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CLASSIFICATION OF FAULT DIAGNOSIS IN A GEAR WHEEL BY USED PROBABILISTIC NEURAL NETWORK, FAST FOURIER TRANSFORM AND PRINCIPAL COMPONENT ANALYSIS

Summary. This paper presents the results of an experimental application of artificial neural network as a classifier of the degree of cracking of a tooth root in a gear wheel. The neural classifier was based on the artificial neural network of Probabilistic Neural Network type (PNN). The input data for the classifier was in a form of matrix composed of statistical measures, obtained from fast Fourier transform (FFT) and principal component analysis (PCA). The identified model of toothed gear transmission, operating in a circulating power system, served for generation of the teaching and testing set applied for the experiment.

KLASYFIKACJA USZKODZEŃ PRZEKŁADNI ZĘBATYCH PRZY WYKORZYSTANIU PROBABILISTYCZNEJ SIECI NEURONOWEJ, SZYBKIEJ TRANSFORMATY FOURIERA ORAZ ANALIZY PCA

Streszczenie. W artykule przedstawiono wyniki z eksperymentów, których celem było wykorzystanie sztucznej sieci neuronowej jako klasyfikatora stopnia pęknięcia u podstawy zębów kół przekładni. W badaniach użyto probabilistycznych sieci neuronowych (PNN). Dane wejściowe dla klasyfikatorów stanowiły miary statystyczne uzyskane z sygnałów drganiowych przy wykorzystaniu szybkiej transformaty Fouriera (FFT) oraz analizy PCA. Zidentyfikowany model przekładni zębatej pracującej w układzie napędowym posłużył jako źródło danych uczących i testujących dla sztucznych sieci neuronowych.

1. INTRODUCTION

Toothed gear transmissions, due to their widespread utilization in drive systems, have been an object of interest of a number of research centres involved in diagnostics of machinery [2-8,12-16,19,21]. Works are conducted to create appropriate tools enhancing failure identification processes, especially in their initial phases. Due to the diversity of structural solutions employed in gears and drive systems, despite a number of algorithms for diagnostic signal analysis and inference principles, developed on the basis of such signals, the dependability of diagnostics proves to be insufficient in many cases. It results from a low-energy character of the early stages of failures, and from various gear failures producing similar interference of the vibroacoustic signal.

Detection of failure in its early stage may prevent from damage to the machine and resultant high economic loss and, in some cases, threat posed to human life.

Non-invasive diagnostics, including vibroacoustic diagnostics, is of particular importance in gear diagnostics procedures [2,3,5,7,8,10,15,16,19,21,22].

At present, failure symptoms found in the signal, are more and more often studied with the aid of artificial intelligence methods [9,10,17,18,20]. Such methods are resistant to interference, and allow modelling of any nonlinearities and generalization of knowledge.

The paper presents results of an experiment, aimed at application of PNN (Probabilistic Neural Network) neural network for classification of the cracking degree of a tooth root. The neural classifier was based on input data derived from spectrum. Classifiers taught by set of variables obtained from statistical measures by used principal component analysis (PCA).

Moreover, the experiment allowed to select the pre-processing method which is most practical in the process of tooth undercutting degree classification.

2. SUBJECT OF STUDY

Toothed gear operating in the circulating power system was subject of the study. Gear specifications are presented in the table 1.

An identified toothed gear model in the drive system has been used in the experiment [11]. It was presented in figure 1.
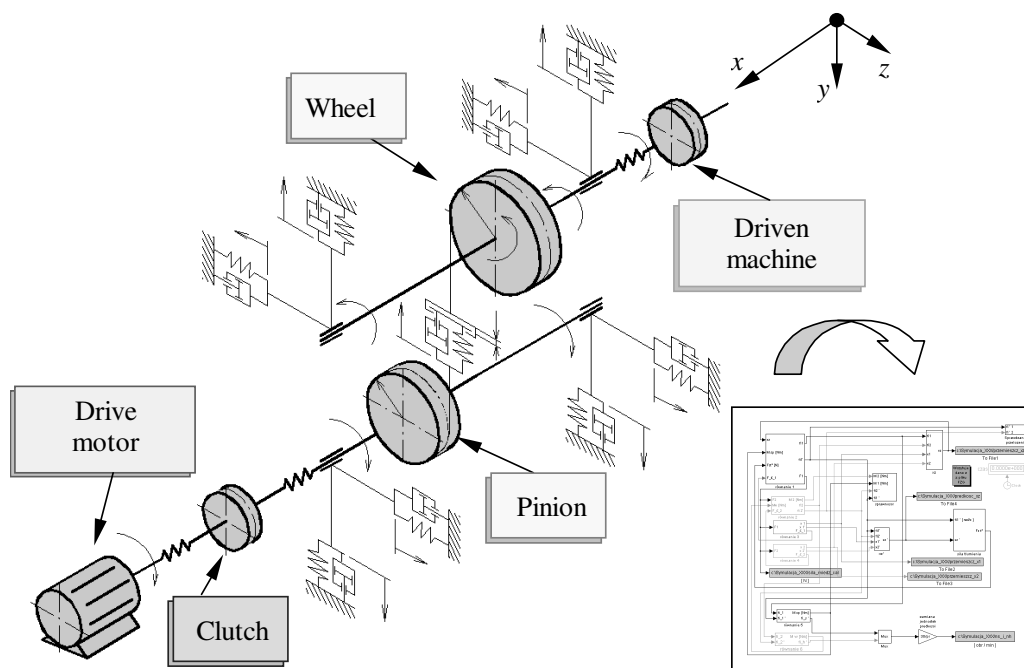

Fig. 1. Toothed gear model
Rys. 1. Model przekładni zębatej

The model was used to simulate the effect of cracking degree at the tooth root on transverse acceleration of pinion shaft vibrations. The variations of cracking degree at the tooth root were achieved by reducing rigidity of the pair of tooth in pressure phase, by a determined percentage in relation to the rigidity of undamaged pair of teeth.

Each simulation was carried out for the rigidity range between 0 and 100%. The simulations were made for various accuracy categories of toothed gears, and for various values of cyclic and random errors.

Tab. 1

Specifications of gearbox

Parameter	Value
Number of pinion teeth	$z_1 = 16$
Number of wheel teeth	$z_2 = 24$
Obliquity angle	$\beta = 0o$
Addendum modification coefficient	$x_1 = 0{,}8635$
Gear modification coefficient	$x_2 = -0{,}5$
Main pressure angle	$\alpha = 20°$
Nominal module	$m_n = 4.5$ mm
Contact ratio	$\varepsilon_\alpha = 1{,}32$
Addendum coefficient	$h_{ao} = 1$
Tip clearance coefficient	$c_o = 0{,}25$
Wheel width	$b = 20$ mm
Nominal torque	$M = 138$ Nm
Pinion rpm	$n = 2680$ rpm

The simulations were carried out in three series, for the error-free gear and the 5th and 6th accuracy class gears:
1) the first series:
   - cyclic deviation of the pinion and wheel: 0 mm/pitch length,
   - random deviation - maximum wheel and pinion fabrication error 0 mm,
2) the second series:
   - cyclic deviation of the pinion: -7 mm/pitch length, for the wheel: 5 mm/pitch length,

-    random deviation - maximum wheel and pinion fabrication error: ± 4,5 mm,

3) the third series:
-    cyclic deviation of the pinion: -14 mm/pitch length, for the wheel: 10 mm/pitch length,
-    random deviation - maximum wheel and pinion fabrication error: ± 9 mm,

Simulations for the 5th and 6th accuracy categories were repeated five times for various random deviations. As a result, 1111 acceleration signals of pinion shaft transverse vibrations in a toothed gear were obtained.

3. DESCRIPTION OF THE EXPERIMENT

The experiment was aimed at application of the neural network to assess the cracking degree at the tooth root.

The basic problem involved in application of an artificial neural network, is to appropriately select the input data [1-6,8-10,12-14,17,18,20,22]. The way to get the input data for neural network is shown in figure 2.

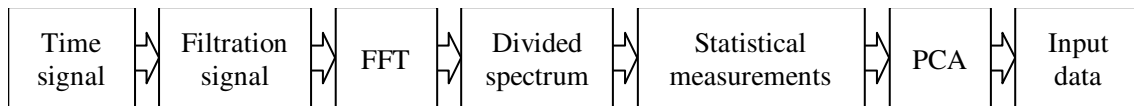| Time signal | → | Filtration signal | → | FFT | → | Divided spectrum | → | Statistical measurements | → | PCA | → | Input data |

Fig. 2. Method for input data created
Rys. 2. Metoda otrzymywania danych wejściowych

Firstly, time signals were filtered by use of one of a few kinds of filtration methods, such as:
-    in the frequency range up to 12.8 kHz (filter no. = 1),
-    in the frequency range up to 6.4 kHz (filter no. = 2),
-    in the frequency range up to 6.4 kHz residual signal (filter no. = 3),
-    in the frequency range up to 6.4 kHz differential signal (filter no. = 4),
-    between 0,5 f_z and 1,5 f_z (filter no. = 5).

Signals obtained from different filtered methods were used in the process of fast Fourier transform (FFT). As results spectrums were created. Next, spectrum was divided into ranges:
-    up to f_o - angular frequency,
-    $(f_o, f_z - f_o]$,
-    $(f_z - f_o, f_z)$,
-    f_z - meshing frequency,
-    $(f_z, f_z + f_o]$,
-    $(f_z + f_o, 2 \cdot f_z - f_o]$, etc.

In additional frequency ranges $(f_o, f_z - f_o]$ and $(f_z + f_o, i \cdot f_z - f_o]$, where $i = 1,2,3...N$, was divided into 20 ($\Delta f \cong 30\,\text{Hz}$), 10 ($\Delta f \cong 65\,\text{Hz}$) or 5 ($\Delta f \cong 150\,\text{Hz}$) smaller bands. The aim of this procedure was checked influence wide spectrum bands on classified results.

The spectrum divided procedure was presented in figure 3.

The next step of the experiment involved the selection of estimators, which sufficiently describe disturbances resulting from damages, as shown in successive frequency range. 35 statistical measures were checked [5].

Because it is better for neural networks when inputs are less, the principal component analysis (PCA) was used for feature extraction. PCA identifies a combination of variables that describe major trends in the data set. It relies on an eigenvector decomposition of the covariance or correlation matrix of the process variables. The most important information can then be described using a small number

of principal components. PCA is a powerful tool for analysing multivariate data sets [4]. With the proper principal components most information can be preserved so they should be adequate to the original samples.
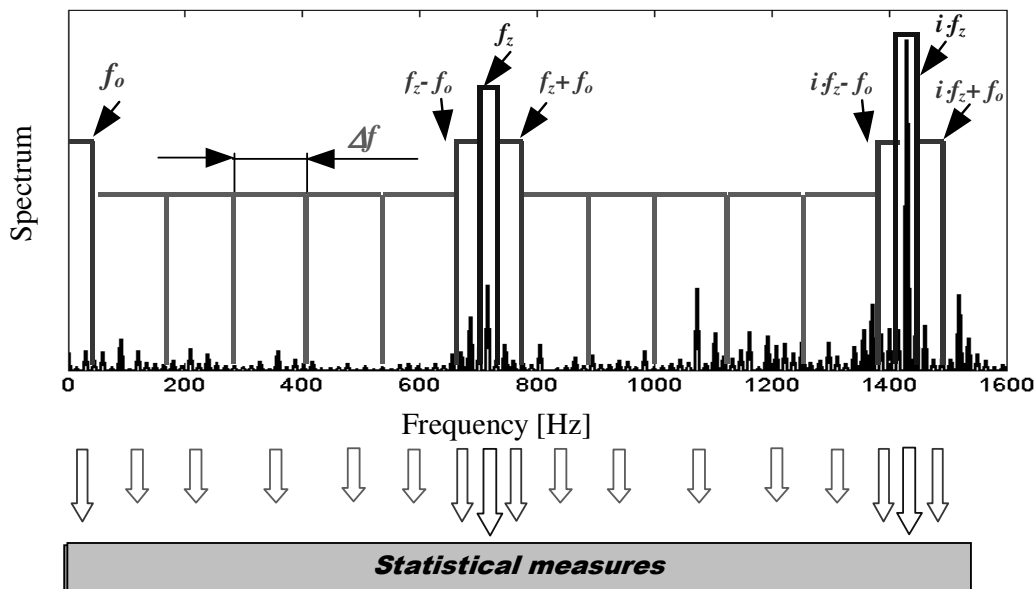

Fig. 3. Method for spectrum divided
Rys. 3. Metoda selekcji widmowej

Principal component, which were acquired in a consequence of PCA procedure, were used as input data for neural networks classifier.

4. RESULTS OF THE EXPERIMENT

The neural network was aimed at classifying the extent of the tooth root undercut. The undercut was characterized by a percentage change of teeth pair rigidity in 5 classes of rigidity loss:
- class 1: 0÷20%,
- class 2: 21÷40%,
- class 3: 41÷60%,
- class 4: 61÷80%,
- class 5: 81÷100%.

In the experiment probabilistic neural network (PNN) was used as a neural network classifier. Optimisation of the neural classifier was based on the change of γ coefficients [9]. The optimisation criterion was the minimum testing error.

The example of influence γ coefficients on testing error is showed in figure 4.

The best results obtained during experiment were presented in table 2.

Research showed that it is not possible to choose one method of spectrum divided or one method of signal filtration which is the best independently of other parameters.

Investigating the experiment results, it can be concluded that it is possible to built PNN neural networks classifier of toothed gear failures.

Next researches will be conducted for testing data obtained from real gearbox.

Tab. 2

The beat of results for PNN classifier

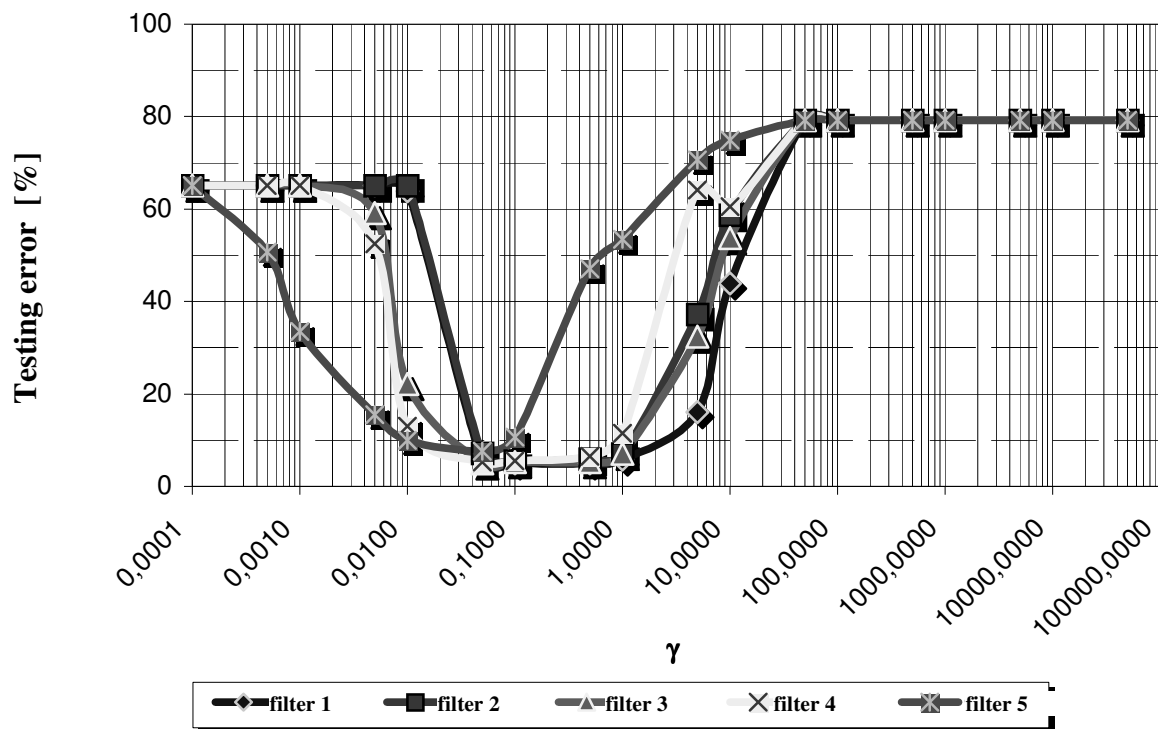| Wide spectrum bands [Hz]	Filter no.	Testing error [%]
30	1	11,77
30	2	9,55
30	3	5,59
30	4	7,21
30	5	9,01
65	1	5,23
65	2	6,67
65	3	4,86
65	4	5,41
65	5	8,11
150	1	10,81
150	2	14,05
150	3	18,92
150	4	6,67
150	5	8,11

Fig. 4. Influence γ coefficients on PNN results (wide spectrum band = 65 Hz)
Rys. 4. Wpływ współczynnika g na wyniki klasyfikatora PNN (szerokość podzakresu = 65 Hz)

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