

Tribo-informatics approaches in tribology research: A review

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Abstract: Tribology research mainly focuses on the friction, wear, and lubrication between interacting surfaces. With the continuous increase in the industrialization of human society, tribology research objects have become increasingly extensive. Tribology research methods have also gone through the stages of empirical science based on phenomena, theoretical science based on models, and computational science based on simulations. Tribology research has a strong engineering background. Owing to the intense coupling characteristics of tribology, tribological information includes subject information related to mathematics, physics, chemistry, materials, machinery, etc. Constantly emerging data and models are the basis for the development of tribology. The development of information technology has provided new and more efficient methods for generating, collecting, processing, and analyzing tribological data. As a result, the concept of “tribo-informatics (triboinformatics)” has been introduced. In this paper, guided by the framework of tribo-informatics, the application of tribo-informatics methods in tribology is reviewed. This article aims to provide helpful guidance for efficient and scientific tribology research using tribo-informatics approaches.

Keywords: tribo-informatics; data-driven; artificial intelligence; information technology; machine learning

1 Introduction

With the development of engineering technology, the structures of various industrial products and exceptional equipments are becoming increasingly complex, and the working conditions are becoming more severe. At the same time, the requirements for operational reliability and stability are increasing. A tribological system generally comprises the tribo-pairs, lubricating medium, and working environment (as shown in Fig. 1). Tribological systems exhibit subject coupling, time dependence, and system dependence, which have led to a wide range of data sources and numerous theoretical models in tribological research. Tribology researchers have often analyzed various simulations [1], experiments, and engineering data to explain tribological phenomena or develop theoretical

or predictive models. In general, data and models are the basis for the study of tribology, and accelerating the transmission of information between them is the key to improving the efficiency of tribology research.

Information technology is a method of generating, collecting, processing, and analyzing information. With the development of information technology, information processing methods are no longer limited to traditional regression, fitting, and induction methods. The development of machine learning and artificial intelligence technologies has dramatically improved the efficiency of information processing methods, and the scope of application has continued to expand. Therefore, the possibility of integrating informatics and other disciplines, such as health information technology [2], supply chain information technology [3], and educational information

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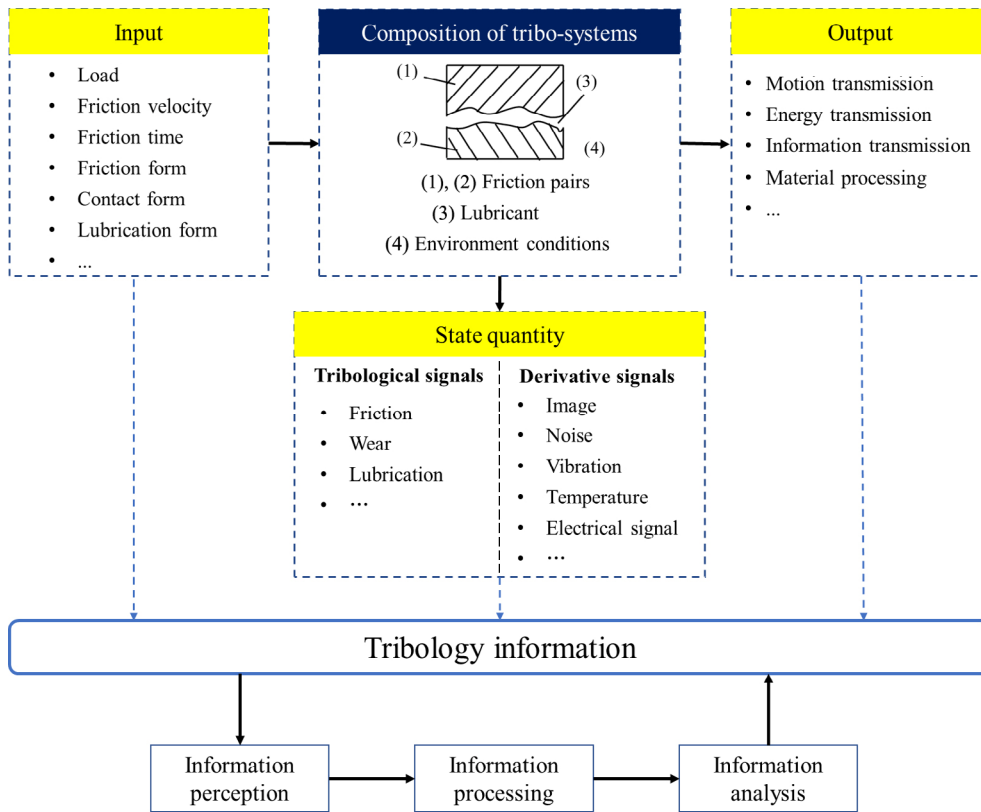


Fig. 1 Components of tribo-systems.

technology [4], has been accelerated. Tribo-informatics was also developed in this context, and it has improved the tribology research efficiency and process by establishing tribology standards, building tribology databases, and using information technology to collect, classify, store, retrieve, analyze, and disseminate tribology information [5].

At present, tribo-informatics methods have numerous functions, such as regression and clustering [6]. The purposes of the application of tribo-informatics mainly include condition monitoring, behavior prediction, and optimization of tribological systems [7–9]. In a sense, the ultimate goal of informatics methods is to obtain the relationship between data. When the goal is to obtain the relationship between the tribological quantity and time quantity, system behavior prediction is employed; when the goal is to obtain the relationship between the tribological quantity and state quantity, system state monitoring is used; and when the goal is to obtain the relationship between the system input and output, system optimization is employed. The tribological model aims

to solve the problem of the attribution of different types of data to facilitate more accurate data analysis using informatics methods. From this perspective, the model can guide the processing of data, and the data can enrich the meaning of the model. Therefore, the collaborative driving of the data and model is an indispensable research method in tribo-informatics. This article reviews the application of informatics methods in tribological research in detail based on the three aspects mentioned above.

2 Meaning of tribo-informatics methods

The functions of a tribological system may include transmitting information, movement, or energy or generating material deformation to achieve processing purposes. The output of a tribological system is the function that it aims to achieve. The state of a tribological system includes tribological and derivative signals. It should be noted that these signals may also be the target outputs of the tribological system. For example, in the bearing tribological system of a

satellite momentum wheel, the output is the moment of momentum, the inputs can be the material of the friction pairs, lubrication methods, surface treatment, etc., and the state quantities are the friction, vibration, wear rate, friction heat, and other parameters.

The tribo-informatics approach is a collection of all of the methods used to process tribological information. It includes not only traditional information processing methods such as the Gaussian regression method, linear regression method, and least squares method, but also advanced machine learning methods. Artificial intelligence methods are the products of machine learning development. The primary purpose of tribo-informatics methods is to obtain the relationship between various quantities in a tribological system.

1) When the relationship between an observable state quantity and unobservable state quantity is obtained, state monitoring of the tribological system is realized.

2) When the relationship between the input quantity or current state quantity and a future state quantity is obtained, prediction of the tribological behavior can be realized.

3) When the relationship between the input and target output is obtained, the tribological system can be optimized to obtain a better output.

Tribology information processing needs to be based on the basic models and principles of tribology to realize the deep integration of informatics and tribology. For example, the peak value of the sound signal can be selected as a characteristic parameter to study its relationship with friction; or gray-scale image information can be processed to study the relationship between image information and the wear rate. In the framework of tribo-informatics, it should be aimed to ensure that the selection of each characteristic parameter has a physical meaning, which is referred to as “model-driven data processing”. Inevitably, in some cases, it is difficult to determine the most suitable characteristic parameters using the basic models or principles of tribology. In this case, it is necessary to evaluate the relationships between multiple characteristic parameters of two physical variables. Correlations can then be used to obtain the optimal characteristic parameters. More importantly, the determination of optimal characteristic parameters can be used to develop new tribological physical

models or principles, referred to as “data-driven model optimization”.

The application purposes of specific tribological informatics technology can be divided into regression, classification, clustering, and dimensionality reduction (as shown in Fig. 2). The quantitative tribological relationship can be determined using regression methods, the tribological behavior characteristics can be determined using classification methods, new tribology laws can be discovered using clustering methods, and tribological research efficiency can be improved using dimensionality reduction methods. Among these methods, artificial neural network (ANN), support vector machine (SVM), k -nearest neighbor (KNN), and random forest (RF) methods are the most commonly used.

2.1 ANNs in tribology research

ANNs, which consist of a large number of node connections (as shown in Fig. 3), are a research topic of considerable interest in artificial intelligence. Each node represents an incentive function, and each connection between two nodes has a corresponding weight [10]. ANNs have a high degree of nonlinearity and have played enormous roles in regression, classification, clustering, etc. There are three main types of units in ANN methods: input, hidden, and output units. The input unit accepts signals and data from the outside world. The output unit realizes the output of the processing results of the system. The hidden unit is located between the input and output units and cannot be observed.

In tribological research, system input information (such as the friction speed and load) is typically used as the input unit. System output information (such as the friction, wear, and lubrication) is used as the output unit. In addition, some easy-to-observe state quantities (such as acoustic signals, electrical signals, and vibration signals) can also be used as input units to obtain difficult-to-observe state quantities (such as the coefficient of friction (COF) and wear rate).

2.2 SVM in tribology research

SVM is a generalized linear classifier that performs binary data classification based on supervised learning [11]. Its purpose is to find the farthest hyperplane

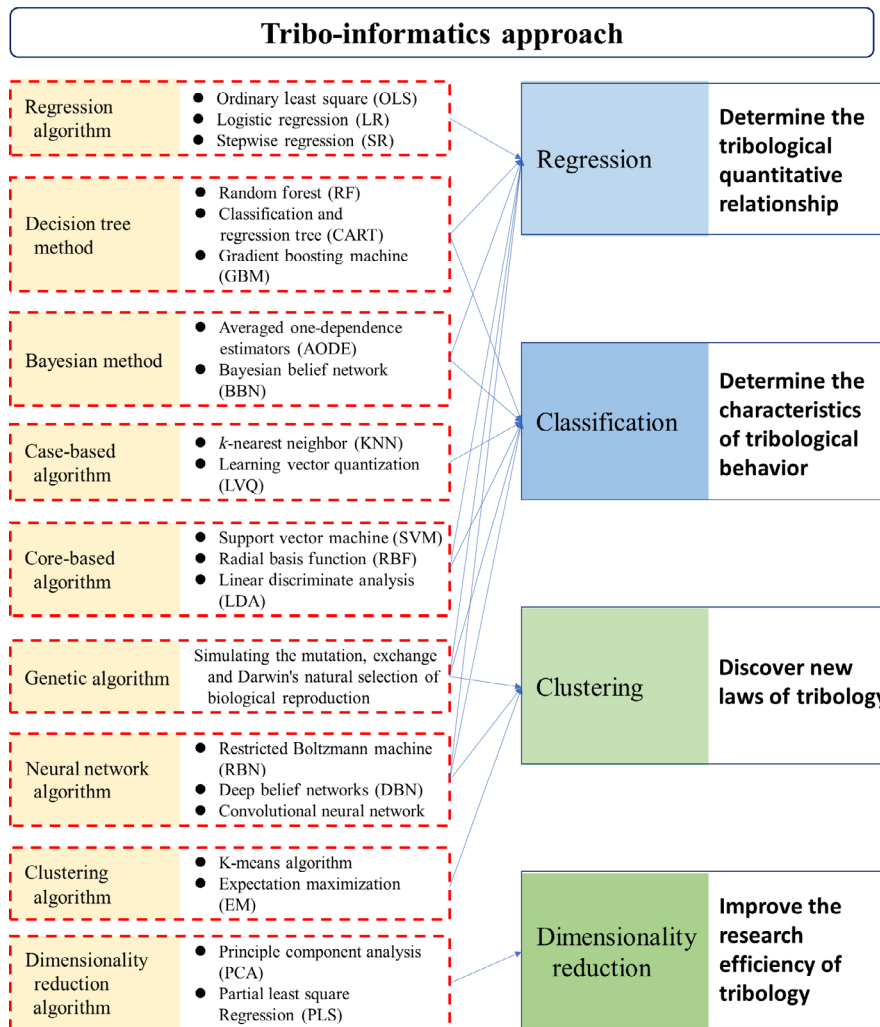


Fig. 2 Classification and function of tribo-informatics methods.

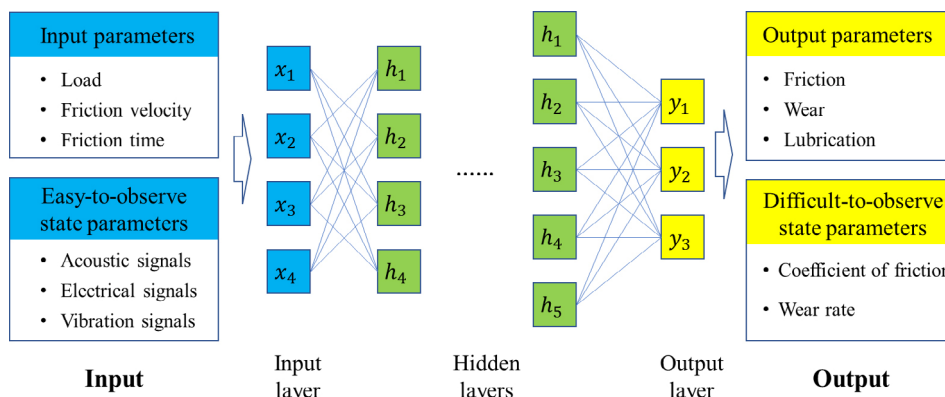


Fig. 3 Application of ANN methods in tribology research.

from various sample points, i.e., the hyperplane with the most significant separation (as shown in Fig. 4). When encountering situations that are not entirely linearly separable, slack variables need to be introduced.

In a situation that is not linearly separable, the sample can also be mapped to a high-dimensional space to enable linear separation. SVM has strict mathematical support and strong interpretability, and thus it is

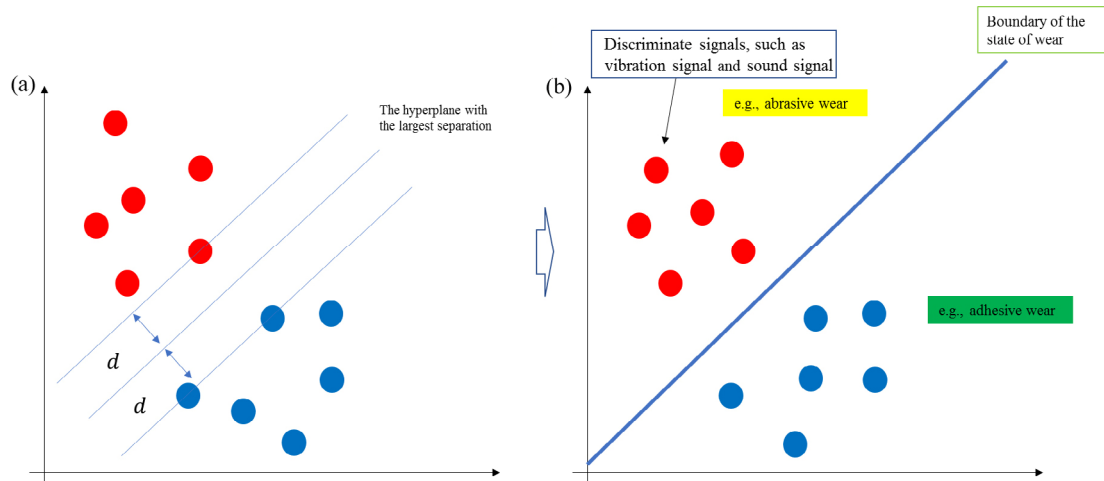


Fig. 4 Application of SVM methods in tribology research: (a) principle of SVM; (b) application of SVM in the classification of tribological behavior characteristics.

usually applied to behavior classification in tribological research.

2.3 KNN in tribology research

KNN is one of the simplest and most commonly used classification algorithms [12]. It uses the categories of the k nearest samples to determine the appropriate category for a data point. The k value in the KNN is very important for the classification. As the k value increases from small to large, the error rate initially decreases and then increases. Therefore, when determining a batch of samples, there is a critical optimal k value (as shown in Fig. 5). In tribological research, KNN is often used to predict the COF and wear rate [13].

2.4 RF in tribology research

The RF method is a classifier containing multiple decision-makers, which is mainly used to solve classification and regression problems. It can achieve high prediction accuracy with a small amount of calculations, and it is not sensitive to the missing parts of the data (as shown in Fig. 6). First, random sampling with replacement is performed on the original training set to form K training sets. Subsequently, m features are randomly selected for each training set to form K classification models; finally, the best classification is determined through a majority vote. In this way, the RF can generally increase the number of decision trees and overcome the shortcomings of a single decision tree, which is prone to overfitting.

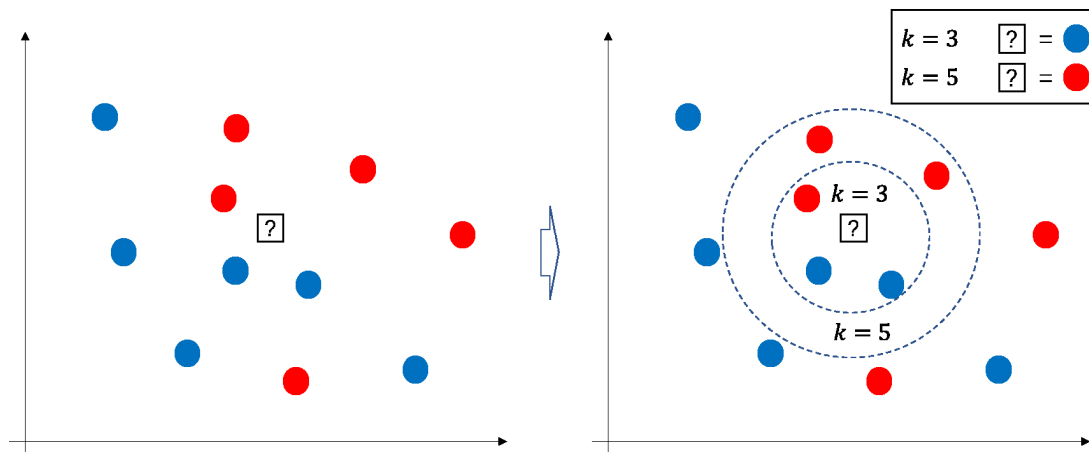


Fig. 5 Simplified schematic of the KNN method.

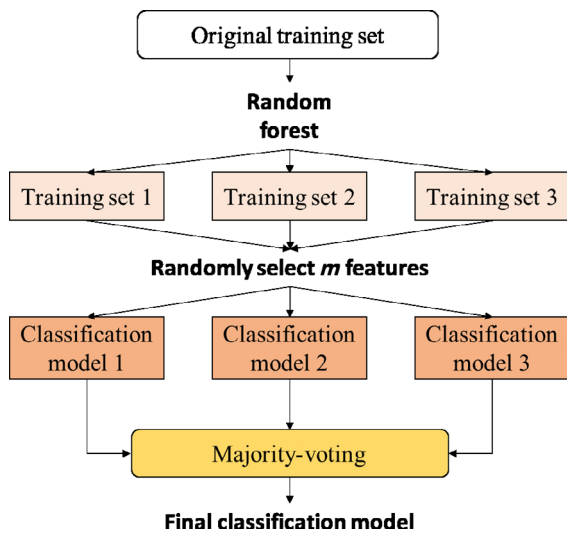


Fig. 6 Simplified schematic of the RF method.

Applying RF to tribological research can easily predict tool wear [14, 15], COFs, and wear rates [13, 16].

3 Application of the tribo-informatics approach in tribology

For the purposes of tribological research, the applications of tribo-informatics can be divided into three main categories: tribological status monitoring, tribological behavior prediction, and tribological system optimization. In this section, the specific operation procedures for each application purpose are discussed in detail. In addition, the application of tribo-informatics approaches is described in the form of a framework. It should be noted that tribo-informatics approaches are not a simple application

of informatics methods to tribological problems. Rather, they are essentially methods driven by data and model collaboration. The tribological physical model can assist informatics methods in completing more accurate and reliable calculations.

3.1 Condition monitoring of tribological systems

State monitoring of a tribological system mainly refers to the use of by-product information of the tribological system to monitor the friction state (as shown in Fig. 7). Condition monitoring of a tribological system plays an essential role in the real-time diagnosis of faults and maintenance of the system. For example, the working state of a bearing can be evaluated based on the state of the friction force and the friction torque of the bearing using RF, gradient boosting classifier (GBC), and extra tree classifier (ETC) methods [17, 18]. Easy-to-observe system state variables, such as images, sound pressure, temperature, lubricating oil quality, and vibration, are often used to monitor tribological variables that are not easy to measure, such as wear, friction, and lubrication.

3.1.1 Wear status monitoring

Abrasion is the factor that most directly affects the performance of mechanical systems. Changes in the state of abrasion usually lead to abnormalities in sound [19], image, and vibration signals [20]. In addition, analyzing the abrasive particles can also provide status information regarding the wear behavior. Wear state monitoring is mainly divided into the wear monitoring of machining and functional parts.

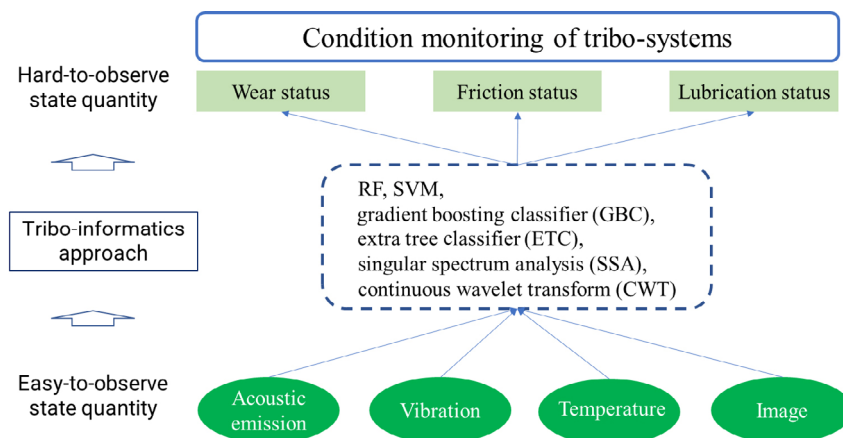


Fig. 7 Application of tribo-informatics approaches in tribological condition monitoring.

(1) Wear monitoring of machining parts

In wear status monitoring, tool wear monitoring is a widespread application that determines the quality and efficiency of processing. If the tool status can be monitored in real-time, the tool repair and replacement times can be accurately selected. Sound pressure, images, and vibration signals have all been used to monitor tool wear. For instance, the SVM learning model can be used to determine the relationship between the sound domain signal and tool wear phenomena [21]. Expanding the regularized particle filtering technique can reduce errors caused by pure data processing [22], which is referred to as a semi-physical model. Advanced machine learning methods with multi-feature multi-model ensembles and dynamic smoothing schemes can also be used to monitor tool wear [23]. Using pseudo-local singular spectrum analysis (SSA) to process vibration signals is also an excellent way to monitor tool wear [24].

In existing research, the status monitoring of tool wear has mostly been qualitative in nature. Therefore, the use of decision-making algorithms can provide improved efficiency.

(2) Wear monitoring of functional parts

Wear behavior is present in the movable connection parts in a mechanical system, and thus wear status monitoring can provide a reference for the working quality and remaining life of the mechanical system. Chang et al. [25] proposed a method for evaluating the degree of wear combined with image data sets. Acoustic emission is an essential technology for monitoring wear conditions, and it can be used to distinguish wear conditions such as running-in, inadequate lubrication, and particle-contaminated oil [26, 27]. Using continuous wavelet transform (CWT) and SVM as classifiers is also an effective method for monitoring wear status [28]. Moreover, the shape characteristics of wear particles can also reflect the wear state. The radial concave deviation (RCD) method has thus been used to elucidate the relationship between the structure of wear particles and the wear state [29, 30].

3.1.2 Friction status monitoring

Friction state monitoring can be divided into the monitoring of friction forms and the monitoring of

friction characteristic quantities (such as the friction force and friction torque). At present, there are more monitoring techniques for friction forms than for friction characteristics [28, 31]. Research on friction state monitoring is scarce, but state monitoring of the frictional force or frictional torque is important for high-precision and high-stability mechanical systems, such as aero-engine shaft-bush adjustment mechanisms and satellite attitude control systems (e.g., momentum wheels). As the requirements for the precision and reliability of industrial products increase, friction state monitoring will play a more significant role.

3.1.3 Lubrication status monitoring

Lubrication is an essential factor that affects wear and friction. Therefore, most of the current monitoring of lubrication status is carried out from two perspectives: the friction status [32] and oil status [33]. In general, ANN and linear discriminant analysis (LDA) can be used to classify the lubricants in different states.

3.2 Prediction of tribological system behavior

Predicting the behavior of a tribological system is the best fusion of information technology and tribology (as shown in Fig. 8). This prediction is of great significance for predicting the failure and remaining service life of mechanical systems. The applications of predictions of tribological system behavior generally include cutting processing [34], friction stir welding [35], geological tribology [36–38], and basic tribological research. The following sections summarize the three aspects of wear prediction, friction prediction, and lubrication prediction.

3.2.1 Wear prediction

In the study of tribo-systems, most researchers have focused on the damage caused by friction to mechanical parts, and most of this damage is caused by wear. Therefore, wear prediction accounts for a considerable proportion of the existing research. Wear prediction mainly includes two categories: quantitative analysis of wear and classification of wear behavior. Quantitative analysis is mainly used to predict the wear rate, wear amount, etc., whereas behavior prediction is mainly used to predict the wear behavior characteristics.

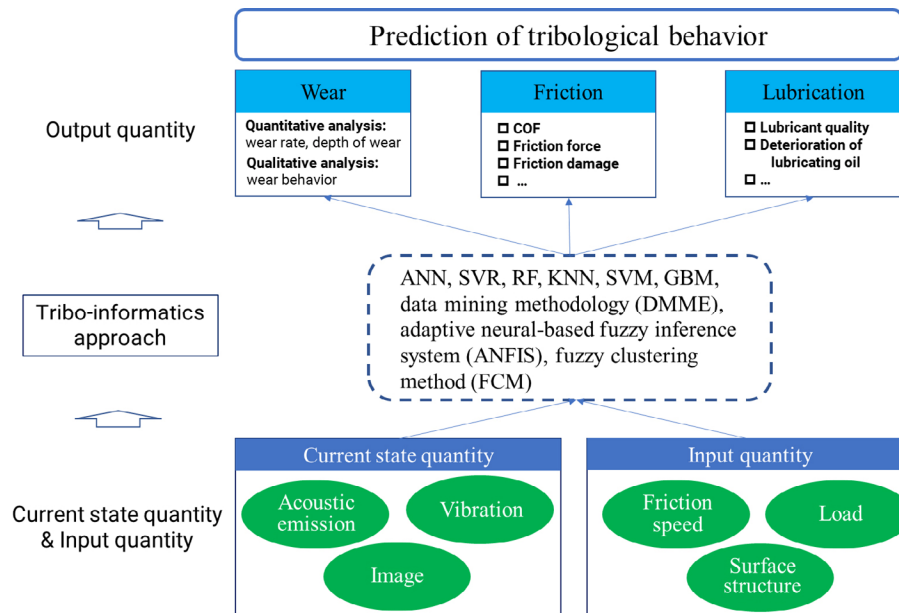


Fig. 8 Application of tribo-informatics approaches for the prediction of tribological behavior.

(1) Quantitative analysis of wear

The quantitative prediction of tool wear mainly involves first collecting a large amount of data and then determining the relationship between the wear amount and time [39–41]. A variety of information technologies can be used in this process, such as ANNs [42–45], support vector regression (SVR) [46, 47], RF methods [14, 15], and the adapted data mining methodology (DMME) [48, 49]. Generally, the process of applying artificial intelligence and machine learning to wear prediction involves using the neural network method to learn from the data, genetic programming to determine the mathematical expression for the wear amount, and a fuzzy inference system to impose rules with physical meaning [50].

Most quantitative research on wear is based on tool wear [23, 42, 51], and machine learning methods have been used to process large amounts of test data to predict the wear rates [52, 53]. At the same time, some quantitative wear analyses aim to elucidate the impact of different materials on the wear. For example, the influence of composite materials [54, 55], biological friction materials [56], and materials with different surface textures on the amount of wear can be investigated using machine learning methods. Hasan et al. [13, 16] compared five different machine learning algorithms, including KNN, SVM, ANN, RF, and gradient boosting machine (GBM), which is

instructive for the application of machine learning methods to tribological problems. They found that GBM was more suitable for predicting tribological behavior, whereas RF was more suitable for predicting wear behavior.

(2) Classification of wear behaviors

Wear behavior is a qualitative state that must be distinguished. It is related to many factors, including the material processing parameters, material composition [57], working conditions, lubrication conditions [58, 59], etc. [60]. To predict wear behavior, it is usually necessary to use clustering, decision-making, fuzzy inference, and other processing methods, such as the ANN approach, adaptive neural-based fuzzy inference system (ANFIS) technique, and the fuzzy clustering method (FCM) [61].

Generally, the determination of the wear behavior state requires the involvement of physical rules. Therefore, combining ANN models, belief rule-based (BRB) inference models, and evidential reasoning (ER) rule models can better identify wear problems [62].

3.2.2 Friction prediction

In cutting work, information technology can predict the cutting force, which is related to the cutting parameters, tool geometry, and tool wear conditions. Therefore, friction prediction is related to the condition monitoring system. The condition monitoring system

inputs parameters to the prediction model, and then establishes the intelligent friction prediction model using deep neural network (DNN) [34] and SVR methods [63]. In addition to tool friction prediction, friction prediction generally includes friction damage [64] and friction prediction during machining [65, 66].

In addition to friction, predicting COFs is of great significance for the operation of tribo-systems, such as the COF of coatings [48, 67, 68], pipe friction coefficients [69–71], and automobile friction coefficients [72]. The COF is a critical indicator in tribology for measuring the advantages and disadvantages of tribological components. The realization of accurate COF predictions can be used not only to evaluate the future functional status of the tribological system but also to guide the selection of pre-preparation processes. The DNN method plays a significant role in predicting COFs [13, 16, 52].

3.2.3 Lubrication prediction

Prediction of the lubrication performance generally involves analyzing the relationship between the surface lubrication performance and surface characteristics (roughness, surface texture, etc.) [73, 74], the evolution of the lubricant performance [75], and life prediction [76]. Prediction of the lubrication performance plays a vital role in the optimization of tribological systems.

3.3 Tribological system optimization

The optimization of a tribological system is a method to improve the operational performance of the tribological system based on predicting the tribological behavior (as shown in Fig. 9). This can be deduced from the

composition of the tribological system. Optimization of a tribological system can be implemented from three perspectives: optimization of the tribo-pair materials, optimization of the lubricant, and optimization of the working conditions. Artificial intelligence and machine learning methods have played a considerable role in this direction by improving design efficiency and reducing design costs. It should be noted that tribological system optimization is usually a systematic engineering problem, and thus the optimization should be performed comprehensively by considering three aspects: tribo-pairs, lubricants, and working conditions.

3.3.1 Optimization of tribo-pairs

The optimization of tribo-pairs can be divided into three research directions: surface texture design, material design, and material selection.

(1) Surface texture optimization

By measuring the friction results under different surface texture modification conditions, artificial intelligence methods can be used to evaluate the impact of the manufacturing process on friction, and the results can be applied to control the friction phenomena by designing surface textures with different parameters [77–79]. When the preparation process or surface texture design is reversed from the expected friction state, the tribological system is optimized [80, 81].

(2) Surface material optimization

Both the design of the composite material [82–84] and the parameters of the carburizing and nitriding processes [85] can be optimized using the ANN

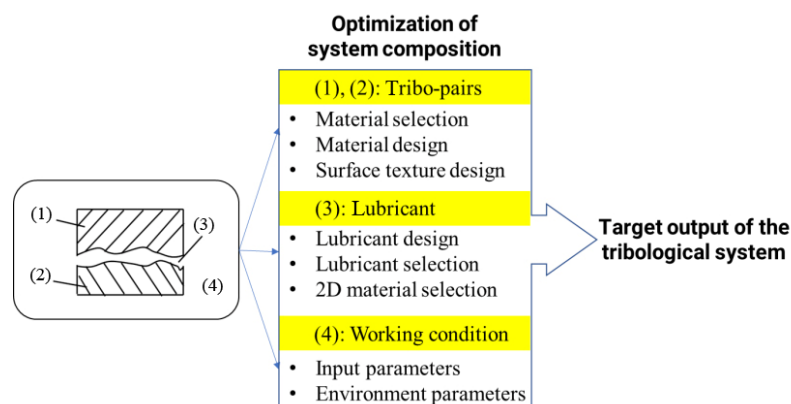


Fig. 9 Optimization of a tribological system.

method. The design of the material comprises only two aspects that can be changed: the composition of the material and the structure of the material (achieved mainly by changing the process parameters) [86].

(3) Surface material selection

Rather than design new tribo-pair materials, it is more common in engineering to select suitable materials to complete specific tribological tasks. This requires engineers to have the ability to screen specific materials from a large number of candidates, and information technology provides this ability. Luo et al. [87] established a database of industrial tribological coatings, and the performance of these coatings was evaluated through simple tests and then screened according to actual engineering requirements. Decision tree-based models play an essential role in the material screening process, as these models can support the high-throughput screening of materials to be selected [88, 89].

3.3.2 Optimization of the lubricant

Lubricants generally have the effect of reducing friction and wear. Designing or selecting a suitable lubricant is crucial for the optimization of the tribological system. The optimization of lubricants is mainly divided into the synthesis of new lubricants [90, 91] and the allocation of lubricant ratios [92, 93]. With the development of two-dimensional (2D) materials, the screening of 2D materials has also become an essential aspect of lubricant material optimization.

3.3.3 Design of the working conditions

The input parameters of the tribological system (such as the sliding speed and load) [94, 95] and environmental conditions in the tribological system (such as the temperature and humidity) [96, 97] will

affect the output of the tribological system. To obtain the target output, it is sometimes necessary to design reasonable working conditions to realize the optimization of the tribological system.

4 Typical application scenarios of tribo-informatics approaches

Tribo-informatics approaches have many application scenarios in the field of tribology. Among these applications, some typical scenarios can be identified. A summary of the successful application of tribo-informatics approaches in these typical scenarios can provide a reference for the comprehensive integration of tribology and informatics in the future. Based on an analysis of a large amount of literature, three typical tribological informatics application scenarios can be summarized: the cutting process, friction stir welding, and wear analysis based on ferrographs. Tribo-informatics approaches have played a significant role in these scenarios and have processed more than one type of tribology information. In a sense, tribo-informatics approaches have changed the research framework of these scenarios and promoted the iterative upgrading of additional tribological research methods in the future.

4.1 Cutting process

Cutting is an important machining process, and it is also a very complex nonlinear process [34]. To ensure a stable and reliable machining quality, it is necessary to monitor and analyze the cutting parameters, cutting force, tool wear, and other parameters (as shown in Fig. 10). The cutting force can reflect the state of the surface processing, and it also affects the tool



Fig. 10 Applications of tribo-informatics approaches in the cutting process.

life, processing roughness, and surface geometry [98]. Tool wear significantly affects the machined surface texture, tool life, and machining costs. Selecting suitable initial settings of the cutting parameters is an important method for optimizing the cutting process. Reasonable settings can effectively improve the tool wear and prepare target surfaces.

4.1.1 Cutting force prediction

Precise cutting force prediction can provide an important reference for computer numerical control (CNC) machining [99]. It is difficult to capture the complex and changeable processing conditions using basic theoretical modeling, and thus it is difficult for the accuracy of these approaches to meet the requirements of engineering applications. To solve this problem, Xu et al. [100] proposed a cutting force prediction model called “ForceNet,” which combined basic physical properties into a structured neural network. Hao et al. [101] proposed a relatively complete model based on ANN, which used the cutting speed, feed rate, depth of cut, and tool inclination along with outputs of the thrust, radial force, and main cutting force as inputs to predict the cutting force in the cutting process. Jurkovic et al. [102] compared three different machine learning methods (SVR, ANN, and polynomial (quadratic) regression) to predict the cutting force, roughness, and tool life, and the results showed that polynomial (quadratic) regression was superior to SVR and ANN for predicting the cutting force. These studies also show that for prediction of the same tribological quantity, multiple tribo-informatics methods can be used. However, the same tribo-informatics approach has different calculation efficiencies and accuracies for the monitoring and prediction of different tribological quantities. For example, ANNs can obtain complex nonlinear relationships but require many parameters. KNN is suitable for the automatic classification of class domains with a relatively large sample size, but it is very computationally intensive. RF can solve some over-fitting problems, but it is not suitable for dealing with noisy sample sets. Therefore, to balance efficiency and accuracy, it is necessary to classify different tribological problems and select appropriate tribo-informatics methods.

The monitoring of the cutting force also plays an important role in the prediction and suppression of machining chatter. Peng et al. [103] proposed a new method based on a dynamic cutting force simulation model and SVM, which could predict machining chatter.

4.1.2 Tool wear prediction

Tool wear prediction is an important basis for evaluating the cutting tool life and machining quality. Tool wear prediction mainly includes data-driven modeling and physics-based modeling methods [44, 104–107]. Tool wear can be predicted by analyzing various signals such as the cutting force, acoustic emissions, temperature [108], and vibration [109, 110]. Gouarir et al. [42] proposed a tool wear process prediction system that used the cutting force to reflect the tool-side wear status and a convolutional neural network (CNN) to predict tool wear; the method was verified based on milling experiments. Thangarasu et al. [111] used the cutting force and surface roughness as inputs and predicted the flank wear of a cutting tool using the ANN method. Subsequently, EN8 steel was used as the cutting material, and different cutting depths and cutting speeds were set to verify the accuracy of the model. Kong et al. [112] presented a tool wear predictive model based on the integrated radial basis function-based kernel principal component analysis (KPCA_IRBF) and relevance vector machine (RVM), which could improve the prediction accuracy compared to traditional prediction methods such as partial least squares regression (PLSR), ANN, and SVM.

Image processing of tool wear marks is another important method for tool wear prediction. This method is representative of non-contact measurement methods. Bergs et al. [113] proposed a deep learning method for image processing, in which the wear state of the tool could be quantified through wear images. Generally, the analysis of wear images is only used as a qualitative analysis of wear status, and the quantification of wear images will be affected by many factors, including pixels, lighting conditions, and material composition differences. With the improvement in image noise reduction and feature value selection methods, wear images will play an increasingly important role.

4.2 Friction stir welding

Friction is an inevitable product of the cutting process. In contrast, friction is a necessary condition for the process of friction stir welding. Friction stir welding is used for welding between workpieces, and thus the prediction and optimization of the welding quality are the main objectives of the application of tribo-informatics methods (as shown in Fig. 11). Many machine learning methods have been used to predict the welding quality of friction stir welding, including ANN [114], regression models (RSM), SVM [115], and ANFIS [116–118]. In the welding process, the required process parameters may affect the welding quality [119–122], and achieving accurate prediction of the welding quality as a multi-objective welding optimization problem provides the basis for these parameters [97, 123].

To predict and optimize the welding quality, it is necessary to obtain the relationship between input quantities (such as the welding speed, rotation speed, cutting depth, and tool type), state quantities (such as welding vibration, sounds, and images), and output quantities (such as the tensile strength, yield strength, hardness, and residual stress) [119, 124]. Friction stir welding is a complex tribological process with many input, output, and state quantities. The purpose of the tribo-informatics approach is to obtain the relationship between several tribological system quantities, and thus it is widely used in friction stir welding.

4.2.1 Welding quality prediction

Because welding quality comprises multiple evaluation indicators, welding quality predictions are mostly used to study the relationship between certain input quantities and output quantities. For example, Verma et al. [126] regraded the speed and feed rate as input variables with the ultimate tensile strength as the output variable to predict the welding quality using ANN, M5P tree regression, and RF. RF was found to be a more suitable algorithm for predicting the quality of joint welding. Das et al. [127] used real-time torque signals to monitor the friction stir welding process, and predicted internal defects in the process. SVR, ANN, and general regression methods were used together, and SVR showed better prediction performance than the other two methods. Mishra et al. [128] used the tool rotation speed, axial force, and welding speed as inputs to the ANN method to predict the corrosion resistance of welded parts. When the quality evaluation index of friction stir welding is changed, more algorithm models will be available to predict the welding quality.

4.2.2 Welding quality optimization

Welding quality optimization is a method to enable proper design of input quantities based on the relationship between the input quantity and output quantity to achieve the target welding quality [116]. Tansel et al. [129] developed a genetically optimized neural network system (GONNS) for intelligent

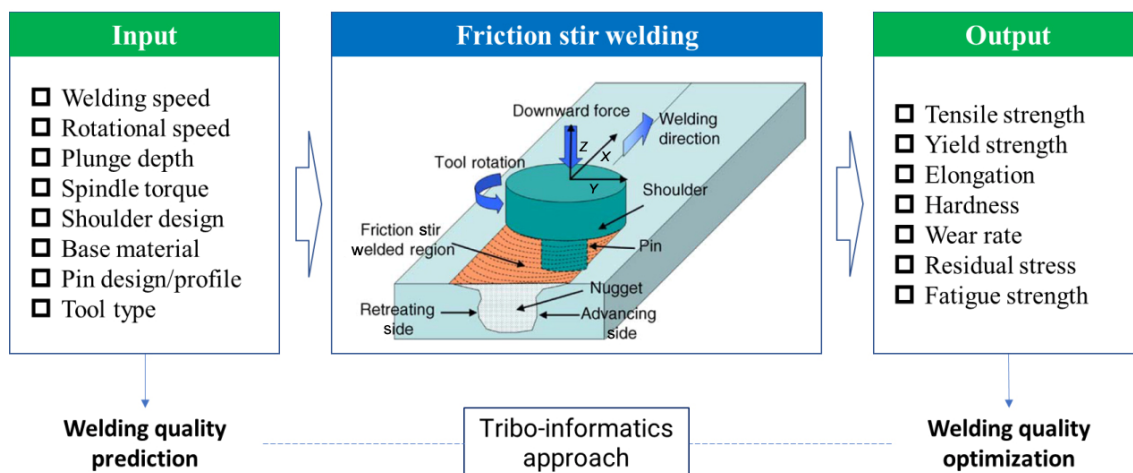


Fig. 11 Applications of tribo-informatics approaches in friction stir welding [119, 125]. Reproduced with permission from Ref. [119], © The Korean Institute of Metals and Materials 2020; Ref. [125], © Elsevier B.V. 2005.

decision-making, and applied it to estimate the best operating conditions for friction stir welding. Mishra et al. [130] used regression algorithms based on supervised learning, such as RF, decision tree, and gradient regression algorithms, to obtain a set of process parameters that yielded the best welding mechanical performance, which were verified experimentally.

4.3 Wear analysis based on ferrographs

Ferro-spectrometry is a new type of wear test method that uses a magnetic force to separate the metal particles in oil and arrange them on a substrate according to the size of the particles. Using this method, researchers can obtain the particle concentration in the oil and the micro-mechanical properties of the wear particles (as shown in Fig. 12). This technology is thus of great significance for wear testing and analysis [131–134].

The application of tribo-informatics approaches can improve the efficiency of particle detection, recognition, and classification in ferro-spectrometry. Peng et al. [135] developed an algorithm model for automatic wear particle detection and classification that improved the analysis efficiency of ferro-spectrometry; an ANN was used for particle detection and recognition, and SVM was used for particle classification. Wang et al. [136] developed a CNN method to classify seven types of ferrograph images,

and the proposed method could be used to determine the severity of wear with an accuracy of 90%. In the actual use of ferrographs, problems such as unclear ferrograph images and a low data collection frequency of the ferrograph may be encountered, which will affect the accuracy and real-time performance of the wear monitoring. Wu et al. [137] used a CNN with a larger convolution kernel to build a degradation model, which reduced the effect of defocus blur in the ferrograph imaging process. To realize the real-time monitoring of the wear state and amplify the amount of ferrograph image data, Nugraha et al. [138] used a data-driven method based on Gaussian process regression approximation to analyze the data, reasonably increase the sample size, and predict the wear based on the larger sample size.

4.4 Other important application scenarios

The friction informatics method also has some important applications in other scenarios, such as the identification of surface friction damage and material processing. Shevchik et al. [139] collected an acoustic data set during the reciprocating motion of bearing metal friction pairs, and used RF methods to predict three friction states: the running-in, steady state, and wear stages. Xiao and Zhu [140] used the ANN method to optimize the friction material formula, and processed a non-asbestos organic friction material containing 16

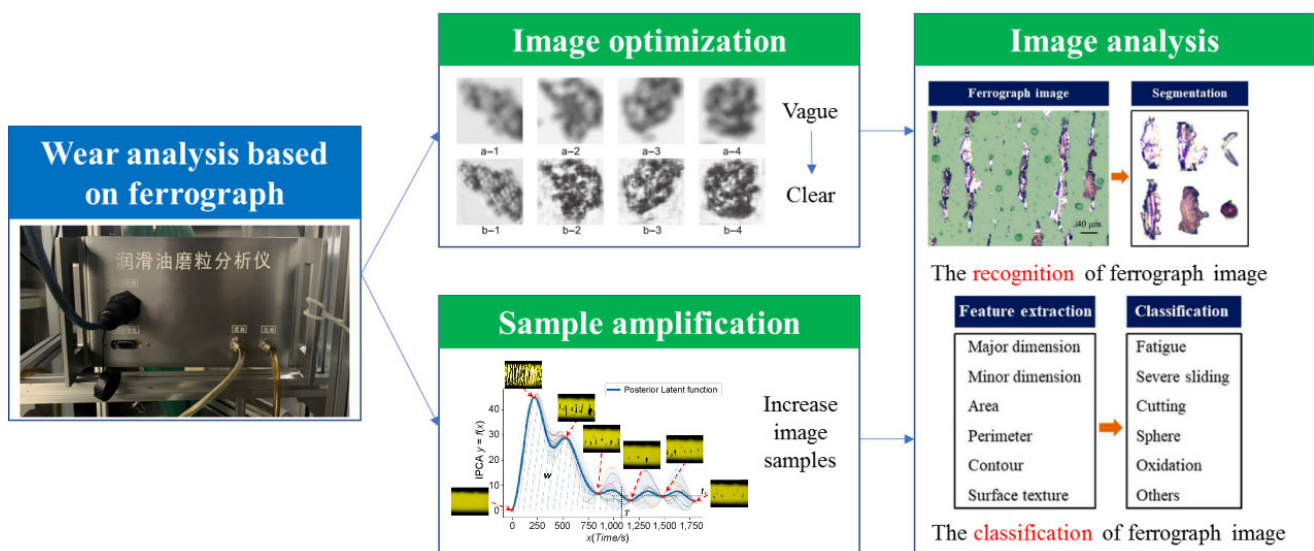


Fig. 12 Applications of tribo-informatics approaches in wear analysis [135, 137, 138]. Reproduced with permission from Ref. [135], © Elsevier Ltd. 2020; Ref. [137], © Elsevier B.V. 2018; Ref. [138], © Elsevier Ltd. 2021.

ingredients. Zhang et al. [141] used machine learning algorithms to predict the band gap of a given 2D material rapidly and accurately, which promoted the application of these materials in the field of semiconductor devices.

In other words, tribo-informatics approaches can be used in many aspects of tribology, such as manufacturing, lubricants, material processing, surface engineering, and drive technology [142]. However, it should be noted that the application of tribo-informatics approaches in these tribological fields is not very systematic. For a certain tribological problem, it is necessary to establish a complete informatics solution from all aspects of condition monitoring, behavior prediction, and system optimization.

5 Outlook and conclusions

5.1 Limitations and outlook

5.1.1 Current application limitations

Informatics methods can easily calculate the relationships between tribological quantities and realize the purposes of tribological state monitoring, behavior prediction, and system optimization. To date, informatics methods have been applied to tribological problems in different fields, such as industrial tribology, lubrication, bio-tribology, friction processing, and geo-tribology. These methods use acoustic, image, vibration, thermal, electrical, and other signals generated by friction to analyze various problems in tribology. These methods can predict the life of the tribological system, monitor the health of the tribological system at any time, and discover new relationships between the physical quantities in tribology. However, tribo-informatics is a complete research direction, not the application of informatics methods to a certain tribological problem. At present, these informatics methods have some limitations in solving practical problems.

1) The tribological system model is rarely considered in the application of informatics methods. This is also why it is currently difficult to integrate informatics and tribology deeply. Tribology is a systematic, multi-disciplinary coupling that is time-dependent, and the relationship between two particular physical quantities

cannot reveal the operating law of the entire system. For this reason, the concept and architecture of tribo-informatics have been proposed [5], and the application of tribo-informatics methods in practical problems should also consider the input, output, and state quantities of the tribological system. In addition, the operating rules of the tribological system should be more comprehensively studied.

2) It is difficult to determine the most suitable informatics method for a specific tribological problem. At present, the general process of most tribo-informatics research is to use a selected informatics method for monitoring or prediction, and the obtained results are compared and verified with tribology experiments. The applicability of different tribo-informatics methods to different tribological problems is an important research direction that can help to balance the efficiency and accuracy of friction informatics methods.

5.1.2 Future directions

With the continuous development of information technology, the meaning of tribo-informatics will continue to be enriched in the future. However, tribo-informatics approaches, including regression, classification, clustering, dimensionality reduction, and other methods, still face application challenges.

1) Tribo-informatics framework. Presently, there is no clear framework for the comprehensive integration of tribology and informatics. Therefore, the current application of tribo-informatics approaches in tribological research is relatively random. For example, with respect to tribo-system condition monitoring, there is more research on wear condition monitoring than friction condition monitoring. To enrich the methods of tribo-informatics and expand applications in tribological research, it is necessary to establish a complete concept and framework of tribo-informatics. Then, a comprehensive fusion study should be carried out based on this framework. In the future, a complete tribo-informatics approach should be able to link the input, state, and output of a tribology system based on the tribology information model to obtain more accurate monitoring, prediction, and optimization results.

2) Standardized tribological tests. The tribo-informatics approach requires a large amount of

input data, but non-standard tribological tests will produce a large amount of wasted data and information. Therefore, standards for tribological testing need to be established, which will allow various tribological test data to be reused. For example, if a researcher designs a standardized pin-to-disc test and uses tribo-informatics approaches to study the relationship between wear scar shape and friction, these tribological test data should not be wasted. Ideally, they could be combined with other standardized pin-to-disc tests to study the relationships of vibration, acoustics, and other information with the friction state. This will allow the significance of the tribo-informatics framework to be revealed, and the circulation, reusability, and dissemination of tribological data will be greatly enhanced, thereby improving the efficiency of tribological research.

3) Advanced tribological data collection technology. Sufficient tribological data are the basis of tribo-informatics. Advanced data perception technology is an important method for obtaining tribological data. Electrical signals are one of the easiest signals to measure and analyze. Therefore, it is reasonable to suggest that self-powered sensors based on triboelectric nano-generators (TENGs) [143–145] and intelligent sensing coatings for active tribology [146] will play an important role in data acquisition. After the factors that affect triboelectric signals (such as temperature, humidity, vibration frequency, and material properties) are decoupled, self-powered sensors can provide a very convenient means for tribological data collection.

5.2 Conclusions

This article systematically summarizes the application of information technology, including traditional methods, machine learning methods, and artificial intelligence methods, in the field of tribology. These tribo-informatics methods can be divided into four types based on the application purpose: regression, classification, clustering, and dimensionality reduction.

First, four standard tribology information methods (ANN, SVM, KNN, and RF) are introduced, and their roles in tribological research are discussed. Then, informatics is introduced, mainly focused on the generation, collection, processing, and analysis of information. Tribology is primarily concerned with

condition monitoring, behavior prediction, and system optimization. The two approaches have been cross-integrated in many aspects, resulting in the emerging discipline of “tribo-informatics.” This introduction provides an understanding of the applications of tribological informatics in various fields of tribology. Finally, three typical scenarios of tribo-informatics applications are introduced in detail, and the future development of the tribo-informatics approach is discussed. With the development of tribo-informatics approaches and the improvement of the framework of tribo-informatics, the research efficiency of tribology can be greatly improved.

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