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A neural network approach to the metallic surface wear on linear dry contact, plastic material reinforced with SGF/steel

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ABSTRACT – The aim of the paper is to approach the study of wear on a metallic surface in the case of dry linear contact, plastic reinforced with SGF on surfaces of alloyed steel, C120 and Rp3, through the method of artificial neural networks. This is because wear processes involve very complex and powerfully nonlinear phenomena, and analytic models are difficult or impossible to obtain. This is also necessary due to the multiple inputs (normal load, contact pressure, sliding speed, measured contact temperature, materials properties) and outputs (width and depth of the wear scar, contact temperature) which influence each other continually.

1. INTRODUCTION

The paper presents the approach to modelling a dependency between the various variables of interest involved in the friction process, using advanced statistical and optimisation algorithms on a dataset obtained from hardware simulation. The subject draws a growing interest from the research community with the advent of highly advanced, intelligent classification, optimisation and regression algorithms.

Abouelatta [1] refers in his paper to the prediction of processing and the surface roughness using artificial neural networks. The surface roughness is considered one of the specified customer requirements in processing. For the efficient use of machine-tools, it is necessary to select the manufacturing process and determine the optimum cutting parameters. The experimental data collected from tests were used as input parameters of a neural network, to identify the sensitivity during processing operations, cutting parameters and surface roughness.

2. MATERIALS AND METHODS

Wear performance of the two steel alloys, C120 and Rp3 has been previously studied in the case of linear dry contact with each polymer (polyamide and polycarbonate) reinforced with different percentages of short glass fibres (SGF). The functional diagram of the friction couple is presented in L. Căpitanu et al., [2], where it looks the linear contact. The friction couple comprises a cylindrical plastic liner and a flat polished steel hardened sample.

2.1. Analytical method

The wear scar occurs by penetration of the cylindrical liner, under the influence of the normal load, in the flat sample material. In theory, the holding the liner is considered as rigid and relatively small in view of the backside imprint, so it can be considered as made up of a sum of cylinder areas of the length equal to p. The radius r can't be found in the couples plastic / metal, with the radius of the cylindrical liner. This is due to elastic deformation of the liner under load, which aims at increasing its radius in the contact area. This is illustrated schematically in [1]. Noting the non-deformed sleeve radius r_1 and the radius r_2 - deformed under load, shown that $r_2 > r_1$. They were considered the following three polymers:

A. Nylonplast AVE Polyamide + 30% glass fibres; $E_{2A} = 40.25$ MPa.

B. Noryl Polyamide + 20% glass fibres; $E_{2B} = 31.76$ MPa.

C. Lexan Polycarbonate + 20% glass fibres; $E_{2C} = 42.08$ MPa.

Numerical values were determined by the elasticity modules (E) listed above, and the deformed liner radii (r_2), imposing p_{max} is provided as $p_{max} < 0.5\,H$, where H is the Brinell hardness for the plastic liner is enough, so it will not be crushed. The approximate depth of the wear scar is calculated with the relation:

$$h \approx l^2 / 8r_2 \quad (1)$$

The imposed condition has allowed to establish the following values of the maximum contact pressure of the dry linear couplings contact, in the case of three plastic materials (A, B, C) reinforced with SGF, the 5 normal loads (contact pressures), indexes 1 to 5 of notations of the pressures that have been subjected to tests, for each of the 7 relative sliding speeds used (18.56; 27.85; 37.13; 46.41; 55.70, 111.4 and 153.57 cm/s):

$p_{A1} = 16.3$ MPa; $p_{A2} = 23.5$ MPa; $p_{A3} = 28.2$ MPa; $p_{A4} = 32.6$ MPa; $p_{A5} = 36.4$ MPa;

$p_{B1} = 12.3$ MPa; $p_{B2} = 17.4$ MPa; $p_{B3} = 21.4$ MPa; $p_{B4} = 24.6$ MPa; $p_{B5} = 27.6$ MPa;

$p_{C1} = 16.9$ MPa; $p_{C2} = 23.9$ MPa: $p_{C3} = 29.3$ MPa; $p_{C4} = 33.8$ MPa; $p_{C5} = 37.8$ MPa.

After inspecting and measuring the wear scars of metal surfaces, the widths (l) of each wear scar were measured, their volume was calculated (the amount of material lost through wear) and were traced their variation curves depending on applied load (contact pressure), the relative speed of sliding contact with the temperature specification of the optical image and presentation of the scar. This quantitative-qualitative assessment was presented in [2]. All tests took place for 60 minutes, so that the calculated wear volumes are actually wear rates.

2.2. ANN method

The data was obtained through experiments run on friction couples with linear contact using three different types of polymers on two different types of steel variants. Aside from alternating the materials used, the speed and pressure applied to them were varied under the same operating conditions. This was done with regard to the particulars of each material combination and levels of speed and pressure.

The code for the various optimisations was developed in Octave for plotting and most of the fitting problems, while Matlab was used for the graphical neural network tool. While the figures provide a good overview of the models' behaviour, they fail to give an analytical measure of model performance. For this, two metrics are used, both of which give a numerical measure of the error: the mean square error (MSE) and the mean absolute error (MAE). Since these are metrics for the error of the model, lower values correlate to better performance. The mathematical expressions are shown below:

$$MSE = \frac{1}{n}\sum_{i=\overline{1..n}}(X_i * \theta - Y_i)^2 \qquad (2)$$

$$MAE = \frac{1}{n}\sum_{i=\overline{1..n}}|X_i * \theta - Y_i| \qquad (3)$$

The approach is divided into two applications, whereby the first application takes the wear depth and wear volume as dependent on speed and pressure, without considering the material differences, and the second application investigates the wear depth, wear volume, friction coefficient and temperature as dependent variables upon speed, pressure.

2.3 The multivariate learning application

The first step is to plot the available data and pre-process any necessary alterations. For the first dependent variable group, the data points resulting from running the experiment with a speed of above 60 cm/s were eliminated, since those were only relevant for a minority of the obtained samples. The outliers can also be identified plotting the data, as can be seen in Figures 1 and 2, some data points, marked in red, are noticeably removed from the main cloud of points.

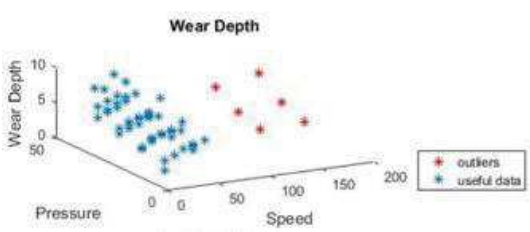

Figure 1 Wear depth experimental data with highlighted outliers.

For each dependent variable, the prediction is a dot-product of the independent variable values and its respective theta vector. The linear regression coefficients show the relative influence a certain independent variable has on the prediction of a dependent variable.

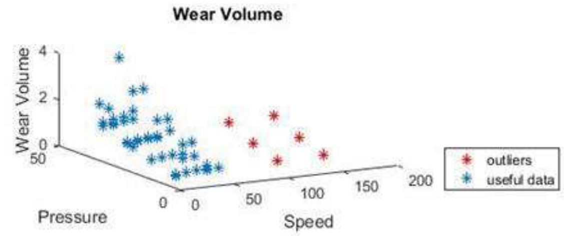

Figure 2 Wear volume experimental data with highlighted outliers.

The intercept term is a baseline starting point for the prediction and models and aggregation of all other factors not considered and the inherent randomness of the model. For the second, more complex, optimisation problem, which models the wear depth, volume, friction coefficient and temperature dependent on speed, pressure and eight material characteristics, the metric results were calculated.

3. DISCUSSION AND CONCLUSION

As the experimental data shows, the single-output neural networks clearly and significantly outperform linear regression for all metrics in the second series. This is because of the far more non-linear behaviour of the data set, as opposed to the first series, which makes it more difficult for a linear model to obtain a good fit of the data. The multi-output neural network fares worse in every category, save for the dependent variable of temperature. This is because if strives to find the best possible solution for predicting all the dependent variables at once. Based on the very non-linear nature of the last dependent variable, the optimum found makes significant concessions in the performance for the other three variables.

The superior performance of the individual neural networks is clear both in the metrics and even in the visual plots. It is these functions that will be further improved through the addition of more data, as it becomes available, and will be used to predict the future behaviour of the experiment. The paper presents the proposed methods, models and algorithms for obtaining a relation, be it explicit or implicit, between various variables of interest found in the tribological process. To that end, a number of options were explored for each tier of the overall modelling process.

REFERENCES

[1] Abouelatta, O. B. (2013). Prediction of machining operations and surface roughness using artificial neural network. *J. Eng. Sci*, *41*(3), 1021-1044.

[2] Căpitanu, L., Rus, D. & Florescu, V. (2014). A qualitative-quantitative correlation of friction and wear processes of steel surfaces in linear dry contact with SGF. *Proceedings of Balkantrib'14, 8th International Conference on Tribology,* 611-623.