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Research Article

# Modeling and prediction of tribological properties of copper/aluminum-graphite self-lubricating composites using machine learning algorithms

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**Abstract:** The tribological properties of self-lubricating composites are influenced by many variables and complex mechanisms. Data-driven methods, including machine learning (ML) algorithms, can yield a better comprehensive understanding of complex problems under the influence of multiple parameters, typically for how tribological performances and material properties correlate. Correlation of friction coefficients and wear rates of copper/aluminum-graphite (Cu/Al-graphite) self-lubricating composites with their inherent material properties (composition, lubricant content, particle size, processing process, and interfacial bonding strength) and the variables related to the testing method (normal load, sliding speed, and sliding distance) were analyzed using traditional approaches, followed by modeling and prediction of tribological properties through five different ML algorithms, namely support vector machine (SVM), K-Nearest neighbor (KNN), random forest (RF), eXtreme gradient boosting (XGBoost), and least-squares boosting (LSBoost), based on the tribology experimental data. Results demonstrated that ML models could satisfactorily predict friction coefficient and wear rate from the material properties and testing method variables data. Herein, the LSBoost model based on the integrated learning algorithm presented the best prediction performance for friction coefficients and wear rates, with $R^2$ of 0.9219 and 0.9243, respectively. Feature importance analysis also revealed that the content of graphite and the hardness of the matrix have the greatest influence on the friction coefficients, and the normal load, the content of graphite, and the hardness of the matrix influence the wear rates the most.

**Keywords:** self-lubricating composites; machine learning (ML); tribological properties; prediction

## 1 Introduction

Metal matrix self-lubricating composites possess both excellent mechanical properties and good lubricating properties, which make them a broad application prospect. Usually, the type and content of metal matrixes and reinforcement are regulated to meet the requirements of composites under different working conditions, such as high/low temperature, high pressure, high vacuum, high radiation, high corrosion, etc. [1]. According to their matrix types, metal matrix self-lubricating composites are mainly Cu-based, Al-based, Fe-based, and Ni-based self-lubricating composites. Herein, Cu-based self-lubricating composites have good lubrication stability, mechanical properties, corrosion resistance, and electrical conductivity [2], and Al-based self-lubricating composites have good fatigue resistance, wear resistance,

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corrosion resistance, damping characteristics, and low coefficient of thermal expansion [3, 4], which make Cu/Al-based self-lubricating composites become the focus of research and application in metal matrix self-lubricating composites.

In Cu/Al-based self-lubricating composites, graphite—the most common inorganic solid lubricant, is added to the matrixes to improve tribological properties. Some ceramic particles as reinforcing phases, such as SiC and $Al_2O_3$, can also be incorporated into the composites to improve the physical and mechanical properties of the composites [5]. As critical indexes, the friction coefficient and wear rate are tested and analyzed to evaluate the tribological properties of the composites. It has been found that the tribological behavior of self-lubricating composites is a complex system response with many influencing factors and complex mechanisms. So far, the complexity between tribological properties and influencing variables has been deeply discussed by some scholars. For example, Pan et al. [6] explored the relationship between tribological properties and influencing factors from multiple perspectives including nanoscience, materials science, surface science, mechanics, and tribology, and revealed their potential coupling/synergy in adjusting the tribological behavior of metal matrix nanocomposites. Therefore, to obtain the optimal properties of self-lubricating composites, it is usually necessary to analyze the interactions of composition, preparation process, and tribological properties of the composites, as well as how these parameters affect their properties [7]. Unfortunately, most of the traditional studies on the tribological properties of self-lubricating composites are based on isolated experiments and two-parameter relationships, which makes it difficult to systematically analyze and understand the tribological properties. However, Pan et al. [6] also quantitatively described the anti-friction and wear mechanisms of metal matrix nanocomposites by incorporating classical friction and wear theories, and elucidated their relationship with the influencing factors, which provides a solid foundation for understanding, predicting, and designing the tribological properties of metal matrix nanocomposites.

With the rapid development of artificial intelligence (AI), machine learning (ML), as an important branch in the field of AI, had been widely researched and applied in many fields such as status monitoring of tool wear [8], life prediction of bearing [9], fault diagnosis of equipment [10]. Practices have proved that ML algorithms have great potential in the analysis and modeling of complex problems [11, 12]. In ML models, not only the relationship between input and output can be fitted by setting multiple input and output parameters, but also the trained model can realize the prediction of unknown data. This provides a solution for analyzing complex problems such as friction coefficient and wear rate under the influence of multiple variables, thereby realizing the prediction of tribological performance under different material compositions and friction experimental conditions [13, 14].

Due to the advantages of ML models, they have been used to try to solve the problems encountered in self-lubricating composites. Yin et al. [13] and Argatov and Chai [14] reviewed the current research status and application potential of ML models in tribological research, the result of various analyses showed that ML models have high accuracy in simulating mechanical and tribological properties of composites as a function of various process parameters. Hasan et al. [15] successfully applied ML models in the studies on friction and wear analysis of graphene-reinforced aluminum matrix composites, prediction of friction and wear of aluminum-graphite composites under lubricated conditions [16], and tribological information modeling of dry friction and wear of aluminum matrix alloys [17]. In this way, not only the effects of multiple variables are combined during the study and analysis of friction coefficients and wear rates to overcome the shortcomings of traditionally isolated experiments and two-parameter studies, but also the tribological experimental data are used to train the ML models, which realizes the prediction of friction coefficients and wear rates under different material compositions and friction experimental conditions [15–17]. Compared with traditional methods, this method is more comprehensive in considering the influencing variables of tribological properties and could achieve the prediction of friction coefficient and wear rate based on material compositions and sliding conditions, which opens a new avenue for the research and analysis of tribological properties of self-lubricating composites.

Considering the similarity and universality among copper, aluminum, and their composites, copper/aluminum-graphite (Cu/Al-graphite) self-lubricating composites were taken as the research subject in this work. We provided a brief analysis and overview of the friction and wear mechanisms, the variables affecting the tribological properties of Cu/Al-graphite self-lubricating composites. And then, taking the friction coefficient and wear rate as the tribological performance indicators, five ML algorithms were adopted to establish unified ML models for two different matrix types of self-lubricating composites by compiling the existing research results of three widely used Cu/Al–graphite self-lubricating composites. Besides, the differences in the predictive performance of five different ML models were compared, followed by analyzing the relative importance of influence variables on the friction coefficients and wear rates based on the RF model feature importance attributes.

## 2 Friction and wear mechanisms of Cu/Al-graphite self-lubricating composites and the analysis of influencing factors

### 2.1 Friction and wear mechanisms

The Cu/Al-graphite composites presenting self-lubricating performances depend mainly on the fact that the graphite can be dragged to the friction surface to form self-lubricating and transferring films during sliding, thus reducing the friction coefficient and wear degree [18]. Generally, the friction coefficient of metal matrix self-lubricating composites can be expressed as the sum of each component according to the mixing rules:

$$\mu = \alpha_{\mathrm{m}}\mu_{\mathrm{m}} + \alpha_{\mathrm{f}}\mu_{\mathrm{f}} \tag{1}$$

where, $\alpha_{\mathrm{m}} = 1-\alpha_{\mathrm{f}}$, and $\alpha_{\mathrm{f}}$ and $\alpha_{\mathrm{m}}$ are the coverage rates of the lubricating films and the area fraction of the matrix material. $\mu_{\mathrm{f}}$ and $\mu_{\mathrm{m}}$ are the friction coefficients of the metal matrix and solid lubricant [19].

However, affected by the microstructure, graphite content, and sliding condition, it is not always possible to form complete self-lubricating and transferring films, but rather a complex and mixed friction state. According to the results of the latest literature, the friction coefficient of metal matrix self-lubricating composites can be further expressed as [20]:

$$\mu = (1-kV)^2\mu_{\mathrm{m}} + (1-(1-kV)^2)\mu_{\mathrm{f}} \tag{2}$$

Where, $kV = \alpha_{\mathrm{f}}$, $k$ represents the lubrication efficiency of the lubricant, that is, the ability of the lubricant to form a lubricating film, and $V$ represents the volume fraction of the solid lubricant.

In order to better understand, predict and design the tribological properties of materials, it is necessary to analyze the factors influencing the friction mechanism. According to the theory of adhesive friction proposed by Bowden and Tabor [21], sliding friction is a leaping process in which adhesion and sliding occur alternately. And the friction force is the sum of the shear force ($T$) at the point of adhesion and the furrow force ($P_{\mathrm{e}}$) generated from the furrow effect. Therefore, the friction coefficient ($\mu$) can be expressed as Eq. (3):

$$\mu = \frac{F_{\mathrm{f}}}{N} = \frac{(T+P_{\mathrm{e}})}{N} = \mu_{\mathrm{T}} + \mu_{P_{\mathrm{e}}} \tag{3}$$

where, $F_{\mathrm{f}}$ and $N$ denote frictional force and normal load, respectively. $\mu_{\mathrm{T}}$ is the component of the friction coefficient caused by adhesion between friction surfaces of materials. $\mu_{P_{\mathrm{e}}}$ is the component of the friction coefficient due to deformation, which is related to the mechanical properties of materials, such as strength, hardness, and surface characteristics, like surface roughness [17, 22].

As metal matrix self-lubricating composites, the wear mechanisms are mainly abrasive wear, adhesive wear, delamination wear, and corrosion wear, according to their matrix properties and the state of self-lubricating films. With the increase of solid lubricant content, it is more conducive to forming self-lubricating and transferring films. At the same time, however, it also affects the mechanical properties of the composites such as strength and toughness, which results in greater degree of wear [23]. Studies have also shown that the wear mechanism of metal matrix self-lubricating composites is not only related to the properties of the matrix materials and the lubricant content, but also influenced by the normal load, sliding speed, sliding distance, and other operating conditions [19, 23–26].

## 2.2 Variables impacting friction and wear of Cu/Al-graphite self-lubricating composites

The variables that influence the friction and wear of self-lubricating composites include the material variables (inherent material properties, such as composition, lubricant content, lubricant particle size, processing process, interfacial bonding strength, etc.) and tribological variables (the variables related to testing methods, such as normal load, sliding speed, sliding distance, etc.). In this section, the effects of these variables on friction and wear of Cu/Al-graphite self-lubricating composites are discussed using traditional analysis.

### 2.2.1 *Effect of the material composition*

In metal matrix self-lubricating composites, the properties of the matrix phase affect the mechanical and tribological properties of the composites. Usually, metallic elements, such as copper, zinc, manganese, chromium, and tin, are added to the matrix to improve the mechanical and tribological properties [27]. Nano-treating, as an emerging metallurgical method, is important to improve the properties of composites [28]. Introducing nanoparticles (such as TiC [29] and WC [30]) into composite systems has an important effect on grain refinement, elimination of thermal tearing, and improvement of properties such as corrosion resistance and hardness of the material, thereby influencing their tribological performances. The friction coefficients and wear rates of several Cu/Al-graphite self-lubricating composites with different material compositions and similar graphite content (5–6 vol%) are shown in Figs. 1 and 2, respectively. In general, these composites consistently show decreased friction coefficients and wear rates compared to their matrix materials. However, it is important to note that a significant decrease in friction coefficients does not necessarily lead to a notable decrease in wear rates, and vice versa. In addition, the degree of reduction in friction coefficients and wear rates varies for composites with different matrixes and reinforcement.

### 2.2.2 *Effect of graphite content and particle size*

As a solid lubricant, graphite is the most important

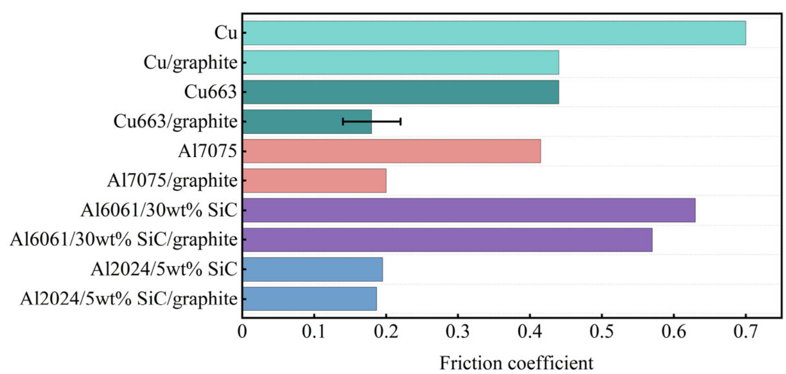


**Fig. 1** Friction coefficients of several Cu/Al-graphite self-lubricating composites [26, 31–34].

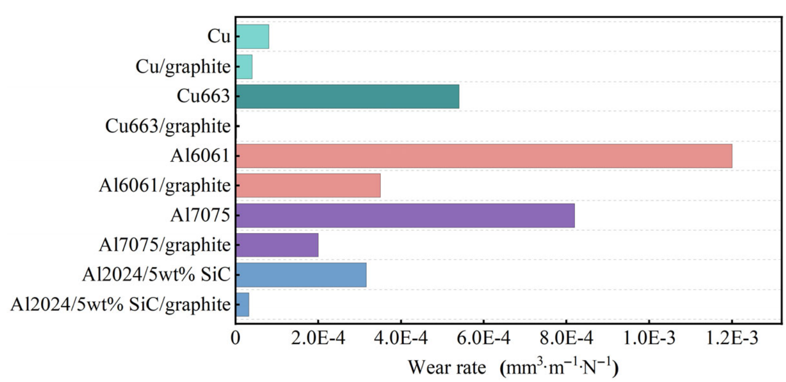


**Fig. 2** Wear rates of several Cu/Al-graphite self-lubricating composites [26, 32–35].

composition for providing self-lubricating performances of the composites. Large amounts of graphite are conducive to forming self-lubricating and transferring films and achieving a lower friction coefficient, but that would also destroy the continuity of the matrix, to decrease the mechanical properties and wear resistance. And too little graphite cannot effectively reduce the friction and wear rate. Therefore, a proper graphite content is essential for these self-lubricating composites. Figures 3 and 4 show the influence of graphite content on the mechanical and tribological properties of Cu/Al–graphite self-lubricating composites, respectively. Obviously, the hardness and tensile strength of the composites show a near linearity decrease trend with increasing graphite content. The tribological properties are improved significantly. More graphite leads to the lower friction coefficients and wear rates. When the graphite exceeds the critical content, the friction coefficients would not remarkably decrease further, and the wear rates increases instead (Fig. 4(b)), as the result of the influence of graphite content on mechanical and tribological properties.

The particle size and distribution of graphite are also non-negligible features of tribological properties of composites [36]. Figure 5 presents the variation of friction coefficients and wear rates of Cu-graphite self-lubricating composites with increasing graphite particle sizes. When the graphite content is certain, the smaller the particle size of graphite, the more uniform its distribution in the matrix, which is more conducive to providing a stable lubricating medium between the sliding surfaces. Therefore, the lower friction coefficients and wear rates are obtained with the smaller graphite particles. However, the too-small graphite particles cause more interfaces, which reduce the strength and hardness of the composites. Due to the difficulty of achieving uniform strength and lubricating properties, resulting in worse wear resistance performance of the composites [37].

### 2.2.3 *Effect of the preparation process*

Although factors such as material composition and graphite content have significant effects on tribological properties, selecting a suitable preparation process

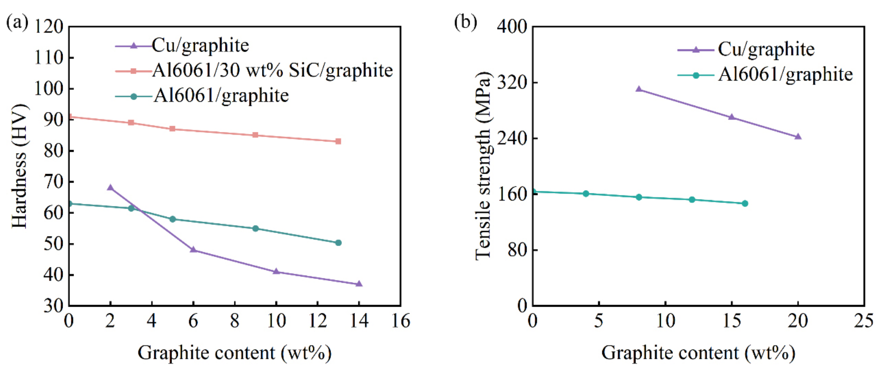


**Fig. 3** (a) Hardness [31, 38] and (b) tensile strength [35, 39] of several Cu/Al-graphite self-lubricating composites with different graphite content.

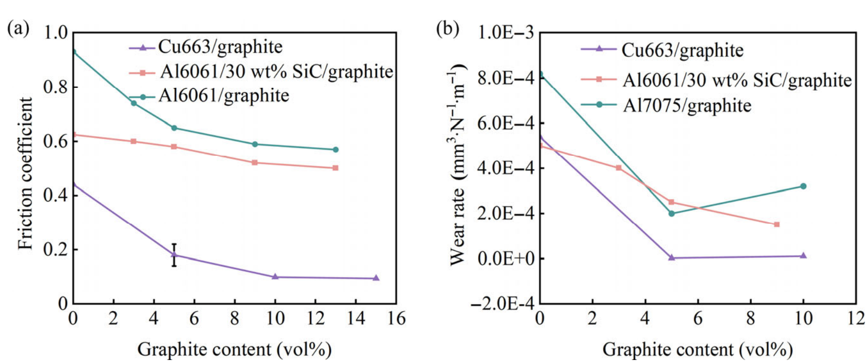


**Fig. 4** (a) Friction coefficients [31, 33] and (b) wear rates [31, 33, 34] of several Cu/Al-graphite self-lubricating composites with different graphite content.

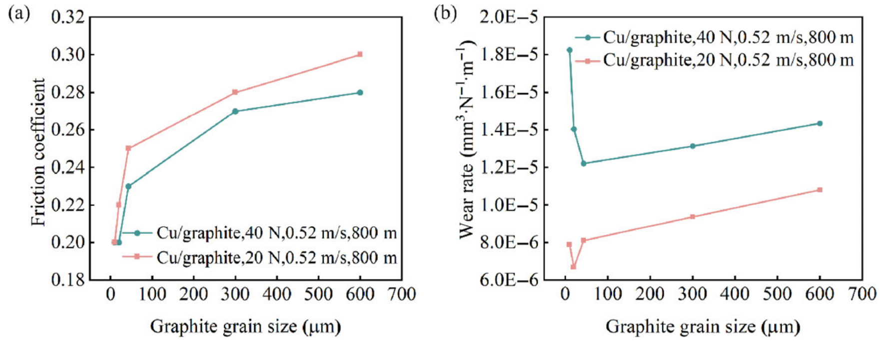


**Fig. 5** (a) Friction coefficients [37] and (b) wear rates [37] of Cu-graphite self-lubricating composites with different grain sizes of graphite.

is a prerequisite for obtaining excellent material properties. On the one hand, the preparation process affects the inherent properties of the matrix materials, such as strength, hardness, toughness, and other mechanical and tribological properties. On the other hand, the distribution of the lubricating phase, wettability of the lubricating phase and matrix, porosity, and other macro-micro structures are related to the preparation processes. Currently, the most used methods are powder metallurgy (such as hot-pressing sintering, microwave sintered, and spark plasma sintering) and stir casting.

As to non-metallic solid lubricants, the powder metallurgy technology allows a relatively easy combination of metal and non-metal; therefore, it has a greater advantage in the preparation of metal matrix graphite self-lubricating composites [40]. For instance, Su et al. [33] prepared Cu/15 vol% graphite self-lubricating composites using hot-pressing sintering, and the friction coefficient of the composite was reduced to 0.09, which is 80% lower than that of the matrix material. Rajkumar and Ararindan [36] prepared Cu-graphite composites by microwave sintering method, and the friction coefficient of the composites was reduced to 0.12. Yang [41] prepared tin bronze/ 0.8 vol% graphite self-lubricating composites by the vacuum hot-pressing sintering method. When the sintering temperature was 875 °C, the graphite distribution was uniform and no agglomeration phenomenon and the density of the material was close to 100%.

The powder metallurgy method allows flexible adjustment of the composition of the material and is superior to conventional casting materials in improving the wear resistance of the material [42]. In contrast, the smelting-cast method can obtain materials with high density and few pores, and the temperature in processing is conducive to promoting interfacial bonding properties. The prepared materials possess better overall properties. Bhaskar et al. [43] prepared the SiC reinforced AA2024 alloy composite material by stir casting method, whose bending strength, ultimate tensile strength, and friction coefficient are 515.97 MPa, 202.27 MPa, and 0.135, respectively.

### 2.2.4 *Effect of interfacial bonding strength*

For multiphase composites, the phase interface of the material is always a feature that cannot be ignored. In self-lubricating composites, the interfacial bonding strength not only affects the mechanical properties of the composites but also affects the friction and wear properties [44]. Su et al. [33] studied the tribological properties of three kinds of lubricating materials having different matrix-types, indicating that the tribological properties of self-lubricating composites with different matrix types were affected by the interfacial bonding strength between the matrix and lubricants. In general, the interfacial bonding strength can be enhanced by modifying the surface of the solid lubricant, thus improving the friction and wear performances of the composites. For example, Moustafa's comparative study of Cu-coated and uncoated graphite composites showed that the Cu-coated graphite composites obtained high interfacial bonding strength and low wear rates due to the high mismatch and good contact between graphite and Cu-matrix [39].

### 2.2.5 *Effect of normal load*

The magnitude of the normal load has an important influence on the formation and retention of self-lubricating and transfer films, the deformation of the material, and the adhesion tendency. Generally, the increase in normal load leads to greater plastic deformation on the subsurface of the self-lubricating composites and increases the rough contact between the rough bodies, thus increasing the friction force. However, the increasing normal load can also promote the diffusion of graphite from the subsurface to the sliding surface, which helps to form self-lubricating films. Figure 6 shows the influence of normal load on the friction coefficients and wear rates of several Cu/Al-graphite self-lubricating composites. The friction coefficients of Al-graphite self-lubricating composites presented a downward trend with the increase of load, but that of the Cu-graphite self-lubricating composite rose. Overall, the wear rates of the three self-lubricating composites increased with increasing normal loads (Fig. 6(b)). However, the SiC-reinforced Al-graphite self-lubricating composites show a trend of decreasing first and then increasing, which may relate to the addition of SiC that enhanced the wear resistance of the composites.

### 2.2.6 *Effect of sliding speed*

The heating, deformation, chemical changes, and wear of the surface layer of composites caused by sliding speed change the nature of the surface layer and the interaction of the friction surfaces, thus affecting the friction coefficient and wear rate. Figure 7 summarizes the effect of sliding speed on the friction coefficients and wear rates of several Cu/Al-graphite self-lubricating composites.

In general, friction coefficients decrease first and then increase with increasing sliding speed (Fig. 7(a)). Firstly, the increase of sliding speed reduces the probability of contact between the rough bodies, so the adhesion component of the friction coefficient decreases. Secondly, the friction heat generated during the sliding also helps to decrease friction by softening the rough body. As a result, the friction coefficients decrease with sliding speed increasing under low-speed sliding conditions. However, when the sliding speed exceeds a critical value, the self-lubricating and transferring films formed on the sliding surface with low graphite content are thin and have poor adhesion, which may easily peel from the sliding surface

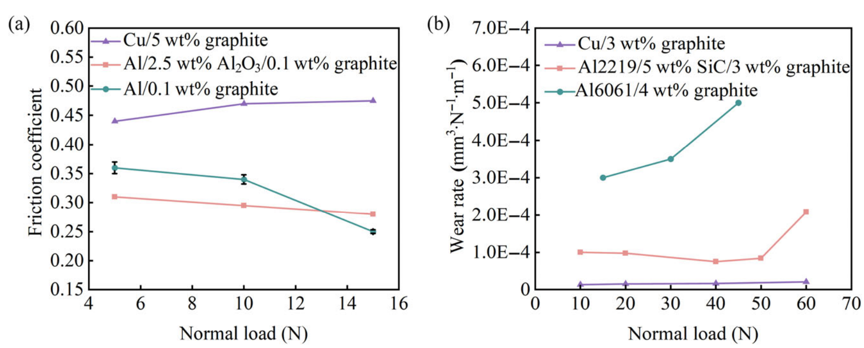


**Fig. 6** (a) Friction coefficients [45–47] and (b) wear rates [35, 48, 49] of several Cu/Al-graphite self-lubricating composites with different normal loads.

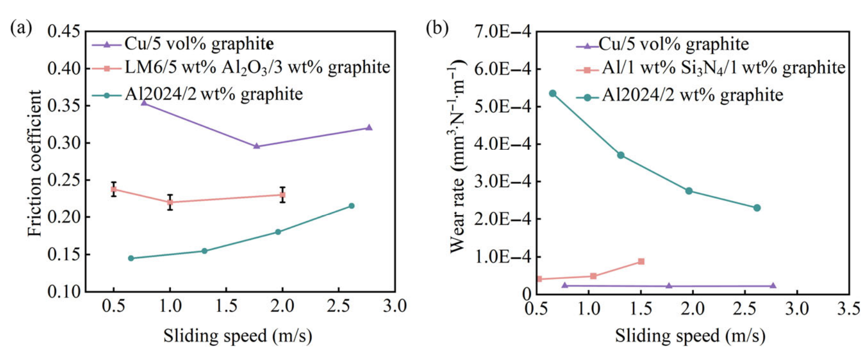


**Fig. 7** (a) Friction coefficients [50-52] and (b) wear rates [50, 51, 53] of several Cu/Al-graphite self-lubricating composites with different sliding speeds.

during the process of high-speed sliding and lead to higher friction coefficients. However, the friction coefficient of Al2024 composites shows a monotonically increasing trend with increasing sliding speed, which may be related to the small critical sliding speed. The softening of rough bodies caused by friction heat also plays a certain role in reducing the degree of wear. Meanwhile, some studies have found that the thickness of the friction layer increases with temperature [41]. Therefore, in the low-speed sliding stage, the wear rates will gradually decrease with the increase in sliding speed. However, when the sliding speed exceeds a critical value, the wear rates increase with the increase in sliding speed.

#### 2.2.7 *Effect of sliding distance*

The influence of sliding distance on friction coefficient and wear rate will vary with the properties of the sliding surface, the forming ability of the lubricating films, and the working conditions. As shown in Fig. 8, both increasing and decreasing trends in friction coefficients and wear rates of Al-graphite self-lubricating composites were observed with increasing sliding distance. The friction coefficients or wear rates of $Si_3N_4$-reinforced LM13 composite, SiC-reinforced Al2024 alloy composite, and SiC-reinforced Al2219 composite increase or decrease monotonically with the increase in sliding distance. In addition, the wear rates of the Al2219-graphite composite present a slight fluctuation. This phenomenon indicates that sliding distance affects tribological properties. The trends and magnitude of change are also largely determined by the composites themselves.

From the above discussions, it can be found that the tribological properties of metal matrix self-lubricating composites are influenced by many factors, and the influence mechanism is also complex. However, traditional research methods are not comprehensive enough in analyzing the relationship between tribological properties and the influencing variables. ML models have a certain research basis in the analysis and solution of complex problems with multiple dimensions. If the ML models are applied to the predict friction coefficient and wear rate of self-lubricating composites, they can not only simplify the analysis process but also help to generate new insights into the relationship between tribological properties and influencing variables by combining the effects of multiple variables.

## 3 Materials and methods

In this section, we will discuss the building and performance enhancement of ML models, including data collection, determination of input and output parameters, pre-processing of the data, introduction of the adopted models, parameter optimization, and performance evaluation methods of the models.

### 3.1 Data collection and input–output parameters

The collection of data points is one of the most fundamental and critical steps in building an ML model since the source of the collected samples and the accuracy of the data themself can have a significant impact on the robustness and generalization ability of the ML model. A high-quality dataset is essential to train an ML algorithm for better predictive performance. The process of collating adequate data for an ML analysis is expensive and time-consuming

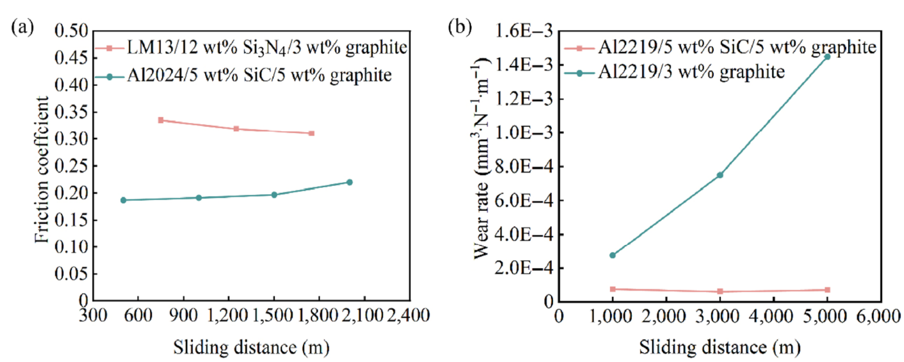


**Fig. 8** (a) Friction coefficients [23, 54] and (b) wear rates [48] of several Al-graphite self-lubricating composites with different sliding distances.

if data collection relies on performing tribological experiments. It is worth noting that there exists a large amount of data in the existing literature [7, 25, 32, 39, 46, 52, 54–56]. Organizing the data among them as the dataset for building ML models can not only meet the data volume requirement of ML modeling, but also the wide range of data sources can cover a wide range of input and output relations, which is conducive to improving the robustness and generalization ability of the model [14].

Therefore, we collected and organized the published data on tribological properties of Al/graphite, Cu/graphite, and Cu/copper-coated graphite studies, and selected a total of 506 friction coefficient samples and 497 wear rate samples as the dataset. A total of 12 material and tribological variables, including hardness, tensile strength, yield strength and elongation of matrixes, reinforcement volume, graphite content, graphite particle size, processing process, interfacial bonding strength, normal load, sliding speed, and sliding distance, were considered as the input features for ML analysis, and the corresponding friction coefficients and wear rates were the output features, respectively. It is worth noting that the interfacial bonding strength was not easily available, and the preparation process only represented the method of preparation without specific numerical meaning. Therefore, the interfacial bonding strength and the preparation process were treated as ordered categorical variables and nominal categorical variables, respectively. The remaining characteristics were numerical variables according to the influencing variables.

### 3.2 Pre-processing of the data

Due to the influence of data point distribution and outliers, the pre-processing of the data is a key step in building high-performance models, including data cleaning, missing value and outlier processing, data shuffling, data standardization, and splitting of the training set and test set.

Firstly, the missing values and outliers were manually removed. Then, the categorical features in the data were converted into categorical values using one-hot encoding and ordered encoding. The data were disrupted by generating random indexes, so that each sample became an independent individual, thus reducing the impact on the model results. Due to the different working conditions and units of measurement of data points, their data feature scales have great differences, which would affect the model's computational speed and performance. To weaken this effect, finally, Z-score standardization was adopted to process the data. The advantage of this method is that it eliminates scale differences in sample attribute values without changing the spatial distribution of the data.

To test the generalization and robustness of the models while training the ML models, we split the dataset into two mutually exclusive training set and test set according to the standard sample division ratio. Herein, 75% of the total data was used for training the models and the remaining 25% was used to test the performance of the models.

### 3.3 Introduction of the adopted models

The advantages of ML models lie in their ability to fit the implied correspondence between input and output parameters from large datasets and make predictions on unknown data through the trained models. ML models built on different algorithmic principles have different prediction performances for the same dataset [57]. In this paper, five ML algorithms: support vector machine (SVM), K-Nearest neighbor (KNN), random forest (RF), eXtreme gradient boosting (XGBoost), and Least-squares boosting (LSBoost) were used to perform the ML modeling to achieve the prediction of friction coefficients and wear rates of Cu/Al-graphite self-lubricating composites. A summary and brief description of these ML models are presented below.

#### *3.3.1 SVM model*

The SVM model is a supervised ML algorithm model developed based on statistical learning theory, which can better realize the idea of structural minimization and has unique advantages in solving few-shot, nonlinear, and high-dimensional pattern recognition problems [58]. The SVM model maps the input vectors non-linearly by the linear kernel, polynomial kernel, radial basis function, sigmoid kernel, and other kernels during the solving processes [59]. In this way, the original feature space is mapped to the higher dimensional feature space, thereby predicting the outputs. The key parameters of the SVM model to be tuned include the selection of kernel functions, the parameters of kernel functions (gamma), and the regularization parameters (*C*).

### 3.3.2 *KNN model*

The KNN model is an instance-based supervised ML algorithm model, which firstly finds K training data points that are closest to the new data points, and then averages or weights the output values corresponding to these K data points as the predicted output values of the new data points. When training a KNN model, the parameters usually need to be considered are the number of neighboring points (NumNeighbors) and the choice of the distance metric function between data points.

### 3.3.3 *RF model*

The RF model is an integrated algorithmic model based on the bagging mechanism (Fig. 9) and a decision tree as the base evaluator, in which the model generalization will be improved by a self-sampling method. In the RF model, the bagging mechanism can reduce the correlation between the trained multiple decision trees, effectively alleviating the problem of overfitting, and the error of the model can be significantly reduced by averaging the results of the base evaluator [60]. During the parameters tuning of the RF model, the performance of the model can be optimized by adjusting the number of decision trees (treesNumtrees) and features considered (minleaf).

### 3.3.4 *XGBoost model*

The XGBoost model is an integrated algorithmic model based on the boosting mechanism (Fig. 10) and a decision tree as the base evaluator. In the XGBoost model, the second-order Taylor expansion of the objective function makes the model highly accurate in solving classification and regression problems, and it is optimized by using distributed computing and parallel sampling sorted by eigenvalues so that the XGBoost model can be efficiently trained and predicted on large-scale datasets [61]. The key parameters that usually need to be optimized in the XGBoost model include the learning rate (LearnRate), the number of base models (NumLearningCycles), and the maximum depth of the tree (depth_max).

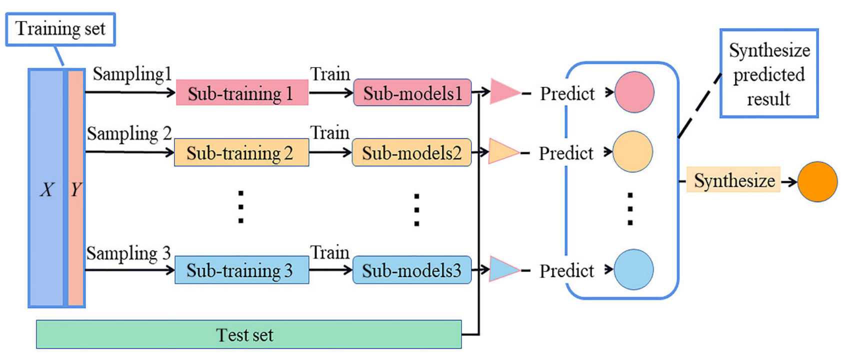


**Fig. 9** Schematic of the bagging mechanism.

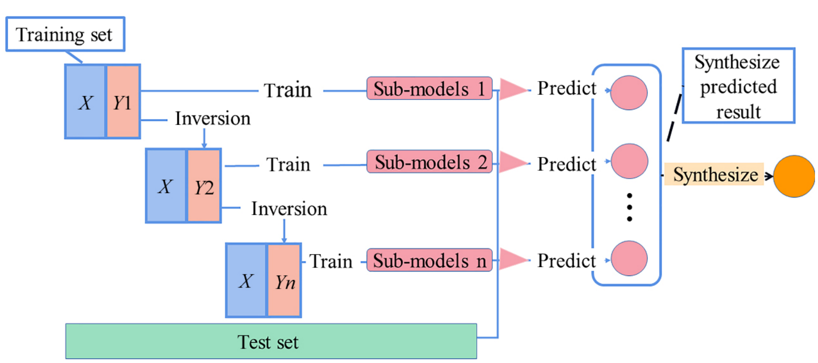


**Fig. 10** Schematic of the boosting mechanism.

*3.3.5 LSBoost model*

As a decision tree-based integration algorithm model, the LSBoost model uses the same integration strategy as the XGBoost model. The least squares method is used in the LSBoost model to optimize the loss function during model training, in which the predictive value of the target variable is adjusted by minimizing the sum of squares of the residuals, thus allowing the next basic model to fit the residuals more accurately [62]. The main advantages of the LSBoost model are its ease of implementation and tuning, as well as good adaptability to high-dimensional, nonlinear, and sparse datasets. Table 1 describes the algorithm for the model. During the parameter tuning of the LSBoost model, the parameters that usually need to be optimized include the learning rate (LearnRate), the number of base models (NumLearningCycles), and the minimum number of leaf nodes (MinLeafSize).

**Table 1** Algorithm description of the LSBoost model [62].

| |
|---|
| **Input**: A training set $\{(x_i, y_i)\}_{i=1}^{n}$, a loss function $L(y, F) = (y - F)^2/2$, number of iterations $M$ |
| Initialize, $F_0(X) = \overline{y}$ |
| For $m$ = 1 to $M$ do: |
| $\tilde{y}_i = y_i - F_{m-1}(x_i)$, i = 1…, $N$ |
| $(\alpha_m, \beta_m) = \text{argmin}_{\alpha,\beta} \sum_{i=1}^{N} \left[\overline{y}_i - \rho_m h(x_{i;\alpha})\right]^2$ |
| End for |
| **Output**: the final regression function $F_m(x)$ |

### 3.4 Performance optimization and evaluation of the models

In the previous section, we briefly discussed five different ML models and the parameters that need to be optimized. Parameter tuning allows for optimal performance of the model. Generally, the parameters that a model needs to be optimized include both the parameters of the model and the hyperparameters that are used to define the model structure or optimization strategy. Here, we found the optimal parameters corresponding to the models by adding automatic optimization algorithms or cross-validation techniques to the ML models.

To evaluate the predictive performance of the models, the following four evaluation indicators were used. Mean absolute error (MAE) avoids the problem of errors canceling each other and thus can accurately reflect the magnitude of the actual prediction error. Mean square error (MSE) measures the performance of a model by calculating the deviation between the predicted and actual values. Root mean square error (RMSE) measures the extent to which the data deviates from the true value. The coefficient of determination (R-squared, $R^2$) measures the goodness-of-fit of the whole regression, in which the value is taken in the range of 0–1. If the value of $R^2$ is closer to 1, it indicates that the model prediction performance is better. The $R^2$ value of the model ranging $0.7 < R^2 < 0.9$ is considered satisfactory while $R^2 > 0.9$ confirms excellent prediction model performance [15]. The formula of the four evaluation indexes are as Eqs. (4)–(7) [62, 63]:

$$\text{MAE} = \frac{1}{N}\sum_{i=1}^{N}\left|\tilde{y}_i - y_i\right| \tag{4}$$

$$\text{MSE} = \frac{1}{N}\sum_{i=1}^{N}(\tilde{y}_i - y_i)^2 \tag{5}$$

$$\text{RMSE} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(\tilde{y}_i - y_i)^2} \tag{6}$$

$$R^2 = 1 - \frac{\frac{1}{N}\sum_{i=1}^{N}(\tilde{y}_i - y_i)^2}{var(y)} \tag{7}$$

where $\tilde{y}_i$ is the observed value corresponding to the *i*th sample, $y_i$ is the actual value (experimentally measured) corresponding to the *i*th sample, and $N$ is the number of observed samples.

## 4 Result and discussion

The optimized parameters and corresponding performance indicators of the five prediction models are shown in Tables 2, 3, 4, and 5, respectively. At the same time, we analyzed the relative importance of the input variables for the friction coefficients and wear rates of the self-lubricating composites using the feature importance attribute of the RF model, and the results are shown in Figs. 12 and 14. These results were also briefly analyzed and discussed in this section.

**Table 2** Optimization of friction coefficient prediction models.

| Model name | Selected parameter |
|---|---|
| SVM | Gamma = 0.25, $C$ = 32, kernel = rbf |
| KNN | NumNeighbors = 2, Distance = 'cityblock' |
| RF | Numtrees = 200, minleaf = 1 |
| XGBoost | LearnRate = 0.13, NumLearningCycles = 200, depth_max = 5 |
| LSBoost | LearnRate = 0.081999, NumLearningCycles = 497, MinLeafSize = 1 |

**Table 3** Performance indicators of the friction coefficient models.

| Model name | MAE | MSE | RMSE | $R^2$ value on the test |
|---|---|---|---|---|
| SVM | 0.0319 | 0.0027 | 0.0515 | 0.8317 |
| KNN | 0.0455 | 0.0044 | 0.0662 | 0.7217 |
| RF | 0.0328 | 0.0022 | 0.0474 | 0.8573 |
| XGBoost | 0.0230 | 0.0013 | 0.0364 | 0.9158 |
| LSBoost | 0.0234 | 0.0012 | 0.0351 | 0.9219 |

**Table 4** Optimization of wear rate prediction models.

| Model name | Selected parameter |
|---|---|
| SVM | Gamma = 2, $C$ = 32, kernel = rbf |
| KNN | NumNeighbors = 2, Distance= 'cityblock' |
| RF | Numtrees = 80, minleaf = 2 |
| XGBoost | LearnRate = 0.11, NumLearningCycles = 100, depth_max = 10 |
| LSBoost | LearnRate = 0.35105, NumLearningCycles = 490, MinLeafSize = 6, NumBins = 5 |

**Table 5** Performance indicators of the wear rate models.

| Model name | MAE | MSE | RMSE | $R^2$ value on the test |
|---|---|---|---|---|
| SVM | 6.9862e–05 | 1.2723e–08 | 0.000113 | 0.9219 |
| KNN | 8.2647e–05 | 2.2117e–08 | 0.000149 | 0.8651 |
| RF | 1.2023e–04 | 7.9136e–08 | 0.000281 | 0.8911 |
| XGBoost | 6.1607e–05 | 1.2694e–08 | 0.000113 | 0.9225 |
| LSBoost | 6.8006e–05 | 1.2335e–08 | 0.000111 | 0.9243 |

### 4.1 Results of friction coefficients prediction

The $R^2$ values of the five friction coefficient prediction models ranged from 0.7217 to 0.9219, with low values of MAE, MSE, and RMSE. Among them, the LSBoost model (MAE = 0.0234, MSE = 0.0012, RMSE = 0.0351, $R^2$ = 0.9219) and the XGBoost model (MAE = 0.0230, MSE = 0.0013, RMSE = 0.0364, $R^2$ = 0.9158) based on the integrated learning algorithm produce the best prediction performances. The comparison between the actual values of friction coefficients and the predicted values of the LSBoost algorithm is shown in Fig. 11. The results show that for most of the sample points, the LSBoost model can accurately predict the friction coefficients of the composites based on the original properties of the matrix material and the sliding conditions. The $R^2$ value of 0.9219 indicated a high prediction accuracy. However, the occurrence of large errors in individual data points is a normal phenomenon that is mainly related to the accuracy of the data itself, the distribution of the data, and the effect of outliers.

Among the other three friction coefficient prediction models, the $R^2$ value of the RF and SVM models are 0.8573 and 0.8317, respectively, showing satisfactory prediction results. When considering 2 proximity points and the "cityblock" is chosen as the distance metric function, the KNN model also presents a satisfactory prediction result with the $R^2$ of 0.7217 (higher than 0.7). However, compared to other ML models, the KNN model performs poorly in processing the friction coefficient dataset, which may be related to the fact that the KNN model is too simple. Moreover, it can be found that the prediction performance of the models based on the integrated learning algorithm are better than that of the traditional ML models such as SVM and KNN. The integrated learning algorithm based on the boosting mechanism performs better in predicting the friction coefficients than that based on the bagging mechanism.

### 4.2 Effect of input variables on friction coefficients

We further analyzed the effect of each input variable on the friction coefficients by the feature importance attribute of the RF model. The score corresponding to each input variable represents the importance of the input variable on the friction coefficients, and higher values represent the more important the variable is for the study of the friction coefficient. The results are summarized in Fig. 12. As discussed in Section 2, graphite content has a significant effect on the friction coefficients of self-lubricating composites and

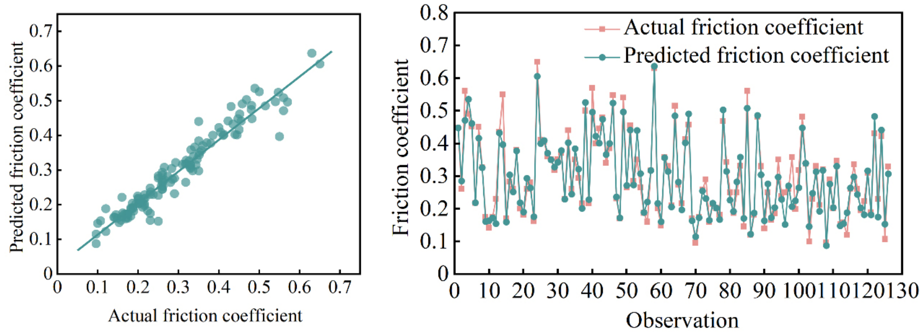


**Fig. 11** Comparison between the actual friction coefficients (experimentally measured) and the predicted values obtained from the LSBoost model.

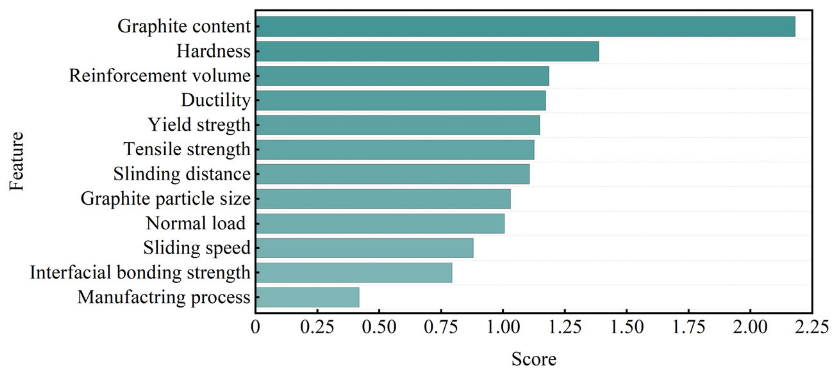


**Fig. 12** Relative importance of input variables for predicting the friction coefficients.

is the most important variable in the analysis of friction coefficients. Previous studies indicated that the deformation of the subsurface is the main factor leading to the transfer of graphite to the sliding surface, while the hardness of the matrix also plays an important role [33]. For Cu/Al-graphite self-lubricating composites, therefore, the hardness of the matrix material is considered to be the second most important variable after the graphite content in the friction coefficients analysis. In terms of the other factors, the properties of the matrix material (tensile strength, yield strength, ductility) have a more significant effect on the friction coefficients compared to the sliding conditions (sliding distance, normal load, sliding speed), indicating that there is a strong relationship between the properties of the matrix phase and friction coefficients as the main body of the self-lubricating composite. Besides, the non-zero score of interfacial bonding strength indicates that the effect of matrix type on the friction coefficients is related to the interfacial bonding strength between the matrix and lubricant, and the preparation process has the least effect on the friction coefficients.

### 4.3 Results of the wear rates prediction

The $R^2$ values of the five wear rates prediction models ranging from 0.8651 to 0.9243, and each of the models performed excellently. Herein, the LSBoost model (MAE = 6.8006e–05, MSE = 1.2335e–08, RMSE = 0.000111, $R^2$ = 0.9243) presented the best prediction performance. The comparison between the actual wear rates and the predicted values of the LSBoost model is given in Fig. 13, indicating that there is still a strong correlation between the actual values and the predicted values. Similar to friction coefficients prediction, some wear rates that failed to be accurately prediction, some wear rates that failed to be accurately predicted still existed, which mainly originated from some errors in the wear rate data itself and the defects of the machine algorithm itself, as well as the model may be affected by the distribution of the wear rate data. Generally, the prediction results of the wear rate are in a satisfactory error range.

Besides, the XGBoost model (MAE = 6.1607e–05, MSE = 1.2694e–08, RMSE = 0.000113, $R^2$ = 0.9225) and SVM model (MAE = 6.9862e–05, MSE = 1.2723e–08, RMSE = 0.000113, $R^2$ = 0.9219) had similar prediction

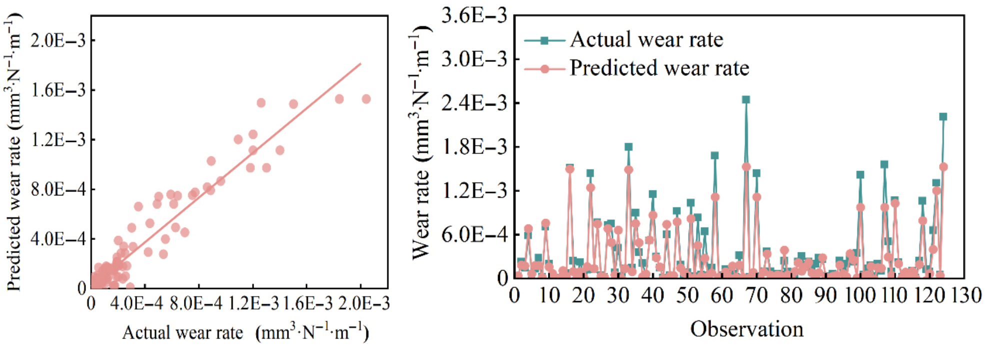


**Fig. 13** Comparison between the actual wear rates (experimentally measured) and the predicted values obtained from the LSBoost model.

performance to the LSBoost model, and they achieved impressive prediction performance in the wear rate dataset. The $R^2$ values of the RF model and KNN model are 0.8911 and 0.8651, indicating that the above two models also have strong processing capability for the wear rate dataset. However, compared to the other four ML models, the KNN model still performs poorly on the wear rate dataset. As to wear rates, likewise, the integrated learning algorithm models based on the boosting mechanism perform better overall than that based on bagging and the traditional KNN model, while the SVM model presented a higher prediction accuracy may be related to the data mapping mechanism of the SVM model and the generalization ability of SVM model improved by maximizing the interval to select the decision boundary.

### 4.4 Effect of input variables on wear rates

Using the same method, the relative importance of each input variable was analyzed by the feature importance attribute of the RF model, and the results are shown in Fig. 14. The graphite content, normal load, and hardness of the matrix are the most important influencing variables when analyzing the wear rates. Graphite content plays a key role both in the mechanical and lubricating properties of metal matrix self-lubricating composites, and therefore graphite content is still considered the most important parameter for the wear rates. The normal load affects the formation and retention of lubricating films, and the transition from light to severe wear of self-lubricating composites, thereby is considered the second most important variable. The hardness affects the deformation, adhesion, and removal of the surface of the self-lubricating composites, so it instinctively has an important influence on the wear rates. In addition, it is found that the interfacial bonding strength and preparation process also had the least effect on the wear rates.

## 5 Experimental verification

To further verify the generalization and robustness of the models, several Cu/Al-graphite self-lubricating

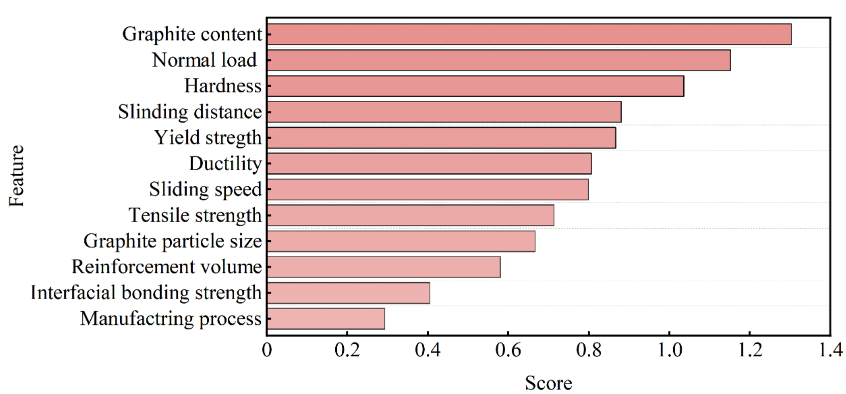


**Fig. 14** Relative importance of input variables for predicting wear rates.

composites were designed and prepared, and their friction coefficients and wear rates were tested and compared with the predicted results of the LSBoost model.

### 5.1 Materials and methods

Commercially available graphite (~5 μm), Cu663 (~6 μm), and Al2024 (~37 μm) were used to prepare four self-lubricating composites with different matrixes and graphite content. Because there is no component volatilization during the sintering process, the graphite content in the original composite powder can directly reflect the graphite content in the composites.

The preparing processes of the composites are as follows: (1) mixing the powders according to a certain proportion; (2) stacking the mixed powder in a steel mold and dry-pressing to form a green body; (3) hot-pressing for 120 min at 800 °C and 60 min at 530 °C for Cu and Al matrix self-lubricating composites respectively, and the heating rate was 10–15 °C/min. The sintered Al matrix composites were solution treated at 540 °C in a muffle furnace for 120 min and water quenched; then, they were naturally aged for 72 h.

The friction coefficients of Cu/Al-graphite self-lubricating composites were measured by standard rotary friction testing machine and reciprocating friction and wear testing machine, respectively. Before the experiments, all samples were polished to obtained a smooth surface with a roughness of ~0.1 μm. The wear volume of the Al-graphite self-lubricating composite are determined by the mass loss of the pins before and after the test. The wear volume of the Cu-graphite self-lubricating composite is determined by measuring the cross sections of the worn track with a stylus profilometer.

### 5.2 Design and verification of friction experiment

The composition of composites and experimental parameters, and the experimental verification results of the model are shown in Table 6 and Fig. 15, respectively. Results demonstrate that the LSBoost

**Table 6** Composition of composites and experimental parameters corresponding to friction experiments.

| S. No. | Matrix | Reinforcement | | Experimental condition | | |
|---|---|---|---|---|---|---|
| | | SiC content | Graphite content | Normal load | Sliding speed | Sliding distance |
| S1 | Al2024 | 5 | 0 | 6.5 | 0.312 | 565.5 |
| S2 | Al2024 | 5 | 0 | 8.0 | 0.210 | 377.0 |
| S3 | Al2024 | 5 | 7.5 | 6.5 | 0.312 | 565.5 |
| S4 | Al2024 | 5 | 7.5 | 8.0 | 0.210 | 377.0 |
| S5 | Cu663 | 0 | 7.5 | 15.0 | 0.080 | 300.0 |
| S6 | Cu663 | 0 | 7.5 | 7.5 | 0.100 | 360.0 |
| S7 | Cu663 | 0 | 12.5 | 15.0 | 0.080 | 300.0 |
| S8 | Cu663 | 0 | 12.5 | 7.5 | 0.100 | 360.0 |

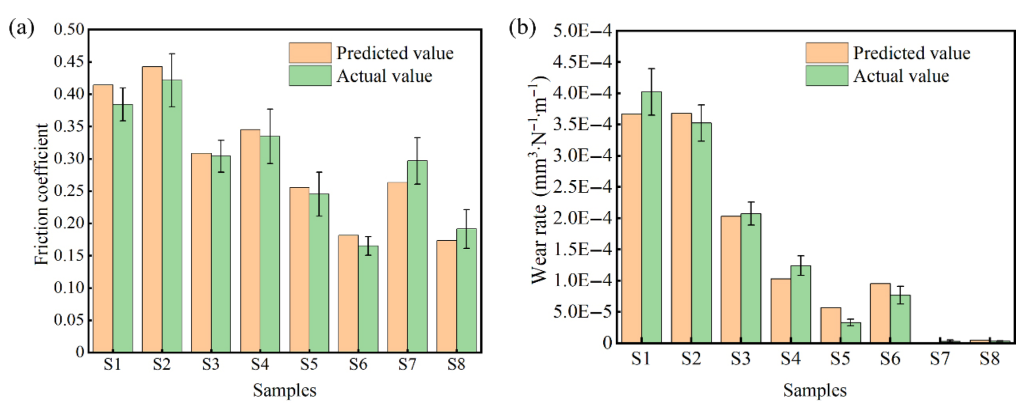


**Fig. 15** Experimental verification results of (a) friction coefficients and (b) wear rates.

model has a strong ability to predict the friction coefficient and wear rate of Cu/Al-graphite self-lubricating composites. Although there are some errors between the predicted values and the actual experimental values, that are within the acceptable error range on the whole.

## 6 Conclusions

Five ML models were trained to predict the friction coefficient and wear rate of Cu/Al-graphite self-lubricating composites using tribological experimental data reported in the literature based on the analysis and discussion of the friction and wear mechanisms and the effects of influencing variables on friction coefficient and wear rate using conventional research methods. It is demonstrated that ML models can satisfactorily predict the tribological properties of Cu/Al–graphite self-lubricating composites. Herein, the LSBoost model based on the integrated learning algorithm is good at predicting the friction coefficients (MAE = 0.0234, MSE = 0.0012, RMSE = 0.0351, $R^2$ = 0.9219) and wear rates (MAE = 6.8006e–05, MSE = 1.2335e–08, RMSE = 0.000111, $R^2$ = 0.9243), showing the best prediction performance compared to the other ML models. Feature importance analysis shows the graphite content and the hardness of the matrix are the most important variables affecting the friction coefficient. Graphite content, normal load, and hardness of the matrix are the most important variables affecting the wear rate. The influence of interface bonding strength and preparation process on tribological properties is weaker than other influencing variables. The LSBoost model was demonstrated a strong ability to predict the tribological properties of Cu/Al-graphite self-lubricating composites through their own experiments.

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## Declaration of competing interest

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



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