TRIBOLOGIA - Finnish Journal of Tribology 1-2 vol 41/2024

https://doi.org/10.30678/fjt.142331

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New Framework for studying High Temperature Tribology (HTT) Using a Coupling Between Experimental Design and Machine Learning

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ABSTRACT

High temperature tribology (HTT) is considered to start at a minimum temperature of 300°C, where organic base oils and polymers begin to decompose, up to a temperature of 1200°C. In this area of application, a tribological test is typically performed under dry or solid friction, unless a solid lubricant is used, as most lubricants oxidize or decompose when exposed to these extreme temperatures. This is the case of hot forming tribology. Therefore, specific tribometers have been developed to study the tribological behavior, wear modes, friction-wear mechanisms, and other tribological aspects in the case of contact workpiece-forming tools. However, as the interdisciplinary character of tribology represents great opportunities, but also a huge challenge to well study the tribological behaviour of materials and systems, particularly at hot temperature, results are well impacted by the proposed hypothesis, the limited number of parameters to study, the dynamic behaviors of solicitations, etc. A new approach to overcoming its limitations remains a necessity in modern research. After giving general definitions of the notions of tribological system and tribometer, an assessment of the different configurations of these test benches is established. The presentation of the tribometers is organized according to the configuration adopted. The study is based on the identification of the "originality" of the benches and the limitations of the approaches used in the study of hot temperature sliding contact. The framework of the coupling between experimentation and machine learning is presented. Different scenarios are discussed in order to develop new approaches/methods of collaboration between the design of experiment, numerical development, and ML algorithms.

Keywords: tribometer, hot temperature, wear, mechanisms, characteristics, artificial intelligence, new approach, coupling

1. Introduction

The increase in the hot forming tools life necessarily requires deep study using simulation and/or experimental investigation to understand the physical mechanisms activated in tool-workpiece contact [1-3]. This simulation is difficult to implement due to the different mechanical, thermal, and tribological solicitations to which the shaping tool is subjected [4-6]. 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. In this context, it is appropriate to distinguish between two types of studies: i) Characterization study of the tribological behavior of tool-part contact, ii) Study to understand tool-part friction mechanisms. For characterization studies, full-scale inertial bench tests are generally implemented using the complete die-forging mechanism. The performance of these benches makes it possible to reach the pressure levels encountered in service, and the tribological triplet thus formed is sufficiently close to scale 1 to obtain an overall friction response comparable to that of stamping in service [7, 8]. Given the cost of such tests, they are generally supplemented by small-scale tests, on test benches called tribometers. These tests allow a comparative study of the materials tested without fully accounting for the behavior in service [9]. For comprehension studies, the tests are most often carried out on a tribometer, whose choice of configuration and test parameters differ depending on the shaping process to be studied and the physical mechanisms to be involved [10-12]. The samples are 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 parameter (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 [13-15]. However, these classic tribometers cannot be used without precautions for the analysis of the tribology of a hot forming process. Indeed, in shaping, friction occurs on a material undergoing global deformation, which is not represented by these tests [16]. This overall deformation of the material can have a great influence on friction, particularly because it can induce a modification of the contact conditions [17]. 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 [18-22]. These tribometers are differentiated from each other by the type of contact, the controlled speed, the measurements carried out, etc. According to the experimental conditions (area to be studied in the tools, lubricant, coating, etc.), several contact configurations are possible [23-25]. They are generally of the type pin-on-disc, disk-on-disc or even cylinder-on-cylinder type [26]. Several authors often use rotating devices which 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 study of hot forming. The specificity of the contact in terms of temperature, activated physical phenomena, interaction between materials in the contact and other elements of the tribological system oriented researchers towards the development of specific high temperature tribometers.

When the objective of the use of tribometers was the study of 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. made the outcomes of a test difficult to analyze. Beside, several types of coefficients 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 nano-scale). Since the end of the last era, the idea of the use of algorithms in the identification of the most influencial parameters or the optimization of the design of experiments has been satisfied [27]. More mature attempts were made to use artificial neural networks in tribological studies, to carry out several experiments in order to classify wear particles during specific sliding experiments [28]. They used different parameters such as width, length, projection area, reflectivity and aspect ratio. Subsequently, another interesting study on the diagnosis of localized faults in ball bearings is carried out using a multi-layer feed-forward neural network trained with a supervised error back-propagation technique and a theory of unsupervised adaptive resonance [29]. A similar study on the wear behavior of lubricated plain bearings was also carried out subsequently [30]. Furthermore, some algorithms are developed using Machine learning to study the interaction between experimental parameters and the effect on the viability of the results [31-35]. 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 [36]. Some approaches are based on the Fuzzy-neuro system which is the combination of the two materials for the contact effect and the characteristics of the sliding system [37-39]. Therefore, successful case Studies using these approaches in a tribological context clearly demonstrate their ability to accurately and efficiently predict these tribological features [40-42]: in the design of material composition [43, 44], lubricant formulations [45, 46], lubrication and fluid film establishment [47, 48], and interaction first bodies-environment [49]. However, no study tested the possibility of coupling experimentation and machine learning through an active learning approach.

The objective of this paper is to established an innovative tool to study High Temperature Tribology problems. It is based on the coupling between experiments and artificial intelligence to reduce the gap between what happened in-service and the activated mechanisms reproduced by the experimental investigation.

2. Methodology

2.1 Experimental procedure in the case of HTT

High temperature tribology is investigated experimentally using tribometers specifically development of the study of this case of application.

2.1.1 Highlights of the commonalities and differences of the HTT

High temperature tribometers are equipped with heating systems to approximate hot forming conditions [50 -52]. Heating can be inductive or resistive. Inductive heating may be possible, because it offers two advantages: the first being its small footprint and the second its easy use, allowing very rapid temperature rises. This is the solution adopted by Semenov's adhesiometer (2000°C/ vacuum 10-4 mbar) [53]. However, this type of induction heating has a disadvantage: its limitation of the volume to be heated and therefore heterogeneity of the atmosphere surrounding the samples [54]. It is for this reason that it is rather intended for studies where the pin and the disk are not subjected to the same temperature (such as the shaping of metals by rolling or hot stamping) like those developed at University of Technology of Compiegne [55]. It is clear that the technological solutions that can be developed in the case of devices equipped with heating means are more delicate and more expensive. This is because of the need to move the guiding elements away from the study part and to integrate a cooling system, which implies additional complexity in terms of waterproofing. Another constraint can be added in the choice of the materials constituting the assembly. The introduction of a heating element requires the use of refractory materials (metallic or ceramic) at the level of the hot parts and a cooling system for the moving parts.

2.1.2 Critical analysis of these specific tribometers

Through the configurations that we have presented, each of them solved its own problem: production of very

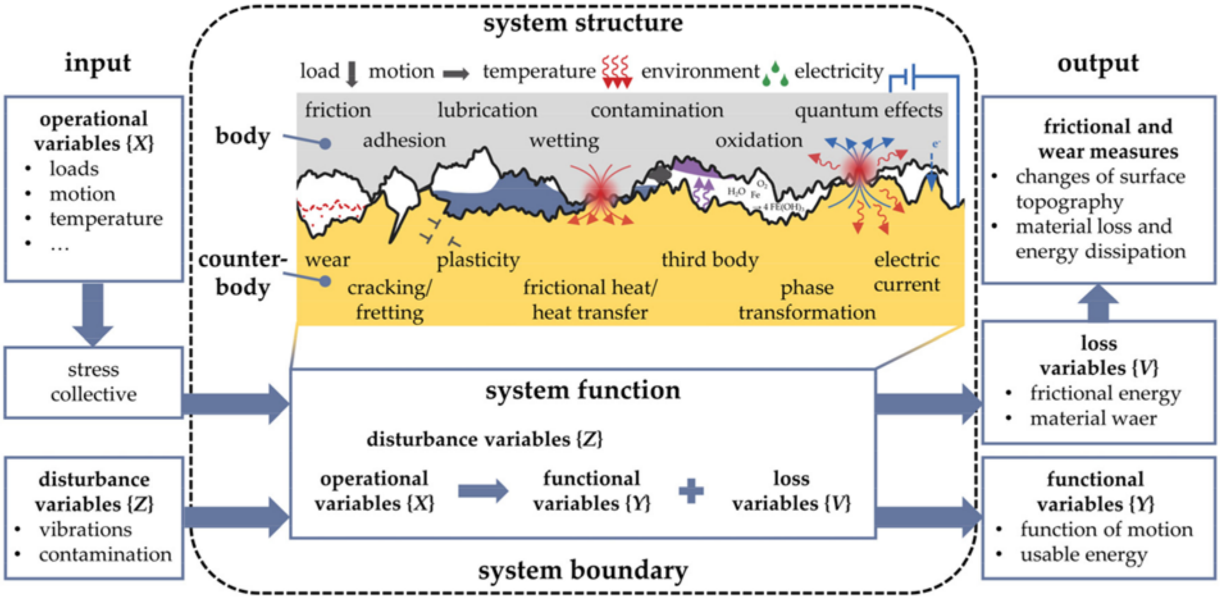

Fig 1. Concept of tribosystem [50, 51]

high sliding speeds, interaction between thermal fatigue 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 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. However, taking into account the nature of the stresses generated during the filling of the tool with the metal of the blank, in particular the thermal cycling-friction coupling, is ignored on the majority of these tribometers. In addition, the intermittent nature of the forming cycles does not figure in the representativeness of the tests on the tribometers. All these challenges require innovative approach to reduce the gap between the in-service activated phenomenon and the reproduced friction mechanisms.

2.2 Innovative Approach

The methodology of investigation is based first on the knowledge and understanding of:

- the principle of tribology, particularly the concepts of tribosystem and tribometer: this information is required to identify all parameters and factors that can affect the contact and influence the tribological behavior

- the specificity of the developed high temperature tribometers in relation to the level of temperature as input of the test of simulation or the level of induced temperature by the friction, the complexity of the interaction between the activated mechanisms in the contact

- the flow process of an experiment using HHT and the different challenges

- the principle of machine-learning (ML) working and development, with at least the most influent parameters.

The second step is the proposition of scenarios of interaction between experimentation and ML, numerical simulation and ML, and possible coupling between experimentation, simulation, and ML. The validation of the proposed approach is based on a retrospective analysis of some published methods, trying to establish possible collaborations between the three methods of investigation.

3. Results and discussion

3.1 Concepts of tribological system and tribometer

A tribological system, or tribosystem, is the 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 in order to precisely isolate each of their roles. The essential elements making up a tribosystem are: i) A main solid, ii) An antagonistic body, iii) an inter-facial boundary, iv) An environment in which the two solids evolve under the action of forces. Figure1 shows the interaction and influence of all these parameters in a tribosystem.

Complex contacts in a tribological system can be reduced to combinations of simple mechanical actions, on the volume and surface of the material. From the kinematic point of view, when a solid S1 (body 1 shown in Fig 1) touches a solid S2 (body 2 shown in Fig 1), any infinitely small displacement of S1 relative to S2 is broken down into: i) a sliding or translation parallel to the tangent plane common to the two bodies at their point of contact, ii) a rolling or rotation around an axis located in the tangent plane passing through the point of contact, iii) a pivot or rotation around the normal common to the two bodies at their point of contact. A tribometer is a testing machine that allows the study of the mechanical behavior

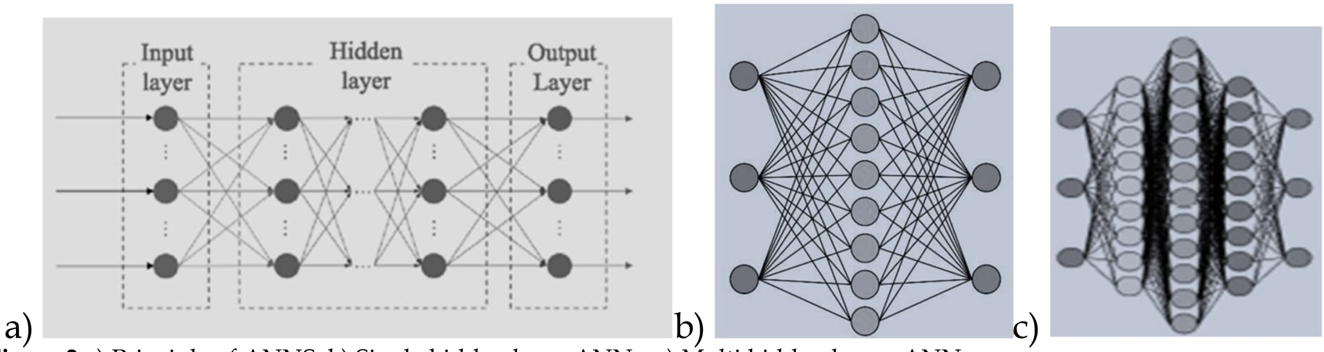

Figure 2 a) Principle of ANNS, b) Single hidden layer ANNs, c) Multi hidden layers ANNs

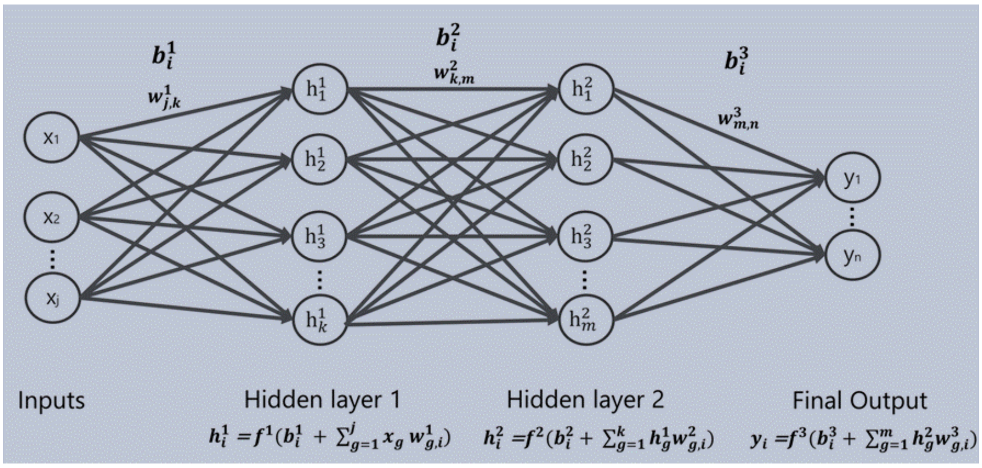

Figure 3 Details of the multi-layer perceptron (x: input layer, h: hidden layers, y: output layer, b: hidden layer bias, W: hidden layer neuron weight, f: activation function)

of friction actions between two surfaces (two surfaces in contact and in relative movement), taking into account the interactions of the tribological system. Generally, tribometers can be divided into two large families: closed contact tribometers and open contact tribometers. In the first case, the stressed surfaces are almost identical. In the second case, one of the surfaces in contact is not permanently stressed. Open contact has more advantages than closed contact. In particular, it allows better evacuation of wear debris, good surface reactivity as well as good cooling [52].

3.2 Principle of Machine Learning (ML)

Machine learning (ML) is a relatively new approach that can validly perform complex pattern recognition and regression analysis. This can be achieved without building or solving physical models. 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 (figure 2). The working principle of Artificial Neural Network (ANN) is based on perceptron. In fact, the perceptron is the simplest neuron consisting of an output layer and an input layer. We use the summation function which processes the inputs incorporated into the perceptron, and then it is then subjected to the activation function in order to obtain the output. As the simple perceptron model has the advantage of its inability to deal with huge data sets and multiple inputs, the number of neurons should be continually increased. A basic artificial neural network architecture consists of an output layer, hidden layers, and an input layer (figure 2.b). It should be noted that the artificial neural network can have multiple hidden layers (figure 3.c), but it must have only one output layer and one input layer. The main objective of the activation function is to obtain an output by converting the weighted sum of the input signals. The working principle of an artificial neural network generally relies on two types of propagation methods, namely forward propagation and backward propagation. If we think of X_1 and X_2 as characteristics of a sample in a given data set, these characteristics are subject to certain mathematical operations to predict the outcome. W_1 and W_2 are the weights associated with each feature. These weights together serve as input to the neuron. At the summation stage, all available features are multiplied by the weights assigned to them and a bias is added as shown in Equation 1. The activation function is further subjected to the function summarized above. The weight W_3 is multiplied by the output of the old neuron and further behaves as the input to an output layer. The backpropagation method is used to update the weights after each initiation.

$$Y = W_1X_1 + W_2X_2 + bias \qquad \text{Eq. (1)}$$

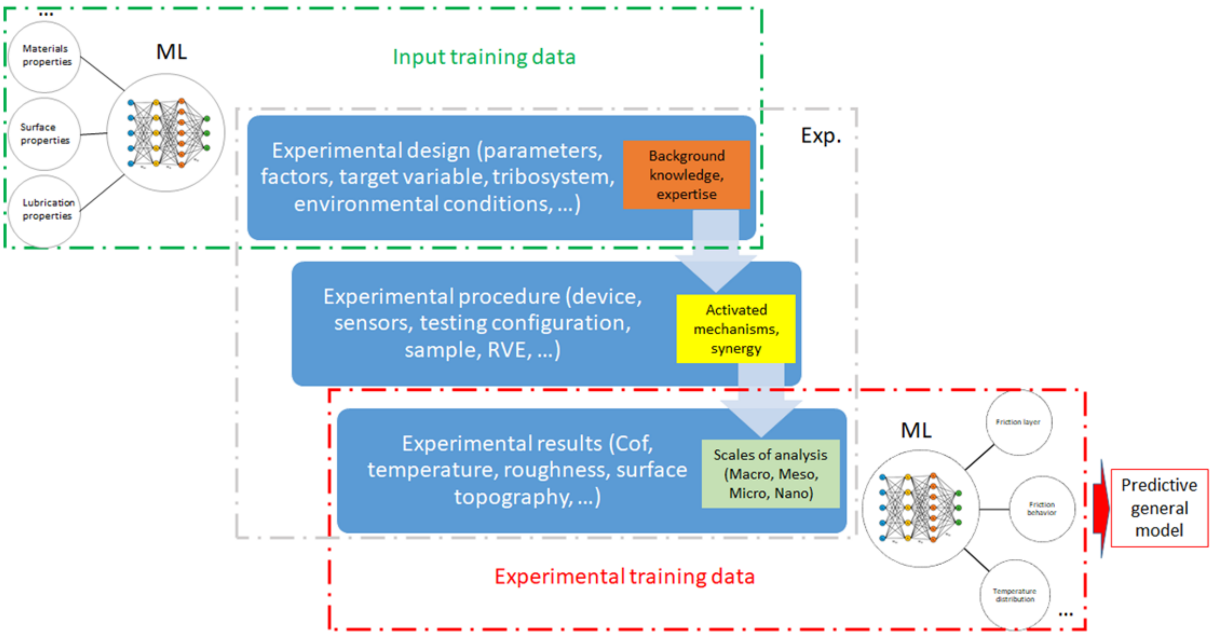

Figure 4 Developed coupling approach between experimentation and the use of ML

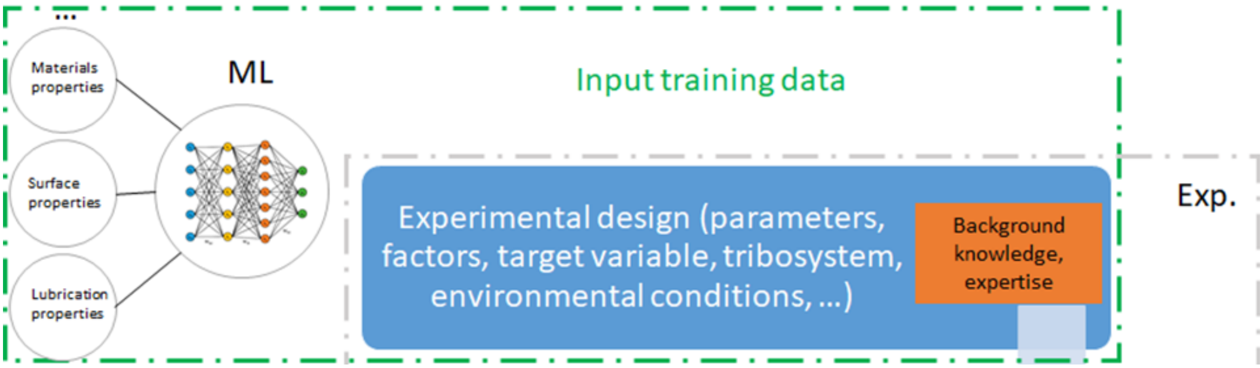

Figure 5. First scenario

3.3 Design of the new framework: coupling experimentation- ML

The coupling approach takes in to 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. Figure 4 shows the possible coupling between experiment and ML.

a. Scenario 1: The coupling is upstream of the experiment (green)

In this case, the integration of ML is used to help in the identification of the experimental design, such as parameters, factors, variables, … from the analysis of the input training data such as materials, surface, and lubrication properties to reduce the number of experiences by the limitation to the more sensitive data, Figure 5.

b. Scenario 2: The coupling downstream of the experimentation (red)

In this case, 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, … ML and AI model training is used to develop a general model to predict film thickness, friction, temperature, etc., figure 6.

For each scenario, a back and forth passage between the data and the model outputs is necessary, allowing to prepare the date, to build the ML model, and to evaluation the outcome as clarified in the figure 7.

As reported by several references, when studding HTT cases using Taguchi methods, the number of DoE is very important and can reach more than 400 [56-59]. As application of our innovative tool, we can imagine a Taguchi experimental design of experiments with the optimum data points in combination with a back propagation ANN to train multilayer feed-forward networks, predicting the tribological behaviour of the contact hot forming tool-workpiece with/without the presence of oxide particles or layers. Another case can be simulated when experiments are carried out in duplicate and averaged values which are used in future data processing. Thereby, the relationships between variation

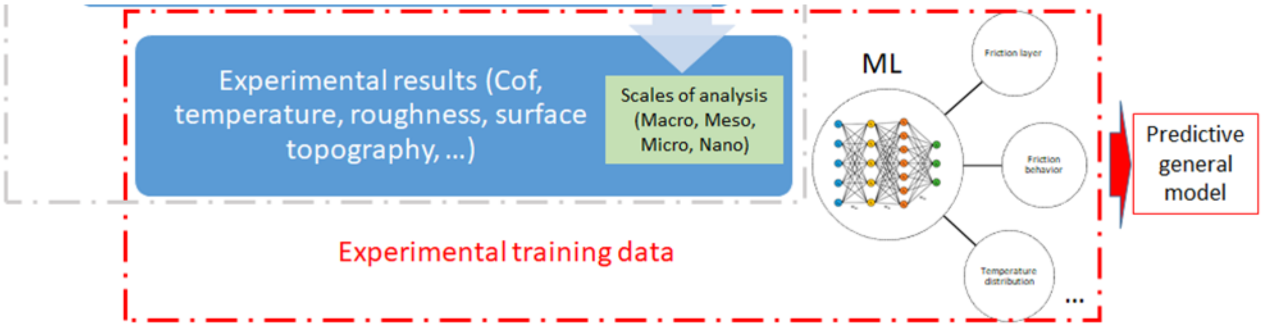

Figure 6. Second scenario

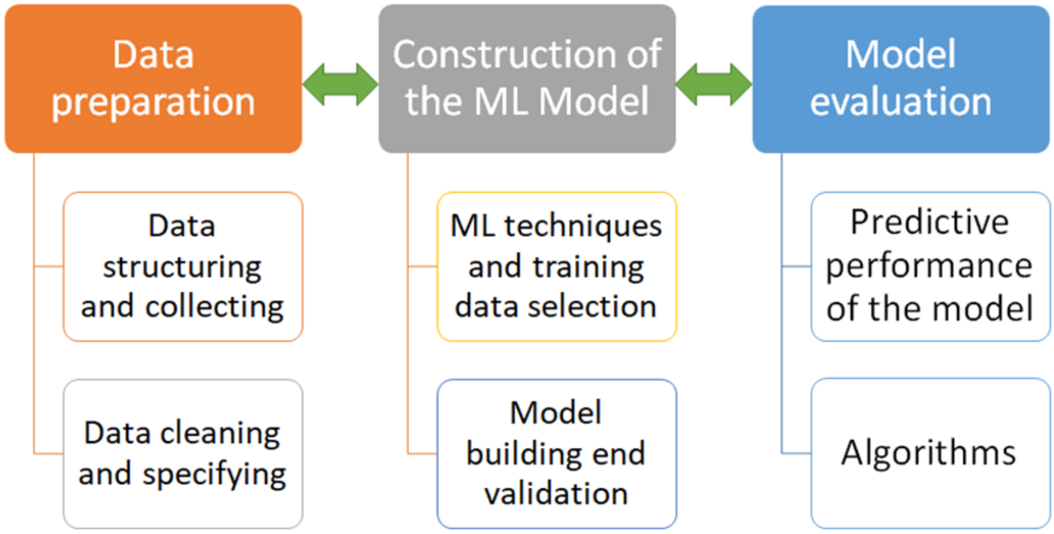

Figure 7 Data driven design of a predictive model using ML

parameters and target values will be expressed by linear regression for example as well as by hidden layers ANNs. In addition to these examples, we hypothesize that the new approach will be useful to predict the size of wear particles expected from the contact to effectively reduce the wear of tools, responsible of damage and nonconformity of the product geometry. Moreover, this innovative approach may be used in the prediction of the composition of the established oxide layer known by the tribo layer, which is the result of a competition between compaction and fragmentation mechanisms as reported by Alimi et al. [4]. Besides, the change of the surface topography induced by friction can be also mapped using the coupling which is predictable by ML algorithms and then involved in the design process of the dry or lubricated forming. Regarding future research directions and trends, we emphasize the extensive use of artificial intelligence and machine learning concepts in the field of tribology, including more strong coupling between experimentation – numerical simulation, and AI.

4. Conclusion

In this paper, an innovative methodology for the investigation of the high temperature tribology is proposed. The approach is based on the identification of the weakness of the experimental work, based on the specificity of this field of research, particularly the complexity induced by the nature of the contact, the metaphysical phenomenon activated on contact, the multiscale aspect of the tribological behavior under high level of temperature. The proposed framework is based on a coupling between experimentation and machine learning tools. This coupling was acting under two scenarios: coupling upstream of the experimentation and coupling downstream. This approach gives several opportunities such the identification of the well impacted parameters, optimization of the experimental design, and the gain in times and cost.

Acknowledgments

The authors are thankful to the Deanship of Graduate Studies and Scientific Research at University of Bisha for supporting this work through the Fast-Track Research Support Program.

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