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Enhancing tribological system performance through intelligent data analysis and predictive modeling: A review

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Abstract

The article presents a systematic analysis of the application of information technologies in tribology, including traditional methods, machine learning and artificial intelligence. The main goal of the study is to generalize and classify tribological informatics methods to improve the efficiency of tribological process analysis. The methodology is based on a review of key algorithms (ANN, support vector machines, K-nearest neighbors, random forest methods), determining their role in tribological research and analyzing information aimed at monitoring the technical condition, predicting behavior and optimizing tribological systems. It is determined that the use of artificial intelligence and machine learning algorithms significantly improves the accuracy of tribological system diagnostics, allows predicting their operational life and optimizing the operating parameters of tribological systems and machine mechanisms. A classification of tribological informatics methods is presented according to their functions: regression, classification, clustering, dimensionality reduction. This makes it possible to determine the most effective approaches for different types of tribological analysis. The practical focus of using intelligent modeling methods is the possibility of integrating the obtained results into production processes, which contributes to increasing the reliability of mechanical systems, reducing the costs of their maintenance and creating more accurate methods for predicting tribological characteristics, properties and tribological efficiency of the functioning of system components and assemblies of machines and mechanisms. It is shown that triboinformatics opens up new prospects for improving tribological research, providing more accurate monitoring, effective forecasting and optimization of tribological systems.

Key words: tribological system, technical condition monitoring, modeling and forecasting, friction, wear, artificial intelligence, machine learning.

Introduction

In the course of modern mechanical engineering development, the design of components, assemblies, and mechanisms has become increasingly complex. This trend leads to heightened requirements for their reliability, operational stability, and tribological efficiency. The achievement of enhanced reliability and efficiency in mechanical systems largely depends on tribological systems (TrBS), which integrate frictional components, lubricants, and technological media tailored to operational conditions (Fig. 1) [1-2].

Tribological systems are characterized by intricate dependencies that span subject-specific, temporal, and systemic dimensions. This complexity necessitates the expansion of relevant databases and the development of multi-component theoretical models capable of describing and predicting the behavior of tribological processes. The integration of existing theoretical concepts with experimental data enables the construction of predictive models aimed at optimizing tribological characteristics and enhancing the operational reliability of TrBS.

To improve the effectiveness of research and development, as well as to increase the reliability of tribological systems, it is essential to accelerate information exchange among their components. In this context, the application of modern information technologies is highly advisable, particularly data processing methods, machine learning (ML) techniques, and artificial intelligence (AI) algorithms [3-6]. By leveraging these strategies, researchers can automate the evaluation of tribological data, uncover hidden regularities, and achieve higher fidelity in predictive modeling of wear and friction-related metrics.

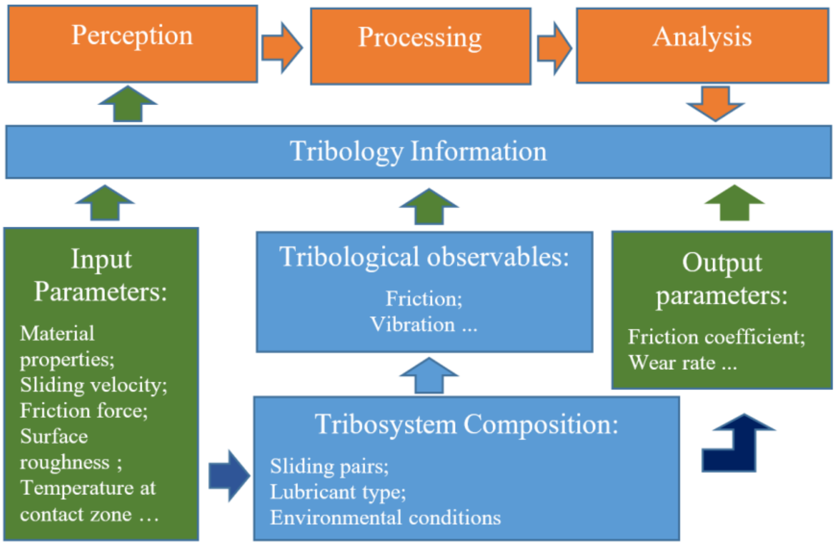

Fig. 1. Components of tribological systems [1]

The incorporation of artificial intelligence techniques alongside triboinformatics significantly enhances the effectiveness of evaluating tribological phenomena, forecasting component wear resistance, and fine-tuning the operational parameters of mechanical systems and assemblies. Advanced data analysis approaches enable the development of intelligent tribological systems with adaptive capabilities, including self-regulation, autonomous organization, and continuous improvement based on real-time wear diagnostics. Such functionality is critically important for ensuring the operational reliability of tribological systems [6]. Furthermore, the evolution of triboinformatics combined with AI-driven methodologies opens new avenues for improving the durability and performance of mechanical structures, which remains a key priority in modern engineering practice [7].

Literature review

Tribo-informatics has emerged as a pivotal interdisciplinary domain within tribology, aimed at formalizing research processes, constructing structured databases, and applying advanced information technologies for the acquisition, classification, storage, retrieval, analysis, and dissemination of tribological data [1]. This approach addresses the growing complexity and volume of tribological information, which often spans multiple disciplines and formats.

Modern tribo-informatics encompasses a broad spectrum of analytical functions, with regression modeling and classification techniques being among the most widely utilized [3]. The core objectives of this field include:

Condition monitoring: systematic collection of operational data related to wear, degradation, and performance of mechanical components [8]

Behavioral prediction: development of models capable of forecasting changes in tribological performance over time and under varying operational conditions [9];

System optimization: identification of parameter configurations that ensure maximal reliability and efficiency of tribological systems [10].

A critical challenge in tribo-informatics lies in establishing robust and time-sensitive correlations between tribological parameters and operational dynamics. This necessitates the integration of predictive modeling techniques and the deployment of intelligent monitoring algorithms [11].

Traditional data analysis methods in tribology often lack the flexibility and precision required to adapt to evolving operational environments. Consequently, the incorporation of AI and ML techniques is increasingly recognized as a promising strategy for enhancing the adaptability and predictive capabilities of tribological data systems [12].

The application of artificial intelligence technologies offers effective tools for addressing key challenges in tribological informatics [13–16]. Among the most promising directions are:

1. Optimization of tribological process dynamics in technical mechanical systems (TMS): Machine learning techniques enable the identification of optimal operating regimes and the selection of appropriate lubricants, which leads to reduced energy consumption and extended service life of mechanical components and assemblies.

2.- Intelligent processing and management of tribological data: AI-based systems facilitate the analysis of both structured and unstructured tribological datasets, support automated classification, and enhance the integrity and reliability of information repositories. These capabilities are essential for the development of advanced tribological materials and technologies.

3. Adaptive modeling and prediction of wear in tribological contacts (TC): The implementation of deep learning architectures allows for the simulation of wear behavior under variable operational conditions. This creates opportunities for dynamic adjustment of system parameters, contributing to improved performance and predictive maintenance of mechanical systems.

The contemporary evolution of tribology increasingly emphasizes the integration of information technologies, particularly AI algorithms, to enable joint management of databases and mathematical models of tribological processes [1-2]. This paradigm shift opens new avenues for predicting the behavior of TC and optimizing their performance. The inherent capabilities of AI systems – such as self-learning and real-time adaptation – facilitate the development of intelligent tribological solutions capable of responding dynamically to changing operational conditions [6-8].

A review of current literature reveals that the application of AI within tribo-informatics significantly enhances automation, improves data processing efficiency, and contributes to increased reliability and wear resistance of mechanical systems. Moreover, it enables cost-effective engineering design and accelerates the development of innovative solutions [3-5]. Despite these advancements, several unresolved challenges persist.

One of the primary difficulties lies in the fragmented and complex interdependencies among tribological parameters, material properties, loading conditions, and thermal regimes. These factors interact in a nonlinear manner, complicating the construction of accurate predictive models for tribosystem behavior [9-10]. Additionally, most existing diagnostic approaches rely heavily on empirical methods, which demand extensive experimental datasets. This reliance limits the adaptability of tribological solutions to novel operating environments and increases the overall cost of research and development [4, 17, 18].

To address these limitations, AI-driven modeling of tribological elements and systems presents a promising direction. One such approach involves the implementation of Digital Twins (DT) – virtual replicas of physical systems that simulate operational behavior under varying load conditions [19]. The integration of engineering simulation software (e.g., ANSYS) with machine learning algorithms enables predictive analysis of wear, load distribution, and structural optimization, thereby enhancing the functional efficiency of mechanical assemblies [20-21].

Another innovative strategy involves the use of generative adversarial networks (GANs), which can synthesize new operational scenarios by modeling the behavior of tribological materials under dynamic conditions. This technique is particularly valuable for the formulation of advanced lubricants and the determination of optimal operating regimes for machinery [5, 8, 22].

The Python programming language plays a pivotal role in the realization of such models, offering a robust ecosystem of libraries tailored for scientific computing and AI development [23]:

– TensorFlow and PyTorch are employed to construct neural networks that analyze extensive tribological datasets and forecast the behavior of components and assemblies [24-25].

– SciPy and NumPy support mathematical modeling, enabling the computation of complex relationships among system parameters and the optimization of operating conditions [26].

– Matplotlib and Seaborn facilitate the visualization of simulation results, thereby improving the interpretability of tribological analyses [22, 27].

The integration of these tools fosters the creation of adaptive tribological systems capable of autonomously adjusting their performance in response to real-time operational inputs. This advancement holds significant promise for mechanical engineering, production optimization, and the deployment of automated manufacturing lines [13-14,16, 23].

Purpose

The purpose of this work is to justify the choice of intelligent methods for modeling and adapting the functioning of the TrBS to changing environmental conditions using AI methods. To achieve the goal, the following tasks were used in the work:

1. To analyze current problems of tribology and triboinformatics:

- to outline the main unresolved issues in the field of tribology, in particular, modeling of friction, wear, and lubrication processes, optimization of triboelements and TrBS, and forecasting their technical condition;

- to consider the possibilities of using digital technologies for analyzing tribological data.

2. To clarify the conditions and effectiveness of implementing digital analogues of DT in tribological research:

- to analyze the concept of DT for simulating the operation of TrBS, machines, and mechanisms in various conditions;

- to determine the methods for modeling tribological processes in ANSYS and their combination with Python algorithms to improve analysis using AI methods.

Methods

TrBS embedded in machines, mechanisms, and production lines perform essential functions such as the transmission of motion, energy, and information, as well as the redistribution of stress and strain within triboelement materials. These processes enhance the reliability of mechanical systems and facilitate effective interaction between components [1, 2, 21]. One of the primary objectives in managing tribological system databases is to enable predictive diagnostics and condition-based monitoring of assemblies and units, thereby supporting efficient control of tribological processes [3, 4, 13]. As a cybernetic system, TrBS have output factors and parameters that describe their technical condition and behavior. Such signals include tribological parameters that can act as target output data. For example, in the case of a bearing, the output signal is the moment of motion, and the input signals can be the characteristics of the material of its elements, lubrication modes, and methods of treating friction surfaces. The main parameters of the TrBS state include stress, friction, vibration, wear, and heat generated in the contact zone of parts in the friction zone [28-29]. Tribological informatics employs a diverse array of techniques for gathering, processing, and interpreting tribological data. Conventional methods include statistical tools such as Gaussian regression, linear regression, and the least squares approach [5–6]. However, modern technologies actively use machine learning algorithms, which significantly expand the possibilities of predicting the tribological behavior of machines and mechanisms and optimizing their characteristics [30-31]. It is worth noting that AI methods are products of machine learning and allow for accurate analysis of complex processes in the TrBS [32-33]. One of the key tasks of tribological informatics is to establish the relationship between the elements, factors and parameters of the TrBS. In this regard, such areas of research as monitoring the technical condition, predicting the behavior of the Tribological System and optimizing their operation are considered [34-35]. Monitoring involves the analysis of the current characteristics of the system, which can be both observable and hidden [36]. Forecasting allows you to determine the dependencies between the input parameters, their changes over time and possible future states of the TrBS [37]. Optimization of tribological processes, in turn, is aimed at finding the best operating conditions for machines and mechanisms to ensure their durability and efficiency [38].

In practice, the processing of tribological information should be based on physical models and fundamental principles of tribology. This provides a deep integration between computer science and tribology, allowing data analysis to be carried out on the basis of the constructed tribological models. It is important that each characteristic parameter has a physical meaning, and its processing is based on the principles of contact interaction mechanics [39]. To increase the efficiency of tribological research, modern data collection technologies are used. The use of sensor systems allows you to register key factors and parameters of the operation of tribological units, systems and assemblies, in particular, temperature, friction force, speed of movement and level of wear [40]. Integration of IoT technologies allows you to combine devices for registering tribological factors and parameters in real time[22-23]. In addition, optical analysis methods using high-precision cameras and microscopes allow you to obtain detailed images of the surface structure after the operation of Tribological Units, machines and mechanisms [24]. The processing of the obtained data is carried out using machine learning algorithms, such as neural networks and clustering. These methods contribute to structuring data, removing noise and identifying key factors that affect the efficiency of the operation of Tribological Units [25-26]. Identifying patterns in changes in factors and parameters of the technical condition helps to create accurate predictive models that provide prediction of the service life of system and assembly units and determine the optimal conditions for their operation [27, 35]. Modern methods of tribological data analysis can be classified according to their purpose. In this case, regression analysis allows to determine quantitative dependencies between the parameters of the TrBS [28, 30]. Database classification helps to identify characteristic types of tribological behavior [31, 36], and clustering groups similar tribological phenomena and helps to find new patterns [32, 33]. Methods of data dimensionality reduction are used to optimize the information array, which improves the accuracy of research [34]. The most effective methods of tribological database analysis include ANNs, which are able to process large amounts of information and increase the accuracy of prediction [29, 37]. Support vector machines (SVMs) are used for binary classification of tribological parameters [38], and the K-nearest neighbors (KNN) and random forest (Random Forest - RF) methods are effective for clustering tribological phenomena and analyzing their features [39, 40]. ANNs consist of a set of node connections and demonstrate high efficiency in the field of AI and tribology. Their structure includes three main blocks:

- input block, which receives data from the external environment;
- hidden block, which performs internal information processing;
- output block, which generates results based on the analysis of input data [28, 29].

In tribological studies, input parameters can be speed and load, and output parameters can be friction, wear and lubrication modes. In addition, easily observable signals, such as acoustic oscillations, electrical characteristics or vibrations, can be used to predict difficult-to-observe quantities, in particular the coefficient of friction (CoF) or the wear rate of the material [30, 31].

It is substantiated that the integration of machine learning methods and intelligent data analysis in triboinformatics significantly improves the accuracy of wear prediction, optimizes the operating parameters of the Tribological Devices and contributes to the development of new tribological models [32-33]. The use of modern data processing algorithms allows the creation of adaptive Tribological Devices capable of self-learning and automatic adjustment of operating parameters [34-35]. In many cases, it is quite difficult to determine the most significant characteristic parameters only on the basis of classical tribology models. Therefore, there is a need to analyze the relationships between several characteristic factors and parameters that affect the Tribology. For this, correlation methods are used that allow determining the optimal factors and parameters of tribological characteristics and properties of triboelements and Tribology as a whole [36-37]. The obtained data can be used to create new tribological models or refine existing principles, which ensures more effective optimization of tribological processes and the functioning of components and assemblies of machines and mechanisms (Fig. 2).

Fig. 2. Classification of tribo-informatics technologies by purpose

Tribological informatics technologies can be classified according to their main purpose:

- regression analysis – used to establish quantitative relationships between parameters of tribological systems;
- classification – allows you to determine characteristic types of tribological behavior of mechanisms;
- clustering – helps group similar tribological phenomena and discover new patterns;
- dimensionality reduction methods – optimize the analysis of large data sets, increasing the accuracy of calculations.

In tribological studies, input factors and parameters can be speed of movement, load and lubrication modes, while output data are friction, wear, temperature and structural changes of surfaces. Additionally, easily observable signals, such as vibration, acoustic or electrical characteristics, can be used to estimate difficult-to-observe parameters, such as CoF or material wear rate

Results

Classification methods are essential components of tribo-informatics, enabling the identification of tribological states, prediction of system behavior, and optimization of operational parameters. Among the most widely used algorithms in tribological research are SVM, KNN, and RF, each offering distinct advantages in terms of accuracy, interpretability, and adaptability to nonlinear data. SVM is a supervised learning algorithm designed for binary classification tasks. Its core principle involves constructing a hyperplane that maximizes the margin between data points of different classes, thereby ensuring robust separation and generalization [30]. In tribological applications, SVM has been successfully used to classify wear regimes, friction states, and lubrication conditions based on acoustic, vibrational, and image-based features [31, 36]. When dealing with non-linearly separable data, SVM employs kernel functions to project input vectors into higher-dimensional spaces, enabling linear separation in transformed domains. This capability is particularly valuable in tribology, where system behavior often exhibits nonlinear dependencies among material properties, operating conditions, and surface interactions [2, 4]. KNN is a non-parametric classification method that assigns class labels based on the majority vote of the k closest training samples. Its simplicity and effectiveness make it a popular choice for tribological diagnostics, especially in scenarios involving limited data and low-dimensional feature spaces [30, 38]. The selection of the parameter k is critical: small values may lead to overfitting, while large values can cause underfitting. Empirical studies have shown that optimal k values vary depending on the complexity of the tribological system and the noise level in the dataset [38]. KNN has been applied to predict coefficients of friction (CoF), wear rates, and lubrication states by analyzing historical data on material composition, load, and sliding velocity [35].

RF is an ensemble learning method that constructs multiple decision trees using random subsets of data and features (Fig. 3). The final prediction is obtained through majority voting (classification) or averaging (regression), which enhances robustness and reduces overfitting [29].

In tribological informatics, RF has demonstrated high accuracy in predicting tool wear, classifying lubrication regimes, and estimating CoF under varying operational conditions. Hasan et al. [28] showed that RF outperformed other models in predicting wear behavior of aluminum–graphite composites. Wu et al. [29] applied RF to tool wear monitoring in manufacturing, achieving reliable classification based on vibration and force signals.

RF also facilitates feature importance analysis, allowing researchers to identify dominant tribological parameters such as reinforcement content, temperature, and surface roughness [39-42]. This interpretability is crucial for engineering decision-making and model validation.

Compared to SVM and KNN, RF offers superior performance in handling high-dimensional, noisy, and nonlinear tribological datasets (Fig. 4). Its ensemble structure mitigates the limitations of single-tree models and provides stable predictions across diverse tribological scenarios [3, 5].

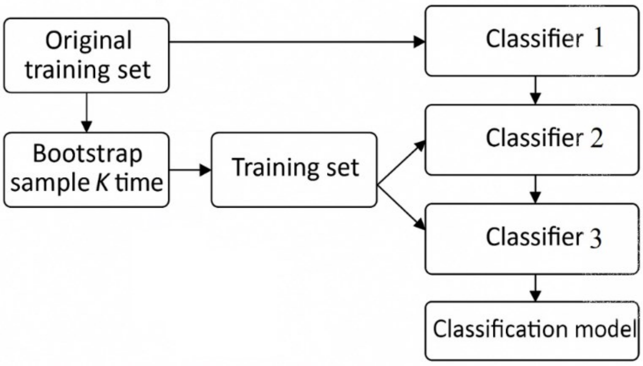

Fig. 3. Simplified diagram of the RF method as a classification algorithm

Algorithm	Task Type	Advantages	Limitations	Typical Use in Tribology
ANN	Regression, Classification	High accuracy, adaptability	Requires large datasets	Wear rate prediction, material optimization [15]
SVM	Classification	Effective with small datasets	Sensitive to kernel selection	Acoustic signal classification, wear stage detection [30]
RF	Classification, Regression	Robust to noise, interpretable	May be slow with large datasets	Friction state prediction, wear pattern analysis [29, 41]

Fig. 4. Comparative analysis of ML algorithms for wear prediction

According to the goals of tribological research, tribological informatics approaches can be classified into three main areas: monitoring the tribological state of the Tribological Functional Region (TFR); predicting the tribological behavior of the TFR; optimizing the TFR [2, 6, 40].

Tribological methods have a structured system and are not a simple adaptation of information technologies to tribological problems. They are based on data analysis and model building. The physical tribological model contributes to the accuracy and reliability of calculations, supporting computer science methods in creating more effective algorithms [1, 3, 8]. Monitoring the condition of friction involves the use of information about the accompanying friction processes to analyze the condition of components, systems, machine units and mechanisms [13, 14, 31]. Monitoring the technical condition of tribological units is an important aspect of real-time fault diagnosis and ensuring the stability of machines and mechanisms [36, 41]. Key parameters that can be observed to determine the condition of the Tribological Units include visual changes, sound pressure, temperature indicators, lubricant quality and vibration characteristics [22, 31, 32]. At the same time, advanced analytical models are used to monitor difficult-to-observe tribological variables, such as wear, friction and lubrication processes. [6, 36].

The use of AI methods in monitoring the technical condition of Tribological Units in real-time mode allows for continuous monitoring of the condition thanks to a set of sensors and data processing algorithms [13, 14, 36]. If the system detects an abnormal increase in temperature or an increase in the level of vibration, this may signal potential problems, such as wear or degradation of the elements of the unit, system or assembly of machines and mechanisms [31, 39]. AI systems provide operational decision-making, which allows preventing breakdowns, minimizing the risks of sudden equipment failure. Early warning systems based on data dynamics analysis predict possible failures or emergencies. This makes it possible to carry out preventive maintenance, which reduces equipment downtime and optimizes resource costs [4, 6, 41]. Research on tribological systems focuses on the analysis of damage to mechanical parts caused by friction, most of which is a consequence of wear processes [5, 10, 35]. Wear prediction can be divided into two main categories:

- quantitative wear analysis - estimates the speed and magnitude of wear [28, 38];
- classification of wear behavior - is used to determine the patterns of wear of machine parts and mechanisms [29, 42].

For quantitative prediction of wear of parts, a large database is first formed, after which the dependence between wear intensity and operating time is analyzed. At this stage, ANN, support vector regression, RF algorithm and adapted data mining methodology (DMME) are used [10, 15, 28, 29].

It should be noted that the gradient boosting algorithm is effective in applying machine learning methods to predict tribological behavior and efficiency of the TBR, while the RF method is more suitable for analyzing wear patterns.

Monitoring of friction processes can be divided into two main areas [38, 41]:

- analysis of the friction shape, which allows assessing geometric changes in surfaces [34, 36];
- control of tribological characteristics, such as friction force and friction torque [18, 20].

In modern research, a significant number of methods for monitoring the form of friction are used, but in-depth analysis of its technical condition remains limited [2, 5]. The assessment of the friction force and its moment is important for high-precision mechanical systems [36, 40].

The friction informatics method has some important applications in other scenarios: identification of damage to friction surfaces, material processing [2, 4]. A set of acoustic data was collected during the reciprocating motion of tribocouplings of parts, a bearing, and the use of RF methods to predict three friction states: running-in; steady state; wear stage [29, 41]. The ANN method was used to optimize the formula of the friction material [15], machine learning algorithms were used to quickly and accurately predict the width of the images of the zone of a given 2D material, which contributed to the application of materials in the field of semiconductor devices [35]. Monitoring the state of wear of machine parts and mechanisms is conventionally divided into:

- monitoring the wear of machined parts;
- monitoring the functional components of the system [13, 14].

Lubrication performance prediction involves analyzing the relationship between the state of the lubricating medium and surface characteristics, such as material roughness and texture. [9, 21]. It also covers the evolution of lubrication performance, which allows predicting the service life of lubricants and optimizing mechanical systems [6, 36]. Analysis of wear processes can be rationally carried out by the method of ferrography and ferrospectrometry. This is a new mechanical wear testing method that uses magnetic separation of metal particles in oil and their placement on a substrate according to particle size. This approach allows for the assessment of the particle concentration in the lubricating medium and the micromechanical properties of wear particles, which contributes to a deeper understanding of wear mechanisms [34]. This technology is an important tool for wear testing and analysis, allowing for detailed tribological studies. The application of triboinformatics approaches can improve the efficiency of particle detection, recognition and classification in ferrospectrometry [2, 10]. An algorithm model for automatic detection and classification of wear particles was developed, which improved the efficiency of ferrospectrometry analysis [6, 31]. ANN was used for particle detection and recognition, and SVM was used for particle classification [30, 32]. A CNN method was developed to classify seven types of ferrograph images. The proposed method can be used to determine the degree of wear with an accuracy of 90% [6, 42]. In the actual use of ferrographs, problems may arise such as fuzzy ferrograph images, which affects the accuracy and fairness, and low ferrograph data acquisition frequency, which affects the accuracy and performance of real-time wear monitoring [42]. A CNN with a large convolution kernel was used to build a degradation model, which reduces the effect of blurring and defocusing in the ferrograph visualization process [6]. In order to realize real-time wear monitoring, the data volume of ferrograph images should be increased. A method based on Gaussian process regression approximation data was used [5]. For data analysis, it is reasonable to increase the sample size and predict wear based on a large sample size [38]. If it is possible to monitor the condition of parts and their mating parts in real time, then it is possible to accurately determine the moment of its replacement or repair. The main signals for such analysis are sound pressure, image and vibration characteristics [22, 31]. Machine learning methods, in particular SVM, are used to establish the relationship between sound signals and wear. Regularized particle filtering helps to reduce errors in the results, providing a more accurate determination of the degree of wear [40]. In this case, the wear behavior is considered as a complex dynamic process that depends on many factors:

- processing parameters of the materials of the mating parts;
- composition and structure of the material of the parts and the lubricating medium;
- operating conditions of the tribological mechanical component (TMC);
- lubrication modes of the TMC [6, 37].

To predict the wear behavior of the TMC, clustering, decision-making, fuzzy logic and neural networks methods are used, such as ANN, adaptive neural systems and fuzzy clustering [15, 40]. As a rule, determining the state of the TMC wear requires the use of physical laws [1, 9]. Combining ANN models, rule-based inference and logical reasoning models allows us to identify patterns in the occurrence of wear processes in the TMC [40]. CoF is a critical tribological characteristic of the TMC, which is used to assess the mechanical elements of the TMC and their shortcomings [18, 35]. The implementation of accurate CoF predictions allows us not only to determine the future state, but also to control the choice of methods for preliminary preparation, strengthening and modification of the TMC of the mating parts of the surfaces [5, 28]. The higher the accuracy and criticality of the design of systems of units and assemblies, the more important friction monitoring becomes, which affects the overall stability of machines and mechanisms [6, 36]. It is known that the process, lubrication, is a decisive factor affecting the processes of friction and wear [9, 21]. Lubrication monitoring systems usually assess both the state of friction and the state of the lubricating medium [6, 36]. ANN and Linear Discriminant Analysis (LDA) neural networks are used to classify the states of the lubrication system, which allows you to effectively determine deviations from the normal operating mode [15, 40]. It is known that lubricants significantly reduce friction and wear, so their correct choice is crucial for the efficiency of the operation of the Lubricating Medium [5, 21]. Optimization of the lubricating medium involves two main areas:

- development of new lubricants [5, 21];
- optimization of the proportions of the components of lubricating mixtures [6, 38].

In connection with the development of two-dimensional (2D) materials, screening of 2D materials has become a key aspect of optimizing the lubricating medium [35].

The application of tribological informatics in tribology significantly expands the possibilities of analyzing, monitoring and predicting the technical condition of the mechanical components of machines and mechanisms [1, 2, 4]. The use of AI and machine learning allows you to increase the accuracy of prediction, optimize the parameters of the mechanical components and prevent premature failure of mechanical components [3, 5, 6]. Thanks to modern technologies, it has become possible to perform real-time condition analysis, which contributes to increasing the efficiency of maintenance and extending the service life of the mechanical components of tribological systems [13, 14, 36]. Tribological condition monitoring systems play a key role in detecting faults in real time and ensuring stable operation of mechanisms [7, 31]. If the mechanical component is a bearing, its condition can be assessed by friction force and friction moment, using RF algorithms, gradient boosting classifier and additional tree classifier [29, 38, 42]. Among the most accessible parameters for analyzing the condition of the mechanism are visual changes, sound pressure, temperature indicators, quality of the lubricating medium and vibration [22, 31]. At the same time, tribological variables that are difficult to measure are often determined through the analysis of wear, friction, and lubrication processes [5, 33]. The introduction of AI into monitoring allows you to track changes in the technical condition of the machine and mechanism in real time thanks to sensors and data analysis algorithms [6, 13, 14]. If the system detects abnormal changes in temperature or vibration levels, this can signal the initial stages of wear or degradation of mechanical components [36, 41]. Such technologies provide efficiency in decision-making, which allows you to minimize the risks of equipment failure [4, 7]. The assessment of friction parameters is critically important for high-precision mechanical systems, such as adjusting mechanisms of car engines or impulse wheels of satellites [6, 20]. The higher the requirements for the accuracy of the mechanism, the greater the role played by monitoring friction characteristics, which affects the stability of the entire system [36]. Lubrication is also an important factor, which affects the efficiency of friction and wear processes [9, 21]. Monitoring of the lubricating medium is carried out through two key parameters:

- monitoring the state of friction;
- assessment of the state of the lubricant and its characteristics [32, 36].

Neural networks and linear discriminant analysis are used to classify the states of the tribological system, which provides an accurate assessment of the operation of the mechanism [15, 30, 40].

Thanks to the use of AI, machine learning algorithms and monitoring methods, it has become possible to analyze the state of the mechanism in real time, which allows preventing emergency situations and increasing the reliability of the operation of the tribological system [6, 7, 41].

This process is the result of the merger of information technology and tribology, which provides a comprehensive approach to the analysis of mechanical systems and their optimization [1, 2]. The method of deep neural networks plays an important role in predicting the coefficient of friction [9, 10, 20]. Optimization of TrBS is based on the prediction of tribological behavior, which allows improving the operational characteristics of mechanisms [5, 6, 38]. Optimization of the TrBS is based on the analysis of its components and can be implemented from three main aspects:

- optimization of materials of tribocoupling elements [35];
- optimization of the lubricating medium [21, 32];
- optimization of Tribological operating conditions [6, 37].

AI plays a crucial role in this direction, contributing to increasing the efficiency of design and reducing the costs of developing Tribological Systems [2, 4, 6]. It is worth noting that optimization of TrBS is a complex engineering task that requires an integrated approach taking into account three main factors: tribocoupling of parts; lubricants; operating conditions [5, 21, 40].

Optimization of the TrBS can be divided into three main areas: design of the texture of friction surfaces; development of materials for parts; selection of the most optimal materials [6, 9, 38].

Regarding optimization of the surface texture, measuring friction changes when modifying the surface structure allows us to assess the impact of production processes on tribological characteristics [6, 21]. AI methods contribute to the creation of optimal surface textures to achieve effective friction control [6, 38]. In the case when the process of preparation or formation of the surface texture does not meet the expected friction parameters, the tribological system must be optimized [40].

Optimization of friction materials is carried out through the development of composite materials, as well as control of the parameters of the cementation and nitriding technological processes. This can be implemented using ANN [15, 28].

When studying materials, two key aspects should be taken into account: material composition; structural properties of the material. Most often, such parameters change due to adjustments to production conditions [5, 35].

When optimizing materials of TC elements, machine learning algorithms make it possible to test numerous combinations of materials in digital models, which significantly reduces the cost of experimental research [4, 28, 38]. Machine learning methods are also used to analyze the chemical, physical and mechanical properties of new materials, which allows you to create components with specified characteristics, for example, materials with high wear resistance or low friction coefficient [5, 35, 38]. AI algorithms can predict the behavior of a material under different operating conditions, which reduces the time and cost of testing new technological solutions [6, 20, 28].

Input parameters of the TrBS, such as sliding speed, load, temperature and humidity, affect the processes of friction and wear [5, 6, 37]. To achieve optimal functioning of the Tribological System, adaptive operating conditions can be developed, which will ensure the effective operation of the tribological system [6, 40]. Since machine learning algorithms can analyze large amounts of data on operating conditions (temperature, humidity, load), it is possible to automatically select optimal settings, which ensures increased tribological efficiency [4, 6, 38]. The introduction of automation in tribology and tribotechnology not only saves operators' time, but also minimizes the likelihood of human errors in the effective functioning of the TrBS [7, 40]. Equipping the TrBS with production robots requires the provision of algorithms AI. This provides high accuracy and efficiency in performing complex tasks, such as coating or precision grinding of TC [6, 20]. In addition, such machines can operate in harsh conditions (for example, at high temperatures or pressure loads), where the use of human labor can be dangerous [6, 7]. Analysis of the results of experiments in TC using AI allows you to identify hidden patterns that are not always obvious with traditional analysis methods [2, 5]. AI helps automate data comparisons, establish relationships between parameters, and optimize the process of further experimental research [4, 6, 40]. Modern tribological informatics methods enable the prediction of the service life of TC, facilitate real-time monitoring of their condition, and uncover previously unknown correlations between physical parameters in tribolog [6, 28, 38]. Triboinformatics represents a comprehensive scientific discipline rather than merely the application of computer science techniques to isolated tribological challenges [1, 2, 5, 7]. When implementing computational tribology methods, the Tribological Model is taken into account - this model reflects a multidisciplinary, time-dependent system that defines the interaction between two specific physical variables [1, 2]. Architectural frameworks for triboinformatics have been proposed, emphasizing that practical applications must consider input/output data, tribological states, and the operational rules of TrBS [2, 6, 7].

Selecting the most appropriate computational method for a given tribological issue remains a complex task. Currently, triboinformatics research typically involves applying a chosen information technology to address specific problems [2, 5]. This approach relies on extensive input data, necessitating standardized tribological testing protocols to enable the reuse and integration of diverse datasets.

Tailored solutions must be developed to suit the unique characteristics of each process or enterprise. Artificial intelligence can incorporate the specific parameters of TC, offering customized strategies for their maintenance and operation. Such advancements highlight the importance of tribological data structures. Enhanced circulation, reuse, and sharing of tribological data will significantly boost research efficiency [2, 5, 7].

A robust foundation of tribological data is essential. Cutting-edge sensing technologies play a vital role in data acquisition. Among these, electrical signals are among the easiest to measure and interpret. Autonomous sensors—utilizing triboelectric effects, nanogenerators, and intelligent coatings—are emerging as key tools in active tribology for efficient data collection [6, 7]. If environmental and material factors influencing triboelectric signals (e.g., temperature, humidity, vibration frequency, and material properties) are properly addressed, autonomous sensors could become highly practical instruments for gathering tribological data [6, 7].

The application of triboinformatics approaches significantly improves the efficiency of particle detection, recognition and classification in ferrospectrometry. An algorithmic model was developed that automatically identifies and classifies wear particles, ensuring higher accuracy of analysis of ferrospectrometric studies [31, 34].

ANN was used for the particle recognition process, and particle classification was performed using the SVM method [30, 31]. In addition, a CNN method was created to classify seven types of ferrographic images. The proposed algorithm allows determining the degree of wear with an accuracy of up to 90% [6, 42].

The actual use of ferrographs can be complicated by the inconsistency of the obtained images, which negatively affects the accuracy of the analysis [31]. Also, the low data collection frequency affects the efficiency of real-time wear monitoring [42].

To solve these problems, a CNN with a large convolution kernel was used, which allows reducing the blurring effect due to defocusing during the acquisition of ferrographic images [42].

To implement reliable real-time wear monitoring, it is necessary to increase the volume of received ferrograph images. The Gaussian process regression approximation method was used, which provides an expansion of the data sample and wear prediction based on a large array of images [7].

Triboinformatics methods can be effective for solving other problems, in particular:

- identification of damage to friction surfaces [2, 5];
- optimization of the materials processing process [6, 28].

A set of acoustic data was collected during the reciprocating motion of tribocoupled parts, including bearings. The use of the RF method made it possible to identify three key stages of friction:

1. Initial running-in.
2. Stable operational state.
3. Active wear stage [36, 41].

Machine learning was used to optimize the friction material formula. And machine learning algorithms were used to quickly predict the width of the zone images of 2D materials, which facilitates the implementation of such materials in semiconductor devices.

Triboinformatics approaches can be applied in various aspects of tribology, such as:

- manufacturing processes [6, 10];
- development and optimization of lubricants [21, 32];
- materials processing technologies [5, 38];
- surface engineering [9, 40];
- applied tribotechnologies [6, 7].

To solve tribological problems, it is necessary to implement information solutions that include:

- monitoring of the condition of the friction material [13, 14];
- prediction of the behavior of the TrBS [6, 28];
- optimization of tribological parameters [5, 38].

To increase the efficiency of the TrBS, optimization algorithms are being developed, such as genetic algorithms and Bayesian optimization, which provide automatic adjustment of the TrBS parameters [40].

Thanks to machine learning algorithms, it is possible to analyze large volumes of operational data (temperature, humidity, load) and automatically determine the optimal settings, increasing the efficiency of the TrBS [37].

Automation in tribology and tribotechnology not only saves operators' time, but also minimizes the risk of human errors, ensuring stable operation of the mechanism [40].

The introduction of production robots into tribological systems requires providing them with AI algorithms, which allows achieving high accuracy and efficiency when performing complex tasks, such as:

- coating application [20];
- precise grinding of mechanical components [20].

The robots can also operate in extreme conditions, such as high temperature or elevated pressure, which makes them an ideal solution for hazardous production environments.

Integrating production process data into digital platforms helps minimize downtime and optimize resource management. These platforms, driven by AI algorithms, are able to predict production performance and adapt tribological processes in real time, which allows to compensate for the shortcomings of existing approaches [6, 7].

Conclusions

1. It was found that to implement effective monitoring of the state of friction, lubricating medium of tribological wear systems in real time, it is necessary to increase the amount of information received from sensors.

The method of Gaussian process regression approximation is used, which provides an expansion of the data sample and improves forecasting.

2. It is substantiated that triboinformatics approaches can be applied in various areas of tribology, such as production, development of innovative materials for tribological system parts, machine parts and mechanisms, lubricants, surface treatment and engineering of tribological systems. It is important to implement information solutions for monitoring the technical condition, predicting the behavior of innovative machines and mechanisms and optimizing the parameters of tribological systems.

3. It was found that optimization algorithms, including genetic algorithms and Bayesian optimization, allow you to automatically adjust the parameters of tribological systems, increasing their accuracy and efficiency. Thanks to artificial intelligence methods, it is possible to analyze large amounts of data on the operating conditions of machines and mechanisms of production systems and lines to determine the best settings.

4. It was determined that the introduction of digital platforms into production processes with increased tribological efficiency of tribo-coupled parts minimizes downtime of machines and mechanisms of elements and ensures effective resource management. Artificial intelligence allows you to predict production indicators and adapt processes in real time, which improves the performance of existing tribological systems.

5. Prospective developments in triboinformatics are anticipated to integrate methodologies such as regression analysis, classification algorithms, dimensional analysis, and predictive modeling. This convergence is expected to establish a cohesive framework that combines advanced tribological techniques with artificial intelligence-driven information technologies, thereby enhancing the precision of monitoring, forecasting, and optimization processes.

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Аулін В.В. , Ковальов С.Г., Гриньків А.В., Ковальов Ю.Г., Головатий А.О., Кузик О.В., Слонь В.В. Підвищення ефективності трибологічних систем за допомогою інтелектуального аналізу даних та прогностичного моделювання

У статті проведено систематизований аналіз застосування інформаційних технологій у трибології, включаючи традиційні методи, машинне навчання та штучний інтелект. Основною метою дослідження є узагальнення та класифікація методів трибоінформатики для підвищення ефективності аналізу трибологічних процесів. Методика ґрунтується на огляді ключових алгоритмів (ANN, опорні векторні машини, методи K – найближчих сусідів, метод випадкового лісу), визначенні їх ролі у трибологічних дослідженнях та аналізі інформації, спрямованої на моніторинг технічного стану, прогнозування поведінки та оптимізацію трибологічних систем. Визначено, що застосування алгоритмів штучного інтелекту та машинного навчання суттєво покращує точність діагностики трибологічних систем, дозволяє прогнозувати їхній експлуатаційний ресурс та оптимізувати робочі параметри трибологічних систем та механізмів машин. Наведено класифікацію методів трибоінформатики відповідно до їх функцій: регресія, класифікація, кластеризація, зниження розмірності. Це дає змогу визначити найбільш ефективні підходи для різних типів трибологічного аналізу. Практична спрямованість використання інтелектуальних методів моделювання полягає у можливості інтеграції отриманих результатів у виробничі процеси, що сприяє підвищенню надійності механічних систем, скороченню витрат на їх обслуговування та створенню більш точних методів прогнозування трибологічних характеристик, властивостей та трибологічної ефективності функціонування вузлів систем і агрегатів машин та механізмів. Показано, що, трибоінформатика відкриває нові перспективи для вдосконалення трибологічних досліджень, забезпечуючи більш точний моніторинг, ефективне прогнозування та оптимізацію трибологічних систем.

Ключові слова: трибологічна система, моніторинг технічного стану, моделювання та прогнозування, тертя, зношування, штучний інтелект, машинне навчання.