MATEC Web of Conferences **252**, 08003 (2019) https://doi.org/10.1051/matecconf/201925208003
CMES'18

Analysis of loading history influence on fatigue and fracture surface parameters using the method of induction trees

Adam Deptuła[1,*], *Wojciech* Macek[2], and *Marian A.* Partyka[1]

[1]Opole University of Technology, Faculty of Production Engineering and Logistics, Poland
[2] Institute of Chemical Engineering of the Polish Academy of Sciences, Poland

Abstract. In fatigue life testing under various loading conditions, researchers observe the profile, surface and morphology of materials. In this study authors research the fatigue life of material and the surface fracture geometry. Areal field and fractal based characterisation are evaluated for the whole fracture surfaces. Results of this test were correlated to notch geometry and loading conditions. It was confirmed, for notched specimens, that the change from torsion to proportional bending with torsion fatigue life increase significantly, the same as changing loading from bending with torsion to bending. The measurement device was equipped with a motorised nosepiece using five dedicated microscopic objective lenses from 2.5× to 100× magnification. This paper presents the application of the induction tree method for analysis of loading history influence on fatigue and fracture surface parameters. In a decision tree, nodes store tests checking values of example attributes and leaves store categories assigned to them. For each of possible test results, there is one branch coming from a node to a subtree. In this way, it is possible to represent any attributes of the hypothesis admissible for a given set. Analysis of selected parameters will estimate their impact on the surface structure.

1 Introduction

Fracture surface topography is one of the basic macroscopic investigations aimed at determining the cause of the fatigue damage [1]. It allows to determine what kind of the fatigue loading material was subjected. Several of typical macroscopic patterns of fatigue damage can be distinguished. Among them, their functions of type and magnitude of loading. The surface analysis reveals localisation of initiation and crack path propagation, as well as identifies the areas for further microscopic examination. Fracture mechanics tests are usually concentrated on crack growth under uniaxial and multiaxial loadings [2]. Some articles deals only with crack growth, while other scientist carried out quantitative analysis of fracture surface. The study on relationship between fracture toughness and fracture surface fractal dimension began in the 1980s [3]. Since then, the quantitative approach to the morphology has led to many interesting studies on the interconnection with loading or ambient environment [4].The topography of fracture surfaces, especially in bending and torsion fatigue, was investigated and published in [5, 6]. Researchers demonstrated, inter alia, the influence of torsion loading constituent on the surface form. Previous studies shown that there are differences in the surface geometry of individual zones (e.g. initiation, propagation) [7].

The optical method Focus Variation Microscope (FVM) was used to measure the entire fracture surface in connection with the relevant Areal parameters [8].

The classification is an important stage in the analysis of acoustic properties. In this stage, properties characteristic for signals of particular microphones are compared with each other. On the basis of obtained results a decision concerning the classification of the signal properties to a given group is made [9] Among the most often applied methods of recognising acoustic signals are: HMM (Hidden Markov Models), VQ (Vector Quantization), LVQ (Learning Vector Quantization), SOM (Self-Organising Maps), ANN (Artificial Neural Network), GMM (Gaussian Mixture Models) [10, 11], SVM (Support Vector Machines). In addition, there are classifiers based on the induction of decision trees, ML-HMM (Maximum Likelihood Hidden Markov Model) [12, 13]. In a general case, the classification includes two stages: creating of patterns for recognition and identification. In general terms of optimisation, groups of measurement data are provided by a measurement station. Discretisation of ranges of individual measurement data leads to a coded record of construction and operating parameters [14].

Multivalent logical trees determine the importance of design and operation parameters, playing the role of logical decision variables. A number of methods can be distinguished in discrete optimisation, e.g. heuristic method – based on searching for deviations between data values [15, 16], decision trees induction algorithm – based on the entropy increase [17, 18] neural networks, evolutionary algorithms [19]. These methods, in particular, are used in fault diagnosis and acoustic analysis of signals [20].

* Corresponding author: a.deptula@po.opole.pl

This paper focuses on a relationship between type of loading, like bending, torsion and combination bending with torsion and surface fracture Height Parameters, Functional Parameters and Fractal dimension. The induction tree method helped in the search for the importance of individual parameters. Additionally, based on the files, the neural network was used.

2 Measurements and calculations

2.1. Fatigue tests

The fatigue tests were made in the lab of the Department of Mechanics and Machine Design, Opole University of Technology, Poland [21, 22]. This scientific body specialises in developing methods for determining the fatigue life of materials [12], as well as performing its own test stands [23, 24, 25].

The object of the study was rectangular cross-section specimens of the EN AW-2017A-T4 aluminium alloy, shown in figure 1. Specimens had an external, unilateral, sharp and blunt one-sided notches, which radius was ρ = 0.2 mm, 5 mm, 10 mm and 22.5 mm.

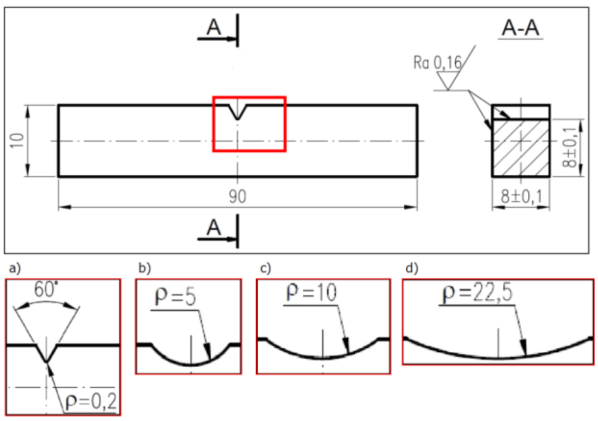

Fig. 1. Shape and dimensions of specimen for: a) ρ = 0.2 mm, b) ρ = 5 mm, c) ρ = 10 mm, and d) ρ = 22.5 mm.

Fractures was caused by different kinds of loadings in bending and torsion fatigue. Stress ratios for this research were R = -1, -0.5, 0.

2.2 Surface parameters measurements

Topography of the surface was measured and calculated using the focus variation microscope (FVM) Alicona Infinite Focus G4 with the MountainsMap 7.4 software.

Fatigue fracture surface was observed on total area with objective magnification 10×. Surface fracture studies were carried out using Height Parameters, according to ISO 25178. The fatigue loading history was checked with selected Height Parameters, such as Root-mean-square height (Sq), Skewness (Ssk), Kurtosis (Sku), Maximum height (Sz), Arithmetical mean height (Sa) and fractal dimension (Df).

Surface parameters are calculated on the whole studied surface, marked in figure 2.

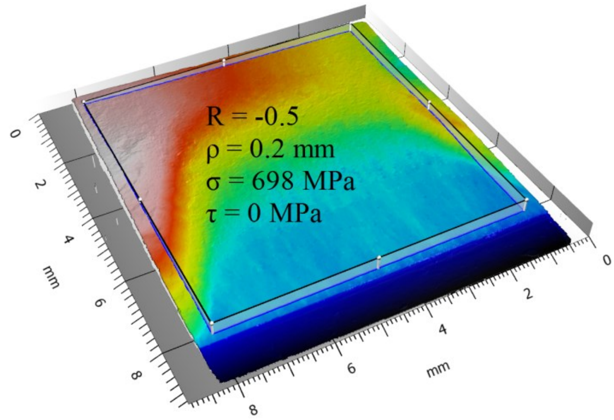

Fig. 2. The whole current surface reduced to the rectangle with dimensions 7.5 mm x 7.2 mm, for example of combination bending with torsion.

3. The classification of validity rank of the parameters with the application of induction trees

A decision tree is a structure which has ordinary properties of trees in the meaning assigned to the tree in the information technology, so it is a structure composed of nodes from which branches come to other nodes or leaves. It is convenient to define tree structures in a recursive way. Assuming that a given branch X on which attributes a_1, a_2 ,..., an and the set of notions C of the category C are determined:

1. The leaf containing any category label d ∈ C is a decision tree.

2. If t: $X \rightarrow R_t$ is a test made on the values of attributes of examples with a set of possible results $R_t = \{ r_1, r_2, \ldots r_m \}$ are decision trees, then the node containing the test t, from which m branches come out, given that for $i = 1, 2, \ldots, m$ branch i corresponds to the result r_i and leads to the tree T_i, is a decision tree.

For any node of n decision tree, by t_n we mean a test connected with it, and for each of its possible results $r \in R_t$ by $n_{[r]}$ node or a child leaf, to which the n branch related to the r result leads from the node. The notation described above is presented in Figure 3.

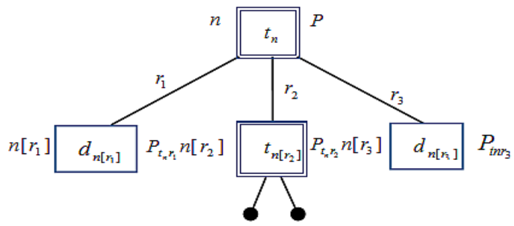

Fig. 3. A sample query "query-by-example" to the decision-making system.

Information included in the set of training examples is equal to:

$$I(E) = -\sum_{i=1}^{|E|} \frac{|E_i|}{|E|} \cdot \log_2 \left(\frac{|E_i|}{|E|} \right) \qquad (1)$$

where:

E - the set of training examples

$|E_i|$ - the number of examples which describe i object

$|E|$ - the number of examples in the training set E

The expected value of information after the division of the set of examples E into subsets $E^{(m)}, m = 1,\ldots,|V_a|$, for which the attribute a has the value V_m, determined as [24]:

$$I(E,a) = \sum_{m=1,K,|V_a|,E^{(m)}=\varnothing} \frac{|E^{(m)}|}{|E|} \cdot I\left(E^{(m)}\right) \qquad (2)$$

where:

$|E^{(m)}|$ - the number of examples after the division of the set E in relation to the value m of a given attribute,

$|E|$ - the number of examples in the training set E.

3.1 Application of inductive decision trees for analysis of loading history influence on fatigue and fracture surface parameters

Tables 1 and 2 present the analysed parameters in the form of a training file.

Table 1. Fracture surface parameters in the training file format-part 1.

Plik Drzewo decyzyjne Pomoc

we	we	we	we	we	we	we	we
Cycles	Moment	R	radiusp	alfak	sigmax	taumax	b
688000	15,84	-1	10	1,11	206,04375	148,47	8
271000	7,92	-1	0,2	3,76	348,975	74,37	8
204000	15,84	-1	5	1,24	230,175	148,47	8
82000	15,84	-0,5	10	1,11	206,04375	148,47	8
33000	7,92	-0,5	0,2	3,76	348,975	74,37	8
16000	7,92	0	0,2	3,76	348,975	74,37	8
35000	15,84	0	5	1,24	230,175	148,47	8
3487000	7,92	0	22,5	1,04	96,525	74,37	8
389000	7,92	-1	0,2	0	0	74,37	8
349000	7,92	-1	22,5	0	0	74,37	8
831000	15,84	-1	22,5	0	0	148,47	8
132000	7,92	-0,5	0,2	0	0	74,37	8
22000	15,84	-1	0,2	3,76	697,95	0	8
52000	7,92	-0,5	0,2	3,76	348,975	0	8
322000	7,92	-1	0,2	3,76	348,975	0	8
24000	15,84	-1	0,2	3,76	697,95	0	8
20000	15,84	-0,5	0,2	3,76	697,95	0	8
17000	7,92	0	0,2	3,76	348,975	0	8
12000	15,84	0	0,2	3,76	697,95	0	8

Table 2. Fracture surface parameters in the training file format-part 2

we	we	we	we	we	we	we	wy
ho	h	ao	bh	k2	sigmaa	tau	#Chropowatosci
8	8	2	1	0,208	185,625	148,47	3021
8	8	2	1	0,208	92,8125	74,37	3733
8	8	2	1	0,208	185,625	148,47	2312
8	8	2	1	0,208	185,625	148,47	4187
8	8	2	1	0,208	92,8125	74,37	3416
8	8	2	1	0,208	92,8125	74,37	2995
8	8	2	1	0,208	185,625	148,47	1747
8	8	2	1	0,208	92,8125	74,37	1505
8	8	2	1	0,208	92,8125	74,37	541
8	8	2	1	0,208	92,8125	74,37	655
8	8	2	1	0,208	185,625	148,47	974
8	8	2	1	0,208	92,8125	74,37	865
8	8	2	1	0,208	185,625	148,47	1442
8	8	2	1	0,208	92,8125	74,37	1336
8	8	2	1	0,208	92,8125	74,37	1411
8	8	2	1	0,208	185,625	148,47	1329
8	8	2	1	0,208	185,625	148,47	1304
8	8	2	1	0,208	92,8125	74,37	1589
8	8	2	1	0,208	185,625	148,47	1193

The classification by means of induction trees was made separately for loading ratio $r=\tau_{max}/(\sigma_{max}+\tau_{max})$ as **output** attributes (wy).

Input attributes (we) are the values of fracture surface parameters: Cycles (we); Moment (we); R (we); notch radius ρ (we); α_k (we) ; σ_{max} (we) ; τ_{max} (we); b [mm] (we) ; h_0 [mm] (we) ; h[mm] (we) ; a_0 [mm] (we) ; b/h [mm] (we); k_2 (we) ; σ_a [MPa] (we) ; τ_a [MPa] (we) ; Chro (we) ; loading ratio r (we).

The DeTreex module (Aitech Software) was used in the classification of validity rank of the construction parameters and it made it possible to form decision trees. In the described system, the module forming the decision tree requires an appropriate data preparation. In Figures 4 and 5, the first and second part of the tree of the induction tree are presented.

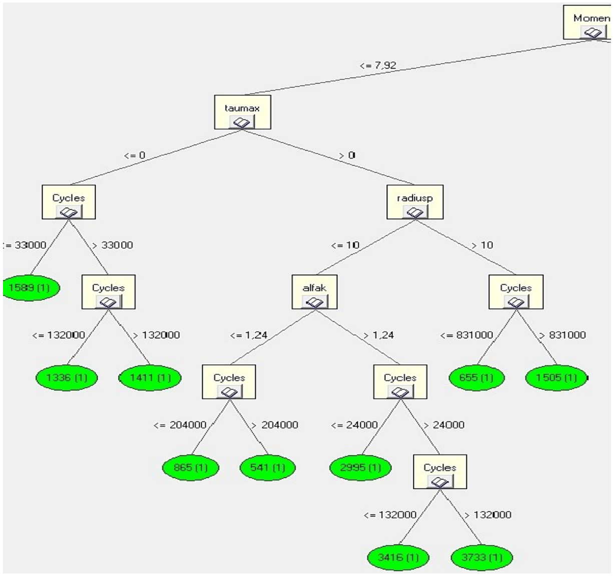

Fig. 4. The first part of the induction tree.

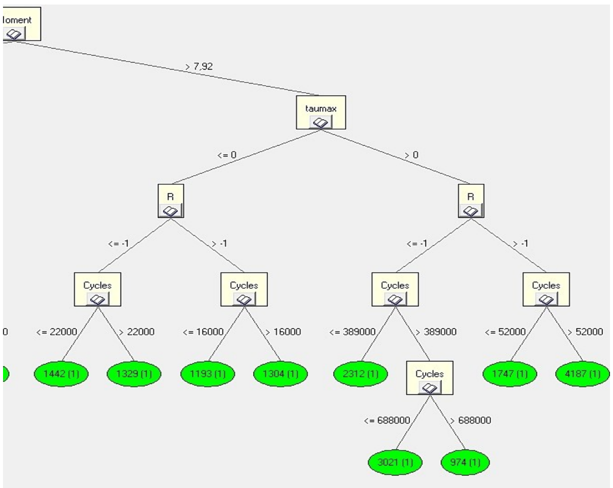

Fig. 5. The second part of the induction tree.

The induction tree determines the degree of importance of the attribute (Moment- **M**) from the most important one placed in the root, through classification of any example. The inductive search algorithm is an approximate method. To make the calculations more accurate, the local localisation algorithm was used. For this purpose, the neural network method was used [26, 27]. Standards for the network were results based on a comparison of surface parameters with the results of fatigue calculations.

4 Results of the comparison of surface parameters with the conditions of fatigue tests

Figures 6a, 6b and 6c show the relationship between Arithmetical mean height Sa, fractal dimension D_f and Skewness Ssk respectively of whole surface fracture area and cycles to failure N_f of EN AW-2017A-T4 specimens, with distinction for different notches radius.

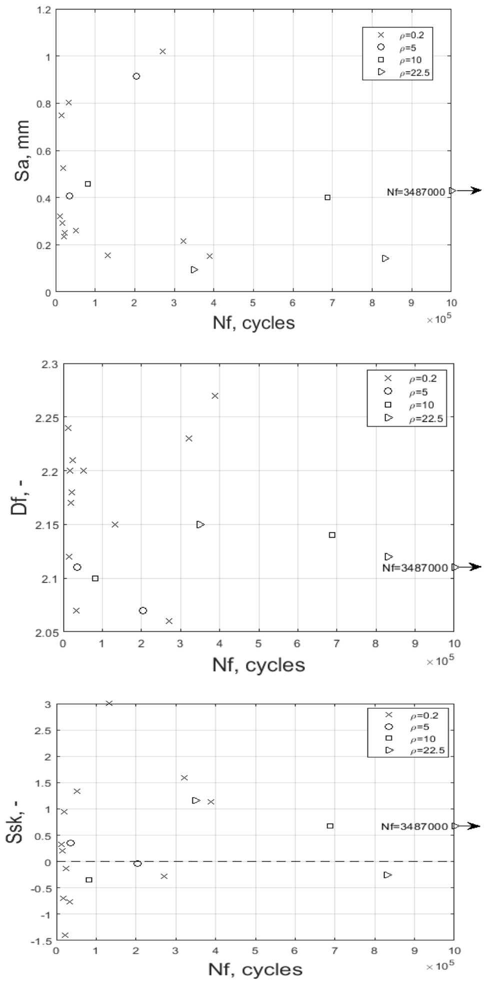

Fig. 6. Distribution of surface parameters appropriate notch radius relationship between N_f and a) Sa, b) D_f, c) Ssk of whole fracture areas.

4.1 Application of neural network

The training process of the applied network was made on the basis of the supervised learning. One of the main parameters determining the receipt of satisfactory results, from the point of view of recognising acoustic emissions of microphones, was an appropriate choice of a training algorithm by the adopted SSN architecture. The following algorithms were tested for the training procedure: GDA (Gradient Descent with Adaptive Learning Rate Backpropagation) and RPROP (Resilient Backpropagation) [28].

The weight correction process of particular neurones for this algorithm takes place according to the dependence described by the formula below:

$$w_{ij}^{(k)}(n+1) = w_{ij}^{(k)}(n) - n_{ij}^{(k)}(n)\,\mathrm{sgn}\left(\nabla_{ij}^{(k)}(n)\right), \qquad (3)$$

$$\eta_{ij}^{(k)}(n) = \begin{cases} \min(a n_{ij}^{(k)}(n-1), \eta_{\max}) & for\ \ \nabla_{ij}^{(k)}(n)\nabla_{ij}^{(k)}(n-1) > 0 \\ \max(b\, n_{ij}^{(k)}(n-1), \eta_{\min}) & for\ \ \nabla_{ij}^{(k)}(n)\nabla_{ij}^{(k)}(n-1) < 0 \\ n_{ij}^{(k)}(n-1) & for\ \ \text{otherwise} \end{cases} \qquad (4)$$

where:

$n_{ij}^{(k)}$ - individual learning coefficient for each scale,

$\nabla_{ij}^{(k)}(n)$ - component of the gradient of the error function

Figure 7 presents the efficacy of recognising analysed acoustic characteristics by the training procedure **GDA** and **RPROP.**

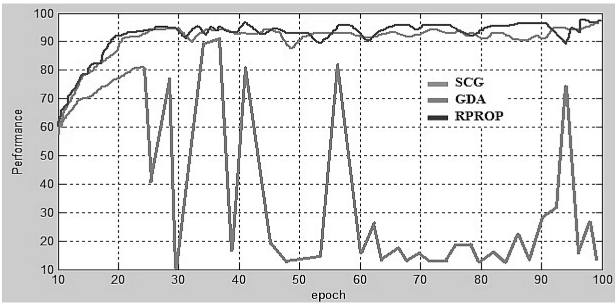

Fig. 7. Comparison of the effectiveness of the recognition of acoustic signals, depending on the type of training algorithm.

The Figure 8 shows the panel when learning the neural network in the Neuronix program

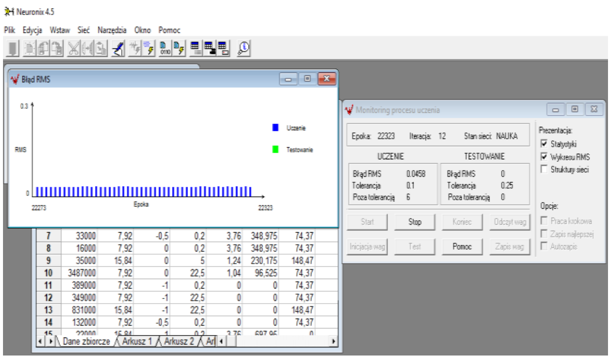

Fig. 8. Learning file for the neural network- training step *n*.

Figure 9 shows the structure of the used neural network.

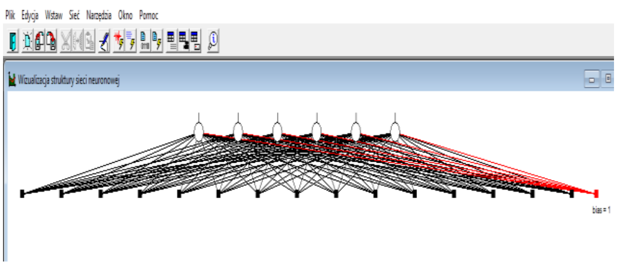

Fig. 9. Structure of the neural network.

In the last step, an induction algorithm for the neural network was used. Induction tree was generated for arithmetical mean height *Sa*, fractal dimension *Df* and Skewness *Ssk* (for charts from figure 6) (Fig. 10).

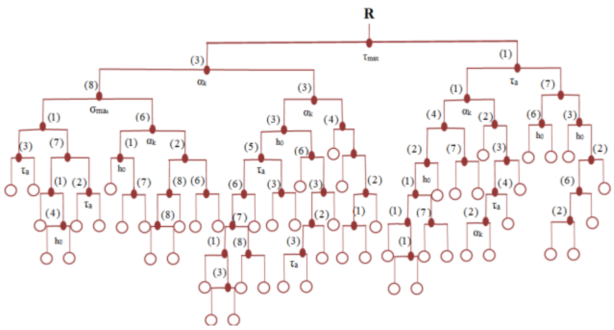

Fig. 10. Parametric inductive tree for neural networks.

5 Conclusions

The article contains analyse of selected features of surface of EN AW-2017A-T4 alloy caused by different kinds of loadings in bending and torsion fatigue.
Induction trees is a method used to examine the importance of individual parameters relative to fatigue life. The parametric tree classifies parameters: R, τ_{max}, α_k, σ_{max}, τ_a and h_0. The parametric tree also determines the importance level. The greatest influence on the topography of the breakthrough area (Sq, Sa, Sz, Sku, Ssk as well as Df) according to the induction tree according to Figure 10 is R, then: τ_{max}, and at the end: α_k, τ_a. The greatest influence on durability (N_f) has the moment *M*.

In a decision tree, nodes store tests checking values of example attributes and leaves store categories assigned to them. For each of possible test results, there is one branch coming from a node to a subtree. In this way, it is possible to represent any attributes of the hypothesis admissible for a given set. Trees have such a property that they start in the root from which branches are built. The use of trees in the optimization of machine systems is fully useful in the sphere of the concept, because it allows you to select (change) the arithmetic values of the relevant construction and/or operating parameters of a given machine system and evaluate the operation of the system in new conditions. At any stage of optimisation, we can make a tree by choosing the optimal decisions. Then you can attach vertices to the tree, which represent optimal system responses to changes in arithmetic values of construction parameters, etc. Another approach would be to use, for example, a backtrack algorithm. The search "with backtrack" is based on a systematic search with the transition from the subproblem.

References

1. K. Slamecka, K., et al., International Journal of Fatigue, **32,** 6, 921-928 (2010)
2. D. Rozumek et al., Key Engineering Materials, **592-593**, 692-695 (2014)
3. A. Carpinteri, A. Spagnoli,S. Vantadori, Fatigue & Fracture Of Engineering Materials & Structures **25**, 7, 619-627 (2002)
4. T. Kobayashi, D. A.Shockey, International Journal of Fatigue, **23**, 1, 135-142 (2001)
5. W. Macek, T. Wołczański, ITM Web Conf., **15** 06002 (2017)
6. K. Slámečka, P. Ponížil, J. Pokluda, *Quantitative fractography in bending-torsion fatigue*, Materials Science and Engineering: A, ISSN: 0921-5093, 462, 1, Page: 359-362, 2007
7. M. Oravcováa, P. Palčeka , M. Chalupováa, Procedia Engineering, **192**, 644 – 648 (2017)
8. G.M. Krolczyk, et al., Measurement, **2**, 464-470 (2016)
9. A. Deptuła, P. Osiński, U. Radziwanowska, **41**, 3, 449- 460. DOI: 10.1515/aoa-2016-0046
10. J. D.Wu, J. M. Kuo J.M, Expert Systems with Applications, **36**, 4278-4286 (2009)
11. L. Xuo, F. F. Jelinek, *Probabilistic classification of HMM states for large vocabulary*, [in:] Proceedings of ICASSP, 2044–2047, Phoenix, USA, 1999
12. A. Deptuła, P. Osiński, D. Kunderman, D. Włostowski, U. Radziwanowska, Archives of Acoustics, **41**, 2, 345-350
13. M. Kirpluk, *Fundamentals of acoustics* (in Polish), Wyd. NTL-M, Warszawa, 2012.
14. A. Deptuła , J. Drewniak, M.A. Partyka, *Analysis of a planetary gear modelled with a contour graph considering the decision making complexity of game-tree structures,* II International Conference of Computational Methods in Engineering Science (CMES'17), Exploitation And Machine Building, ITM Web Conf. **15**, 04002 (2017)
15. S. D. Lee, D. Cheung , Kao B, *Is sampling useful in data mining a case in the maintenance of discovered association rulet*, Data Mining and Knowledge Discovery, **2,** 3, 233–262 (1998)
16. A. M. Law, W.D. Kelton, *Simulation Modeling and Analysis*, McGraw-Hill, Boston
17. F. Basciftci, S. Kahramanli, Advances in Engineering Software, **42**, 6, 316- 321, (2011)
18. J. R. Quinlan, Rivest R.L., Information and Computation, **80**, s. 227-248 (1989)
19. K. Gurney, *An introduction to neural networks*. UCL Press. ISBN 1857286731, 1997
20. A. Głowacz, W. Głowacz, Z. Glowacz, J. Kozik, Measurement, 113 (2018) https://doi.org/10.1016/j.measurement.2017.08.036
21. D. Rozumek, S. Faszynka, Materials Science, **53**, 3, (2017)
22. S. Faszynka, D. Rozumek, *Solid State Phenomena*, **250**, 10-15 (2016)
23. W. T. Macek, T. Lagoda, N. Mucha, Fatigue & Fracture of Engineering Materials & Structures, **41,** 2, 249-259 (2018)

24. W. Macek, E. Macha, Archive of Mechanical Engineering, **62**, 1, 85-100 (2015)
25. R. Owsinski, A. Nieslony, *Analytical Model of Dynamic Behaviour of Fatigue Test Stand-Description and Experimental Validation*. in 13th Conference on Dynamical Systems - Theory and Applications, Lodz, POLAND: Springer (2015)
26. A. Ultsch, Self-organising neural networks for visualisation and classifi-cation, Information and Classification, Opitz O., Lausen B., Klar R., 864–867, Springer-Verlag, Berlin (1993)
27. L. Xuo, F. Jelinek *, Probabilistic classification of HMM states for large vocabulary*, [in:] Proceedings of ICASSP, 2044–2047, Phoenix, USA.
28. K. F. Thang , R.K. Aggrwal, D.G. Esp,A. McGrail *Statistical and Neural Network Analysis of Dissolved in Power Transformer*, IEEE Dielectric Materials, Measurements and Applications Conference (2000)