Krzysztof GOCMAN, Tadeusz KAŁDOŃSKI
Military University of Technology, Warsaw

NEURAL NETWORKS AS A FRICTION CLASSIFIERS

Key words

Boundary friction, seizure, modelling of friction processes, artificial neural networks.

Summary

Preliminary results of the influence of load and rotational speed on the moment of friction and wear of a tribological pair are presented in the paper. Tests were carried out at rotational speeds of about 100–2000 rpm and loads of about 500–6000 N. During the tests, the moment of friction, oil temperature and weather conditions were registered. After the tests, the conditions of the wear of tribological pairs were measured. The analysis of results was developed, and a friction classifier was built using artificial neural networks (ANN). The different training algorithms were applied to obtain the best quality models.

Introduction

The complicated and non-linear nature of tribological processes prompts the search for new methods to analyse all of the occurrences that proceed in friction pairs. Finding models of tribological quantities, like wear, friction coefficient, moment of friction, and temperature, is one of the most important problems in present tribology [5]. Only models of hydrodynamic friction are well-known and generally applied. In the case of boundary friction, we are not able to predict the values of definite tribological quantities [2]. We do not know how and when the boundary layer will be destroyed or which is "the safe" load and rotational speed range to prevent seizing of tribological pairs. In view of their properties, the artificial neural networks (ANN) could become very useful instruments. They let us carry out some dimensional analysis, define the influence of single parameters and, most importantly, the interaction between these parameters [4]. Because ANN has proven to produce good models of tribological wear and the moment of friction [1], the authors undertook the attempt to use ANN to model friction classifiers, which discriminate two states: "lubrication" and "seizure" for respective input functions – load and rotational speed.

1. Description of the test stand and the research method

Studies were undertaken on a four-ball tester T-02. This machine let us estimate the lubricating abilities of greases and oils.

The basic parameters that characterise the tribological pair are as follows [3]:

- Contact (Fig. 1): concentrated, point, created by the surfaces of four balls (diameter – ½');
- Motion: sliding (constant rubbing speed which is equivalent to 50 to 1500 revolutions per minute of upper ball);
- Load: changing from 0 to 7848N (800kG) – may increase constantly with speed 408.8N/s;
- Lubrication: oil bath lubrication (about 8ml of grease or oil).

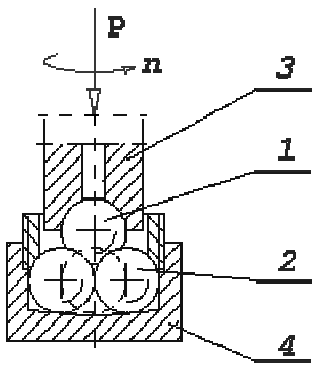

Fig. 1. Scheme of tribological pair: 1 – upper ball, 2 – lower balls, 3 – spindle, 4 – lower ball grip

Research on the four-ball tester was undertaken using the author's method, based on PN-76/C-04147 standard [3] (with only one lubricant – Antykol TS120 oil). The parameters of method are as follows:

- Time (t): 60s,
- Load (P): constant during one run, from 500 to 6000N,
- Rotational speed (n): from 100 to 2000 r. p. m.

During the research the following variables were recorded:
- Motion resistance (moment of friction),
- The temperature of the lubricant,
- Weather conditions: temperature, atmospheric pressure, air humidity.

At the end of every run diameters of wear traces was measured.

2. Research results

Selected results of the research are shown in the figures below.

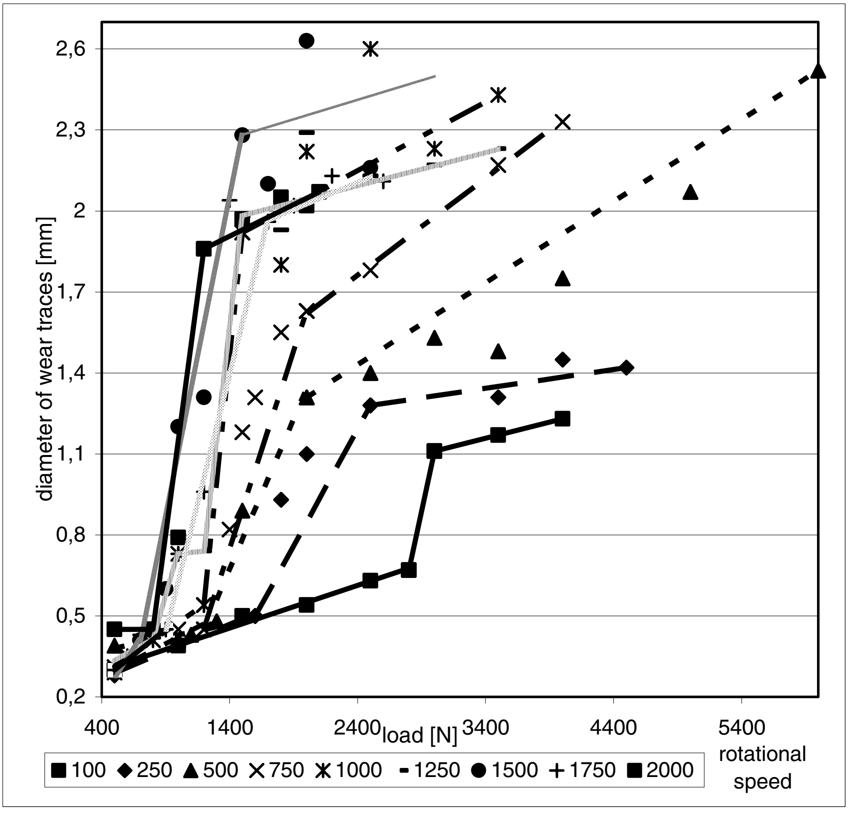

Fig. 2. The diameter of wear traces as a function of load for different rotational speeds

Analysing the results, we can conclude that, when the load is increased in relation to the value of the rotational speed, the diameter of wear traces also increase. Significantly, this is not a linear dependence (Fig. 2).

Selected runs of the moment of friction as a function of time are depicted in Fig. 3.

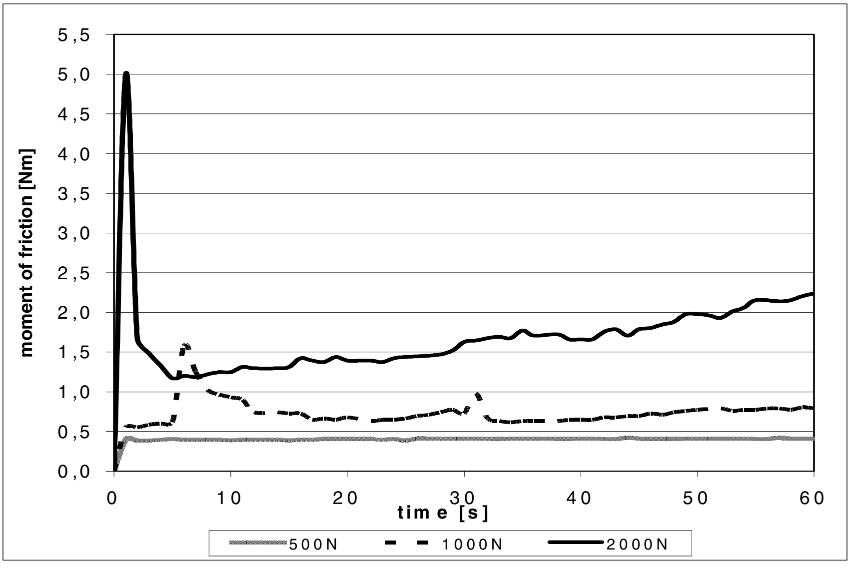

Fig. 3. Moment of friction for n = 1250 r. p. m.

3. Neural model

Based on the obtained results, the artificial neural networks (ANN) were created. The ANN is an instrument that is created on the foundation of knowledge about the structure and working of biological neural networks [4]. Their basic task is processing and analysing the information. The ANN system was created with the help of STATISTICA Neural Networks packet.

The ANN is built of combined neurons – the elements which process input signals to one final signal. To create ANN we have to conduct a teaching process, during which network parameters are chosen. This selection depends on customary criterion of the minimisation of errors committed by the network [4].

4. Methods of modelling

Data used during modelling was divided into three groups: teaching, verifying and testing. The teaching group was built from vectors that took part in modifying the network parameters, especially involved with neuron connection. After the presentation of each period, teaching errors were calculated. When teaching period ended, the network was verified by a second group of data, which is the verifying group. After this period verifying errors were calculated. When all this part of the teaching ended, every model was tested by a third group of data, the testing group, to check the model's adequacy for a specific object. Significantly, the data used for testing each model did not take part in the teaching process; the network had simply not "seen" the data before. Data used during modelling consisted of 219 occurrences.

Created neural models contained two inputs, load and rotational speed, and one output signal that was the state of "lubrication" or "seizure."

"Lubrication" is a state in which the boundary layer is not destroyed (low values of the moment of friction, insignificant wear). "Seizure" is a state in which the boundary layer is destroyed (fast growth and high values of moment of friction, significant wear).

As a criterion of selection for the definite state, the growth of the moment of friction was chosen. When the value of the moment of friction increased to over 25% during one second, it meant that state changed from "lubrication" to "seizure".

5. Types of networks and teaching methods

During the search for the most suitable model, different types of networks were tested:
- Multilayer perceptrons (MLP),
- Radial basis function (RBF),
- Linear networks.

Different teaching algorithms are attributed to each type of network as follows:
- Back propagation method (BP) – MLP,
- Conjugate gradient method (CG) – MLP,
- Quasi-Newton method (QN) – MLP,
- Subsample method (SS) – RBF,
- Means method (KM) – RBF.

6. The results of modelling

Many models were analysed paying special attention to their variety, teaching methods and another parameters, e.g. teaching speed, number of teaching periods, number of layers and neurons. Consequently, we received many different models, which imitated friction process to a more or less accurate extent. The best networks are composed in Table 1.

As we can see, quite good models were obtained. RBF networks gave the best results (94–96% of correct classifications), although MLP networks showed good quality too. The worst results were from linear networks (only 60–72% of correct classifications). Teaching, verifying and testing errors are errors committed on each part of creating the network. Although the output value is a state, not a number, the network counts this as an error during modelling. The rule is very simple: When a neuron's output value equals 0.0, it is interpreted as one state; when the output value equals 1.0, it is interpreted as second state. Errors are the results of differences between obtained values and 0.0 or 1.0 (for suitable state). Taking into account every parameter, the final model was chosen from RBF networks. Comparison of RBF models indicated that the best model was network number 1: RBF 2:2-9-1:1, because it had low values of testing error and a larger quantity of correct classifications. This network has three layers: input, output and one hidden layer (9 neurons). The structure of this network is presented in Fig 4.

Table 1. Summary of the best models

	Type	Error			Quantity of correct classifications [%]	
		teach.	ver.	test.	„lubrication"	„seizure"
1	RBF 2:2-29-1:1	0.23	0.24	0.12	96	94
2	RBF 2:2-29-1:1	0.23	0.24	0.15	96	93
3	MLP 2:2-7-1:1	0.41	0.09	0.22	90	90
4	MLP 2:2-8-1:1	0.40	0.09	0.20	85	90
5	Linear 2:2-1:1	0.30	0.39	0.35	60	72

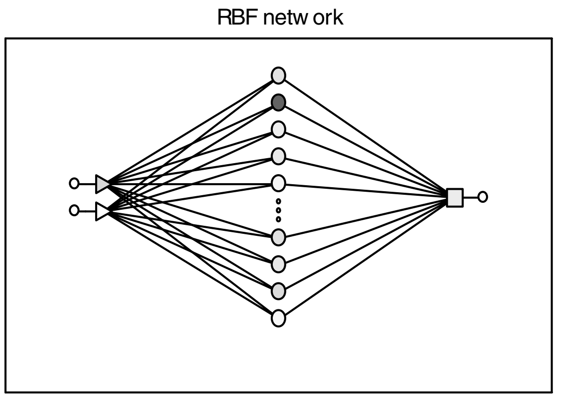

Fig. 4. Scheme of RBF network

One of useful abilities of ANN is the analysis of input's sensitiveness, which is especially important when the network contains many initial parameters. In this analysis, the network computes the quotient of error committed by network without suitable input and error committed with this input. This analysis shows us which inputs influence the final result the most.

Table 2. Analysis of inputs sensitiveness

	rotational speed	load
quotient	2.16	3.26
rank	2	1

The larger the quotient value, The more influential is the considered input on the final results. When the quotient is lower than one, we receive a better model when we skip this input. If the quotient is very large and we skip this input, the model will be worst than before skipping [4].

Another parameter which lets us estimate the quality of neural classifiers is the Receiver Operating Characteristic curve – ROC curve (Fig. 5). It sums up classifier efficiency. Perfect classifiers produce a curve located near the top, left edge of the chart that has an area under the curve of about 1.0. For random classifications, the area under the ROC curve equals about 0.5. (A classifier with an area under the curve less than 0.5 could be improved by inversion of classes).

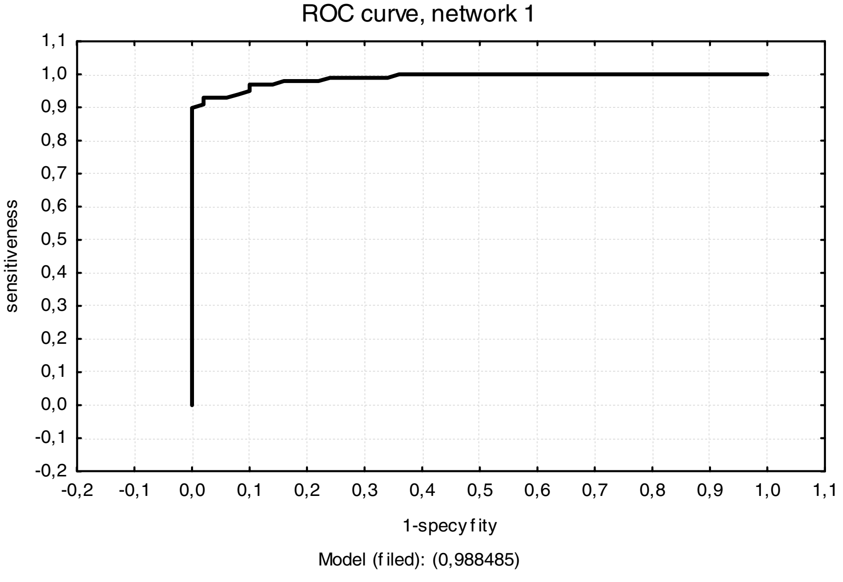

Fig. 5. Receiver Operating Characteristic curve for chosen model

Conclusions

All research indicated that artificial neural networks are very useful as classifiers in tribological processes. The analysis proved that RBF networks are better models for classification than another tested networks (linear, MLP). The obtained model achieved very good precision. For RBF networks, we get less than 15% error for testing data and a high quantity of correct classifications

(94–96%). We have to remember that the model was tested only for definite values of load and rotational speed. What is more, only one type of lubricant was used and weather conditions were not taken into account during modelling. To obtain a model that will give us better characterisation of processes taking place in tribological pairs, we have to conduct much more experiments to increase teaching data.

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Recenzent:
Magdalena TRZOS

Sieci neuronowe jako klasyfikatory tarcia

Słowa kluczowe

Tarcie graniczne, zatarcie, modelowanie procesów tarcia, sztuczne sieci neuronowe.

Streszczenie

W artykule przedstawiono wstępne wyniki badań wpływu obciążenia i prędkości obrotowej na wartość momentu tarcia i zużycie pary ciernej. Badania przeprowadzono w szerokim zakresie obciążeń (500–6000 N) i prędkości obrotowych (100–2000 obr./min). W czasie pomiarów rejestrowano wartość momentu tarcia, temperaturę środka smarnego oraz warunki otoczenia. Po zakończeniu testów wyznaczono zużycie elementów pary ciernej. Po przeprowadzonej analizie wyników, na bazie sztucznych sieci neuronowych zbudowano klasyfikator tarcia. W czasie budowy modeli zastosowano różne algorytmy uczące, tak aby uzyskać jak najlepszą jakość klasyfikatorów.