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REGRESSION USING MACHINE LEARNING AND NEURAL NETWORKS FOR STUDYING TRIBOLOGICAL PROPERTIES OF WEAR-RESISTANT LAYERS

ZASTOSOWANIE REGRESJI Z WYKORZYSTANIEM UCZENIA MASZYNOWEGO I SIECI NEURONOWYCH W BADANIACH WŁAŚCIWOŚCI TRIBOLOGICZNYCH WARSTW TRUDNOŚCIERALNYCH

Key words: machine learning, neural networks, regression, tribology, tribological characteristics, wear indicators.

Abstract: Artificial intelligence is becoming commonplace in various research and industrial fields. In tribology, various statistical and predictive methods allow an analysis of numerical data in the form of tribological characteristics and surface structure geometry, to mention just two examples. With machine learning algorithms and neural network models, continuous values can be predicted (regression), and individual groups can be classified. In this article, we review the machine learning and neural networks application to the analysis of research results in a broad context. Additionally, a case study is presented for selected machine learning tools based on tribological tests of padding welds, from which the tribological characteristics (friction coefficient, linear wear) and wear indicators (maximum wear depth, wear area) were determined. The study results were used in exploratory data analysis to establish the correlation trends between selected parameters. They can also be the basis for regression analysis using machine learning algorithms and neural networks. The article presents a case study using these approaches in the tribological context and shows their ability to accurately and effectively predict selected tribological characteristics.

Słowa kluczowe: uczenie maszynowe, sieci neuronowe, regresja, tribologia, charakterystyki tribologiczne, wskaźniki zużycia.

Streszczenie: Zastosowanie sztucznej inteligencji w różnych dziedzinach nauki i przemysłu jest coraz bardziej powszechne. Duża różnorodność metod statystycznych i predykcyjnych umożliwia użycie ich również w tribologii. Analiza danych liczbowych w postaci charakterystyk tribologicznych, struktury geometrycznej powierzchni oraz wielu innych wymaga zastosowania narzędzi informatycznych oraz statystycznych. Wykorzystanie algorytmów uczenia maszynowego i budowanie modelu sieci neuronowej umożliwi prognozowanie wartości ciągłych (regresja) oraz klasyfikowanie poszczególnych grup. W artykule autorzy dokonują przeglądu możliwości aplikacyjnych algorytmów uczenia maszynowego i sieci neuronowych do analizy wyników badań w szerokim kontekście. Dodatkowo zaprezentowano studium przypadku dla wybranych narzędzi uczenia maszynowego na podstawie przykładowych badań tribologicznych napoin, dla których przeprowadzono testy, w których wyznaczono charakterystyki tribologiczne (współczynnik tarcia, zużycie liniowe) oraz wskaźniki zużycia (maksymalna głębokość wytarcia, pole wytarcia). Wyniki badań były podstawą do przeprowadzenia analizy eksploracyjnej i posłużyły do wykazania korelacji pomiędzy wybranymi parametrami. Autorzy przekonują, że mogą one być podstawą do analizy regresji z wykorzystaniem algorytmów uczenia maszynowego i sieci neuronowych. W artykule zaprezentowano studium przypadku z wykorzystaniem tych podejść w kontekście tribologicznym oraz pokazano ich zdolność do dokładnego i skutecznego przewidywania wybranych charakterystyk tribologicznych.

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INTRODUCTION

In recent decades, tribology has become an important field not only in science but also in technology and, more and more often, in the context of everyday life. Understanding the importance of tribology can pave the way for innovative solutions in the broadly understood industry. In the context of tribology and triboinformatics, advanced data processing or machine learning contributes to the development of extensive databases, thereby creating opportunities to enhance existing knowledge **[L. 1, 2]**.

Recently, particular progress has been made in the use of Machine Learning (ML), Deep Learning (DL) and Artificial Intelligence (AI) to improve the tribological properties of materials. Artificial intelligence or machine learning tools are based on a wide set of methods, including computational tools and modelling for inferring from broad data sets that can ultimately be used to perform predictions of parameters investigated **[L. 3–5]**. ML and AI enable the exploration of complex processes of tribological systems and are capable of describing their performance even in real-time **[L. 6]**.

Machine learning is part of artificial intelligence, and deep learning is a machine learning subset **[L. 12]**.

This study aimed to present the possibilities of machine learning and deep learning applied in tribological research. The methods of ML algorithms and artificial neural networks in tribology are presented along with a case study.

Machine learning in tribology

Machine learning covers learning strategies such as supervised learning, unsupervised learning, and reinforcement learning.

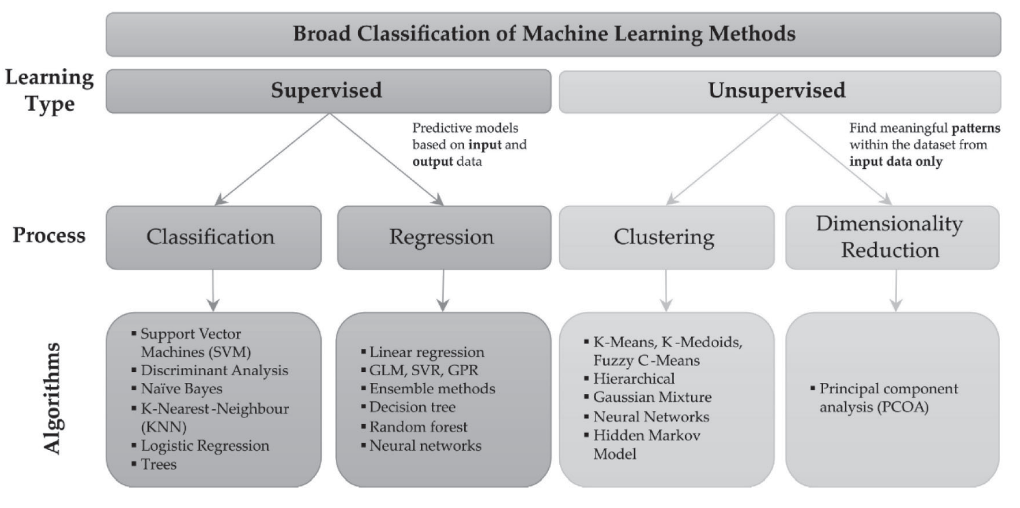

Fig. 1. Machine learning types [L. 1]
Rys. 1. Rodzaje uczenia maszynowego **[L. 1]**

The authors of **[L. 1]** presented the types of machine learning (**Fig. 1**) with supervised learning and unsupervised learning as the two main approaches. Reinforcement learning is not included in this figure. The most commonly used type of learning is supervised learning, including regression and classification. Unsupervised learning is often used, the so-called clustering, and in the case of a large number of predictors, or independent variables, algorithms of LDA – Linear Discriminant Analysis – and PCA – Principal Component Analysis – are used for dimensionality reduction.

A typical supervised learning task is to forecast a numerical target value – the continuous value. For example, based on a set of features (alloy chemical composition, type and amount of modifier, type of friction, type of layer) called predictors, we predict the maximum wear depth and area measured from the surface profile. This type of problem is called regression.

In regression, classic machine learning and deep learning algorithms can be used, such as:

- Linear regression,
- SVR – Support Vector Regression,
- Decision trees,

- Random forests,
- Neural networks.

Classification is also a classic task of supervised learning, and it is a task that breaks down a data set into individual classes. We distinguish a binary classification when dealing with two classes and multi-class classification.

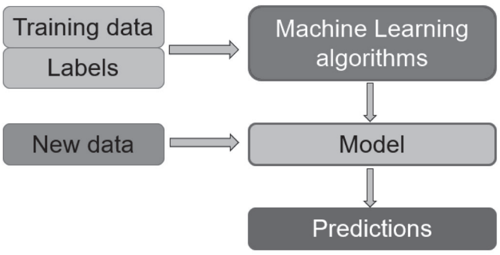

Fig. 2. Machine learning diagram [L. 2]
Rys. 2. Schemat uczenia maszynowego **[L. 2]**

Figure 2 shows a flowchart of machine learning. One of the training algorithms is used when having a set of labelled data, and this is how the model is trained. In order to develop predictions based on the trained model, we add new input data and obtain the predictions based on them.

Supervised learning uses labelled data. The label can determine whether the wear area exceeds a certain value (classification). The label can also be a numerical value that determines, for example, the value of the tensile strength (regression). The training data and the labels are used to train the model using a selected algorithm. The model trained in this way can be used to predict the response variable using new data (explanatory variables).

Figure 3 shows an artificial neural network architecture. The first layer on the left is the input layer, and the input data is represented by the so-called predictors or features. The next four layers are hidden layers, and the last layer is the output layer. The output layer represents the desired result. The output can be represented by one neuron having two states (True, False) for binary classification or expecting a continuous value for regression. Neural network architecture is designed individually for each application. Artificial neural networks are the basis of deep learning and are used for very demanding and complex machine learning tasks. The concept of deep learning is derived from the large number of hidden layers shown in **Figure 3**.

Figure 4 [L. 1, 8, 9] shows a diagram of the use of a neural network to calculate the degree of

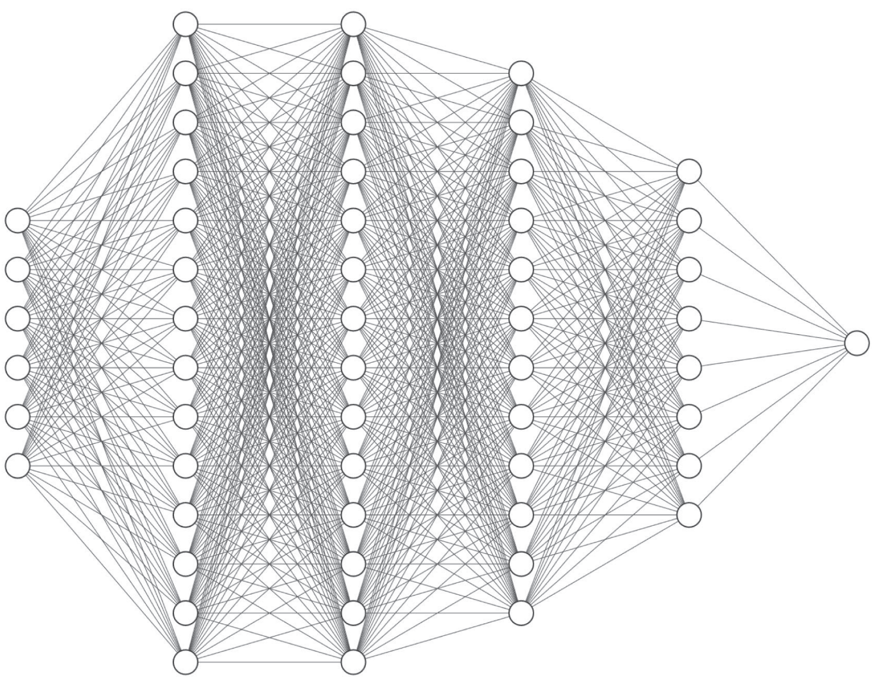

Fig. 3. The architecture of an artificial neural network with three hidden layers
Rys. 3. Architektura przykładowej sztucznej sieci neuronowej z trzema warstwami ukrytymi

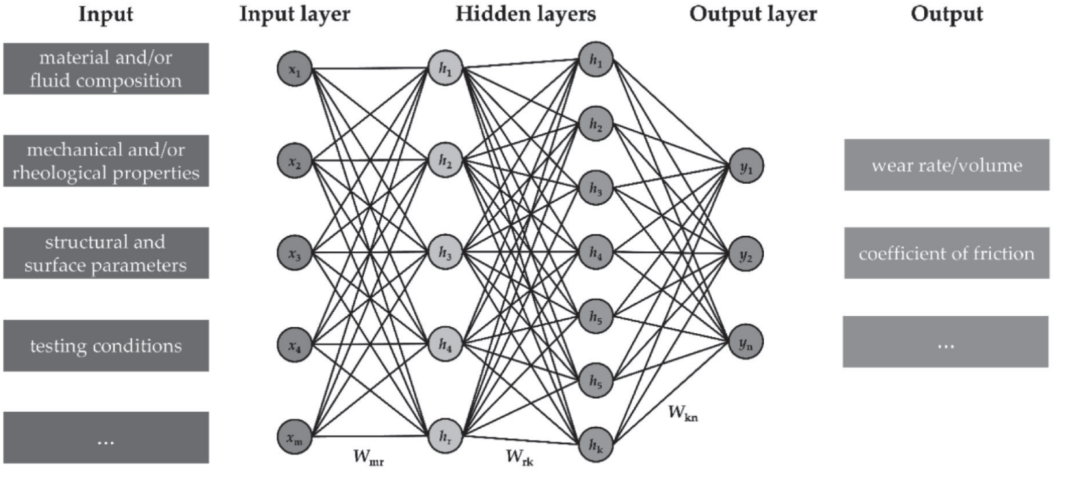

Fig. 4. Example of artificial neural network architecture in tribology [L. 1]
Rys. 4. Przykładowa architektura sztucznej sieci neuronowej w tribologii **[L. 1]**

wear (y1) and the coefficient of friction (y2). The input parameters include:

- Chemical composition of the material,
- Mechanical properties,
- Microstructure and surface parameters,
- Experiment parameters, etc.

The amount of input data, the number of records, and the artificial neural network architecture have a huge impact on the computation time. Neural networks are used for large data sets because they are not good at dealing with small sets. In order to train the model, the network architecture is modified by changing the number of hidden layers and the number of neurons in each layer. If the computation time is relatively long, the so-called dimensionality reduction shown in **Figure 1** is applied. The essence of this solution is to reduce the number of features (predictors) and select the best-correlated features with the value sought. There are several algorithms for dimensionality reduction. The most important algorithms include the Principal Component Analysis (PCA) and the Linear Discriminant Analysis (LDA).

The use of machine learning elements in the study of wear-resistant layers

The best predictions for both machine learning and deep learning are obtained from well-correlated input parameters (features). In order to check the correlation between the features, the so-called linear Pearson correlation or the nonlinear Spearman correlation is used.

Such a correlation was determined for the tribological characteristics of the pad welded layers containing modifiers in the form of rare earth oxides (CeO_2, Y_2O_3, La_2O_3) (further in this paper marked as classes). As a case study, padding welds made using welding consumables and intended for machine elements and tools in the mining and recycling industry were analysed. The aim was to increase their wear resistance. The padding welds were produced by metal active gas (MAG) welding combined with plasma arc welding (PAW). The padding weld consisted of a base layer and a wear-resistant working layer. The working layer was made with binders – powders doped with cerium, yttrium and lanthanum oxides.

For all padding welds, the hardness measurement, scratch test, tribological tests in dry friction and fluid friction were carried out, and the measurement of the maximum wear depth and area were measured from the surface profile. The type and parameters of the tests are presented in **Tables 1** and **2**.

Leica DCM8 optical profilometer was used for the maximum wear depth and area measurements, which were taken to measure the sample wear.

Table 3 presents the examined features and their symbols. **Table 4** shows the strength of the correlation and its type.

Table 4 shows the strength of the correlation and its type (positive or negative correlation).

The heat map in **Figure 5** shows correlations between various parameters. In addition to the value, colour intensity also represents the correlation.

Table 1. Hardness measurement and scratch test parameters

Tabela 1. Parametry pomiarów twardości oraz scratch testu

Test	Device	Nominal loading force	Loading/unloading rate	Loading force	Indenter
hardness test	ANTON PAAR MCT^3	2000 mN	4000 mN/min	Initial 30 mN	Vickers
scratch test	ANTON PAAR MCT^3	–	59979.8 mN/min	Final 15000 mN	Rockwell

Table 2. Tribological test parameters

Tabela 2. Parametry pomiarów twardości oraz scratch testu

tribological tests under dry and fluid friction:	
device	Anton Paar Tribometer TRB3
movement	reciprocating
amplitude	10 mm
frequency	1Hz
number of cycles	10000
friction	Dry/fluid (SiC 10% aqueous solution)
temperature	23±1°
humidity	50±1%

Table 3. Tribotests of the pad welded layers and their designations [L. 11]

Tabela 3. Badania tribologiczne warstw napawanych oraz ich skróty **[L. 11]**

Designation	**Description**	Unit
cof1	Friction coefficient (dry friction) – tribotests	
lw1	Linear wear (dry friction)	[μm]
cof2	Friction coefficient (fluid friction) – tribotests	
lw2	Linear wear (fluid friction)	[μm]
vh	Vickers hardness	[HV]
ih	Instrumented indentation hardness	[MPa]
ym	Young's modulus	[GPa]
cof	Friction coefficient – scratch test	
mpdi	Maximum penetration depth of indenter	[μm]
mtd1	Maximum wear depth (dry friction)	[μm]
ta1	Wear area (dry friction)	[μm^2]
mwd2	Maximum wear depth (fluid friction)	[μm]
ta2	Wear area (fluid friction friction)	[μm^2]
dw1	Disk mass loss (dry friction)	[g]
bw1	Ball mass loss (dry friction)	[g]
dw2	Disk mass loss (fluid friction)	[g]
bw2	Ball mass loss (fluid friction)	[g]
class	1 – without additives, 2 – with an addition of CeO_2 3 – with an addition of La_2O_3 4 – with an addition of Y_2O_3	

Table 4. Correlation type and strength [L. 11]
Tabela 4. Rodzaj i siła korelacji **[L. 11]**

Correlation	Negative	Positive
Very strong	-0.7 to -1	0.7 to 1
Strong	-0.5 to -0.7	0.5 to 0.7

In predictive modelling problems, a class of techniques called Feature Importance is often used. It aims at determining the relevance of each feature for further calculations. Weakly correlated or least relevant features adversely affect prediction quality and unnecessarily drain computing resources. **Figure 6** shows examples of relationships between features and their relevance level. It can be seen that depending on the algorithm used (decision trees, random forests), feature relevance may vary, but the general trend is kept. Therefore, this technique is a supplement to the conducted analyses. The relevance of the features reduces the number of predictors that do not affect the modelling. The use of such a method reduces the number of features, at the same time, shortens the computation time and improves the quality of the model. The least significant features such as Si, Cr, Fe were identified and removed from the data set based on the analyses.

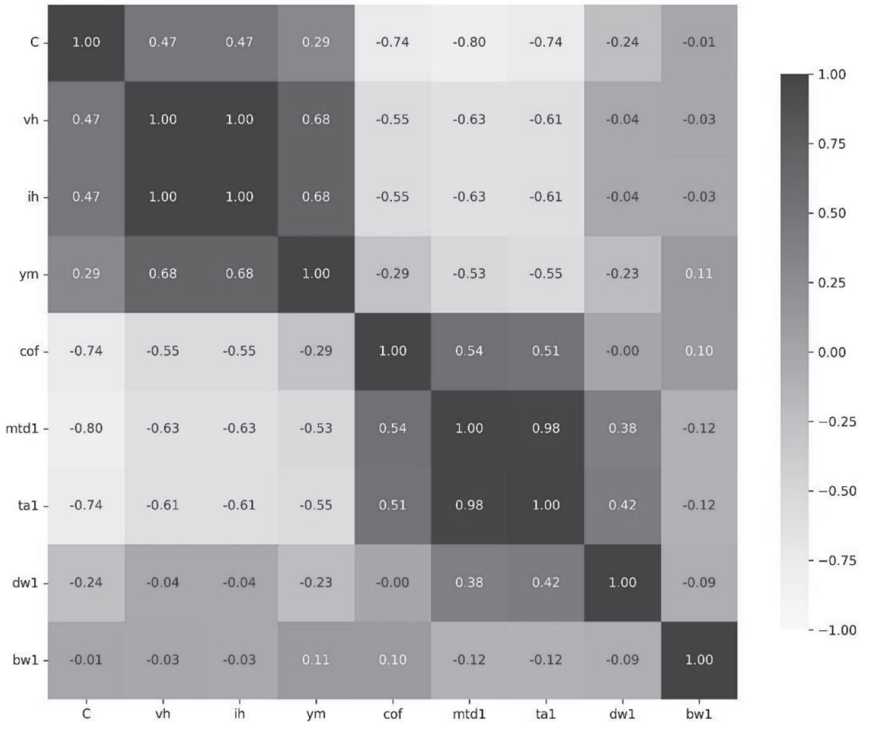

Fig. 5. Pearson correlation heatmap [L. 11]
Rys. 5. Mapa cieplna przedstawiająca korelację liniowa Pearsona **[L. 11]**

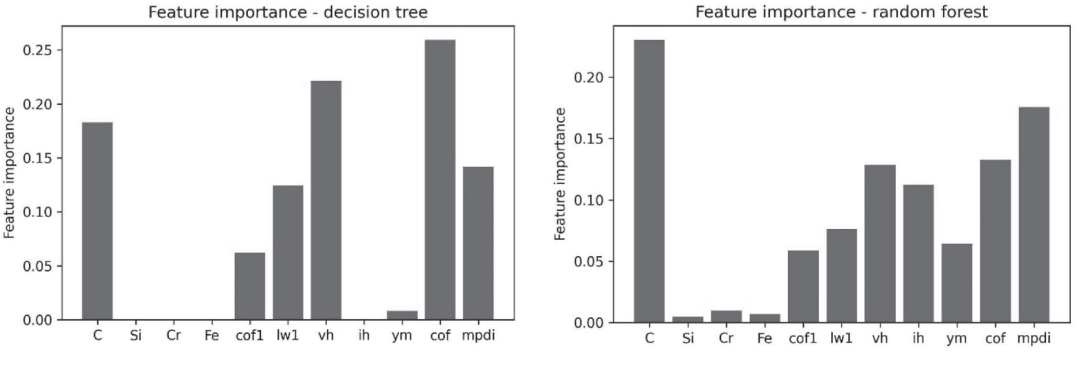

Fig. 6. Feature importance from the decision tree and random forest algorithms
Rys. 6. Istotność cech przedstawiona dla algorytmu drzewa decyzyjnego oraz lasu losowego

In the case of a small number of predictors, it is necessary to carry out the so-called Feature Engineering, which refers to a process of creating new features based on already existing ones.

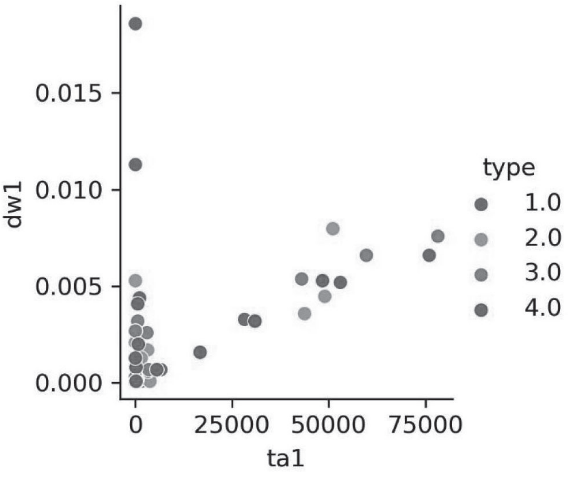

Fig. 7. Relationship between the disk wear rate and wear area by class [L. 11]
Rys. 7. Zależność zużycia tarczy od powierzchni wytarcia z podziałem na klasy **L. 11]**

Figure 7 shows an example of the relationship between the disk wear parameter and the wear area with a breakdown by class. The classes are divided as in **Table 3**.

Two dark blue points in **Figure 7** are outliers. Furthermore, it can be seen that the individual classes are arranged in a single trend. It is not possible to extract the best class from this graph because too few experiments were performed, and "large" amounts of data are needed for machine learning.

Exploratory data analysis carried out for the presented case study showed relationships between individual parameters. Among other things, a very strong negative correlation was found between carbon content ("C" parameter), hardness and the friction coefficient. Different wear types were also demonstrated for dry and fluid friction. It was shown that despite an increase in hardness and a decrease in the coefficient of friction, the remaining parameters, i.e., the wear depth and wear area were not as strongly correlated to fluid friction. Friction tests for the fluid with SiO_2 particles changed the nature of wear to tribocorrosion. Analyses confirmed the complexity of the effect of test parameters on wear processes and the varied relationships between them **[L. 10]**.

SUMMARY

The use of AI tools is inevitable in many areas of life and the economy. Since tribology combines physical and chemical phenomena as well as material technologies and structural issues, therefore, the use of AI tools can be interesting and, with time, necessary for researchers. There are also some challenges, such as correct interpretation-classification of input and output data in tribological studies **[L. 14–17]**.

The presented case study showed that exploratory data methods capture non-trivial relationships among the test results. Dependencies between indicators of geometric structure and mechanical properties were demonstrated. Exploratory data analysis helped determine directly proportional (positive correlations) and inversely proportional (negative correlations) relationships. Analysis using machine learning elements confirmed the beneficial effect of modifying the padding welds with rare earth oxides.

The paper shows that using machine learning is possible to effectively determine correlations between individual tribological parameters and their strength, classify the test samples, and determine their influence on individual parameters such as wear area or depth. Machine learning algorithms and artificial neural networks allow predictions based on the data collected from tribological tests.

The work was carried out using the PLGrid Infrastructure.

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