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Prediction of Abrasive Weight Wear Rate Using Machine Learning Methods

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Abstract. The paper applies machine learning methods to the prediction of the abrasive weight wear rates for a set of wear resistance experiments with model samples made of electrical copper and pure aluminum. To assess the effect of rotation frequency and abrasive grit sizes on the results of the evaluation of wear resistance and the determining quantities, the samples are tested with various disc rotation frequencies and various sandpaper grit sizes. It is noteworthy that, during experiments with materials comparable to copper in hardness and with harder ones, the path specified by the test design is implemented completely. However, this test design is not always suitable for the analysis of the mechanical characteristics of aluminum since, in some cases, the sample becomes fully worn before the end of the test. To overcome this problem, machine learning (ML) methods are proposed.

INTRODUCTION

Creation of new materials is impossible without solving a scientific problem of studying tribotechnical and mechanical properties by advanced testing methods. Wear resistance of materials is an important performance characteristic. Currently, various machine learning algorithms are widely used in different areas, e.g. speech and handwriting recognition, technical diagnostics, loan scoring, computer vision. The trend involves prediction of the wear process as well. Back propagation artificial neural networks are used to predict the wear rate of a composite aluminum alloy reinforced with an aluminum oxide matrix (Al₂O₃). Sliding distance, weight percentage of the reinforcement material and applied load are considered as influencing factors. The height decrease due to wear has been nonlinearly related to density, applied load, weight percentage of reinforcement, and sliding distance. A good agreement between experimental and model-predicted results was observed in [1]. The paper [2] presents an in-process tool wear prediction system, which uses a force sensor to monitor the progression of the tool flank wear and ML, more specifically, a Convolutional Neural Network (CNN) as a method for predicting tool wear. The proposed methodology is experimentally illustrated using milling as a test process. The experiments are conducted using dry machining with a non-coated ball endmill and a stainless steel workpiece. Pin-on-disc experiments are widely used in tribological tests for various friction couples. They enable the wear rate to be quantitatively evaluated and the overall picture of profile and debris shaping to be determined. However, according to [3], the results of these experiments are hard to compare for polyethylene, and causes problems when the technique is applied. ML methods for creation of controlled models allow one to predict the wear of polyethylene in new experiments based on performance parameters. The wear of wheels and rails is a serious problem for railway transport. The accurate prediction of wear rates in this industry can increase cost efficiency and riding comfort, improve planning of maintenance activities and prevent derailment. To predict the wear of wheels and rails, a nonlinear autoregressive model with exogenous input neuron network (NARXNN) is employed [4].

As is obvious, the use of ML methods covers all the new areas of tribological problems with adoption of various approaches from simple algorithms of regression prediction to complex multilayer neuron networks.

EXPERIMENTAL

The authors of [5, 6] assessed the influence of rotation frequency and grit size of an abrasive material on the results of the evaluation of wear resistance and the determining quantities and tested the samples at different values of the rotation frequency of an abrasive disc with different grit sizes. With due regard for the hardware and software constraints of the SRV-III testing machine, a variant of solution for the problem of the Archimedes spiral test conducted with a fixed abrasive (sandpaper) rotating at a constant speed was found. The Spiral test design is based on the use of transient process duration when changing the radius R_i ; it consists in conducting the full wear cycle over the course of sample movement by a radial feed drive from R_0 to R_K (Fig. 1a, b). Combined with simultaneous rotation of the sample, this situation enables exact reproduction of the Archimedes spiral, this being seen from the actual wear track (Fig. 1b).

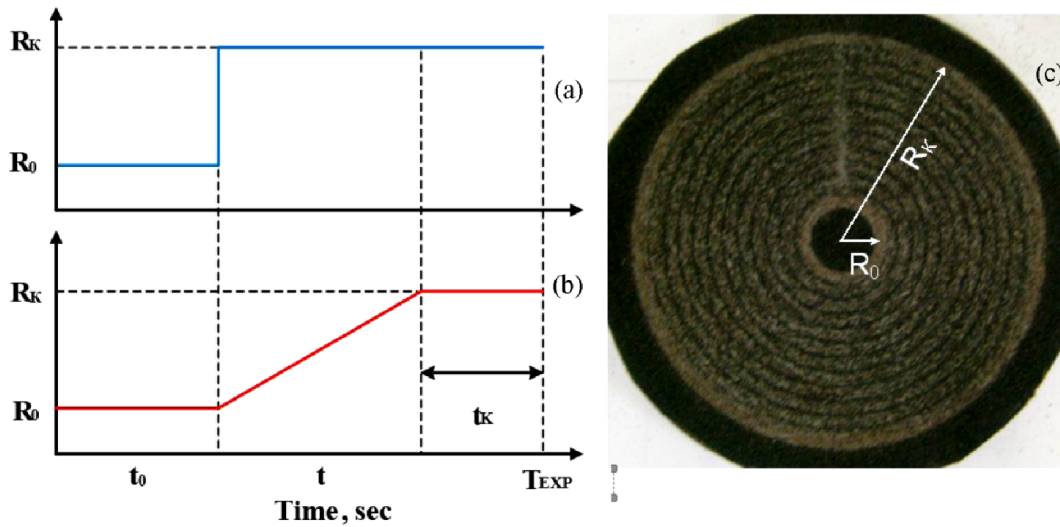


FIGURE 1. The function of sample radial feed control according to the Spiral variant: a – preset, b – actual (transient process); c – copper sample wear track (Archimedes spiral) on the abrasive (sandpaper P80)

Aluminum and copper were chosen for the prearranged experiment. The choice of aluminum as the test material was based on the requirements of regulatory documents. According to the Russian national standard GOST 17367, aluminum is the reference material for the determination of the wear resistance of materials with hardness below HV 150. Copper is chosen due to the fact that, among all the materials with the above-mentioned hardness ($< HV 150$) it is most widely used. To assess the influence of rotation frequency and grit size of an abrasive material on the results of the evaluation of wear and the determining quantities, the samples were tested at different values of rotation frequency of an abrasive disc with different grit sizes (hereinafter referred to as the abrasive type).

RESULTS AND DISCUSSION

Note that, in the case of the Spiral design tests of materials comparable to copper in hardness and of harder ones, the path specified by the test design is completed. This test design is not suitable for analysis of mechanical characteristics of aluminum since, in this case, the sample becomes fully worn before the end of the Spiral design test. In order to overcome this, one of machine learning algorithms is used.

To analyze the obtained results and develop a machine learning model, a widely used Scikit-learn library for the Python programming language was applied [7]. Table 1 presents the obtained data on weight wear rates (the results are presented only partially).

TABLE 1. The results of abrasive wear tests with copper and aluminum samples (a part of the results)

ID	Rotation frequency, min ⁻¹	Abrasive type	Material	Wear, mg
1	4	P80	Cu	16.2
2	4	P80	Al	12.5
3	4	P120	Cu	14.8
4	4	P120	Al	11.2
5	4	P180	Cu	12.9

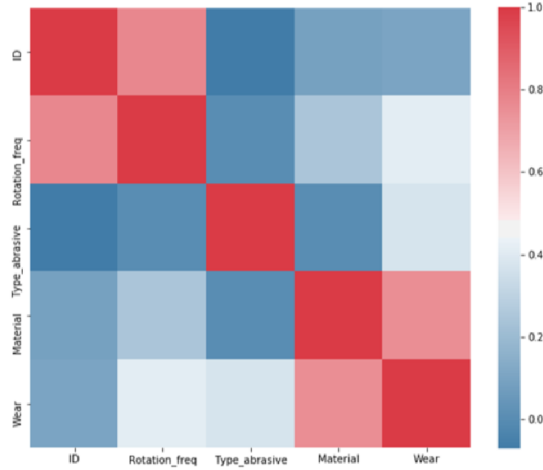
It is obvious that there are three features determining the rate of abrasive wear in the tests: one is quantitative (rotation frequency) and two are categorical (abrasive type and material). In order to be able to develop predictive models and establish correlation of wear rate and categorical features, encoding is necessary. The following coding is assumed: Cu = 1, Al = 0 for the material and P80 = 2 (200 to 250 μm), P120 = 0 (100 to 150 μm), P180 = 1 (63 to 80 μm) for the abrasive type.

The pairwise correlation of wear rates and the determining features is calculated as follows (Table 2).

TABLE 2. Pairwise cross correlation of features with wear rates

ID	Feature correlation
Abrasive type	0.372734
Rotation frequency	0.407712
Material	0.754140
Wear	1.000000

Heat map is convenient for visual estimation of the correlation (Fig. 2).

**FIGURE 2.** Heat map of the pairwise correlation of wear rates and determining features

The analysis of Table 2 and the heat map clearly demonstrates that wear rate is determined (in the order of decreasing influence) by material, rotation frequency, and abrasive type. In what follows we consider the total and material-specific distribution of abrasive weight wear rates (Figs 3a and 3b, respectively). It can be generally concluded that the non-linearity of wear rates can be derived from the change in a wear mechanism caused by the peculiarities of the experiment.

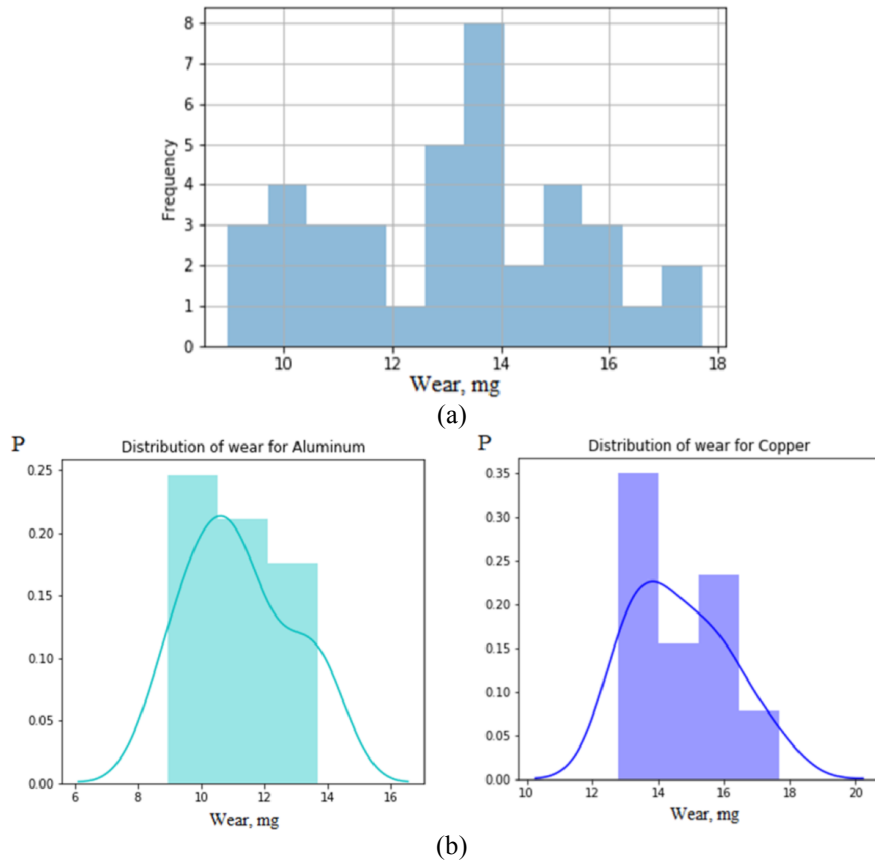


FIGURE 3. The total (a) and material-specific (b) distribution of abrasive weight wear rate in the set of experiments

One more useful categorial diagram should be analyzed (Fig. 4). The diagram demonstrates a significant spread of abrasive wear rate readings for the P120 abrasive type on copper and a reverse result on aluminum. This allows us to make a reasonable conclusion about the strong influence of rotation speed on abrasive weight wear rate. The comparative analysis of abrasive wear patterns for aluminum and copper for the P180 sandpaper displays that the wear of aluminum varies more greatly than that of copper. A more uniform probability distribution for aluminum is also worth mentioning in this case.

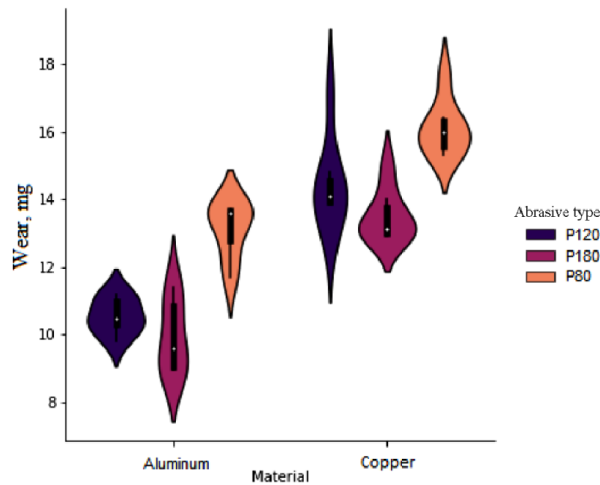


FIGURE 4. Distribution of abrasive wear rates for several categorial features

We will now proceed directly to the development of a machine learning model and the model-based prediction of the results for abrasive weight wear rate. First, a simple Linear Regression of the Scikit-Learn library is used; then we discuss the variant with the addition of polynomial interpolation and the random forest method. The prediction results for abrasive wear rates obtained with the application of the above-mentioned methods are shown in Table 3.

TABLE 3. Abrasive wear rates predicted by machine learning methods

ML Model	Model determination coefficient	Abrasive wear for aluminum at a rotational frequency of 42		
		K80	K120	K180
Linear Regression	0.762	14.15	12.06	13.10
Linear Regression with Polynomial Features	0.926	18.15	15.93	15.21
Random Forest	-	13.60	10.62	10.62

CONCLUSION

Machine learning methods can be successfully applied to the prediction of abrasive wear rates. This enables one to overcome possible difficulties arising during testing. Thus, in the variant discussed in this paper one of the tested materials, namely aluminum, did not undergo the whole experiment cycle; therefore, abrasive wear rate for aluminum could not be determined experimentally. The computational experiments have shown that the Linear Regression with Polynomial Features method predicts abrasive wear in the most accurate way for the test set.

On the basis of experimental data, a methodology and prediction models have been developed to enable the influence of various factors on abrasive wear resistance to be taken into account in order to evaluate the service life of various components of machines and mechanisms, such as steel wire ropes in construction, mining and agricultural machinery employed in abrasive-containing media.

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