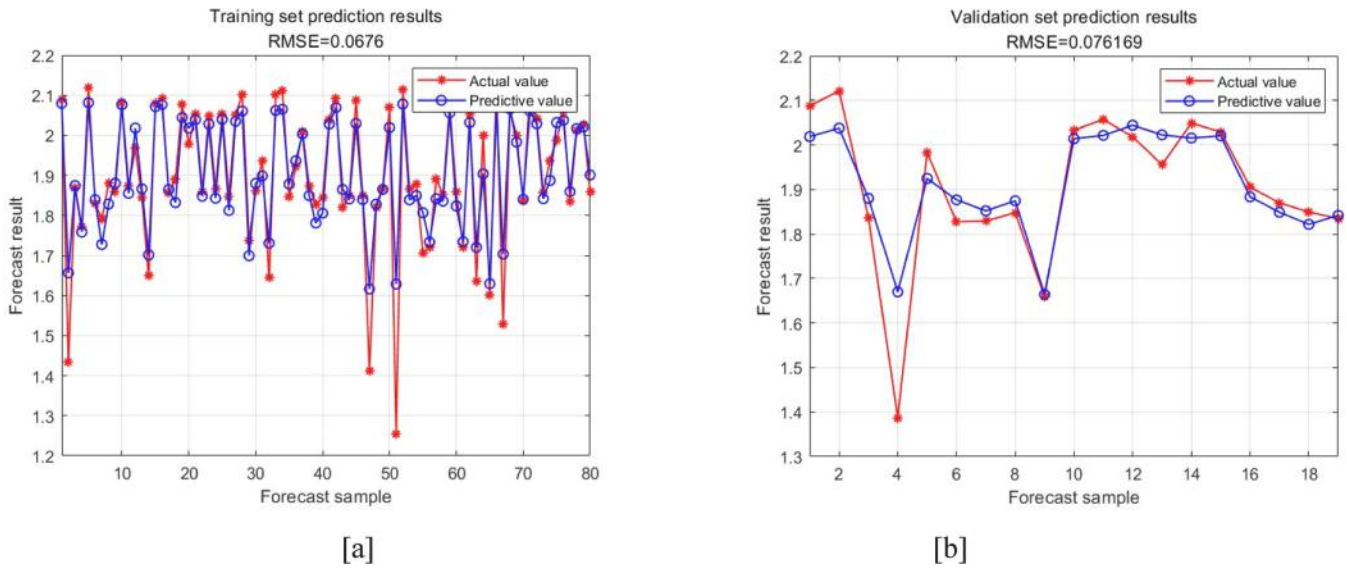


Fig. 9. RF regression results for 100 data sets.

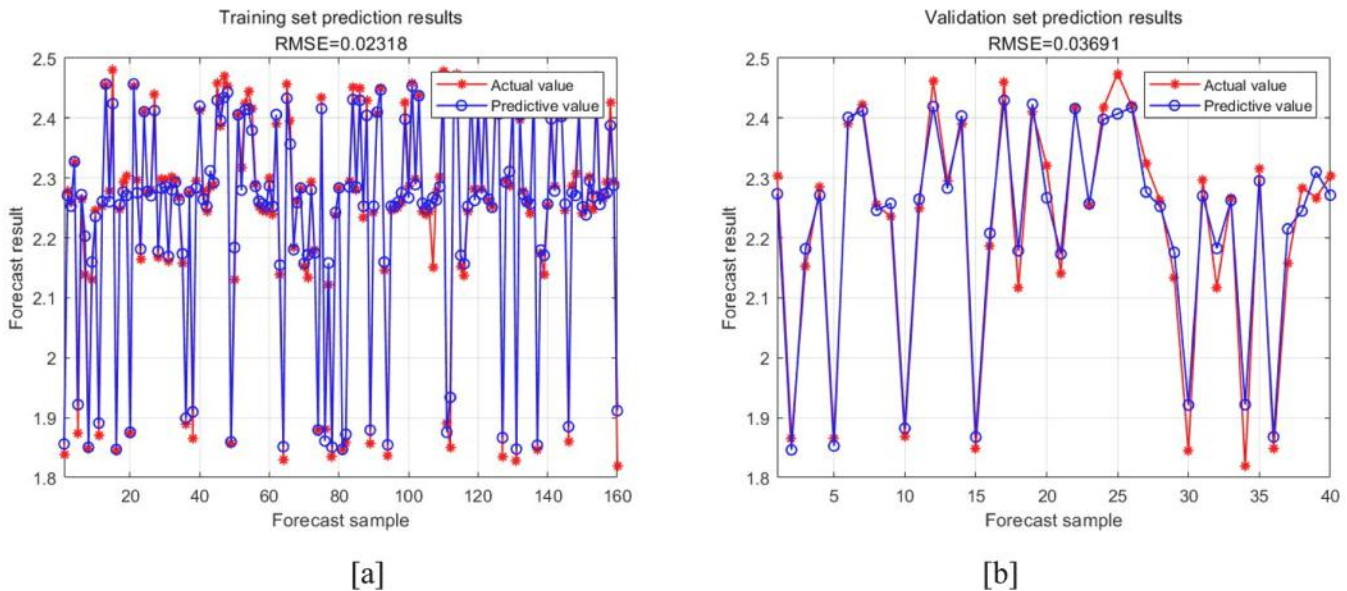


Fig. 10. RF regression results for the 200 data sets.

experimental data obtained under the two materials of aluminium and iron when the training data set is 200 and 600. Since the wear volume of these two materials is an order of magnitude larger compared to the previous mid steel material in a real experimental environment, the RMSE values obtained from the regression for aluminium and iron materials will increase compared to the previous results.

3.5. Random forest regression results for aluminium material

The experiment was carried out, and the data were collected when the material of the disc was aluminium, and the sliding distance and sound pressure were still used as the features, and the RF regression model was used for training. The RMSE values of the training set and the validation set are 0.71567 and 0.75964, the R2 value of the test set is 0.62037, and the MAE and MBE values are 0.44673 and 0.033823 respectively.

After increasing the sample size to 600, the regression result of switching to aluminium material is shown in Fig. 14. The RMSE values of

the training set and the validation set are 0.43337 and 0.35957, the R2 value of the test set is 0.92569, and the MAE and MBE values are 0.2017 and -0.022227, respectively. Comparing the training results of the two sample sizes, it can be found that when the sample size is 600, the prediction results are better.

3.6. Random forest regression results for iron material

When the material is iron, the regression result is better than that of aluminium. When the sample size is 200, the training result is shown in Fig. 15.

The RMSE values of the training set and the test set are 0.094607 and 0.16001, the R2 value of the test set is 0.96622, and the MAE and MBE values are 0.11439 and 0.023872, respectively.

When the sample size is expanded to 600, the regression prediction results are shown in Fig. 16. The RMSE values of the training set and the validation set are 0.0996972 and 0.11444, the R2 value of the test set is 0.93157, and the MAE and MBE values are 0.088249 and 0.0068997,

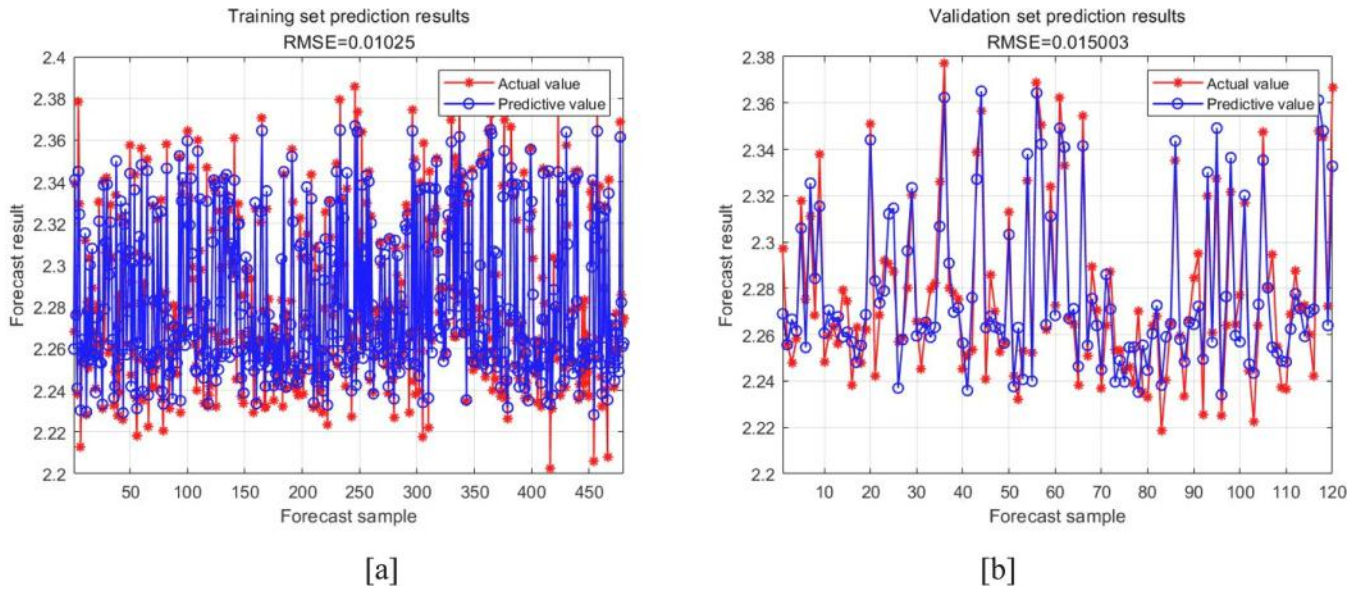


Fig. 11. RF regression results for the 600 data sets.

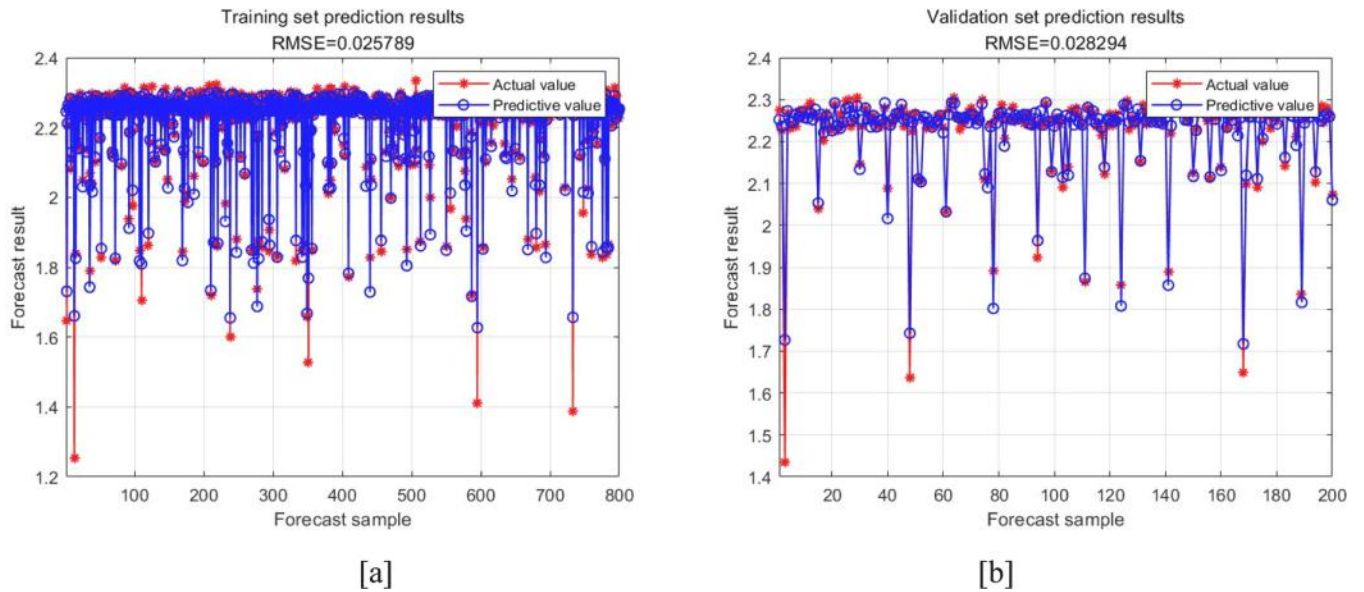


Fig. 12. RF regression results for the 1000 data sets.

respectively.

According to the comparison of regression results, it is evident that the differing wear resistance of metals results in variations in the amount of heat energy generated during friction. These material-specific differences likely contribute to variations in prediction accuracy. Additionally, measurement errors, data acquisition inconsistencies, and the presence of outliers can influence the regression outcomes. To contextualise the performance of the proposed regression models, a comparative analysis with recent studies in wear prediction has been conducted. Our Random Forest model, trained on 600 samples, achieved an RMSE of 0.015003 and an R^2 of 0.91026, outperforming several recent models. For example, Wang et al. (2022) reported RMSE values ranging from 0.02 to 0.09 using XGBoost, while Jones and Cao [42] employed an ensemble approach (RF, ANN, and XGBoost) and achieved an RMSE of 0.058237 and R^2 of 0.955. Although the ensemble model offers a marginal improvement in R^2 , our model achieves comparable accuracy with reduced complexity and enhanced interpretability.

Furthermore, deep learning-based models, such as the multi-sensor fusion network proposed by He et al. (2025) and the Bayesian regularised ANN by Truong et al. [43], demonstrate high predictive performance but require extensive sensor input and lack transparency. In contrast, our method relies on a minimal feature set (sliding distance and sound pressure), incorporates feature selection, and shows strong generalizability across three material types (mid-steel, aluminium, and iron). These findings highlight the robustness and practical applicability of the proposed Random Forest model, particularly in industrial contexts where material diversity and data variability are prevalent.

While the Random Forest model demonstrated strong predictive performance, the variation in regression accuracy across different materials, particularly the higher RMSE observed with aluminium, indicates the influence of material-specific properties such as thermal conductivity, surface hardness, and microstructural composition on wear behaviour. These factors, although not explicitly included as features in the current model, may significantly impact the accuracy and

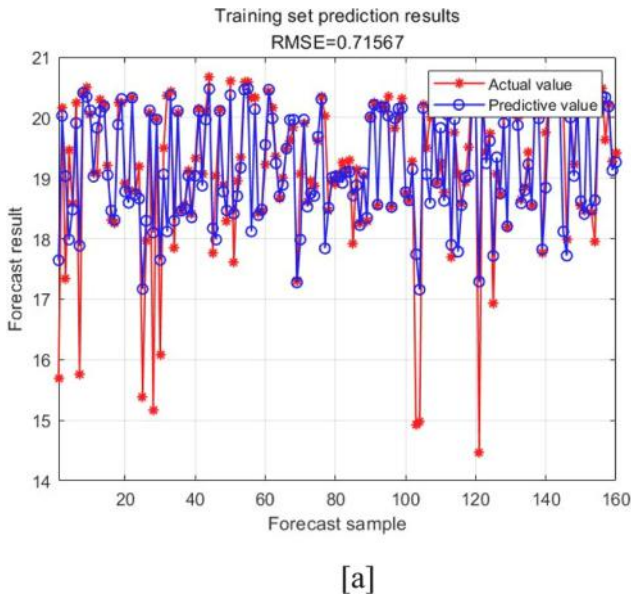
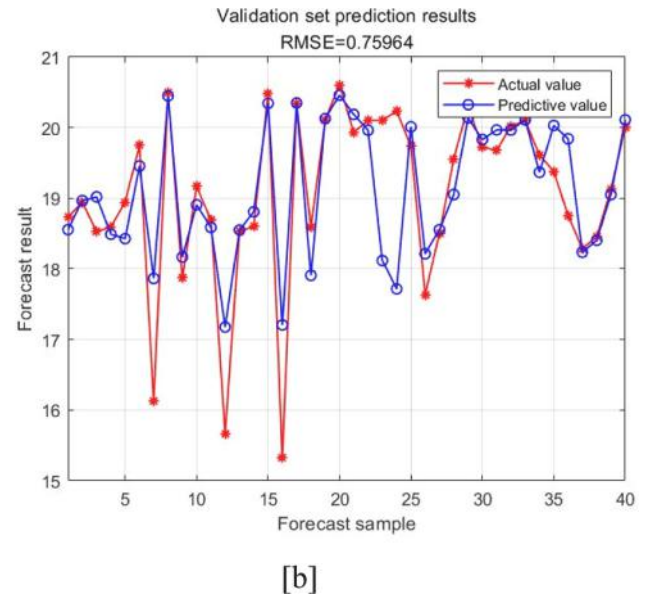


Fig. 13. RF regression results for 200 datasets of aluminium materials.

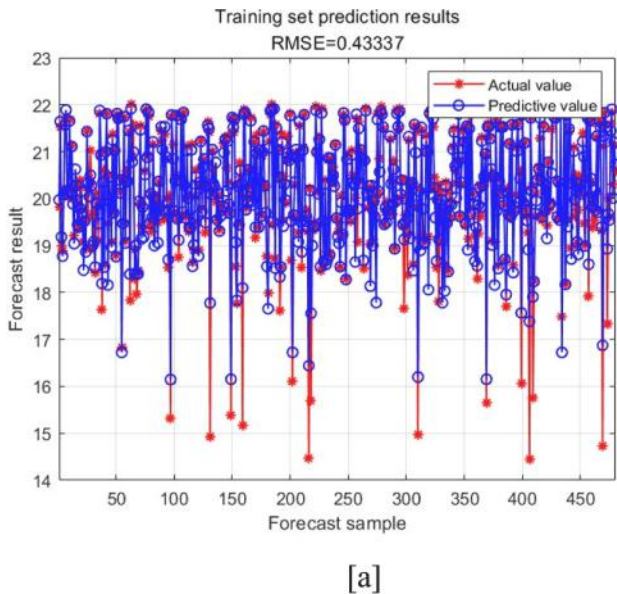
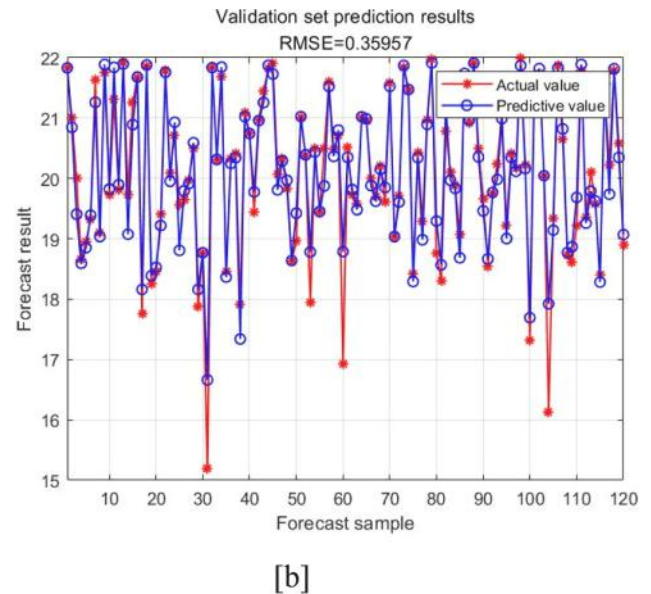


Fig. 14. RF regression results for 600 datasets of aluminium materials.

stability of predictions. Therefore, incorporating additional material descriptors or sensor-based measurements such as temperature, force, or vibration could further enhance model robustness. Moreover, although the current study focused on static regression analysis, integrating time-series modelling techniques (e.g., LSTM or GRU networks) could offer better insight into the progression of wear over time. Future work will aim to expand the dataset, explore neural network-based hybrid models, and investigate the interpretability of complex models using SHAP or LIME to maintain transparency in industrial applications. This direction would help bridge the gap between model accuracy and practical usability in real-world predictive maintenance systems.

4. Conclusion

This study demonstrates the significant potential of integrating machine learning into wear prediction for industrial applications. By evaluating the effectiveness of two feature selection methods, wrapping

and embedding techniques, the research highlights the importance of choosing appropriate methods for accurate wear predictions. The wrapping method, although robust, proved computationally intensive, while the embedding method offered a more efficient solution by combining feature importance analysis with regression model training. Among the features analysed, "sliding distance" and "sound pressure" emerged as the most relevant for predicting wear.

Linear regression was initially tested but was found inadequate for modelling the relationship between features and wear volume. Consequently, more advanced algorithms, such as SVM and RF, were employed. Both demonstrated strong predictive capabilities, with RF yielding the best performance after model training. The RF model, trained on 600 experimental samples, achieved a Root Mean Squared Error (RMSE) of 0.015003 and a coefficient of determination (R^2) of 0.91026, demonstrating superior predictive performance compared to several recent models reported in the literature.

Among the input features analysed, sliding distance and sound

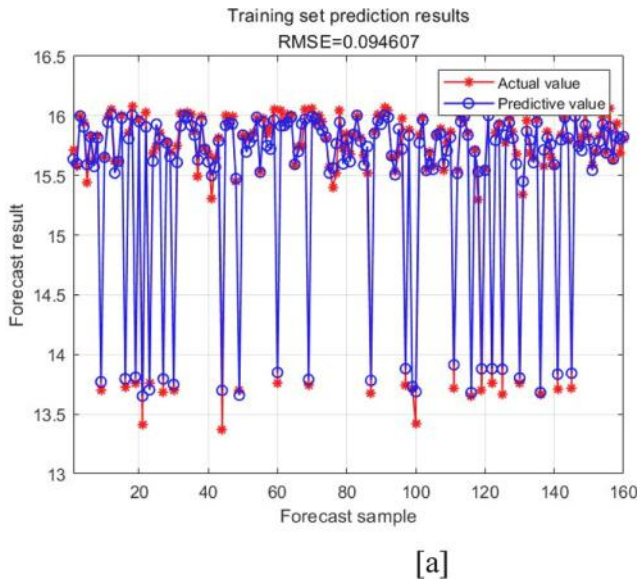
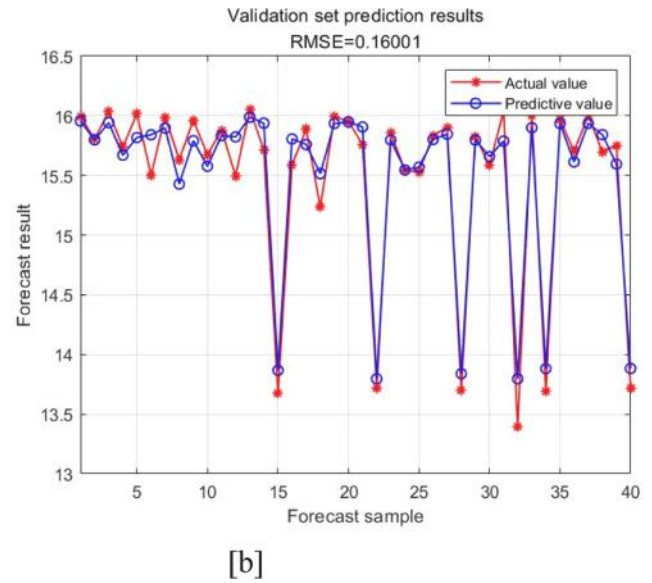


Fig. 15. RF regression results for 200 datasets of iron materials.

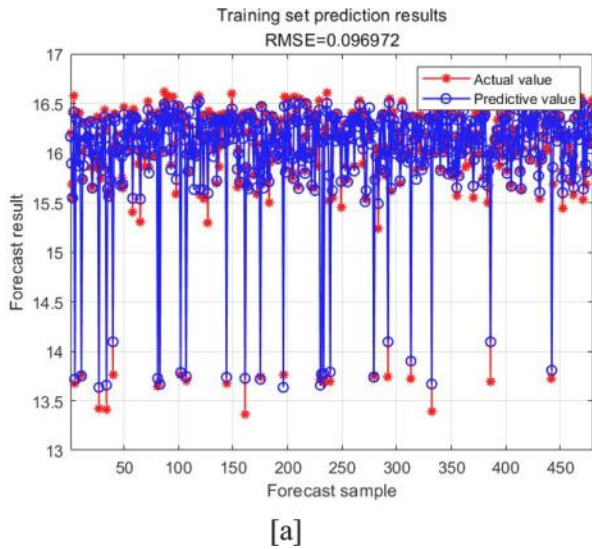
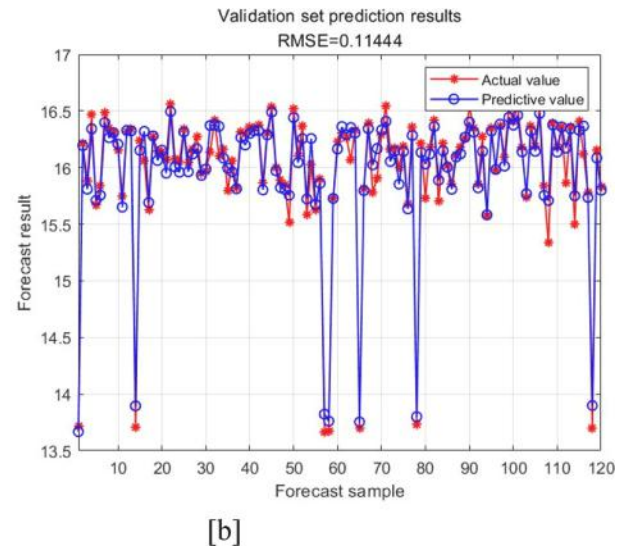


Fig. 16. RF regression results for 600 datasets of iron materials.

pressure were found to be the most significant in influencing wear volume. The model performed best for mild steel, followed by iron and aluminium, highlighting the effect of material-specific properties such as wear resistance, heat generation, and contact mechanics on prediction accuracy. While the embedding-based feature selection proved efficient and interpretable, the wrapper method, though slightly more accurate, was computationally intensive.

Despite these promising results, the study is limited by the scope of the dataset, which was restricted to constant speed and load conditions. Additionally, important tribological parameters such as temperature, lubrication status, and material microstructure were not included, potentially limiting the generalizability of the model across broader operational environments. Future research should address these limitations by:

- Incorporating real-time adaptive learning algorithms that dynamically update wear predictions in response to changing operational conditions, enabling more responsive and resilient predictive maintenance systems.

- Integrating multi-physics simulation data (e.g., finite element wear and heat generation models) with experimental data to enhance model accuracy and interpretability through physics-informed machine learning.
- Developing hybrid models combining mechanistic wear theories with data-driven methods to leverage domain knowledge and improve predictions in data-scarce environments.
- Exploring transfer learning techniques to adapt wear prediction models trained on one material or operating condition to others, reducing the need for extensive retraining and data collection.

In conclusion, this study reinforces the potential of machine learning in advancing wear prediction for industrial applications, emphasising the importance of effective feature selection, algorithm choice, and material considerations. By addressing the outlined future research avenues, subsequent studies can further enhance the accuracy, robustness, and practical utility of wear prediction models, thereby supporting improved machinery reliability and optimised maintenance strategies.

CRediT authorship contribution statement

Intisar Omar: Validation, Formal analysis, Data curation. **Jianjie Jiang:** Formal analysis, Data curation. **Muhammad Khan:** Supervision, Project administration, Methodology, Investigation, Conceptualization.

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Declaration of Competing Interest

Jianjie Jiang, Intisar Omar, and Muhammad Khan have no financial interests, affiliations, or relationships that could be interpreted as potential conflicts of interest in connection with the research, authorship, or publication of this paper. The research presented in this paper focuses on the development of a predictive model for estimating wear volume in pin-on-disc systems utilizing machine learning methodologies. The goal of this study is to contribute to the advancement of accurate wear prediction techniques, which have significant implications for industries relying on machinery. It is important to note that this submission does not have any financial or personal relationships that could potentially affect the research findings or the interpretation of the results.

The authors believe that the findings and insights presented in this research paper are of value to both the academic and industrial communities interested in predictive wear analysis and related applications. Our ultimate aim is to contribute to the advancement of knowledge in this field and to foster meaningful discussions and collaborations among fellow researchers and practitioners.

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**Predicting wear damage in moving mechanical contacts:
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