SERBIATRIB '25

19th International Conference on Tribology

14 – 16 May 2025, Kragujevac, Serbia

PROCEEDINGS

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Serbian Tribology Society

University of Kragujevac
Faculty of Engineering

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EDITOR: Slobodan Mitrović

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19th International Conference on Tribology – SERBIATRIB '25

ISBN: 978-86-6335-128-8

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Publisher:	**Faculty of Engineering, University of Kragujevac** Sestre Janjić 6, 34000 Kragujevac, Serbia
For the Publisher:	**Slobodan Savić** Faculty of Engineering, University of Kragujevac
Technical editor:	**Dragan Džunić, Živana Jovanović Pešić** Faculty of Engineering, University of Kragujevac
Printed by:	**Inter Print** Jurija Gagarina 12, 34000 Kragujevac, Serbia
Circulation:	200 copies

The publication of this Proceedings was financially supported by the Ministry of Science, Technological Development and Innovation, Republic of Serbia.

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SERBIATRIB '25
19th International Conference on Tribology
Serbian Tribology Society
Faculty of Engineering University of Kragujevac
Kragujevac, Serbia, 14 – 16 May 2025
Research paper
DOI:10.24874/ST.25.198

POSSIBILITIES OF APPLYING ARTIFICIAL INTELLIGENCE IN THE FIELD OF TRIBOLOGICAL RESEARCH

Milan ERIC[1], Miladin STEFANOVIC[1], Slobodan MITROVIC[1], Dragan DZUNIC[1], Vladimir KOCOVIC[1], Zivana JOVANOVIC PESIC[1], Suzana PETROVIC SAVIC[1], Aleksandar DJORDJEVIC[1,*], Marko PANTIC[2]
[1]Faculty of Engineering University of Kragujevac, Kragujevac, Serbia
[2]Faculty of Technical Sciences University of Priština in Kosovska Mitrovica, Kosovska Mitrovica, Serbia
*Corresponding author: adjordjevic@kg.ac.rs

Abstract: *Tribological behavior is a complex, time-dependent process influenced by multiple factors, making it difficult to precisely model and predict the performance of tribo-systems. Tribology research has relied on labor-intensive experimental methods to understand these intricate mechanisms. However, the advancements in artificial intelligence (AI) and machine learning (ML) have introduced new methods for analyzing and interpreting complex tribological processes with greater accuracy and efficiency. The integration of AI into tribology has led to the development of "tribo-informatics," a field that merges tribological data with computational techniques to perform predictions and system optimization. ML models, such as neural networks (NN), contrastive learning frameworks, and Bayesian inference methods, have demonstrated remarkable improvements in wear prediction, lubrication analysis, and failure diagnostics. Furthermore, computational approaches such as physics-informed neural networks (PINNs) have enabled more precise modeling of fundamental tribological equations, improving the understanding of surface interactions and material wear mechanisms. This paper examines the potential of AI in tribology, showcasing how modern computational tools are driving innovations in wear assessment, lubricant performance analysis, and the design of advanced tribological materials. The findings highlight the growing role of AI in optimizing tribological performance and advancing the predictive capabilities of tribology research.*

Keywords: *tribo-informatics; machine learning; artificial intelligence.*

1. INTRODUCTION

Tribology is the science and engineering of interacting surfaces in relative motion, encompassing the study of friction, wear, and lubrication [1]. It has a significant role in a wide range of industries, including manufacturing, automotive, aerospace, and biomedical fields [2]. Peter Jost highlighted the term "tribology" after identifying the significant economic and operational losses caused by friction and wear in mechanical systems [3]. Understanding and controlling tribological behavior is essential for improving the efficiency, and reliability of mechanical systems. Friction and wear may lead to energy loss, material degradation, and increased maintenance costs [4].

The behavior of friction, wear, and lubrication is influenced by a wide range of mechanical, chemical, and physical factors that interact at different scales, making it difficult to develop accurate and generalizable predictive models. Additionally, environmental factors like humidity and temperature can modify the lubrication film and the material's tribological properties, making it difficult to isolate the contribution of individual factors and establish direct cause-effect relationships [5].

A major challenge in tribology research stems from the nonlinear and stochastic nature of tribological behavior [6]. Friction and wear often exhibit unpredictable fluctuations due to the complex nature of surface contacts and environmental variability. The coefficient of friction (COF) may show abrupt changes during sliding due to microscopic surface roughness or material deformation. Similarly, wear mechanisms, such as adhesive and abrasive wear, can transition from one state to another depending on load and temperature, making the system behavior difficult to predict accurately using traditional analytical models [7].

Thus, tribology remains complex field due to the interplay of mechanical, chemical, and thermal processes at different scales. Traditional tribology research has relied heavily on experimental testing to understand these interactions. However, the complexity and variability of real-world conditions make it difficult to develop universal models for predicting tribological behavior [8]. The introduction of artificial intelligence (AI) and machine learning (ML) has created new opportunities to address these challenges by enabling the analysis of large datasets, identifying hidden patterns, and improving the predictive accuracy of tribological models [5].

Machine learning models are particularly suited for handling this type of nonlinearity and randomness, where conventional approaches often fail to capture these dynamic changes [9].

Tribological phenomena also occur at different scales, from atomic interactions at the nanoscale to macroscopic surface contacts, which creates additional challenges in scaling up findings from laboratory tests to real-world applications [10]. Material and environmental variability further complicates tribology research. The performance of tribological systems depends heavily on material properties and environmental conditions, which can vary significantly in real-world applications [11]. The dynamic nature of these factors makes it difficult to create universal tribological models that remain valid under varying operating conditions. Machine learning approaches, with their ability to adapt to complex and dynamic data, present new opportunities to address these challenges [6].

Traditional experimental methods in tribology, such as pin-on-disc and ball-on-plate tests, are often limited by cost, time, and the ability to replicate real-world conditions. While these methods provide valuable insights into wear and friction behavior, they are time-consuming, costly, and restricted to controlled laboratory environments [12]. AI-based approaches, such as neural networks and deep learning, offer the ability to analyze large datasets, identify complex patterns, and provide more accurate predictions based on real-world data, thus complementing and enhancing traditional experimental methods [13].

Building upon these perspectives, the paper seeks to explore the potential of applying AI and ML in tribological research. It emphasizes recent advancements, key challenges, and emerging opportunities in the field. Particular attention is given to how ML-driven approaches have contributed to a deeper understanding of wear mechanisms, frictional behavior, and lubrication performance, thereby offering novel insights for the design and optimization of tribological systems.

2. FUNDAMENTALS OF TRIBOLOGY AND AI

This section lays the ground for understanding the integration of AI into tribological research. Subsection 2.1 offers a concise overview of tribology, including its core principles, key phenomena such as friction, wear, and lubrication, and their significance in various engineering applications. Subsection 2.2 then introduces the fundamentals of AI and ML, with a focus on their growing role in enhancing tribological analysis, modeling, and system optimization.

2.1 Tribology Overview

The field of tribology has witnessed significant growth over the past decades, expanding into diverse research areas such as surface engineering [14], biotribology [12, 15, 16], high-temperature tribology [17], and computational tribology [18]. Tribological interactions occur at the interface of materials in relative motion, where the mechanical, chemical, and thermal interactions between surfaces influence system behavior [19, 20].

Friction is one of the most studied aspects of tribology. It refers to the resistance encountered when two surfaces slide or roll against each other. The COF, which measures the intensity of this resistance, depends on factors such as material properties, surface roughness, contact pressure, and lubrication conditions. Understanding friction behavior is essential for improving the efficiency of mechanical systems, reducing energy losses, and minimizing material degradation [21].

Wear, another fundamental aspect of tribology, involves the gradual loss of material from surfaces due to mechanical, thermal, or chemical interactions. Common wear mechanisms include abrasive wear (material removal by hard particles), adhesive wear (material transfer between surfaces), fatigue wear (surface degradation due to repeated stress), and corrosive wear (material loss due to chemical reactions). Wear behavior is influenced by the material's hardness, microstructure, and environmental conditions [22].

Lubrication serves to reduce friction and wear by introducing a substance between contact surfaces. Lubricants can be liquids (e.g., oils), solids (e.g., graphite, molybdenum disulfide), or gases (e.g., air). Advancements in lubrication technology, including the development of superlubricity and bio-lubrication, have greatly enhanced the performance of modern mechanical systems [23].

In recent years, tribology research has extended into new and specialized areas. Biotribology, for example, studies friction, wear, and lubrication in biological systems such as human joints and dental implants [12, 15]. High-temperature tribology explores friction and wear behavior under extreme temperature conditions, such as those encountered in aerospace and manufacturing applications [24]. Computational tribology leverages numerical methods and machine learning algorithms to model complex tribological phenomena and predict system behavior under varying operational conditions [25].

Despite significant progress, accurately predicting friction and wear behavior in complex systems remains difficult due to the interplay of multiple variables at different scales. The integration of ML in tribology holds promise for improving predictive accuracy and enabling real-time monitoring and optimization of tribological performance [26].

2.2 AI and Machine Learning in Tribology

ML have emerged as powerful tools for addressing the complexities of tribology, enabling more accurate predictions, real-time monitoring, and optimization of tribological systems [8]. ML techniques have introduced new ways to analyze large datasets, identify hidden patterns, and develop predictive models that improve the understanding and control of tribological behavior [27].

ANN: ANN is one of the most widely used models in tribology due to its ability to capture complex, nonlinear relationships between input and output variables. In tribological studies, ANN models are trained to predict wear rates, friction coefficients, and lubrication film thickness based on parameters such as surface roughness, load, speed, and material properties [9, 26]. ANN models have been applied to predict the tribological performance of 3D-printed materials and to optimize lubricant formulations [28].

CNNs are particularly effective in analyzing surface topography and wear patterns from high-resolution imaging data. CNNs have been used to evaluate wear severity from multidimensional surface images and to classify different wear mechanisms [28].

SVM models are effective for classification and regression tasks, often used to predict the failure of tribological components and to classify wear debris based on particle morphology [29].

Random Forest and Gradient Boosting are frequently used for ranking the importance of tribological parameters and for predicting friction and wear under varying operational conditions [26].

Physics-Informed Neural Networks (PINNs) combine machine learning with fundamental physical laws to model tribological behavior more accurately [30]. They have been used to solve the Reynolds equation for lubrication and to predict elastohydrodynamic film thickness in complex systems [31].

The combination of AI with advanced experimental techniques (such as scanning electron microscopy and atomic force microscopy) has enhanced the ability to model complex tribological phenomena at micro and nanoscale levels [32]. Furthermore, the rise of "tribo-informatics" — the integration of tribology with big data and AI — represents a promising future direction for improving the understanding and performance of tribological systems [33].

Despite these advances, challenges remain in applying AI and ML to tribology. The scarcity of large-scale, high-quality tribological datasets limits the performance of AI models.

3. CURRENT APPLICATIONS OF AI IN TRIBOLOGY

3.1. Prediction of wear and friction behaviour

The complex nature of friction and wear, which involves nonlinear relationships between surface roughness, contact pressure, sliding speed, material properties, and environmental factors, makes traditional modeling approaches inadequate. AI models have shown the ability to capture these complex interactions and provide accurate predictions [34].

ANN have been widely used for predicting the COF and wear rates in tribological systems [34]. ANN models trained on tribological datasets have achieved high predictive accuracy, with correlation coefficients exceeding 0.98 in some cases [35TRIBO]. CNN models have been employed to analyze surface topography data and predict wear severity based on high-resolution imaging, demonstrating improved accuracy over traditional methods. For example, an ANN model trained on wear and friction data under different lubrication conditions was able to predict the COF with a mean squared error (MSE) below 0.01 [36].

AI-based optimization of wear and friction has also been explored using reinforcement learning and evolutionary algorithms. Reinforcement learning models have been applied to optimize lubrication strategies in real-time, adapting to changing surface and environmental conditions. Genetic algorithms, Monte Carlo and particle swarm optimization have been combined with ML models to optimize material composition and surface texture for improved wear resistance [26, 37].

3.2. Surface topography and lubrication performance

AI models have been successfully applied to analyze and predict surface roughness and lubrication performance in tribological systems [38]. Surface topography analysis is critical for understanding wear patterns, surface defects, and lubrication film formation [39]. CNN have been used to analyze high-resolution surface images and predict roughness parameters with high accuracy [40].

AI-based approaches have also been employed to optimize lubrication film thickness and pressure distribution. Finite Difference Method and ANN have been used to solve the Reynolds equation for elastohydrodynamic lubrication, improving the prediction of lubrication film behavior under varying load and speed conditions. Machine learning models have also been used to predict the optimal lubricant composition based on experimental data, enhancing the lubrication performance and reducing wear [38].

In one study, a quantitative structure–property relationship (QSPR) model combined with AI techniques was used to optimize the molecular structure of synthetic lubricants. The model identified key molecular features that enhance lubrication performance, leading to the development of high-efficiency lubricants with reduced viscosity and improved thermal stability [41].

Tribological sensing systems have also benefited from AI. CNN-based models have been used to analyze real-time sensor data from ferrograph-based wear debris analysis systems, enhancing the ability to detect and predict wear state changes with high accuracy. These models have demonstrated the ability to identify early signs of failure, enabling predictive maintenance and reducing downtime [42].

3.3. Material performance and failure prediction

AI has shown considerable promise in predicting material degradation and failure in tribological systems. ANN models have been used to predict bearing failure under varying load and speed conditions, with predictive accuracy exceeding 95% in some cases [43]. SVM models have been employed to classify different failure modes based on material composition and operational data [44].

In one study, Bayesian inference was combined with an ANN model to predict the remaining useful life (RUL) of bearings under mixed friction conditions. The model was able to accurately predict failure progression and identify the optimal maintenance interval [45].

AI has also been used to predict scuffing failure in lubricated systems. A multiphysics coupling model combined with machine learning techniques was used to capture the breakdown of lubricant films and tribofilms during scuffing. Experimental validation confirmed that the model could accurately predict the onset of scuffing under different loading and temperature conditions [46].

Furthermore, AI models have been employed to predict material performance in composite materials. ANN and decision tree models have been used to analyze the wear behavior of self-lubricating composites, predicting the COF and wear rate with high accuracy [34]. AI-based optimization of composite material composition has led to the development of materials with enhanced tribological performance, including improved wear resistance and lower friction coefficients [47].

The integration of AI with experimental and computational tribology methods has created new opportunities for optimizing tribological systems and improving the performance and longevity of mechanical components.

3.4. Tribology Databases as a Foundation for AI Applications

In addition to the existing AI applications in tribological modeling and prediction, certain efforts have focused on the development of an extended tribology database architecture capable of supporting AI-driven analyses. This system was designed not only for storing numerical and textual data from standard tribological experiments but also for accommodating complex data types such as high-resolution images, video recordings, measurement reports, and results obtained from advanced laboratory equipment—including atomic force microscopy (AFM), scanning electron microscopy (SEM), nanoindentation, and nanotribometry [48].

The database architecture was expanded to include experimental outputs in both structured and unstructured formats, making it suitable for machine learning training and inference. For instance, CNN models can be trained on 3D surface topographies and SEM images for wear pattern recognition, while ANN models can utilize numerical outputs such as friction coefficients and wear rates for prediction tasks. The inclusion of metadata such as experimental conditions, material properties, and equipment settings further enhances the contextual richness of the dataset and supports the creation of comprehensive input vectors for machine learning models.

An important feature of this platform is its compatibility with mobile computing systems. A client-server architecture enables researchers to collect, synchronize, and analyze tribological data in real time, even while working remotely. Mobile devices equipped with embedded databases (e.g., SQL Server CE) are synchronized with a central server using merge replication, allowing two-way data exchange during ongoing experiments. This approach facilitates faster data capture, preliminary analysis, and efficient integration into the centralized database—supporting timely decision-making and adaptive experimental workflows [48].

Furthermore, the database includes modules for bibliometric tracking, enabling quantification of scientific productivity (e.g., number of publications, citations, equipment usage, researcher activity) and economic metrics (e.g., project-based revenue, equipment cost-efficiency). These features are essential for data-driven research evaluation and support the growing need for integrated research management and performance monitoring systems [48].

Table 1 summarizes key research studies and systems that apply AI in tribological analysis, highlighting the tested materials, experimental methods, ML models used, and available data types. The last row refers to the extended tribology database, which supports both traditional data storage and AI-driven analysis.

Table 1. Overview of AI Applications in Tribology and Available Data Types for ML

Study Theme	Material / System	Test Method	Parameters Tested	ML Model	Available Data Types	Key Findings
Influence of 3D Printing Parameters on PLA [35]	PLA (Polylactic Acid)	Pin-on-disc	Nozzle temp, Layer height, Infill ratio, Bed temp	ANN (5-10-4)	Friction, Wear, Pin temp, 3D Surface Data	Low wear at 200°C, 0.15mm, 70°C, 50% infill
Tribological Performance of Recycled Polymers [50]	PLA, PETG	Pin-on-disc	Lubrication, Load, Speed, Temp	Gradient Boosting	Energy Dissipation, Load, Friction	Lubrication significantly reduces wear; GB outperforms RF

Study Theme	Material / System	Test Method	Parameters Tested	ML Model	Available Data Types	Key Findings
Hard Coating Wear Prediction [51]	WC20Cr3C27Ni	Thermal Spray	Load, Velocity, Temp	ANN	Friction force, Wear rate	High R values (>0.99) for both outputs
Bearing Fault Diagnosis [52]	Steel Bearings	Vibration	Load, Speed, Signal-to-noise ratio	RF, SVM, KNN	Vibration signals	RF model most accurate for fault classification
Prediction of COF in Sliding Contact [53]	Various Metals	Pin-on-disc	Velocity, Surface Roughness	SVM, XGBoost	Friction coefficient, Acoustic emission	XGBoost and SVM performed best
Composite Tribological Behavior [28, 47]	Cu/Al–Graphite	Tribometer	Load, Speed, Temp	ANN, Gradient Boosting	COF, Wear Rate, SEM Images	AI predicts performance; contributing factors ranked
Biotribology AI Application [12, 15, 16]	Human Joint Materials	In-vitro	Wear, Friction, Lubrication	ANN, CNN	SEM images, Force data	AI improved implant performance prediction
Extended Tribology Database (System) [48]	Various Tribo-materials	Multiple (AFM, SEM, Tribometer)	All above + Environmental factors	Compatible with CNN, ANN, etc.	Numerical data, SEM/AFM images, Video, Bibliometric & Economic data	Designed to support ML training, mobile integration, and tribo-informatics

This integration of experimental data with AI-ready formats demonstrates the growing potential of data-centric approaches in advancing tribological research and system optimization. The enriched database thus serves as a foundational component in the emerging field of tribo-informatics, where the fusion of tribological experimentation, informatics, and artificial intelligence enables more intelligent, automated, and scalable research practices [48].

4. CONCLUSION

AI has emerged as a transformative tool in tribology, significantly enhancing the understanding and performance of complex tribological systems. Traditional tribology research has long faced challenges in accurately modeling and predicting the behavior of friction, wear, and lubrication due to the nonlinear and multi-scale nature of surface interactions. The introduction of AI and ML has addressed many of these limitations by enabling data-driven analysis, pattern recognition, and predictive modeling, which have improved the accuracy and efficiency of tribological research and applications.

AI has demonstrated success in predicting tribological behavior under varying operational conditions. ANN and CNN models have shown high predictive accuracy in forecasting wear rates, friction coefficients, and lubrication performance, often outperforming traditional analytical models. The ability of AI to handle complex and nonlinear relationships between input and output parameters has made it particularly effective in modeling tribological phenomena such as surface roughness, lubrication film thickness, and wear progression.

Furthermore, AI has played a critical role in predicting material performance and failure in tribological systems. ANN and SVM models have been used to forecast bearing failure, scuffing, and fatigue with high accuracy. Bayesian inference models have been employed to predict the remaining useful life (RUL) of tribological components, allowing for better maintenance planning and reduced costs. AI-based approaches have also driven advancements in material design by enabling the discovery of new self-lubricating composites and wear-resistant materials through the integration of machine learning with computational materials science [28].

The potential for AI to transform tribology research and applications is substantial. The ability of AI to process large datasets, identify hidden patterns, and provide accurate real-time predictions opens new possibilities for designing more durable materials, improving lubrication efficiency, and reducing frictional losses in mechanical systems. The rise of "tribo-informatics," which integrates AI with big data and computational tribology, is expected to drive further innovation in the field. Future research will likely focus on developing hybrid models that combine AI with traditional physics-based approaches, enhancing the accuracy and reliability of tribological predictions across different scales and operating conditions.

In conclusion, AI may enhance tribology research by improving the predictive accuracy, efficiency, and understanding of complex tribological phenomena. The integration of AI with experimental and computational methods has created new opportunities for optimizing tribological systems and developing more efficient and reliable mechanical components. The continued advancement of AI and machine learning in tribology holds the potential to drive significant technological breakthroughs in material science, manufacturing, and engineering.

ORCID iDs

Milan ERIC 0000-0001-8691-4863
Miladin STEFANOVIC 0000-0002-2681-0875
Slobodan MITROVIC 0000-0003-3290-7873
Dragan DZUNIC 0000-0002-1914-1298
Vladimir KOCOVIC 0000-0003-1231-0041
Zivana JOVANOVIC PESIC 0000-0002-1373-0040
Suzana PETROVIC SAVIC 0000-0002-5629-6221
Aleksandar DJORDJEVIC 0000-0003-2856-6578
Marko PANTIC 0000-0002-9327-5227

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