ISSN 1392–1320 MATERIALS SCIENCE (MEDŽIAGOTYRA). Vol. 21, No. 3. 2015

Neural Networks as a Tool to Characterise Oil State After Porous Bearings Prolonged Tests

Artur KRÓL [1] *, Krzysztof GOCMAN [1], Bolesław GIEMZA [2]

[1] *Military University of Technology, Faculty of Mechanical Engineering, Gen. Kaliskiego St. 2, 00-908 Warsaw, Poland*
[2] *Air Force Institute of Technology, Księcia Bolesława St. 6, 01-494 Warsaw, Poland*

crossref http://dx.doi.org/10.5755/j01.ms.21.3.7506

Received 02 July 2014; accepted 08 November 2014

The paper presents the results of research of durability tests of porous sleeves under differed conditions (600, 1000 and 1400 rpm, duration of the tests: 100, 200 and 1000 hours, temperature 60, 80 and 130 °C) of one oil. During the tests a temperature of the bearing and a friction torque were measured. After each durability test oil samples were extracted from the bearings and some chosen properties were carried out (FTIR spectrums and total acid number).

In the second stage the neural networks were used to describe achieved tribological characteristics. The data collected during the tests were used as an input to different neural networks models and as an output the investigative results of oil parameters were used. Different models of neural networks were checked to achieve the smallest training error and the best correlation between output from the network and the target.

Keywords: oil state, oxidation process, porous bearings characteristics, neural networks.

1. INTRODUCTION

Porous sliding bearings manufactured by sintering a metallic powder are produced in wide selection with use of various high-strength components (the load-bearing matrix of the material) and antifriction components, preventing seizure [1]. They can be characterised by low friction coefficient and high wear resistance, long durability, silent–running work and high load-carrying capacity, especially at small sliding velocities.

The matrix can be filled with appropriate lubricant to sustain self-lubricating mechanism. However during work unfavourable effects decreasing their performance are observed, i.e. the leakage and evaporation of oil and the aging process of the lubricant. Therefore selection of lubricant is a crucial phase in porous bearing design [1, 2], as the properties of the lubricant can influence the main features of the bearing – non-service operation and lifetime. These characteristics are dependent on the complex of oil parameters, i.e. volatility, oxidation resistance, lubricating properties [2].

Knowledge of lubricant parameters and its chemical constitution could give appropriate information about its state. However small amount of lubricant in porous bearing enables only few parameters to be tested, for instance total acid number (TAN) [3], presenting concentration of acid oxidation products and FTIR spectrum providing information due to spectral changes [4].

Acceptable work temperature, load and sliding velocity give appropriate conditions to sustain bearing work for a long period. Thus, durability tests of porous bearings should be performed to create models and predict service life of a bearing. However, service life tests are not widely performed and the prediction models of the durability are seldom presented and are based on the work conditions [5] (temperature T, sliding velocity v, load p) or porous bearing parameters [6]. There are only few examples of lubricant research after the durability test [7, 8]. As it was revealed the process of oil deterioration could be much deeper than in conventional sliding bearings with solid bushes, because of temperature, catalyst metal–porous structure and oxygen accelerating oxidation of the oil [7]. Oil samples, extracted from the bearings after durability 1000 hour tests, had high values of the total acid number and deeply changed FTIR spectra. In one more research, examination of FTIR spectrum of greases after the real tests showed full decrease of peaks presenting the lithium soap thickener and the antioxidant [8].

There are also few examples of service-life prediction of porous bearings with use of neural networks [9].

Artificial neural networks (ANN) as a statistic and mathematical tool in data analysis and prediction are becoming more and more popular finding numerous applications in industry, finance, banking, medicine and in many others disciplines [10]. What makes them very useful is an ease of use and their capability of learning and pattern recognition. Consequently, in the field of tribology there are numerous examples of theoretical and practical implementations of ANN, i.e. wear debris analysis [11, 12], evaluation of surface parameters [13], condition monitoring of machines [14]. There are also articles discussing on usefulness of training algorithms of neural networks in various tribology problems [15].

Few researches predict a relationship between oil parameters, as in [16] modelling relation between oxidation resistance and tribological properties of non-toxic lubricants or predicting remaining useful life with use of ANN [17], basing on the critical values of oil parameters such as viscosity, flash point, water content, insoluble rating. Oil FTIR spectrum data are very seldom used with ANN [18].

* Corresponding author. Tel.: +48-22-6839410; fax: +48-22-6837366.
E-mail address: *artur.krol@wat.edu.pl* (A. Król)

It could be finally emphasised that the application of ANN analysis to predict oil state after tribological test is not often presented.

The idea of the article is to present a preliminary step of neural networks use in evaluation of lubricant state after porous bearings prolonged tests.

2. EXPERIMENTAL DETAILS

The object of the research were porous sliding bearings sintered from iron powder Höganas (Sweden) and impregnated with mineral gear oil, often used by porous bearings manufactures. After the investigation of the basic parameters of the chosen oil they were performed two kind of stand tests:

- test 1: research of tribological characteristics during 1000, 200 and 100 hour durability test at three rotational speeds (600, 1000 and 1400 rpm) and three values of load p (consequently 2.72, 1.45, 1.04 MPa) described previously [7, 19];
- test 2: research of tribological characteristics during 1000, 500 and 100 hour durability test at 1000 rpm, under chosen load and three stable controlled temperatures (60 °C and 1.12 MPa, 80 °C and 130 °C under 1.45 MPa).

The basic parameters of the porous bearing and shaft were as follows: material of the bearing was Fe powder 97.5 %, Cu powder 2.5 %, material of the shaft was steel NC6 (60 HRC). Porous bush size was $25^{-0.1}/35.2^{-0.16} \times 20^{-0.3}$ mm and its mean open porosity was 21.5 %. Diametrical clearance during the tribological tests was in the range of 40…60 μm.

The measurements of fresh oil parameters were performed according to standardised methods, i.e. density by hydrometer method [20], kinematic viscosity by capillary method and dynamic viscosity [21], lubricity parameters by four-ball method [22], TAN by potentiometric method [23].

The stand test was previously described [19] and its details are shown in Fig. 1 and in Fig. 2. For the test under stable temperature the housings of the bearings were modified (Fig. 3) with electric heating module to control and stabilize (± 5 °C) a temperature of the bearing during the tests. During each test a temperature and friction torque were measured. However the test 2 was slightly modified, i.e. the 1000 hour test at 80 °C was prolonged to 4008 hours, as after 500 hour tests no significant changes of lubricant properties were observed.

After the tests oil samples were extracted from the bearings and chosen parameters of the oil were checked, as TAN and FTIR spectrum.

The most significant tests were FTIR spectrum investigation of oil samples extracted from the bearings, as it is excellent tool to observe an oxidation process of oils and chemical changes of lubricant base and comprised functional additives.

The tests of FTIR spectrum were performed with use of Nicolet is10 spectrometer by Thermo Scientific having IR source, DTGS KBr detector and KBr beamsplitter. within the spectral range 4000…650 cm^{-1}, 32 scans, 4 cm^{-1} resolution, Happ-Genzel apodization. As a consequence of small amount of oil extracted from bearings after the tests (c.a. 0.8 g) the measurements were conducted with ZnSe ATR accessory (Attenuated Total Reflection).

Attenuated total reflection (ATR) is a very popular sampling technique having attributes as little or no sample preparation (no dilution required), results can be obtained with relatively little care or expertise, radiation is not transmitted through the sample, so it does not have to be thin enough to allow transmission [24].

Fig. 1. View of the research module

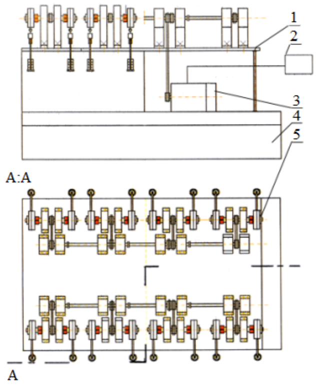

Fig. 2. The durability tester of sliding bearings: 1 – main plate; 2 – frequency converter; 3 – electric motor; 4 – base slab; 5 – research module

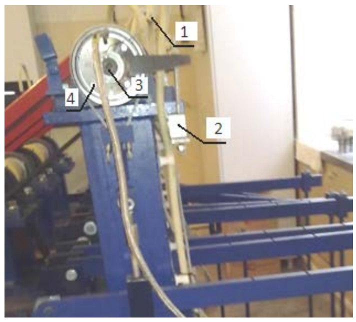

Fig. 3. View of modified research module: 1 – thermocouple; 2 – sensor of friction force; 3 – shaft; 4 – research module with heater

The FTIR test procedures were based on ASTM standards [25, 26, 27] presenting practices for condition monitoring of in-service lubricants and used to assist in the determination of general machinery health. The standards recommend appropriate measurement area and baseline points for components observable in the mid-infrared spectrum. Information on components used in FTIR spectrum research is presented in Table 1.

Table 1. Basic parameters of fresh mineral gear oil

Component	Measurement area [cm^{-1}]	Baseline range [cm^{-1}]
Water	Area 3500…3150	Minima 4000 to 3680 and 2200 to 1900
Oxidation	Area 1800…1670	Minima 2200 to 1900 and 650 to 550
Sulfate by-products	Area 1180…1120	Minima 2200 to 1900 and 650 to 550
Antiwear components	Area 1025…960	Minima 2200 to 1900 and 650 to 550

Collected data was used in a learning process of different ANN and the best models were chosen.

3. NEURAL NETWORKS CREATION

ANN are computational models inspired by an animal's central nervous systems and generally act as systems of interconnected neurons which can compute values from inputs.

A single neuron is a nonlinear, parameterized, bounded function $y = f\,(x_1, x_2\ ..x_n; w_1, w_2,..w_k)$ with variables called inputs (x_1, x_2, ... x_n) of the neuron and a value as its output y (Fig. 4). Thus, a network of neurons is the set of the nonlinear functions of two or more neurons with input, hidden and output layer (Fig. 5). In a neural network each neuron has also an activation function to scale the output of the neural network into proper ranges.

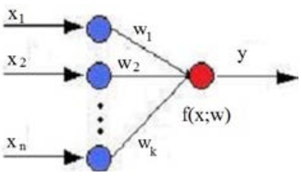

Fig. 4. A single neuron as a nonlinear function of the variables (inputs x_1, x_2, ... x_n) and of the parameters (connections or weights w_1, w_2, ... w_k)

Neural networks come in two classes: feedforward networks and recurrent (or feedback) networks [10]. A network has a feedforward structure if signals flow from inputs, forwards through any hidden layers, eventually reaching the output layers. Such a structure has stable behaviour and fault tolerance. Feedforward neural networks are often called static networks in contrast with recurrent or dynamic networks. If feedforward networks are multilayered and with sigmoid nonlinearities they are termed multilayer perceptrons, or MLPs.

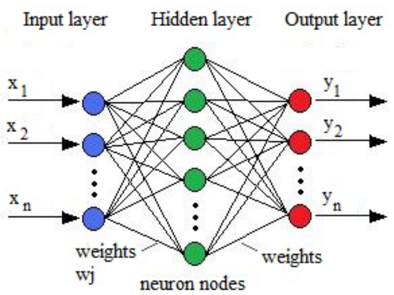

Fig. 5. A neural network model with input layer (x_1, x_2, ..x_n), hidden layer and output layer (y_1, y_2, ..y_n) with the parameters (connections or weights w_j: w_1, w_2, ... w_k)

In recurrent neural network (RNN) at least one path called a cycle exists that, following the connections, leads back to the starting neuron. However, a neuron cannot be a function of itself, at the same moment of time, but it can be a function of its past value. Therefore, each connection of RNN is assigned a delay (possibly equal to zero), in addition to being assigned a parameter [10]. Such architecture of RNNs enables to use their internal memory to process arbitrary sequences of inputs.

In the presented paper all calculations were performed with Statistica Neural Networks program and MLP networks were used as they are stable, simplified and very often used to resolve real problems [15, 16, 18].

Basing on the data from the tribological tests regression MLP were created with different activation functions (sigmoid, hyperbolic, exponential etc.).

Important matter was to decide about the input and output parameters. The target variable is believed to depend on the inputs, so the chosen variables were work conditions of the bearings during the tests, i.e. p – pressure in the bearing from load, v – sliding velocity, T – work temperature, t – duration of the test. As the outputs were set of the oil parameters investigated after the tests, such as TAN of oil samples and area of selected peaks from FTIR spectrums.

Next step in ANN creation was a learning process with different iterative techniques, to adjusts the weights of the neural network so that for any given input data x the neural network can produce an output which is as close as possible to y. The performance of achieved ANN is measured by how well they can predict unseen data, i.e. not used during training, what is known as generalization. Therefore the part of collected data was used in testing and validation process to achieve the best performance of build ANN.

4. RESULTS

The basic parameters of fresh mineral oil are presented in Table 2, where G_{OZ150} is lubricity parameter, so-called limiting load of wear, determined at the rotational speed of 500 rpm, under constant load of P = 147.15 daN (150 kG) within the 60-second run [22].

Table 2. Basic parameters of fresh mineral gear oil

Density [g/cm^3]			Dynamic viscosity [mm^2/s]			G_{OZ150} [MPa]	TAN [mgKOH/g]
20 °C	40 °C	100 °C	20 °C	40 °C	100 °C		
0.896	0.880	0.853	643.16	171.84	15.30	38.31	1.01

The characteristics of friction torque and temperature were very stable for all chosen conditions in the test 1, as it is shown in Fig. 6. Mass decrease of oil was generally about 0.05 to 0.3 g and was in good and significant correlation with averaged bearing temperature (r = 0.7438). TAN values of oil samples from the bearings were in the range of 1.04 – 4.24 mgKOH/g and did not change significantly compared to the fresh oil. The tendency was also confirmed in the research of FTIR spectrums and showed no meaningful structural changes in oxidation products area (Fig. 7). Antiwear additive peak was not also decreased dramatically.

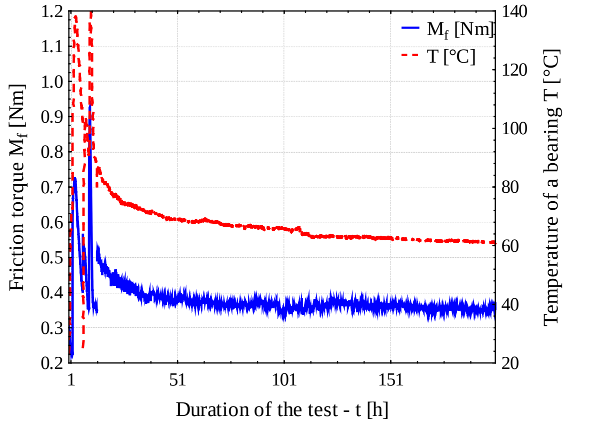

Fig. 6. An example of tribological characteristics measured at 1000 rpm during 200 hour test

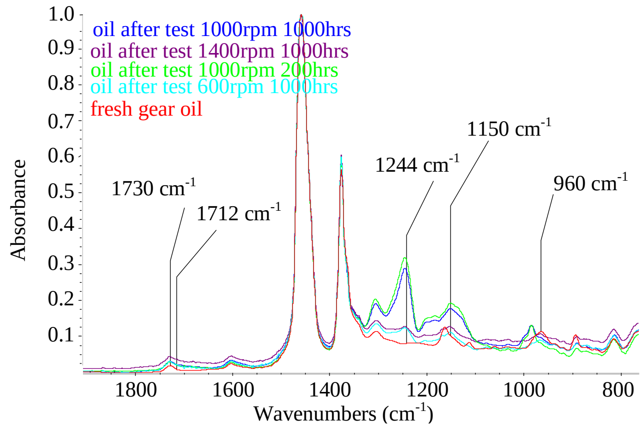

Fig. 7. FTIR spectra of oil samples after durability tests 1 under different rotational speed and duration of the test – absorbance versus wavenumber [cm^{-1}]

It was characteristic for the test 1 that the most intensive changes were observed for peaks 1244 cm^{-1} and 1150 cm^{-1} indicating the presence of C–O structure.

Comparing the results after test 2 achieved characteristics of friction torque were stable at temperature of 60 and 80 °C. During the tests at 130 °C friction torque was unstable and all the bearings were seizured shortly before 500 hour. Consequently, a 1000 hour test at highest temperature was not performed. The mass loss of oil was also measured and its highest value was observed for the bearings tested at 130 °C.

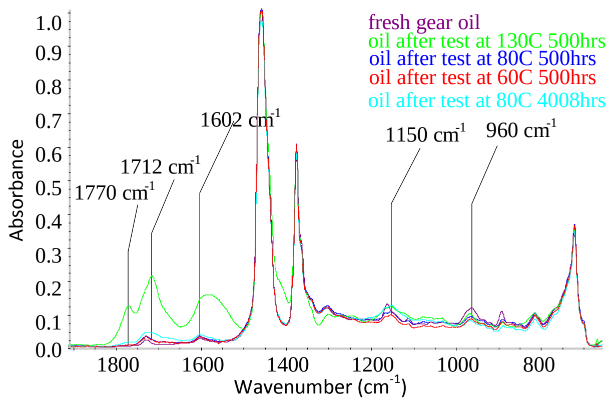

Fig. 8. FTIR spectra of oil samples after durability tests 2 at different temperature and duration of the test – absorbance versus wavenumber [cm^{-1}]

TAN values of oil samples extracted from the bearings were in the range of 1.29…4.02 mgKOH/g after the test at 60 and 80 °C. However increase of the temperature resulted in much higher values of TAN reaching even 27.07 mgKOH/g. FTIR spectrums of investigated oils proved that tendency (Fig. 8).

The FTIR spectra showed high changes within oxidation products area (1850 – 1670 cm^{-1}) for oil samples tested at 80 °C for 4008 hours and the biggest increase was achieved for oil samples tested at 130 °C. Within the antiwear additive area the changes were comparable with those observed after the test 1 (applied load was smaller in the test 2). It was also visible smaller intensity of peaks 1244 cm^{-1} and 1150 cm^{-1}, representing C–O structure.

5. RESULTS OF ANN CREATION

ANN were created separately for the test 1 and test 2, as they were different work conditions. As mentioned, ANN had strictly specified inputs, as a consequence of performed tribological tests (work parameters), i.e. p, v, T and t. The outputs of ANN were parameters of oil investigated after the tests, i.e. TAN value, S_{AW} antiwear additive peak area, S_{OP} oxidation products peak area, S_{SUM} summarized area of selected peaks. Finally, ANN had 3 or 4 inputs and 1 target.

In Table 3 – Table 10 there are presented examples of calculations of ANNs, having the best training performance P_{tr}, test performance P_t and validation performance P_v (as possible close to 1) and the smallest training and test error (E_{tr} , E_t). Output activation functions A_F are also listed and sensitivity analysis parameters, estimating the importance of the models' input variables.

As for TAN value of oil samples after both test, the best ANNs were achieved for oil samples after test 1. It was confirmed by high value of training performance P_{tr} (Table 3). ANN created for TAN output for the test 2 showed also high value of training performance P_{tr} (Table 4).

Table 3. ANNs with v, p and t inputs and TAN output – test 1

Net. name	P_{tr}	P_t	P_v	E_{tr}	E_t	A_F
3-4-1	0.9740	0.346	1.000	0.021	0.019	Exponential
	Sensitivity analysis of ANN inputs					
	v	126.395	p	18.593	t	11.492

Table 4. ANNs with p, t and T inputs and TAN output – test 2

Net. name	P_{tr}	P_t	P_v	E_{tr}	E_t	A_F
3-2-1	0.961	1.000	-1.000	3.890	0.001	Logistic
	Sensitivity analysis of ANN inputs					
	p	2.124	t	2.094	T	12.714

Sensitivity analysis of ANNs created for TAN output showed strong influence of v velocity (3 – 4 – 1 ANN) on TAN value – Table 3) after test 1. On the other hand, during the test 2 (Table 4) the strongest influence on achieved TAN values had temperature T.

In Table 5 and Table 6 there are presented results of ANNs created for antiwear additive peak from FTIR spectrum for oil samples after test 1 and test 2. As it can be seen for the test 1 (Table 5.) training performance P_{tr} was not very high, however value of testing performance P_t was acceptable. The results of ANN creation for antiwear peak S_{AW} as an output after test 2 (Table 6) present higher values of training performance P_{tr} (0.799) compared to the results after test 1 (0.498).

As previously, the best ANNs after test 1 and test 2 are created with different inputs: for test 1 – *v*, *p* and *t*, for test 2 – *p*, *t* and *T*. Sensitivity analysis showed that inputs variables had after test 1 (Table 5) slightly differed impact on the S_{AW} and the highest influence was noticed for velocity *v*. As for the results after test 2 (Table 6) comparable values were observed and almost equal influence on the values of S_{AW}.

Table 5. ANNs with *v*, *p* and *t* inputs and S_{AW} output – test 1

Net. name	P_{tr}	P_t	P_v	E_{tr}	E_t	A_F
3-3-1	0.498	0.861	1.000	1.483	0.215	Linear
	Sensitivity analysis of ANN inputs					
	v	4.756	p	3.995	t	1.108

Table 6. ANNs with *p*, *t* and *T* inputs and S_{AW} output – test 2

Net. name	P_{tr}	P_t	P_v	E_{tr}	E_t	A_F
3-1-1	0.799	1.000	1.000	0.023	0.016	Logistic
	Sensitivity analysis of ANN inputs					
	p	2.855	t	2.855	T	2.855

In the last stage the summarized peaks area S_{SUM} was set as the output for created ANNs, as this parameter could represent the observed changes in chemical composition of oil samples after aging process. The results of the calculations are presented in Table 7 and Table 8.

The best results for oil samples after test 1 were reached for ANN MLP 3 – 1 – 1 (Table 7), having quite good performance and small errors. Activation function for output was hyperbolic tangent (tanh).

Sensitivity analysis showed comparable influence of all the input variables on the output for presented ANN.

Table 7. ANNs with *v*, *p* and *t* inputs and S_{SUM} output – test 1

Net. name	P_{tr}	P_t	P_v	E_{tr}	E_t	A_F
3-1-1	0.547	1.000	1.000	0.025	0.056	tanh
	Sensitivity analysis of ANN inputs					
	v	1.094	p	1.177	t	0.992

Table 8. ANNs with *p*, *t* and *T* inputs and S_{SUM} output – test 2

Net. name	P_{tr}	P_t	P_v	E_{tr}	E_t	A_F
3-3-1	0.975	1.000	0.981	0.001	0.001	Identity
	Sensitivity analysis of ANN inputs					
	p	4989.62	t	194.20	T	380.19

Performance parameters of ANN created for S_{SUM} output after test 2 had high values and small errors were noticed. Sensitivity analysis showed that the strongest influence on S_{SUM} had load *p* value.

6. DISCUSSION

Created ANN for the results of two tribological dissimilar tests showed quite high training and testing performance and small errors. However, as it was noticed (Fig. 9 – Fig. 12.) residuals values were not always small, so it meant that the model was not fully satisfactory. Moreover distribution of residuals should be evaluated for normality. That would give information if created ANN had the same effectiveness along all the cases.

In Fig. 9 residuals for TAN of oil samples after test 1 are presented, showing small values. On the other hand, the results after test 2 were not so satisfactory (Fig. 10).

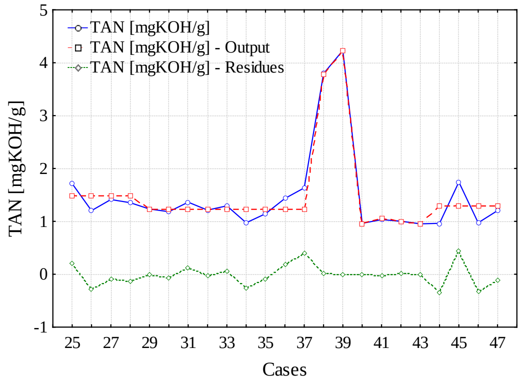

Fig. 9. Comparison of TAN, TAN output and residuals of 3-4-1 ANN and for consequent cases after test 1

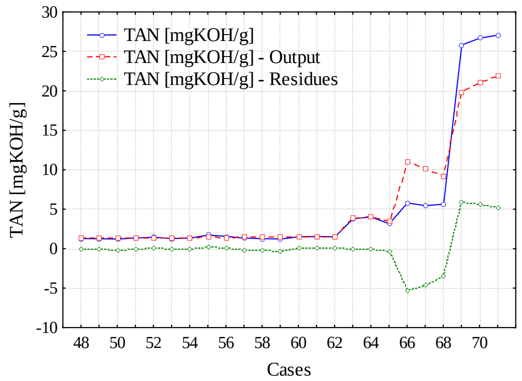

Fig. 10. Comparison of TAN, TAN output and residuals of 3-2-1 ANN and for consequent cases after test 2

In the next two Fig. 11 and Fig. 12 there are presented results of residuals distribution for S_{SUM} after test 1 and 2. As it appeared the values of residuals after test 1 were rather high and the modelled output did not fit well to the real values.

Finally, for observed residuals distribution normality was estimated. The estimation of normality distribution was performed according to the Shapiro-Wilks, as it has become the preferred test of normality because of its good power properties as compared to a wide range of alternative tests (for example widely used the Kolmogorov-Smirnov test) [29]. Moreover it is rather seldom discussed the problem of statistical evaluation of neural networks experiments [30].

In Table 9 there are collected results of the Shapiro-Wilks test indicating the normality of residuals distribution. If the *W* statistic is significant ($p_{SW} < 0.05$), then the hypothesis that the respective distribution is normal should be rejected.

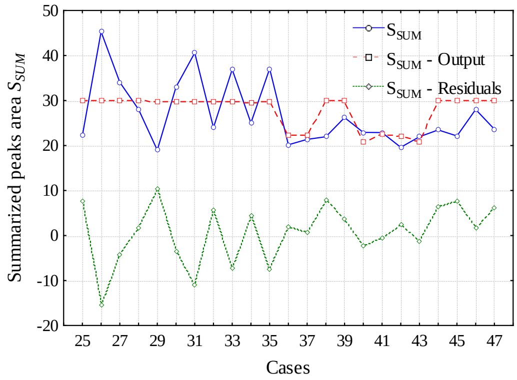

Fig. 11. Comparison of S_{SUM}, S_{SUM} output and residuals of 3-1-1 ANN and for consequent cases after test 1

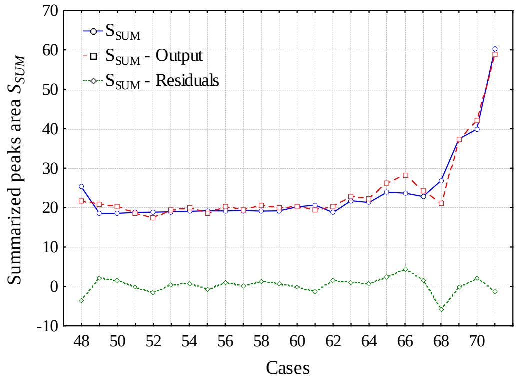

Fig. 12. Comparison of S_{SUM}, S_{SUM} output and residuals of 3-3-1 ANN and for consequent cases after test 2

Table 9. Shapiro-Wilks test results for different ANNs

Test	Net. name	Output of ANN	Shapiro-Wilks parameters
1	3-4-1	TAN	SW-W = 0.9366; p_{SW} = 0.1521
	3-3-1	S_{AW}	SW-W = 0.8629; p_{SW} = 0.0047
	4-2-1	S_{OP}	SW-W = 0.9316; p_{SW} = 0.1186
	3-1-1	S_{SUM}	SW-W = 0.9435; p_{SW} = 0.2138
2	3-2-1	TAN	SW-W = 0.7426; p_{SW} = 0.00004
	3-1-1	S_{AW}	SW-W = 0.797; p_{SW} = 0.0003
	3-1-1	S_{OP}	SW-W = 0.6615; p_{SW} = 0.0000
	3-3-1	S_{SUM}	SW-W = 0.917; p = 0.0501

As the results showed, normality of residuals distribution is observed for ANNs after test 1 with outputs TAN, S_{SUM} and S_{OP}. After the test 2 residuals normality is observed only for S_{SUM}.

It was clearly seen that ANN having more nodes in hidden layers had better parameters and smaller residuals, so better fitting of the model to the real values. However the growing total number of all nodes needed higher number of cases, according to recommended factor 1 : 10 or acceptable 1 : 3 or 1 : 4 [10, 29].

7. CONCLUSIONS

Achieved results of ANN creation showed possibility of use of neural networks to characterise oil state after durability test with chosen parameters of oil. ANN had rather high performance parameters and small errors. However it should be noticed that the main problem was number of cases, which could be used in training, testing and validation process, as it was quite complicated because of time consuming durability test of porous bearings.

The results from two tribological tests needed different ANNs to describe the output variation from independent input variables.

Next step of the research will be creation of ANNs for different kind of oil and collection of higher number of cases.

REFERENCES

1. **Kostornov, A. G., Fushchich, O. I.** Exchange of Experience. Sintered Antifriction Materials *Powder Metallurgy and Metal Ceramics* 46 (9-10) 2007: pp. 503 – 512. http://dx.doi.org/10.1007/s11106-007-0078-5
2. **Miller, H., Tetzlaff, C.** Well Oiled. Special and Additional Lubricants for Sintered Metal Plain Bearings *Klüber Lubrication Tribojournal* 1 2002: pp. 6 – 11.
3. **Giemza, B., Kałdoński, T., Król, A.** Problem of the Service Life of Self-lubricated Friction Couples *Solid State Phenomena* 113 2006: pp. 399 – 40.
4. **Van De Voort, F. R., Sedman, J., Cocciardi, R. A., Pinchuk, D.** FTIR Condition Monitoring of In-Service Lubricants: Ongoing. Developments and Future Perspectives *Tribology Transactions* 49 (3) 2006: pp. 410 – 418. http://dx.doi.org/10.1080/10402000600781432
5. **Lawrowski, Z.** The Principles of Materials Selection for the Self-lubricating Sliding Bearings *Tribology* 5 – 6 1997: pp. 734 – 743 (in Polish).
6. **Olexa, J.** Investigation of the Relations between the Permeability and the Service Life of Porous Self–lubricated Bearings *Wear* 58 1980: pp. 1–14.
7. **Król, A., Giemza, B., Kałdoński, T.** Study on the Oxidation Process of Mineral Gear and PFPE Oil During Durability Tests of Porous Sliding Bearings *STLE/ASME 2010 International Joint Tribology Conference* 2010: pp. 223 – 225.
8. **Hänel, E., Pahl, W., Haspinger, E., Schuster, K. D.** Optimized Tribology in Sintered Metal Plain Bearings. Joint research project of GKN and Klüber Lubrication at the Westsächsische Hochschule Zwickau *Klüber Lubrication Tribojournal* 2 2007: pp. 20 – 23.
9. **Giemza, B.** Investigations and Modeling of Operating Characteristics of Porous Sliding Bearings Impregnated by Greases. Doctoral thesis, Military University of Technology, Warsaw, 2007 (in Polish).
10. **Dreyfus, G.** Neural Networks. Methodology and Applications. Springer, Berlin, 2005: pp. 16 – 80.
11. **Zhixiong, Li., Xinping, Y., Zhiwei, G., Peng, Liu., Chengqing, Y., Zhongxiao, Peng.** A New Intelligent Fusion Method of Multi-dimensional Sensors and its Application to

Tribo-system Fault Diagnosis of Marine Diesel Engines *Tribology Letters* 47 2012: pp. 1 – 15.

12. **Peng, Z., Kirk, T. B.** Automatic Wear-particle Classification Using Neural Networks *Tribology Letters* 5 1998: pp. 249 – 257. http://dx.doi.org/10.1023/A:1019126732337
13. **Gürcan, S.** Measurement and Evaluation of Surface Roughness Based on Optic System Using Image Processing and Artificial Neural Network *International Journal of Advanced Manufacturing Technology* 73 (1-4) 2014: pp. 353 – 364.
14. **Cao, Y., Xie, X., Liu, Y., Ding, T.** Fault Diagnosis of Gear Using Oil Monitoring Samples and Vibration Data *Advanced Tribology Proceedings of CIST2008 & ITS-IFToMM2008* 2010: pp 934 – 939.
15. **Gocman, K., Kałdoński, T.** Application of Artificial Neural Networks in Tribology – Prediction and Classification Models *Journal of KONES* 16 (1) 2009: pp. 137 – 144.
16. **Drabik, J., Trzos, M.** Modelling Relation Between Oxidation Resistance and Tribological Properties of Non-Toxic Lubricants with the Use of Artificial Neural Networks *Journal of Thermal Analysis and Calorimetry* 109 2012: pp. 521 – 527.
17. **Sinha, A. N., Mukherjee, P. S., De, A.** Assessment of Useful Life of Lubricants Using Artificial Neural Network *Industrial Lubrication Tribology* 52 2000: pp. 105-109.
18. **Wanwimol, K., Soraya, K., Rakesh, K. S.** Application of Artificial Neural Networks to Predict the Oxidation of Menhaden Fish Oil Obtained from Fourier Transform Infrared Spectroscopy Method *Food Bioprocess Technology* 4 (3) 2011: pp. 475 – 480.
19. **Giemza, B., Kałdoński, T., Król, A.** The Research on the Lubricant Aging under Durability Test of the Porous Sliding Bearings *Advanced Tribology Proceedings of CIST2008 & ITS-IFToMM2008* 2010: pp 142 – 143.
20. ASTM D287 Standard Test Method for API Gravity of Crude Petroleum and Petroleum Products (Hydrometer Method).
21. ASTM D445 Standard Test Method for Kinematic Viscosity of Transparent and Opaque Liquids (and Calculation of Dynamic Viscosity).
22. PN-C-04147:1976 Petroleum products. Test for lubricating properties of oils and greases (Polish standard).
23. ASTM D664 Standard Test Method for Acid Number of Petroleum Products by Potentiometric Titration.
24. **Griffiths, R.P, de Haseth, J. A.** Fourier Transform Infrared Spectrometry. Second Edition. John Wiley & Sons, New Jersey, 2007: pp. 321 – 347. http://dx.doi.org/10.1002/9780470106310.ch15
25. ASTM E2412-04 Standard Practice for Condition Monitoring of Used Lubricants by Trend Analysis Using Fourier Transform Infrared (FT-IR) Spectrometry.
26. ASTM D7412 Standard Test Method for Condition Monitoring of Phosphate Antiwear Additives in In-Service Petroleum and Hydrocarbon Based Lubricants by Trend Analysis Using Fourier Transform Infrared (FT-IR) Spectrometry.
27. ASTM D7418 – 07 Standard Practice for Set-Up and Operation of Fourier Transform Infrared (FT-IR) Spectrometers for In-Service Oil Condition Monitoring.
28. **Coates, J. P., Setti, L. C.** Infrared Spectroscopic Methods for the Study of Lubricant Oxidation Products ASLE Transations 29 (3) 1986: pp. 394 – 401.
29. (Electronic Version): StatSoft, Inc. (2013). Electronic Statistics Textbook. Tulsa, OK: StatSoft. WEB: http://www.statsoft.com/textbook/
30. **Flexer, A.** Statistical Evaluation of Neural Network Experiments: Minimum Requirements and Current Practice *Cybernetics and Systems '96, Proceedings of the 13th European Meeting on Cybernetics and Systems Research. Austrian Society for Cybernetic Studies* 2 1996: pp. 1005 – 1008.