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A data-driven approach for studying tribology based on experimentation and artificial intelligence coupling tools

Mohamed Kchaou[1*]
[1] Department of Mechanical Engineering, College of Engineering, University of Bisha, Bisha, Saudi Arabia

*Corresponding author E-mail: kchaou.mohamed@yahoo.fr

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Abstract

Tribology problems generally, and particularly high-temperature tribology (HTT), is a critical and complex topic based on the interaction between several intrinsic and extrinsic parameters. This involved complex phenomena, resulting in synergistic effects between mechanical, physical, chemical, and thermal solicitations. Introducing artificial intelligence tools, coupled with the design of the experiment, is an original approach to implement a successful transition from traditional "experimental guidance" to "experimental guidance associated with a data-driven" approach. The current study delves into the utilization of machine learning (ML) with simulation to help in the choice of the parameters for experimentation, and the development of predictive models. A detailed framework that takes into account the coupling between such tools is presented. Different scenarios are discussed to data drive the collaborative schema between the design of experiment, numerical development, and ML algorithms. This approach gives several opportunities such as the identification of the well-impacted parameters, optimization of the experimental design, and the proposition of predictive models. With the suitable proposed model, time loss, production costs, precision results, and man-hours could be saved or improved.

Keywords: Tribology, Coupling tools, New framework, Prediction, ML

1. Introduction

For an engineering application, that involves tribological phenomenon such as friction, wear, lubrication, sliding, and sometimes failures, a good similarity of the experimental tests with the operating conditions of the tools remains necessary to reproduce on the test benches for a fruitful study on a laboratory scale using tribometers [1, 2]. Tribology based on experimentation requires many intrinsic and extrinsic parameters to take into account the involved and activated phenomenon in a contract. As a consequence, it is crucial to define optimum parameters that have a substantial impact on the impacted factor. This thereby the unitization of advanced techniques such as ANOVA and Taguchi for meticulous parameters optimization. Taguchi analysis was also investigated to achieve the desired outcome such as the number of experience to design, the degree of regression for the precision of the results, etc. [3, 4]. Besides, as the firstly developed tool, the analysis of variance (ANOVA) was used to identify and validate the linear friction model [5, 6] or the optimization of tribological behavior such as wear behavior [7]. The sample composition to be the most critical component of volume loss was identified. More recently, some algorithms have been developed using Machine learning to study the interaction between experimental parameters and the effect on the viability of the results [8, 9]. With the presence of a high level of temperature, Fuzzy systems can be used in this case of activated complexity because they work well with nonlinear systems and in particular with time-dependent functions [10]. Some approaches are based on the Fuzzy-neuro system which is the combination of the two materials on the contact effect and the characteristics of the sliding system [11]. Therefore, successful case studies using these approaches in a tribological context demonstrate their ability to accurately and efficiently predict tribological features [12] in the design of materials composition [13], lubricant formulations [14], lubrication and fluid film establishment [15], and interaction first bodies-environment [16]. However, certain models had certain limitations like they cannot be applicable for estimating the tribological behavior of wider varieties of materials that contain rigid structures with high wear resistance levels [17]. Besides the prediction of tribological properties has become a difficult problem in the field of tribology because of the complex non-linear relationship between service conditions. Therefore, the application of AI in tribology, where influencing factors are non-linear, is still in its infancy. The challenge is moving from traditional "experimental guidance" to "experimental guidance associated with data-driven". As a consequence, the priority of the development of efficient experimentation is the investigation of possible coupling between Ml and the design of the experiment to study a tribological problem.

The objective of this paper is to establish an innovative framework based on the coupling experiments-artificial intelligence. The proposed tool utilized data mining in conjunction with a limited amount of experimental data to select the most impacted parameters to design the experience using machine learning algorithms, to predict tribological properties, and to develop well-represented models to reduce the gap between what happened in-service and the activated mechanisms.

2. Research methodology

For evaluating the tribological behavior of materials in contact, it is crucial to define optimum parameters that have a substantial impact on multiple variables and to predict the most representative behavior. Therefore, the developed approach is based on innovative tools, which act upstream and downstream of a tribological test. The investigation has the following flow data:

- Fixation of the tribosystem
- Identification of the input of the test in terms of parameters and factors that can affect the contact and influence the tribological behavior
- Selection of the most influenced parameters to optimize the test using ML algorithms
- Design of the experiments and experimental setup
- Data collection and application of stepwise regression
- Prediction of the friction behavior, wear lost and rate, and temperature evolution

3. Results and discussion

3.1. Tribometry: concept and simulation, and critical analysis

3.1.1. Concept of tribosystem

A tribosystem is a set of parameters that enclose a contact between two materials. These parameters are never present in the same way, and we often find synergistic effects, which require more testing and analysis to precisely isolate each of their roles. As shown in Figure 1, the essential elements making up a tribosystem are i) main solids called first bodies, ii) An inter-facial boundary called third body, iii) An environment in which the two solids evolve under the action of forces, and induce certain mechanisms. Several input parameters can be imposed such as load, speed, temperature, movement type, test duration, composition and amount of grease, vibration, lubrication, etc. The friction force, contact temperature, wear rate, etc. are the most recorded output of a tribological test.

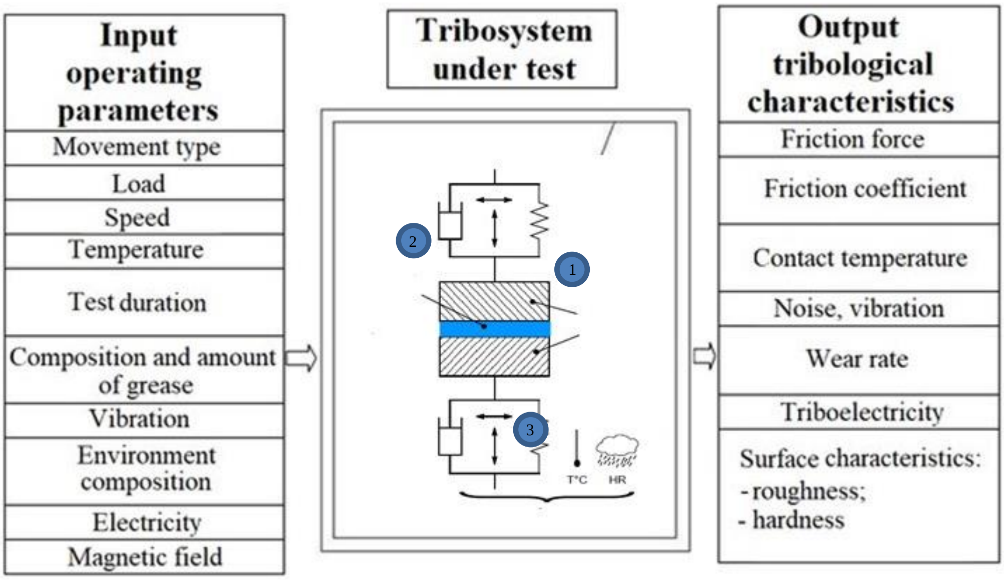

Figure 1. Tribological system: (1) first bodies, (2) third body, (3) mechanisms

3.1.2. Simulation

To simulate tribological phonemes, tribometers are used. The choice of configuration and test parameters differs depending on the process to be studied and the physical mechanisms to be involved. The samples are generally small and the studies allow an analysis of the contact for a given pair of materials under certain test conditions. They consist of measuring, under given contact conditions (temperature, contact pressure, etc.), macroscopic parameters (generally forces or torques), and deducing an apparent friction coefficient, for example, Coulomb. Thus, these tests make it possible to study the influence of pressure, speed, temperature, atmosphere, etc., but under friction conditions that are very different from service conditions. In according to the experimental conditions (area to be studied in the tools, lubricant, coating, etc.), several contact configurations are possible. They are generally of the type pin-on-disc, disk-on-disc, or even cylinder-on-cylinder type. These classic tribometers cannot be used without precautions for the analysis of the tribology of more complicated processes like hot forming. Indeed, in shaping, for example, friction occurs on a material undergoing global deformation, which is not represented by these tests. This overall deformation of the material can have a great influence on friction, particularly because it can induce a modification of the contact conditions. Thus, the specificity of tribological phenomena and the nature of the stresses applied in hot forming have led to the design and use of tribometers and specific test benches. These tribometers are differentiated from each other by the type of contact, the controlled speed, the measurements carried out, etc. Several authors often use rotating devices that allow access to very significant sliding lengths. Many of these machines concern more particularly and classically experimental tests at room temperature. Some devices have recently been produced to carry out high-temperature tests, mainly in the case of the study of hot forming. The specificity of the contact in terms of temperature, activated physical phenomenon, the interaction between materials in the contact, and the other elements of the tribological system were oriented researchers for the development of specific high-temperature tribometers. When the objective of the use of tribometers was the study of the friction behavior, the identification of wear mechanisms, and the analysis of the damage mode, the complexity of the in-situ solicitation of the contact, and the activation of synergistic phenomena such as mechanical, chemical, physical, dynamic, etc. hade made the outcomes of a test difficult to analyze. Besides, several types of coefficient of friction were deduced: max, min, medium, at the beginning, at the end, etc. As a consequence, several mechanisms are still not well analyzed and highlighted for the different scales of investigation (from the macro to the nanoscale). Since the end of the last era, the idea of the use of algorithms in the identification of the most influenced parameters or the optimization of the design of experiments was been satisfied.

3.1.3. Critical analysis

Through the configurations that we have presented, each of them solved its problem: production of very high sliding speeds, the interaction between thermal phenomenon and tribology, taking into account the effect of the environment (lubricated contact) and constant renewal of the surface of the material which is deformed. In the majority of cases of contact, especially at high temperatures, it is interesting to observe what happens on the surface under the effect of friction while avoiding plastic deformations which can occur on materials more easily at high temperatures. In other words, the temperature which determines the quality of friction is the temperature of the contact surface. Researchers are therefore interested in heating only the extreme surface of the track. Other parameters are involved in a tribological analysis such as sliding distance, variability of the applied load (continuous, intermittent, sinusoidal, cyclic, etc.), the introduction of the external body in the contact (generation of squeal, augmentation of the gap between surfaces in contact, acceleration of the wear rate, etc.). As a consequence, it is quite complicated to manage a huge number of variables and their interrelationship affecting the wear phenomenon. Understanding the factors and variables controlling friction, and wear, and their observational impact on tribological properties is also not clearly defined.

3.3. Coupling experimentation – machine learning (ML)

3.3.1. Principle of ML

Machine learning (ML) is a relatively new approach that can validly perform complex pattern recognition and regression analysis. It is used to endow computers with the capacity to learn, comprehend, and reason like human beings, and as a consequence translate the cognitive process into data processing procedure [18]. Among the different ML algorithms, artificial neural networks (ANN) are widely used due to the availability of large datasets as well as sophisticated algorithm architecture. The working principle of Artificial Neural Network (ANN) is based on perceptron (Figure 2). Currently, ML, as an emerging artificial intelligence technique, has been used in many aspects; compared to the traditional experiment-driven data, ML as a data-driven method, is considered a global solution for prediction, optimization, and correlation [19]. Modern engineering research is based on the incorporation of AI tools and learning [20]. The application of Machine Learning technology in the field of materials science and mechanics has witnessed a gradual increase in recent years, primarily focusing principally on performance prediction, and analyzing complex and multi-dimensional functional relationships. Several ML models can be used such as gradient boosting regression (GBR), random forest regression (RFR), and extreme gradient boosting (XGBoost) to predict materials properties or engineering behavior under different service conditions [21]. Continuous improvements are crucial components of ML systems, to adapt to new challenges, and changing conditions, and to assimilate new data and concepts.

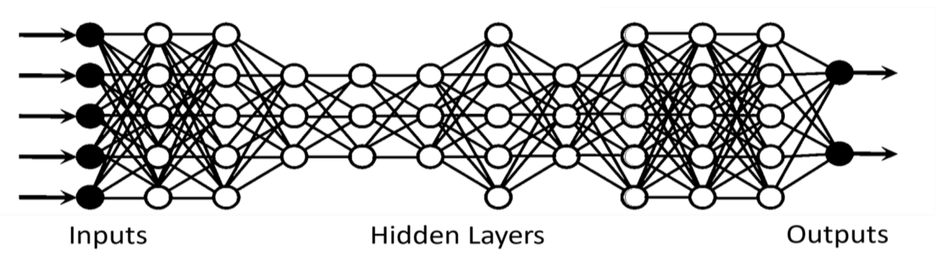

Figure. 2 Principle of ANNS: details of the multi-layer perceptron

3.3.2. Concept of coupling

The coupling approach takes into account the notions of empirical science, based on phenomena, theoretical science based on simplified models, computational science based on computational tools, and information science based on big data. In our case, modeling coupled tools (Experimentation and Artificial Intelligence) to study a tribology problem requires parameters and processes to describe the tribological behavior, the temperature evolution, and the stability of friction… based on the optimum design of the experiment validated by machine learning.

3.3.3. Idea of the innovative framework

Machine learning algorithms are used for parameters chosen as input of the experiment design (Figure 3a) and for the choice of the well-important results as output of the testing (Figure 3b). Therefore, supervised ML is used for regression analysis to discover possible correlations between parameters such as materials, surface, and lubrication properties, normal load, sliding speed, temperature, sliding distance, etc., and output parameters such as friction layer, friction behavior, temperature evolution, wear depth, etc.

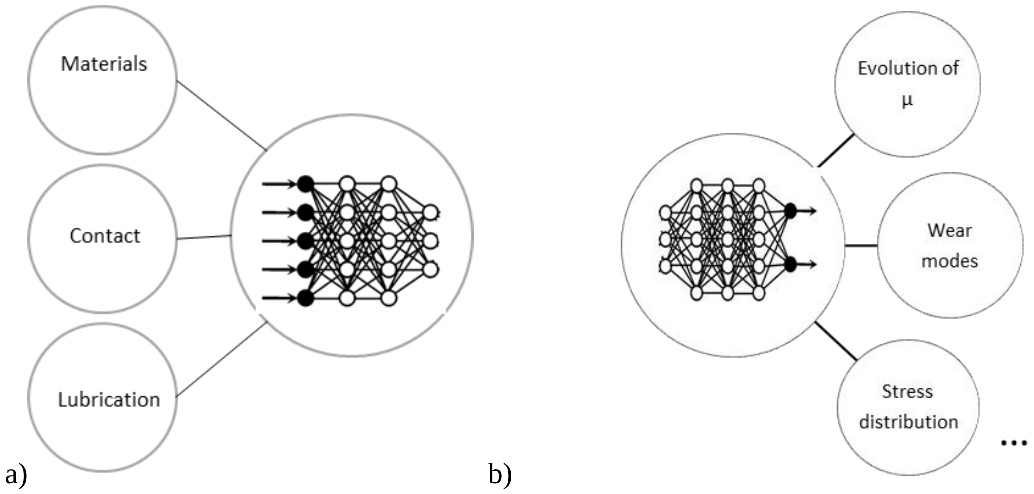

Figure 3. ML is used for a) input, b) output of the design of the experiment

3.3.4. ML for input data used for experimentation

In this case (Figure 4), the integration of ML is used to help in the identification of the experimental design, such as parameters, factors, and variables from the analysis of the input training data such as materials, surface, and lubrication properties. Therefore, the number of experiences could be reduced by the limitation of the more sensitive data. It reduces the time, cost, and variability of the experimentation, especially when the experimental design parameters are well chosen, based on background, knowledge, and expertise (parameters, factors, target variable, tribe system, environmental conditions, etc.).

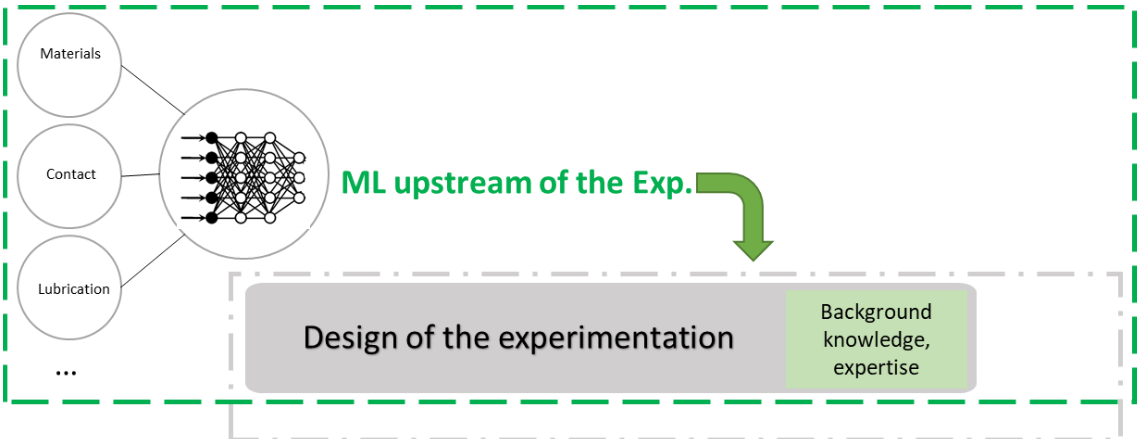

Figure 4. ML used upstream the experimentation

3.3.5. Simulation of the design of the experiment

Once the parameters are selected and optimized, the experience is running according to the following methodology (Figure 5):

i) Design of experimentation, which is the result of deep knowledge of the tribological test requirement, a retrospective analysis of the specificity of the materials in contact, and a global understanding of the planned and possible friction-wear mechanisms that can be the result (based on the feedback of preview expertise),

ii) Driven of the experimentation, by the specification of devices and sensors (characteristics, calibration, regulation), choice of the test configuration (pin-on-disc test or other, open or closed sliding, conform or con-conform contact) sample size and properties (preparatory steps of polishing, drilling holes for fixing sensors if necessary (such as thermocouples), checking flatness and parallelism), identification of the representative elementary volume in the case of composite materials. Once the experiment is defined, and the test is launched, particular interest will be given to the activated mechanisms, synergistic effect of solicitations, the evolution of the surface of contact, the effect of the different loads and reciprocating frequency, etc.,

iii) Counting of the results, from the evolution of the coefficient of friction to the modification of the sliding surfaces and the variation of the temperature.

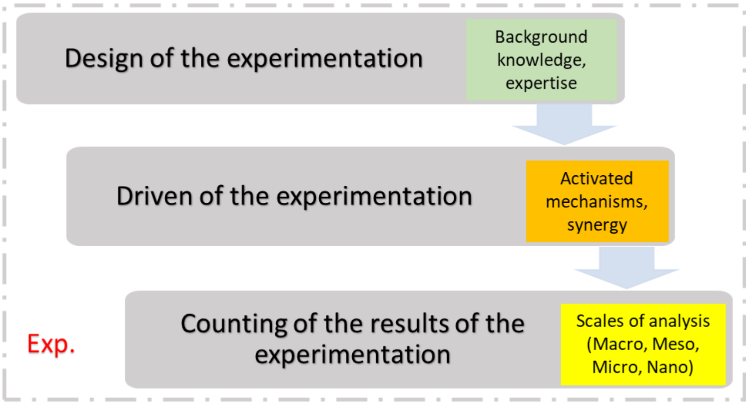

Figure 5. Simulation of an experimental test using a tribological approach

3.3.6. ML in the downstream of the experimentation

In this case (Figure 6), the results of experimentation are the data of the input layer: it can be the coefficient of friction, the evolution of the temperature in the surface and in the depth of the contact, the topography of the surface, the roughness, etc. As the problem is a complex, multiscale, and metaphysical topic, many results could be collected from the tribological aspect itself, but also from the synergy between, mechanical, chemical, thermomechanical, physical, and tribological phenomena. Post-mortem analysis can be established to correlate the tribological behavior to the microstructure and the different activated mechanisms of friction, to identify the wear types from the Meso scale to the Nano scales when necessary, the evolution of the temperature, the failure modes, the impact of lubrication, the stress distribution, etc. This increases the dispersion of the results and limits the effectiveness of the test towards the choice of the response representative of the studied phenomenon.

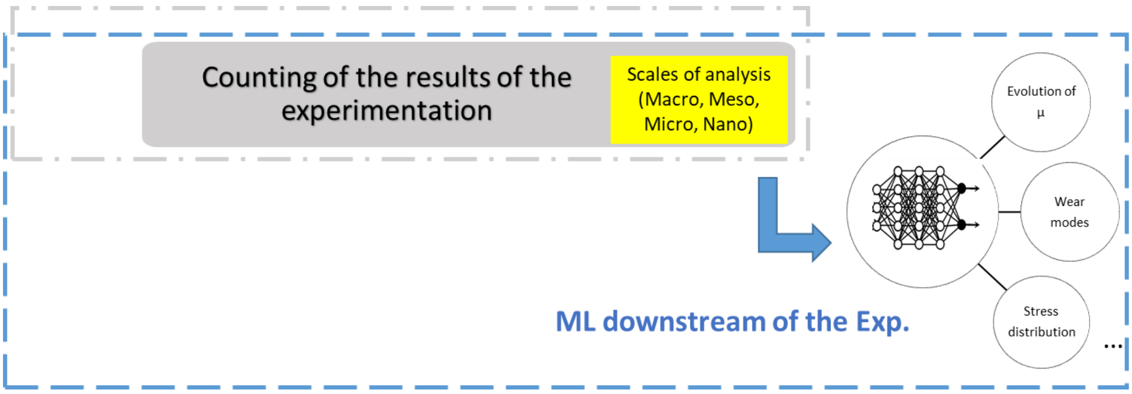

Figure 6. Coupling ML experimentation downstream of the test

3.4. Validation of the innovative framework

3.4.1. Optimization of the experimental tribological test

The potential of using artificial neural networks for the selection of the most influenced parameters in relation to the type and classification of materials in contact can be explored when driving a tribological test. It is established by using a measured dataset of a certain number of independent pin-on-disc tests for example. The methodology of optimization of the used parameters is shown in Figure 7. It takes into account the different information from data sources to select the most influenced parameters. This framework was tested by [22, 23] and reported by [24, 25].

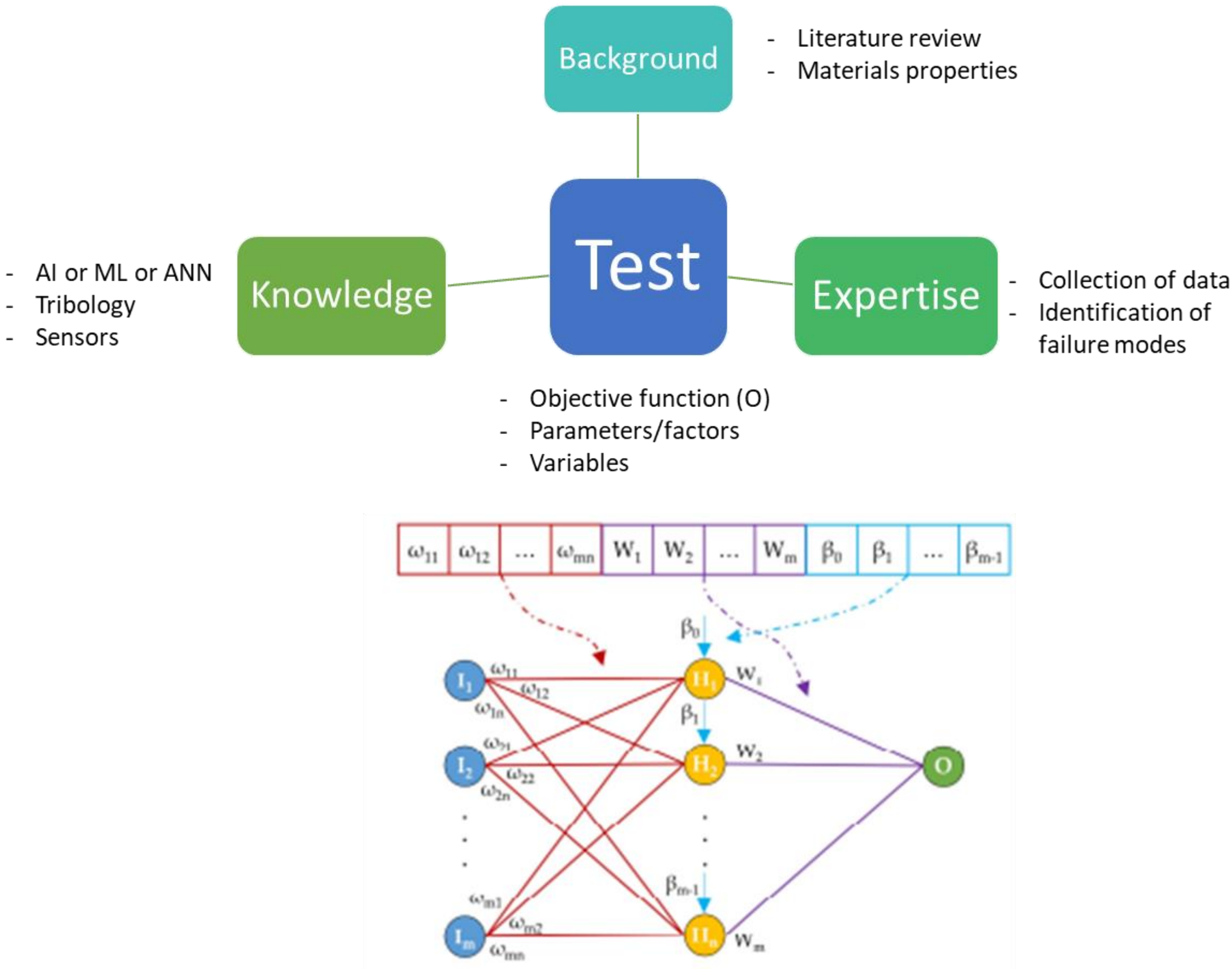

Figure 7. Schematic representation showing the mean steps and parameters associated with the training process of ML models, based on background, knowledge, and expertise, to identify the objective function (O) and predict the most influenced parameters

3.4.2. Correlation of tribological and materials properties

The machine learning approach is employed to predict tribological properties under diverse operational conditions. The gradient boosting regression (GBR) model can be used to predict performance. Besides, the Pearson correlation coefficient quantifies the impact of the temperature and speed on the friction coefficient and wear, and a possible comparison with the effect of the load can be established. The result depends on the nature of the material (polymer, composite, metal, etc.) and the level of load, speed, and temperature. Python 3 environment can be used as an open-source learning package for the implementation of ML algorithms. After collecting the database from friction and wear experiments, they are randomly divided into a training set and a testing set, ensuring both the generality and accuracy of the used models. The coefficient of determination R2 can be used to illustrate prediction errors and to evaluate the models. Preliminary studies published by Yan et al. [26] demonstrated good correlations, especially at high levels of speed and temperature. The degree of influence varies from 1 to 0.6 10^{-7}. Wang et al. reported a good simulation of the tribological behavior of PTFE composite materials by varying wt% of charges [27]. Jia et al. established a factor 2 predictive model of FeCoCrNiAlN high entropy coatings using experimental and ML data [28].

3.4.3. Identification and classification of wear modes and wear debris

Wear is a complex phenomenon, which is the result of competition between different mechanisms and flow: internal flow, feeding flow, lost flow, external flow, etc. This aspect involves several parameters consisting of booth experimental conditions and materials properties. The investigation focuses on the establishment of correlations between composition, microstructure, hardness as materials characteristics and load, sliding distance, and temperature, etc. as extrinsic parameters to predict the materials loss, the wear rate, the wear debris, etc. The approach to detection, identification, and classification of the wear debris is illustrated in Figure 8. This approach is tested and reported by [29, 30].

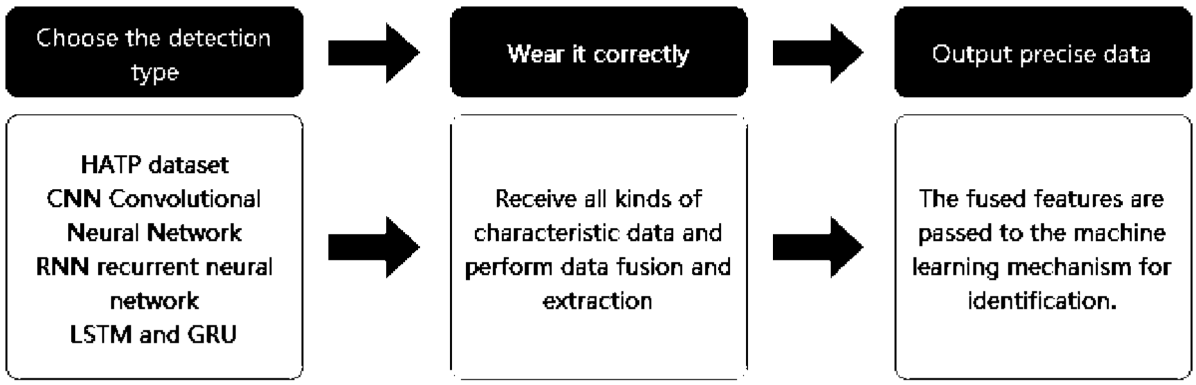

Figure 8. Workflow to detect and identify wear

3.4.4. Prediction of the coefficient of friction

When a material rubbing against another, the coefficient of friction changes randomly with time, which has a high degree of randomness, periodicity, and trend. Time-series analysis could be adopted to establish mathematical models through curve fitting and parameters estimated from ML data. ML regression models could be employed to predict COF using input features such as microstructure, coating deposition process, element compositions, grain size, and mechanical properties (hardness, Young's modulus). Also, friction conditions including friction load, velocity, and sliding mode could be taken into account. Besides, prediction could be established based on the identification of the link between the contact roughness and the friction-induced vibration. Some authors proposed the variation mode decomposition along with ML algorithms to predict the COF [31, 32]. Algorithm optimization is achieved through the implementation of L1 and L2 regularization methods.

3.4.5. Development of predictive wear models

For each scenario, a back-and-forth passage between the data and the model outputs is necessary, allowing to preparation of the data, to build the ML model. The ML algorithm trained different possible models such as RF, KNN, XGB, and SVM. The purpose of selecting different models is to determine the most appropriate by comparing the prediction accuracy of different models.

4. Conclusions

In this paper, an original framework based on the coupling between the design of an experiment and the tool of AI in the study of a tribological problem is presented and discussed. The idea is based on the exploitation of the potential of ML on the assignment assistance of a tribological test. The validation of the data-driven approach is articulated in the discussion of the different possible scenarios and the prediction of the input and the output of the experimentation. This approach gives several opportunities such as the identification of the well-impacted parameters, optimization of the experimental design, and the proposition of predictive models. With the suitable proposed model, time loss, production costs, precision results, and man-hours could be saved or improved.

Declaration of competing interest

The authors declare that they have no known financial or non-financial competing interests in any material discussed in this paper.

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