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Editorial

Machine Learning in Tribology—More than Buzzwords?

Stephan Tremmel [1,*] and Max Marian [2,*]

[1] Engineering Design and CAD, University of Bayreuth, Universitätsstr. 30, 95447 Bayreuth, Germany
[2] Department of Mechanical and Metallurgical Engineering, School of Engineering, Pontificia Universidad Católica de Chile, Macul, Santiago 6904411, Chile
* Correspondence: stephan.tremmel@uni-bayreuth.de (S.T.); max.marian@ing.puc.cl (M.M.)

Tribology has been and continues to be one of the most relevant fields, being present in almost all aspects of our lives. The understanding of tribology provides us with solutions for future technical challenges. At the root of all advances made so far are multitudes of precise experiments and an increasing number of advanced computer simulations across different scales and multiple physical disciplines. Based upon this sound and data-rich foundation, advanced data handling, analysis and learning methods can be developed and employed to expand existing knowledge. Therefore, modern machine learning (ML) or artificial intelligence (AI) methods provide opportunities to explore the complex processes in tribological systems and to classify or quantify their behavior in an efficient or even real-time way. Thus, their potential also goes beyond purely academic aspects into actual industrial applications.

To help pave the way, this Special Issue (SI) aimed to present the latest research on ML or AI approaches for solving tribology-related issues. The focus was less on presenting new ML or AI methods but rather on demonstrating the possible applications of existing methods and their adaptation to problems in tribology. We are pleased that the SI has collected ten articles including a perspective [1], a technical note [2], seven original research articles [3–9], and a review [10]. The contributions came from both academia and industry all around the globe and presented cutting-edge research in the field and provided deep insights into the development or the application of sophisticated ML or AI approaches to resolve problems broadly related to friction, lubrication and wear.

Rosenkranz et al. [1] opened the SI by highlighting successful case studies using AI methods in a tribological context, e.g., online condition monitoring, designing material compositions, lubricant formulations, or lubrication and fluid film formation.

Almqvist [2] derived a physics-informed neural network (PINN) applicable to solve initial and boundary value problems described by linear ordinary differential equations in the context of hydrodynamic lubrication. In contrast to finite-element- or finite-difference-based methods, the fully explicit mathematical description of the PINN is a meshless method, and the training did not require large amounts of data as are typically employed for other AI/ML training procedures.

Prost et al. [3] trained a semi-supervised Random Forest (RF) online classifier for the operational state of a self-lubricating steel shaft/bronze pairing using experimental data. Thereby, automatically generated labels or full manual labelling by an expert user can be employed. They reported that the labelling of the individual cycles from the lateral force tribometer data was crucial for a high prediction accuracy.

Zambrano et al. [4] utilized Reduced Order Modeling (ROM) to predict the friction behavior of dynamic rubber applications under different operating conditions and to find optimized micro-texture parameters such as depth, diameter, or distance. The approach was also used to evaluate the influence manufacturing deviations of the surface textures on friction. With respect to an industrial context, it is believed that the product performance of rubber products could be optimized by tailoring micro-textures and controlling nominal texture tolerances prior to production.

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Ruan et al. [5] combined a Convolutional Neural Network (CNN) with a Generative Adversarial Network (GAN) for bearing fault diagnosis with unbalanced datasets. Thereby, the GAN provided a more balanced dataset for the CNN, and the CNN gave the fault diagnosis as a correction term in the GAN generator's loss function. The envelope spectrum error between the generated data and the original measurement of the fault characteristic frequencies was taken as another correction in the GAN generator's loss function. Thus, it was reported that the CNN's fault classification accuracy was substantially improved.

Kügler et al. [6] employed semantic annotation and natural language processing (NLP) techniques for generating knowledge graphs in the domain of tribology. The pipeline was built on Bidirectional Encoder Representations from Transformers (BERT) and involved some NLP tasks such as information extraction, named entity recognition and question answering. The authors verified a satisfactory performance compared to a manual annotation of publications on tribological model testing. It is believed that the approach will decrease manual effort involving time-consuming literature review by providing a semi-automatic support in knowledge acquisition.

Schwarz et al. [7] utilized ML regression methods trained by multibody simulations to predict the dynamic behavior of various cages in angular-contact ball bearings. Thereby, the hyperparameters of RF, extreme gradient boosting (XGBoost), and ANN models were optimized by an evolutionary algorithm. It was reported that all regression algorithms predicted the highly non-linear interplay of operational conditions and cage geometry with satisfactory accuracy. The authors emphasized that the ML approaches will allow to analyze a new dataset in the shortest time without the need to perform new dynamics simulations.

Sauer et al. [8] compared various supervised ML approaches for predicting the elastic and hardness characteristics of diamond-like carbon (DLC) coatings on polymeric medical materials in dependency of the sputter process parameters. It was reported that Gaussian Process Regression (GPR) featured the highest accuracy compared to polynomial regression, support vector machines (SVM), or ANN. Slicing-based data visualization and process maps can further provide support to experts when designing coating systems and processes.

Bienefeld et al. [9] used RF regression for predicting the remaining useful life (RUL) of deep-groove ball bearings from temporal information, such as the means of structure-borne sound signals. The authors reported that by taking temporal past information into account, the prediction quality could be increased by 37% compared to conventional lifetime prediction.

Finally, we [10] systematically reviewed the trends and applications of ML in tribology. We demonstrated that ML has already been employed in many fields of tribology, from composite materials and drive technology to manufacturing, surface engineering, and lubricants. It was emphasized that the intent of ML might not necessarily be to create conclusive predictive models but can be seen as complementary tool to efficiently achieve optimum designs for problems, which elude other physically motivated mathematical and numerical formulations. Therefore, ML and AI might change the landscape of what is possible, going beyond the mere understanding of mechanisms towards designing novel and/or potentially smart tribological systems. One of the challenges is that ML approaches do not necessarily guide towards specific solutions and the selection/optimization of ML algorithms is crucial.

This SI shows that there already is a wide variety of approaches that have been successfully applied to tackle tribological challenges generating true added value beyond just buzzwords. In this sense, the SI can support researchers in identifying initial selections and best practice solutions for ML in tribology.

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