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Perspective

The Use of Artificial Intelligence in Tribology—A Perspective

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Abstract: Artificial intelligence and, in particular, machine learning methods have gained notable attention in the tribological community due to their ability to predict tribologically relevant parameters such as, for instance, the coefficient of friction or the oil film thickness. This perspective aims at highlighting some of the recent advances achieved by implementing artificial intelligence, specifically artificial neutral networks, towards tribological research. The presentation and discussion of successful case studies using these approaches in a tribological context clearly demonstrates their ability to accurately and efficiently predict these tribological characteristics. Regarding future research directions and trends, we emphasis on the extended use of artificial intelligence and machine learning concepts in the field of tribology including the characterization of the resulting surface topography and the design of lubricated systems.

Keywords: artificial intelligence; machine learning; artificial neural networks; tribology

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1. Introduction and Background

There have been very recent advances in applying methods of deep or machine learning (ML) to improve tribological characteristics of materials by means of artificial intelligence (AI). AI is generally concerned with the design and construction of intelligent agents, which is anything that acts in the best way possible in any situation [1]. ML refers to a vast set of data-driven methods and computational tools for modelling and understanding complex datasets. These methods can be used to detect automatically patterns in datasets thus creating models to predict future data or other outcomes of interest under uncertainty [2–4]. Generally, ML methods can be divided into supervised learning and unsupervised learning [3,5], see Figure 1. Regarding predictive or supervised learning approaches, the aim is to learn a mapping from input vectors (training data) to their corresponding output vectors (target data). Depending on the nature of the target data, supervised approaches can be subdivided into classification or regression methods. When the output is a categorical or nominal variable from a finite set of discrete categories (e.g., type of surface finish, oil grade, lubricant additive, etc.), the problem is known as classification or pattern recognition. In contrast, when the output consists of one or more real-valued continuous variables (e.g., coefficient of friction, film thickness, temperature rise, etc.), the problem is defined as regression. The second type of machine learning approaches is denoted as descriptive or unsupervised learning. In this case, only inputs are provided without any corresponding output vectors. The goal is to find meaningful patterns and groups of similar features within the dataset (clustering), to determine the distribution of data in the input space (density estimation), or to reduce high-dimensional data space to two or three dimensions for visualization purposes (dimensionality reduction) [5]. Unlike supervised learning, for which comparisons can be made between the predictions to the observed values, problems involving unsupervised learning are not well-defined since no additional information or obvious error metric is provided about the patterns to be 'discovered' in the dataset [5].

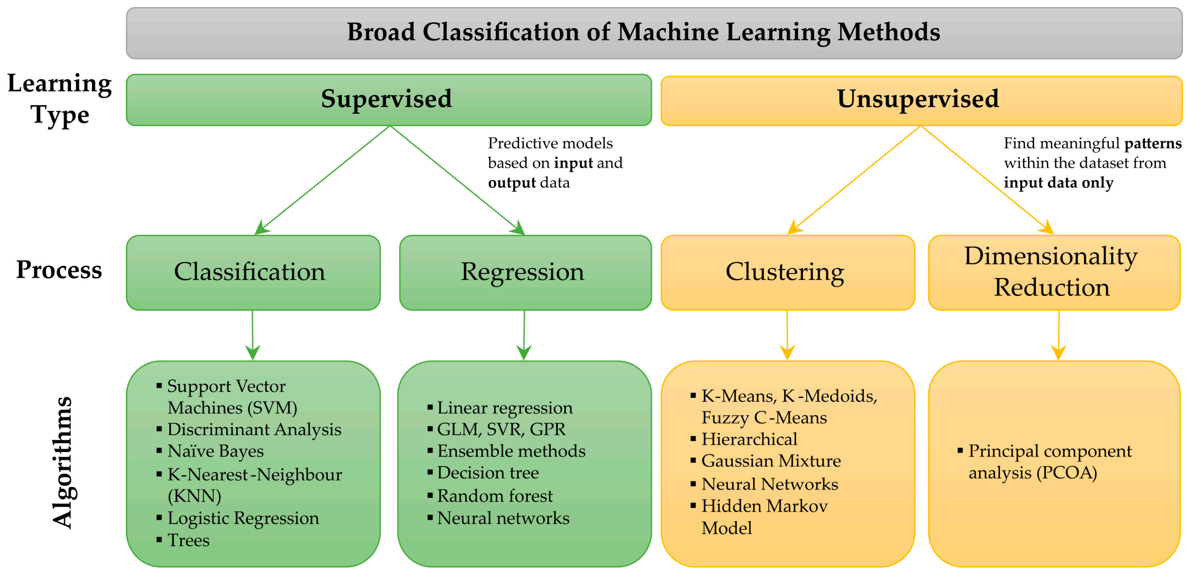

Figure 1. Diagram generally classifying existing machine learning methods and algorithms.

A prominent method that machines employ to learn is by using artificial neural networks (ANNs). These networks are based upon the network of neurons in the human brain and have the ability to "learn" in a fashion similar to the way humans do. An ANN is made of a network of model neurons, which can use algorithms to make them function like biological neurons. In this context, each model neuron has a threshold. The model neurons will receive many different inputs, which are summed up and sent an output equal to 1, if the sum is larger than the threshold. Otherwise, the output is 0. Machines are able to learn by modifying the thresholds of each model neuron, when a new example is introduced, until the thresholds reach a point to where they don't change much [6].

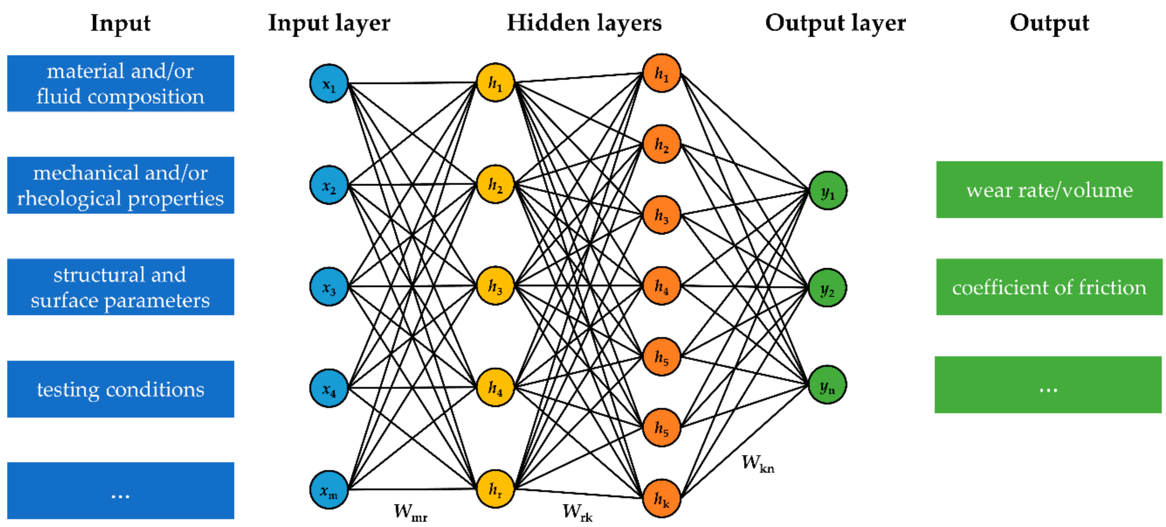

Figure 2. Correlation between material properties and testing conditions using artificial neural networks. Redrawn from [7,8].

In addition to ANNs, fuzzy systems are another type of models used in AI. These systems are based on fuzzy logic and represent a more human way of thinking in their application of inference. They are characterized by displaying a range of truth from 0 to 1 instead of displaying Boolean true/false results [9]. In the field of tribology, many tests on materials are typically performed, which define a set of tribological properties. This dataset can for example be incorporated to develop an ANN (Figure 2), which can be used for further optimization [8,10]. This perspective attempts to display some of the recent advances done in implementing AI, specifically but not limited to ANNs. Furthermore, we intend to address current challenges and future research directions towards tribological-related problems.

2. Application Fields of AI in Tribology

As briefly evidenced by several examples below, the use of AI and ML approaches already covers various fields of tribology, ranging from condition monitoring over the design of material compositions to lubricant formulations or film thickness predictions.

2.1. Online Condition Monitoring

As early as in 1998, Umeda et al. [11] trained a multilayer and a self-organizing feature map ANN with microscopy data from lubricated ball-on-disk sliding experiments to classify wear particles by means of various descriptors (width, length, projection area, perimeter, representative diameter, elongation, reflectivity etc.). When trained with representative data, the multilayer ANN successfully predicted the relation between the experimental conditions and the obtained particle features. The self-organizing feature map ANN was found to be capable of classifying the data without any supervised data. Thus, on the one hand, characteristic particle features can be identified, and, on the other hand, the authors suggested that these approaches could be used for condition monitoring, while the (partly unknown) sliding conditions can be derived from the automated particle analysis. Shortly after, Subrahmanyam and Sujatha [12] applied two ANN approaches, namely a multilayered feed forward neural network trained with supervised error back propagation (EBP) technique and an unsupervised adaptive resonance theory-2 (ART2) based neural network for the detection and diagnosis of localized defects in ball bearings. These networks were trained with vibration acceleration signals from a rolling bearing test-rig under various load and speed conditions. Thereby, the EBP and the ART2 model were found to be accurate in distinguishing a defective bearing from a normal one (100% reliability), with the ART2 being 100 times faster. Moreover, the EBP network was capable to classify the ball bearings into different states, i.e., ball or raceway defect, with a success rate over 95%. A more recent ANN-based approach for monitoring and classifying the multivariant wear behavior of lubricated journal bearings was presented by König et al. [13]. As illustrated in Figure 3, an autoencoder was used for anomaly detection. Moreover, acoustic emission signals with continuous wavelet transformation were utilized to train a convolutional neural network to classify the modes of running-in, insufficient lubrication and particle-contamination of the oil. While the first and second were sometimes mistaken, the contaminated lubricant was detected with an accuracy and a sensitivity of 97 and 100%, respectively.

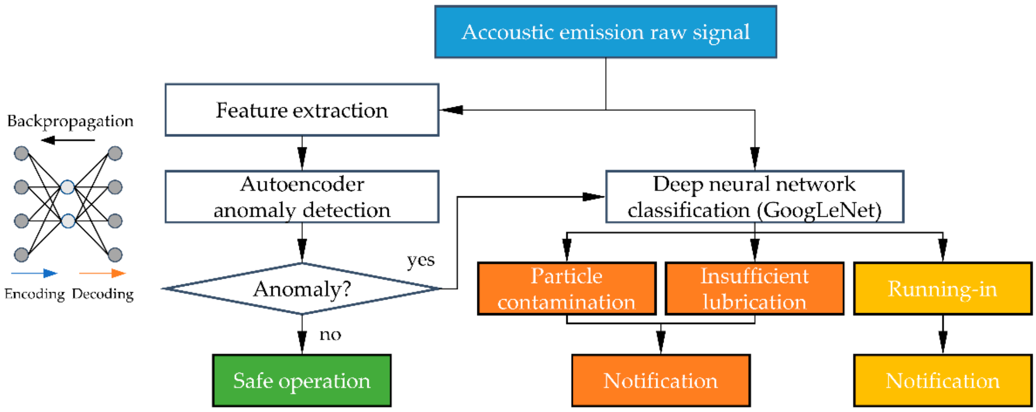

Figure 3. Framework of the machine learning approach from [13]. Redrawn and adopted with permission.

2.2. Design of Material Composition

In addition, various researchers have applied ML and AI approaches to predict and optimize the tribological behavior of different materials and operating conditions with manifold applications in mind [14–20]. For instance, Alambeigi et al. [21] investigated the accuracy of predictive AI models by comparing them with experimental results obtained by testing the dry sliding contact of sintered steels [21]. The steel for this study was manufactured by powder metallurgy, which is known to have many industrial applications in engine parts and transmission systems with problems related to friction and wear. Three different types of predictive models were used in this study. The first approach made use of an ANN. ANNs have a significant advantage in their learning ability and their handling of nonlinear functions, which the wear tests of these steel materials are mainly characterized by. The second model used is known as a "fuzzy system," specifically known as a fuzzy C-means clustering algorithm (FCM). Fuzzy systems also work well in decision making with nonlinear functions and for systems with many time-dependent parameters. The third model was based upon a fuzzy-neuro system known as adaptive neuro fuzzy inference system (ANFIS), which combines the qualities of both ANNs and regular fuzzy networks. Their tests were conducted using input parameters such as cooling rates, applied loads, sliding distances, and the type of powders. Therefore, tests were done at three different cooling rates and three different applied loads. In this study, all three methods displayed high accuracy in predicting the behavior of the wear tests with the ANN model performing the best, generating an R^2 value above 0.9911 and a root mean square error of 3.98×10^{-4} for testing data sets [21].

Apart from steels, composite materials have also been the subject of investigations based upon AI and ML approaches. Senatore et al. [22] developed an EBP model to study the tribological behavior of different brakes and clutch materials thus elucidating the influence of different materials, loading, sliding and acceleration conditions. Therefore, the three-layer ANNs were optimized by an evolutionary genetic algorithm to maximize the prediction quality and the data base was extracted from experimental pin-on-disc tests. By means of a sensitivity analysis, it was demonstrated, for instance, that the sliding velocity particularly contributed to the friction coefficient in the experiments carried out. Moreover, it was verified that the behavior within the data limits was predicted well, whereas an extrapolation rather serves merely as a first indication for future research directions. Besides, Busse and Schlarb [23] developed an ANN architecture with the Levenberg–Marquardt (LM) training algorithm and mean squared error with regularization (MSEREG) as performance function to predict the tribological properties of polyphenylene sulfide (PPS) reinforced on different scales. Using this approach, the coefficient of friction (COF) was predicted with two times and the wear rate with six times higher accuracy than with conventional ANN pruned by the optimal brain surgeon (OBS) method. In addition, the predicted error scales for both friction and wear were ten times smaller than the standard deviations from the tribological pin-on-disk experiments of the database. Both tribological properties were predicted well by using the material composition, sliding speed and contact pressure as input variables. It was also demonstrated that additional input variables such as tensile or compression properties only slightly improve the predictions for friction and wear.

2.3. Lubricant Formulations

In addition to material composition, AI/ML approaches can be used for designing lubricant formulations. Bhaumik et al. [24] used the ANN approach to create a biolubricant with optimized properties and characteristics. They used a genetic algorithm to optimize the properties and the ANN acted as the objective function for the genetic algorithm. Their goal was to create a blend of different vegetable oils, including castor, coconut, and palm oils using multiple friction modifiers, including carbon nanotubes and graphene, which were intended to be optimized using an ANN. The ANN was used to verify the effect of these inputs on the COF. Two different ANN models were used to optimize and design two different lubricants. The first lubricant (Lube A) had a composition of 40% palm oil, 40% castor oil, and 20% coconut oil with 0.7 wt.-% carbon nanotubes and no graphene. The second lubricant (Lube B) contained equal percentages of all oils with 1 wt.-% each of carbon nanotubes and graphene. Based upon the experimental results, it was shown that the COF was reduced by the addition of friction modifiers in both lubricants. Additionally, experimental work demonstrated a sensitivity regarding the respective testing conditions (four-ball versus pin-on-disk tester). A similar study was performed by Bhaumik et al. [25], in which a genetic algorithm and ANN were used to optimize and design a castor oil lubricant with graphite, graphene, multi-walled carbon nanotubes, and zinc oxide nanoparticles. Pin-on-disk tests were used to gather tribological data for the castor oil with different concentrations of these modifiers. The ANN used concentration, load, and speed as input parameters and the COF as output parameter. The composition of the designed lubricants using the ANN came out to have a total concentration of friction modifiers of 2 wt.-% with a distribution of 0.66 wt.-% each of graphite, carbon nanotubes, and zinc oxide nanoparticles. There was no graphene in the designed lubricant since the amount of graphene was shown to have a negligible effect. Afterward, it was experimentally verified that the designed lubricant induced a friction reduction by about 50% compared to most conventional mineral oils.

Other researchers [26] also analyzed the use of ANNs to design lubricants with significantly lower COFs (Figure 4). They considered the optimization of mixtures of vegetable oil (sunflower and rapeseed oils) with diesel oil for use in diesel engines. The ANN predicted a lower COF for a mixture of 4 wt.-% sunflower oil and 0 wt.-% rapeseed oil compared to a mixture of 0 wt.-% sunflower oil and 20 wt.-% rapeseed oil. The ANN also predicted a lower COF for a mixture of 6.5 wt.-% sunflower oil and 0 wt.-% rapeseed oil compared to a mixture of 0 wt.-% sunflower oil and 0 wt.-% rapeseed oil. Both predictions aligned well with experimental results.

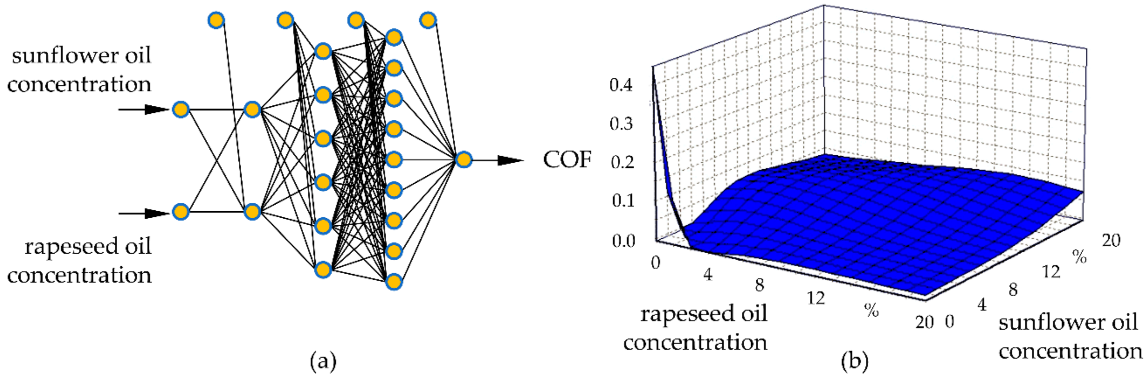

Figure 4. Artificial neural network (ANN) architecture (**a**) and coefficient of friction for different vegetable oil concentrations (**b**) according to [26] (CC BY 4.0).

2.4. Lubrication and Fluid Film Formation

In addition, AI/ML algorithms can be used to predict lubricant film formation and friction behavior in thermo-hydrodynamically (THL) and thermo-elastohydrodynamically lubricated (TEHL) contacts. For example, Moder et al. [27] used highspeed data signals of a torque sensor obtained from a journal bearing test-rig to train ML models for predicting lubrication regimes (Figure 5). Main results showed that deep and shallow neural networks performed equally well, reaching high accuracies. Furthermore, logistic regression yielded the same level of accuracy as neural networks. It was also emphasized the potential use of the proposed methodology for further investigations of ML applications on other tribological experiments.

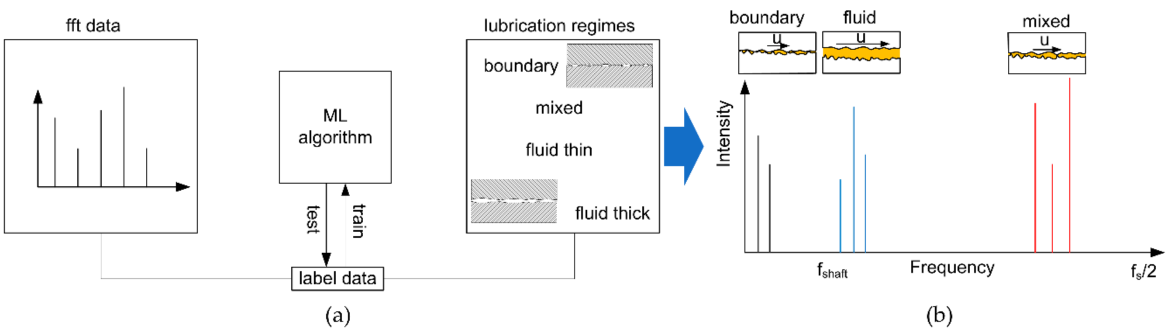

Figure 5. Lubricant regime classification approach (**a**) and schematic illustration of lubricant regimes and frequency ranges (**b**) according to [27] (CC BY 4.0).

Senatore and Ciortan [28] trained an ANN with excellent prediction quality to optimize the frictional performance of the piston-liner using data obtained from numerical HL simulations. Wang and Tsai [29] proposed a surrogate model using ANN for fast prediction of the THL lubrication performance of a slider bearing. The goal of creating the meta-model was to reduce the computational efforts of conventional THL analysis without compromising the solution accuracy. The dataset used to train and validate the ANN were obtained from numerical simulations. Results showed that when using an appropriate, results can be predicted with reasonable accuracy. Furthermore, it was also verified that the training algorithm and the sample size affect the prediction accuracy significantly. Gorasso and Wang [30] proposed a journal bearing optimization process, in which the performance functions were an ANN trained with a dataset obtained from numerical solutions of the Reynolds equation and Computational Fluid Dynamics (CFD) simulations. The optimization strategies adopted for the calculations were non-sorted genetic algorithm and artificial bee colony algorithm. Otero et al. [31] investigated the use of ANNs for predicting the friction coefficient in EHL point contacts. The model was fed with friction data obtained from tribological tests carried out for different lubricants and a range of operating conditions. It was shown that properly trained networks are capable to offer excellent predictions with a high level of correlation with the corresponding experimental data. Nonetheless, it was highlighted that special care is needed when using ANNs models as predictive since they are accompanied with the loss of relevant information, or intermediate results of interest (e.g., the complex rheological response of the lubricant at high pressure, temperature and shear-strain rate conditions), associated with the physical phenomena taking place in TEHL contacts. However, the supervised ML approach could be extended by using data from mixed-TEHL simulations for a wide range of materials and lubricant properties, contact geometries and working conditions. This would enable a fast and powerful design tool to predict the lubrication performance (e.g., film thickness, friction, temperature rise, leakage, among others) of different types of bearings and other lubricated systems [32]. For example, Marian et al. [33] applied a metamodel of optimal prognosis (MOP) to predict the influence of surface micro-textures on the frictional behavior of EHL point-contacts, see Figure 6. Thereby, the database was generated by numerical simulations considering mixed lubrication, whereby geometrical micro-texture parameters such as dimple depth and diameter were varied. Non-significant variables were then filtered and various metamodels, such as polynomial regression, moving least squares and kriging were trained. The most suitable approach was then automatically selected using a coefficient of prognosis and used for optimization by a genetic algorithm. Thus, tailored and load-case dependent surface textures can be determined.

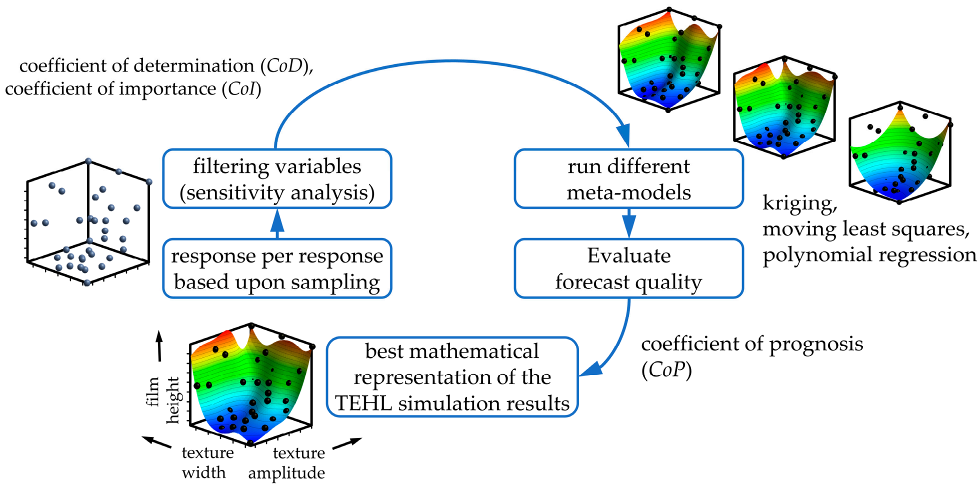

Figure 6. Framework of the metamodel of optimal prognosis to predict the tribological behavior of micro-textured EHL contacts utilized in [33].

Furthermore, Boidi et al. [34] employed the radial basis function (RBF) method for predicting the friction coefficient in lubricated contacts with textured and porous surfaces. The RBF model was trained with friction data obtained from tribological tests conducted on surfaces with different features and for a range of entrainment velocity and slide-roll ratio. The main results show that the hardy multiquadric radial basis function provided satisfactory overall correlation with the experimental data. It was also pointed out that the application of the suggested methodology could be extended to other experimental results to train more robust ML models for predicting tribological performances of textured and structured surfaces. In this respect, unsupervised ML methods could be used to construct design charts and to identify patterns of optimum performance. Furthermore, the reliability and accuracy of these ML-based tools are expected to improve continuously as more data is available. Regarding the analysis of the involved surface topography, unsupervised ML methods could be applied to achieve robust segmentation procedures for the characterization of real surface topographies. In this regard, clustering methods can help to identify and separate different surface features with tribological functionalities, such as plateau regions, bumps, honing grooves, textures, pores, wear zones, among others. Once the surface features are detected and separated in clusters, specific characterization methods and statistical assessments can be individually applied to each cluster. Furthermore, the analysis of the surface topography could further benefit from the use of supervised ML methods, in which ML algorithms are trained using post-processed data (e.g., roughness parameters, features statistics, etc.) of a variety of surfaces to create classification learning models. These trained models are intended to be used to assess surface finishing processes or correlated with tribological results to reveal specific characteristics of the surfaces that most affect the tribological performance.

3. Current Challenges, Future Research Directions and Concluding Remarks

Summarizing, the application of AI and ML has been shown to be a powerful and efficient way in predicting tribological characteristics and performance of materials with respect to valuable resources and time. Thereby, these techniques combine statistics and machine learning, imitating human intelligence at a more unconscious or untransparent level. ANNs are suitable for highly complex, non-linear fundamental and applied problems, which makes them particularly interesting for various fields of tribology. In addition, however, there are some other approaches that should certainly receive attention from tribologists. With this perspective, we intended to highlight some successful examples that show the potential for further research and future applications. In the future, AI methods could be applied in a lot more fields of tribology, e.g., the additivation of base oils with viscosity and friction modifies (for instance, nano-particles) to predict the results of experiments done on various materials compositions and test conditions.

Besides the prediction of optimal concentration, we hypothesize that AI and ML approaches will be useful to predict the size of the nano-particles (x-, y- and z-dimension) to effectively reduce friction and wear. Moreover, these approaches may be used to predict the likelihood of a tribo-layer formation, which largely depends on a complex interplay between different operational conditions. Moreover, AI and ML methods may be useful to support the characterization and classification of the involved surface topography in case of a stochastic surface roughness or even deterministic textured surfaces. Thereby, the change of the surface topography during running-in or wearing may also be addressed. From a more applied point of view, it can be also expected that AI and ML methods will be greatly involved in the design process of dry or lubricated components, see Figure 7. Apart from the prediction of optimum oil film thicknesses in machine components depending on the operational conditions such as sliding speed or load, surface topographies and textures, which are designed for specific conditions resulting in certain oil film thicknesses, are likely to be predictable by AI and ML algorithms.

With the fast-paced developments in the area of algorithms and computing power as well as the increasing availability and reusability of data [35], the utilization of AI in tribology will certainly increase in the upcoming years. To increase the range of applications and enhance the accuracy of the AI models, an online open platform could be created, on which the tribology community could share data of numerical simulations, surface characterizations and experiments. It is also conceivable that the database will not only be based on numerical simulations or experimental work on a research/laboratory scale but will also include actual operating data from real applications such as machine elements or engine components. This would enable controllers with ML/AI algorithms to be incorporated directly into these applications, e.g., rolling/sliding bearings, gears, brakes, clutches or the piston assembly, and used for performance prediction and adaptation to discontinuous and critical operating conditions.

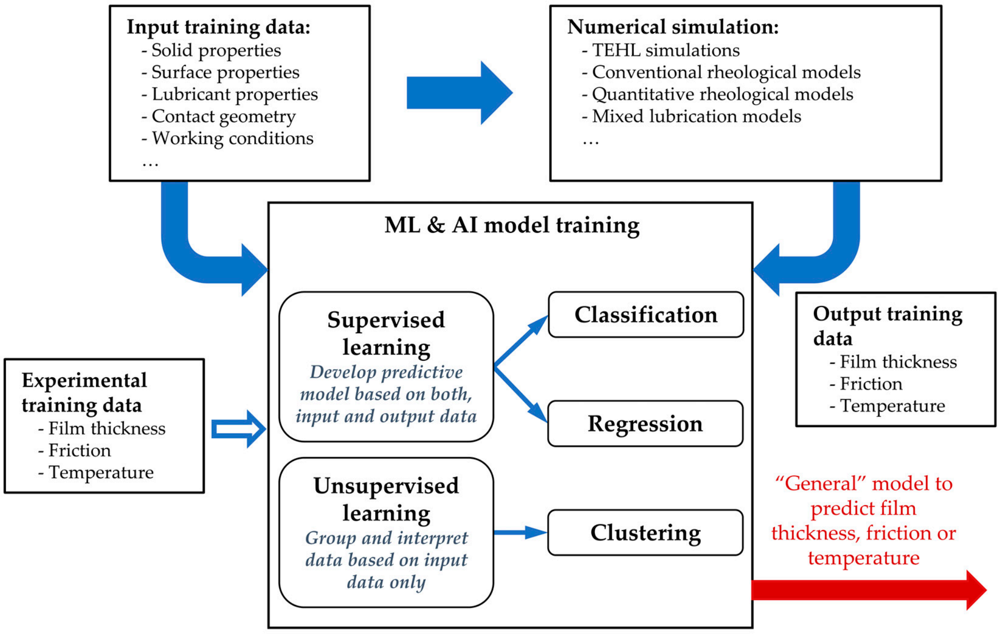

Figure 7. Schematic showing the main steps and parameters associated with the training process of ML/AI models to predict the lubrication performance from experimental and simulation data-sets.

The recently emerging big data trend won't bypass tribology and AI techniques have already be shown to be effective for many tribological questions. However, one of the biggest obstacles remaining is the handling of uncertainties in experimental and practical data sets due to differences in setups and sensor systems as well as the inherent multi-scale and statistical character of tribology with partially pronounced scattering of targeted parameters. These are not hard data but correspond to time-dependent and very specific loss variables, also resulting in frequently difficult transferability to other conditions or even tribosystems. Therefore, further fundamental research is essential for the application of new AI methods to ensure suitability and reliability in solving tribological issues. In particular, strongly domain-specific expert knowledge is crucial. The interdisciplinary character of tribology represents a great opportunity, but also a great challenge for the intense collaborations between different disciplines including physics, chemistry, materials science, mechanical engineering and computational science. Therefore, we would like to encourage tribologists all over the world to be open to new approaches/methods and interdisciplinary collaborations. Together with the aid of AI/ML algorithms, this can enable deeper insights in the incredibly important domain of tribology thus guiding us towards a new, greener and more energy-efficient era.

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