A Methodological Approach Ball Bearing Damage Prediction under Fretting Wear Conditions.

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Abstract—The industrial demand for higher reliability of various components is one of the main flywheels of the research and development in the field of modelling of complex phenomena. There is a need to characterize the wear behaviour of the interface under fretting wear conditions in ball bearing application. Pre-treated experimental data was used to determine the wear of contacting surfaces as a criterion of damage that can be useful for a life-time prediction. The benefit of acquired knowledge can be crucial for the industrial expert systems and the scientific feature extraction that cannot be underestimated. Wear is a very complex and partially-formalized phenomenon involving numerous parameters and damage mechanisms. To correlate the working conditions with the state of contacting bodies and to define damage mechanisms different techniques are used. The use of our approaches in the prediction of the response of the system to different test conditions is validated. Two physical models, based on Archard and Energetic approach, are compared with Artificial Neural Network model and Genetic Programming. Decisive factors for a comparison of used AI techniques are their: performance, generalization capabilities, complexity and time-consumption. Optimization of the structure of the model is done to reach high robustness of field applications. Finally, application of the wear level information to forecast a probability of damage is presented.

Index Terms—multisensor classification, neural classifier, quality assessment

I. INTRODUCTION

AI is not only seen in computer science and engineering [1] but as well it is studied and applied in various different sectors such as psychology, philosophy, neuroscience, linguistics, economics, control theory, probability, optimization and logic [2]. It can be applied to model complex relationships between inputs and outputs or to find patterns in data. Two different innovative techniques that go beyond the standard AI methods typically considered as Computational Intelligence (CI): Artificial Neural Network and Genetic Programming are presented and validated in this paper. The greatest advantage of Artificial Neural Networks (ANNs) is their ability to be used as an arbitrary function approximation mechanism which 'learns' from observed data. However, using them is not so straightforward and relatively good understanding of the underlying theory is essential. A review of many engineering applications of that technique was presented by Bhadeshia [3]. Broad area where ANN was successfully implemented starts from the prediction of cracking of welds, overall strength of superalloys, structural transformations in steels through bearing fault detection [4] and many other applications.

Artificial Neural Networks, which are trainable systems mainly used for pattern recognition, are similar to the biological neural networks in the sense that the functions are performed collectively and in parallel by the units and no clear delineation of subtasks, to which various units are assigned, exists. In principal, the neural network model can be used to examine the effect of an individual input on the output parameter, especially when it is extremely difficult (or costly) to do it experimentally.

As well as Artificial Neural Networks the Genetic Programming (GP) bases on a biological principle as it is a variant of Evolutionary Algorithms (EA). The aim of using this method is to find a representation (a model) of a problem, which cannot be previously predefined by set of parameters and its advantage over traditional methods, is an automatic optimization of functional form and the coefficient values. Time series prediction [5], classification tasks [6] and a machine control [7] are the fields where GP is found to be interesting and robust technique.

Most of the publications that are using AI to model wear deal with presenting the wear response of a tool during different machining procedures (i.e. turning, milling or boring). The influence of the machining parameters on

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wear of machine cutting tools (i.e. tool flank wear) under various operational conditions (cutting speed, depth of cut etc.) was studied by means of ANN [8, 9, 10] and GP [11, 12, 13] to find the balance between the wear of the tool and the efficiency of the machining procedure. In general it was found that neural networks deduce the relationship between variables, including any interactions, while genetic programming is showing its best in multi-objective optimization. In complicated cases, where a lot of variables are present, examination of the predictions reveals quantitatively and qualitatively interesting interactions.

In the present study the comparison between the physical models, based on regression analysis, and an empirical models, based on artificial neural network and genetic programming is shown. As the neural network is a regression method of which linear regression is a subset (Fig. 1) it is possible to describe the behaviour by the equation that is precise and reproducible for given set of inputs.



Fig. 1. (a) Neural network representation of linear regression and (b) non-linear representation.

The problem of fretting damage in bearing-related applications is used as a case study. Bearing quality is increasingly determined by its acoustical and vibrational performance and the bearing is always in the transmission path of vibrations generated between the shaft and the bearing housing [14]. Due to small oscillatory movements the interface can get fretted and then the life of the bearing predicted by simple fatigue [15] is shortened. The wear response at the interface is modelled and the empirical models, base on the data gained from the fretting tests, are created. The AI models are compared with the friction dissipated energy and Archard approaches, which represent the physical description of the fretting wear behaviour, to validate the approach.

II. EXPERIMENTAL PROCEDURE

Tests were carried out using specific Laboratory of Tribology and Dynamics of Systems fretting wear apparatus (Fig. 2). An electrodynamic shaker induced the reciprocating movement with a constant frequency of 10 Hz. The upper specimen (AISI 52100 - chromium steel ball) rubbed against the lower fixed flat sample (AISI 52100) to simulate ball-on-flat dry point-contact conditions [16].

The spherical samples used for the experiments had 2 different grades, which resulted in different average roughness of the surface (R_a). Flat surfaces were ground and subsequently polished to reach similar roughness values. Before being tested, the specimens were cleaned with acetone.



Fig. 2. The scheme of the fretting rig.

The normal force (P) was kept constant during the test, while the tangential force (Q) and displacement (δ) were recorded. A fretting test program was carried out by applying a normal force and displacement amplitude according to the test matrix (Table I). It should be mentioned that a large spectrum in terms of displacement amplitude, pressure and test duration was used in comparison with the work of Ramesh et al. [17]. It allowed promoting both gross slip and partial slip conditions. Tests were conducted in a closed chamber in which the relative humidity and the temperature could be controlled. The humidity level was measured as close as possible to the contact and all the tests were conducted at 40±5% of relative humidity (HR) level and at 23±2°C temperature.

III. PRESENTATION OF THE MODELS USED

A. Physical models – regression analysis

Three wear approaches are considered in this work:

1. The first one is the classically Archard's wear criterion [18] used commonly during the second half of the 20th century. The wear volume versus the product of the normal force (P) and the sliding distance (S) is presented. Transposed to the gross slip fretting condition, the Archard's product is expressed by the following relationship:

$$\mathbf{P} \cdot \mathbf{S} = \sum_{i=1}^{N} 4\mathbf{P}_i \cdot \boldsymbol{\delta}_{gi} \tag{1}$$

with N the number of cycles and δ_{gi} the sliding amplitude of cycle i. The Archard's approach does not take into account the friction coefficient which is an important parameter of the stressing loading (strongly depending on third body effect) and consequently of the material damage evolution.

2. To integrate the friction coefficient effect in the wear analysis, the wear volume can be compared with the accumulated friction work dissipated through the interface (the friction coefficient is directly proportional to dissipated energy) [19]. The dissipated energy corresponds to the accumulated energy determined from the sum of fretting cycle area:

$$\sum E_{d} = \sum_{i=1}^{N} E_{di}$$
 (2)

3. Finally, an extended approach, which is combining sliding amplitude and cumulated dissipated energy (wear

factor: $\frac{\delta_g}{\delta_{g_{ref}}} \sum E_d$) was applied by Fouvry et al. [20] to

describe wear behaviour of titanium alloys which are sensitive to adhesion. Indeed, due to adhesion mechanisms, a significant part of the dissipated energy is consumed to carry out and eliminate the third body from the interface. The direct connection between the debris flow and the interfacial relative sliding can explain why the dissipated energy has to be weighted with sliding amplitude for adhesive material. The studied contact (chromium steelchromium steel) is not an adherent contact so this method is not applied for physical description of the system.

Linear regression analysis was performed for both Archard and energetic approach. From Archard wear parameter (α) and energy wear parameter (α) theoretical values of wear were calculated and the graphs presenting theoretical vs. experimental wear are presented on Fig. 3.



Fig. 3. Experimental wear volume compared with theoretical one a) from Archard and b) dissipated energy approach.

The results of both models are similar and the variance of the method is almost the same for two approaches. It confirms that regression analysis normally gives similar responds when the assumed dimensionality of two different approaches is the same (linearity of Archard and energy wear approaches). Similar results obtained from physical modelling of Archard and energy dissipation can be explained by the fact that the studied interface displays stable friction behaviour. If the friction coefficient remains constant the two approaches are indeed equivalent. To increase the searching space and to find the optimal solution of the problem without narrowing down the range of the possible outcomes the AI is used.

B. Static ANN model

Pre-processing has two steps: first all the data was normalized and then random noise was added/deducted to/from the normalized data. Every measurement is encumbered with errors, there can be systematic errors caused by the fact that measurement method does not take into account influential parameter(s) and there are also random errors normally caused by the sensitivity and resolution of the method and user-measuring instrument interaction. First step to prepare both variable and invariable test datasets is the regularization process. Practical reasons for including regularization are twofold: 1) regularization overcomes numerical sensitivity in the parameter estimation; and 2) in the presence of noise in the observed values of the outputs, regularization acts as low pass filter.

After PCA four inputs were chosen as most meaningful and having the highest influence on the final value: pressure, amplitude of displacement, number of cycles and roughness.

A normal additional random noise (with different magnitude for different cases studied) was added to the data in order to ensure that the network is able to perform correct predictions for different studied conditions (e.g. the environmental conditions are controlled during the test but it is impossible to keep the constant and strict value, so temperature and humidity are kept in the range of about \pm 5% of uncertainty). This additional random noise was used as well to enlarge the data set for training of the network.

A commercial Neural Network Toolbox was used for designing and validation. For visualization and the control of the robustness of the model a multidomain simulation platform was used. The structure of the network that was found to be the best one, when it comes to the training and validation error, is a 3-layer feed-forward network with 4 neurons in input layer, 3 neurons in hidden layer and one in output layer (Fig. 4).

For the first two layers, the transfer function used was sigmoidal tangent (tansig) and for the last layer linear function was used (purelin). The network was trained with noisy data and real data was used for the early stopping of training. The initial weights were randomly chosen and for training of the network backpropagation is used to calculate the Jacobian jX of performance PERF with respect to the weight and bias variables X. Each variable is adjusted according to Levenberg-Marquardt. This is a non-adaptive training, which uses interpolation between gradient-based methods and Gauss-Newton one with iterative recursive algorithm.

This ensured that the network has good generalization capabilities as it shows small error of prediction for firsttime seen data.



Fig. 4. Scheme of the structure of neural network used for the prediction of fretting wear. Details have been omitted for simplicity.

C. Genetic Programming model

Genetic Programming API that bases on a plug-in structure was developed with the Java language. To reduce the search space, which is straightforward with lower computational cost, strongly typed GP was used. For fast and efficient calculation a divide and conquer strategy [21] and Hyper-Volume Error Separation (HVES) [22] were implemented.

Normalized data was used for optimization of the GP parameters and final calculations. All the calculations were performed with the use of a standard strategy of the generation growth. Fitness function used was scaled mean square error (ScaledMSE - MSE divided by the true parameter value and expressed in percentage) and gives information about the error variance, which discriminates good candidates from bad ones. Ramped half-and-half method was used as a generation algorithm for initialization of the population of the individuals. Half of the individuals is a result of grow method (a tree of arbitrary depth generated by selecting terminals or functions according to uniform probability distribution) and the second one is produced by full method (the functions are only selected for the nodes until the tree size reaches specific depth, right after that terminals are selected), as the grow fraction was fixed at value of 0.5. Survival-of-the fittest mechanism uses an idea of elitism and only the best candidate (with the highest fitness from the ones that take place in the tournament) is copied to the next generation.

The parameters of the variation: duplication, crossover and mutation (Table I) and the size of the population and maximum generation number (Table II) were optimized to get the highest mean fitness (lowest Scaled MSE) of the 10 runs with respect to calculation cost.

TABLE I

OPTIMIZATION OF PARAMETERS OF VARIATION WITH RESPECT TO THE SCALEDMSE

| Crossover rate [%] | Mutation rate [%] | ScaledMSE [%] | | | |
|-----------------------|----------------------|------------------|--|--|--|
| 30 | 65 | 1.8 | | | |
| 60 | 35 | 1.4 | | | |
| 65 | 30 | 1.3 | | | |
| 70 | 25 | 1.0 | | | |
| 75 | 20 | 1.1 | | | |
| 80 | 15 | 1.2 | | | |
| 90 | 5 | 1.3 | | | |
| 95 | 0 | 1.8 | | | |

Duplication rate is kept constant at value of 5%





MGN – Maximum generation number

ScaledMSE [%]

Calculation cost [min]

It was found that parameter settings presented in Table III result in calculation time lower than 10 minutes with the ScaledMSE value of about 1%.

| TABLE III | |
|-----------|--|
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| PARAMETER SETTINGS | | | | |
|---|---|--|--|--|
| Parameter | Setting | | | |
| Population size | 1000 | | | |
| Maximum generation number | 100 | | | |
| Initialization method | Ramped Half-and-Half | | | |
| Initialization depths | 3-5 levels | | | |
| Maximum depth of trees | 10 | | | |
| | | | | |
| Selection | Tournament of size 7 | | | |
| Elitism | Tournament of size 7 1 | | | |
| Selection Elitism Internal node bias for crossover | Tournament of size 7 1 90% internals, 10% terminals | | | |
| Selection Elitism Internal node bias for crossover Duplication rate | Tournament of size 7 1 90% internals, 10% terminals 5% | | | |
| Selection Elitism Internal node bias for crossover Duplication rate Crossover rate | Tournament of size 7 1 90% internals, 10% terminals 5% 70% | | | |
| Selection Elitism Internal node bias for crossover Duplication rate Crossover rate Mutation rate | Tournament of size 7 1 90% internals, 10% terminals 5% 70% 25% | | | |

Terminal sets and functions used are presented in Table IV. Extended description of the technique employed in this case study was presented in [23].

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| TERMINALS AND FUNCTIONS SETS | | | |
|--|---------------|--|--|
| Terminals set | Functions set | | |
| NoC, $p_{0H}^{}$, δ^* , $R_a^{}$, V, 0, 1, ERC ⁽¹⁾ | +, -, /, × | | |
| (1) EBO Esterna and Dan dam Organization | | | |

⁽¹⁾ ERC – Ephemeral Random Constants

IV. RESULTS AND DISCUSSION

It becomes clear that the prediction from ANN and GP model follows data much more closely than the multiple regression analysis (MRA) (Fig. 5, Fig. 6). For the model based on Archard's approach the mean relative error was found to be 5.1% and for the energy dissipation model the value of the error was a little smaller -4.8%.

Artificial neural network model is showing very good correlation with experimental data as the mean relative error came to 1.8% (Fig. 5). Moreover, even smaller error is found for GP as it does not exceed 1.5% (Fig. 6).



Fig. 5. Experimental wear volume compared with the results of ANN predictions.

It is valuable to verify this result with the work of Ramesh et al. [17] by comparing the relative mean error as well as the spectrum of studied conditions. The calculated mean relative error presented in [17] for the predicted wear loss was 4.3% which is almost 3 times higher than in the present study, where the dimensionality of the problem is higher as

Ramesh used only two inputs in his model (5 treatment types and 3 different applied loads) and presented the results only for one constant value of slip amplitude (60 ± 3 µm) and constant number of cycles (100 kcycles).



Fig. 6. Experimental wear volume compared with the results of GP predictions.

As mentioned earlier, the difference between the AI and MRA lies mainly in nonlinear regions, where underprediction takes place. Big differences between the prediction and the experimental wear in the range of high values of wear were found for MRA (Fig. 3). This could be due to the fact that both AI analyses are able to map the data between higher dimensional spaces and the dimensionality of the problem does not need to be known (as it is totally necessary in classical regression analysis).

In [8] regression analysis is compared with neural network technique for the modelling of the tool wear during the composites machining and similar comparison was made in [24] for fretting wear prediction of short fibre reinforced polymeric bearing materials. The published results do agree with the ones from the present study that both techniques are giving satisfactory outcomes and that difference between them is quite marginal. Thus, neural networks have proven to be able to further improve the performance and to discover easily the patterns and mutual correlations in data. Moreover, for more severe conditions and when the data is not easily available for all studied parameters the regression analysis is prone to over- or underestimation of wear value, while optimally scaled neural network can predict the behaviour of the system correctly. In the light of the substantial wear volume measurement error, even relatively uncertain predictions are found to be helpful in the tribological investigation and material structure optimization. Unfortunately, there are only a few publications describing the usefulness of GP in the field of wear prediction [25], but the results presented in this paper are showing that it can be a robust tool for fretting damage prediction. Future investigations should take into account the possibility to introduce the units to the model, which can make the resulting equation physically meaningful (no need for normalization of data).

V. APPLICATION OF THE WEAR LEVEL INFORMATION TO FORECAST THE PROBABILITY OF DAMAGE

The information of the wear level obtained using the neural network model can be used in order to provide a forecast of the future reliability for a given moment $t + \tau$, where τ

represents the horizon of prediction and t the current moment. Indeed, let V_s be a threshold of unacceptable wear involving the failure of the system. The principle consists in determining if the future wear level, evaluated at time t + τ , is higher or equal to the given threshold V_s . Of course this forecast cannot be carried out in a deterministic way, it is solely possible to give an interval of the possible values for wear, in other words, it will be solely possible to give a probability of failure related to the statistical characteristics of the predictor used. The probability of failure at time t + τ , can then be defined as:

$$\Pr\{\mathbf{V}(t+\tau) \ge \mathbf{V}_{s}\} = \int_{\mathbf{V}_{s}}^{\infty} f(\hat{\mathbf{V}}(t+\tau)) d\hat{\mathbf{V}}(t+\tau)$$
(3)

where $f(\hat{V}(t+\tau))$ represents the probability density function of the predictor for the considered time $t+\tau$. Figure 1 illustrates the principle of forecast of the probability of failure; this one is measured by the hatched area.



Fig. 7. Forecast of the probability of failure.

Let $m(t + \tau) = E[\hat{V}(t + \tau)]$ and $\sigma^2(t + \tau) = Var[\hat{V}(t + \tau)]$, be respectively the mean and the variance of the level wear estimation given by the predictor at time $t + \tau$. Assuming a normally distributed law for the estimate, the probability of failure can be evaluated as follows:

$$\Pr\left\{V(t+\tau) \ge V_{s}\right\} = \frac{1}{\sigma(t+\tau)\sqrt{2\pi}} \int_{V_{s}}^{\infty} e^{\left(\frac{-(\hat{V}(t+\tau)-m(t+\tau))^{2}}{2\sigma^{2}(t+\tau)}\right)} d\hat{V}(t+\tau)$$
(4)

The prediction at time $t + \tau$ of the wear level can be done via the predictor known as the exponential smoothing method. Holt's method of smoothing is also known as the double exponential smoothing (DES). The procedure is used for data that exhibits a piecewise linear trend. Let b(t)be the growth rate at time t and both the level and growth rate are updated with the smoothing equations:

$$l(t) = \alpha V(t) + (1 - \alpha)[l(t - 1) + b(t - 1)]$$

b(t) = \beta[l(t) - l(t - 1)] + (1 - \beta)b(t - 1) (5)

where α and β are smoothing constants between 0 and 1.

A τ -step ahead forecast from t for $\hat{V}(t+\tau)$ is:

$$\hat{\mathbf{V}}(\mathbf{t} + \tau) = \mathbf{l}(\mathbf{t}) + \tau \mathbf{b}(\mathbf{t}) \tag{6}$$

From [26], the τ -step ahead forecast error variances in Holt's smoothing procedure can be estimated using:

$$\hat{\sigma}^{2}(t+\tau) = [1 + (\tau-1)\alpha^{2}(1+\tau\beta + \frac{1}{6}\tau(2\tau-1)\beta^{2})]s_{1}^{2}$$
(7)

where s_1^2 is the average of the squared 1-step forecast errors:

| $\varepsilon(t+1) = V(t+1) - \hat{V}(t+1),$ | $s_1^2 = \sum_{t=1}^{n-1} \frac{\varepsilon^2(t+1)}{n-1}$ | (8) |
|---|---|-----|
| TABLE V | | |

| WEAR DATA AND 1-STEP AHEAD FORECAST | | | | | | | | |
|---|------|------|------|-------|------|------|------|------|
| Index (t) | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 |
| Number of cycles | 250 | 500 | 750 | 1000 | 1250 | 1500 | 1750 | 2000 |
| Wear volume V(t) | 0.79 | 0.91 | 1.06 | 1.14 | 1.28 | 1.43 | 1.60 | 1.71 |
| Wear volume forecast $\hat{V}(t)$ for τ =1 | - | 0.91 | 1.03 | 1.17 | 1.27 | 1.40 | 1.56 | 1.71 |
| Forecast error ε(t) | - | 0 | 0.03 | -0.03 | 0.01 | 0.03 | 0.04 | 0 |

As an example, consider the data set obtained via neuralnetwork estimator of wear volume (cf. Table V, column 1 to 3). We will fit a double smoothing model with $\alpha = 0.8$ and $\beta = 0.05$. These are the estimates that result in the lowest possible error when comparing the original series to one step ahead at a time forecasts. The chosen starting values are l(1) = V(1) = 0.79 and b(1) = V(2) - V(1) = 0.12. The smoothed results for the example are given in 4th column of table V. The last column gives the corresponding

column of table V. The last column gives the corresponding 1-step forecast error. The MSE for DES model is then computed as follows:

$$s_1^2 = \sum_{t=1}^{n-1} \frac{\varepsilon^2(t+1)}{n-1} = \sum_{t=1}^7 \frac{\varepsilon^2(t+1)}{7} = 0.0063$$
(9)



Fig. 8. Forecast of wear data.

A plot of these results is presented in Figure 8, which shows also the predicted values for index t = 9 (i.e for a number of cycles of 2250) to t = 15 (i.e for a number of cycles of 3750). In addition, this figure shows the probability so that $Pr{\hat{V}(8+\tau) \ge V_s}$, with $\tau = 1,...,5$ and $V_s = 2$.

For instance the probability so that $\hat{V}(11) \ge 2$ is 0.74. With this result we can then admit 500 cycles before the wear volume exceed the threshold $V_s = 2$ with a probability 0.74.

VI. CONCLUSIONS

Both AI techniques used are showing better results as physical approaches. Influence of various mechanical parameters on the response of the network was evaluated and is in good agreement with the physical understanding of fretting phenomenon. The superiority of Artificial Intelligence methods over classical statistical ones has been confirmed by:

- 3 times lower relative mean error of the ANN model and higher stability for all studied conditions in comparison with physical approaches (Archard and energy dissipation).

- Especial usefulness when good simulators to test the performance of candidate solutions are available, but no methods to directly obtain good solutions exist.

- Robustness when the conventional mathematical analysis (e.g. MRA) cannot provide analytic solutions.

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