THE APPLICATION OF NEURAL NETWORK TO THE ANALYSIS OF ACOUSTIC SIGNALS FOR THE GEAR PUMP WITH UNDERCUT TOOTH

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Abstract: Hydraulic machines are one of the most widespread machine classes, without which it would be hard to imagine the functioning of modern industry and of society today. Among cavity pumps used in hydraulic drive systems as energy generators, gear pumps are the most widespread. Apart from their numerous advantages from the point of view of noisiness and the delivery fluctuation coefficient, they are inferior to others. Steps are undertaken to decrease the noisiness. The paper is restricted to the analysis of acoustic properties of an innovative gear unit after tooth root undercutting. Acoustic properties have been described with taking into consideration neural networks.

Key word: a gear pump after tooth root undercutting, acoustic properties, chamber reverbs, decision-making system.

1. Introduction

From among the displacement pumps, gear pumps are most commonly used (their share is estimated at about 60%) as energy generators in hydraulic drive systems [9]. This is owing to their simple and compact design, operational reliability, high resistance to working medium pollution, high efficiency and small overall dimensions in comparison with other pumping units. Nevertheless, despite their numerous advantages, pumps of this kind because of their noisiness and nonuniform delivery are considered to be inferior to other pumps [2, 3, 4, 7, 9]. It has been attempted to reduce the noisiness of gear pumps in either of the two ways:

a) the active way, consisting in removing the causes of the noise or reducing noise emission in the noise source itself;
b) the passive way, consisting in reducing the propagation of sound waves from the source of their emission, through scattering or absorption.

The noise is most effectively reduced through a combination of the two ways (the active way being the most effective of the two). Detailed studies have shown that the noisiness of the displacement pump is due to the flow of the working medium (Fluid Born Noise) and to the vibrations of its structural components (e.g. the unbalance of the rotating parts, excessive clearance in the moving joints, improper workmanship and assembly). The main causes of noise generation, having the most significant bearing on the sound pressure emission level, are the pressure fluctuation on the delivery side and the trapping of the fluid in gear wheel tooth spaces [5, 10].

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. Among the most often applied methods of recognising acoustic signals are: HMM (Hidden Markov Models) [16], VQ (Vector Quantization) [17], LVQ (Learning Vector Quantization), SOM (Self- Organising Maps) [15], ANN (Artificial Neural Network) [13]. The present study is limited to the analysis of the acoustic properties of a gear pump with tooth root relief, in particular with the use a neural network.

2. Tested pump

The designed and built prototype pump [8, 10] has a three-plate structure shown schematically in Fig. 1. The front plate (1) is used for mounting the pump on the drive unit. The middle plate (2) contains gear wheels, slide bearing housings and suction and forcing holes for connecting to a hydraulic system. The whole construction is closed with a rear plate (3).

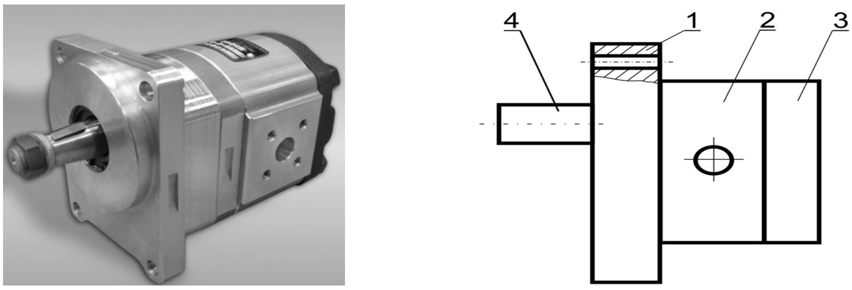


Fig 1. Three-plate design of gear micropump with external meshing.
1 – front (mounting) plate, 2 – middle (rest) plate, 3– rear plate,
4– driving shaft.

The tested prototype unit was designed in-house and manufactured by the Hydraulic Pumps Manufacturing Company Ltd. in Wroclaw. The pump was designed having in mind the technological capacities of this company. The novelty of the prototype pump consists in the modification of the involute profile in its upper part through the so-called tooth root relief (undercut) [8, 10].

2.1. Measuring rig.

The reverberation chamber for acoustic testing meets standard ANSI S1.21-1972 and standard PN-85/N-01334 and can be used for the vibration and noise certification of machines and equipment. The chamber’s sound insulating power against external noise in a frequency range of 20-20 kHz amounts to 50 dB. This insulating power ensures the elimination of disturbances originating from the drive system and from the hydraulic system supplying the tested pump.

Figure 2 shows a schematic of the rig for the testing of acoustic parameters. For measurements the tested pump together with a microphone array was placed in a reverberation chamber.

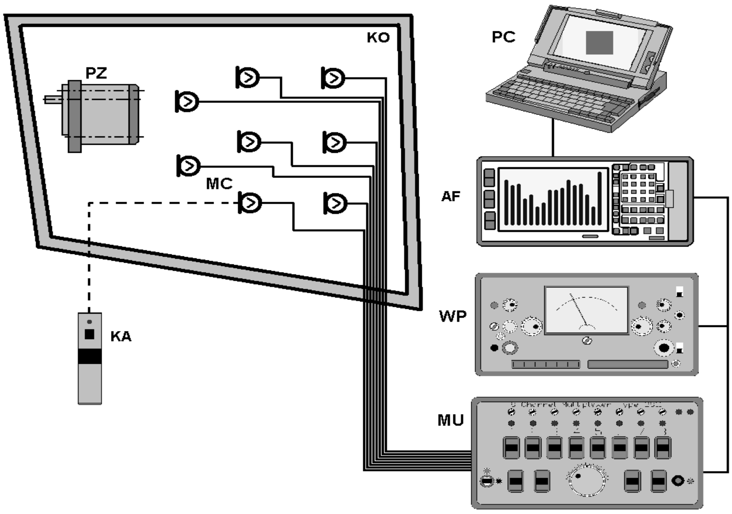


Fig 2. Block diagram of gear pump noisiness measuring rig: KA-calibrator, MC-eight free sound field microphones, MU-multiplexer, WP-instrumentation amplifier, AF-two-channel frequency analyzer, PC-computer, PZ-gear pump, KO-chamber

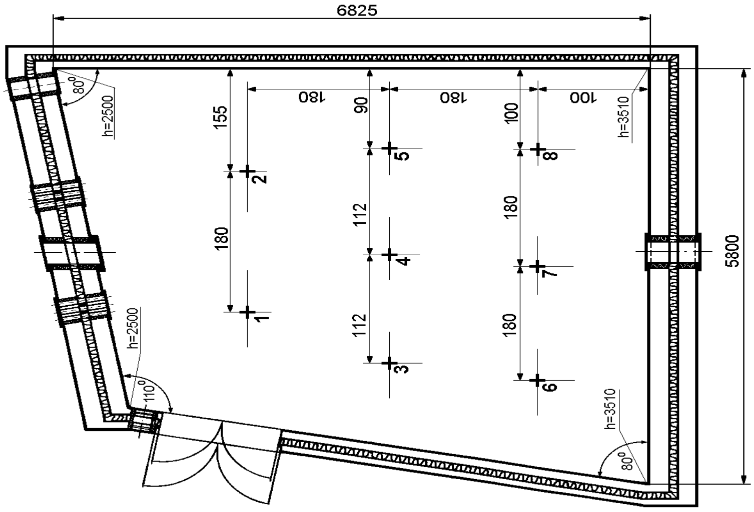


Fig 3. Reverberation chamber

3. Acoustic research

Acoustic measurements of an experimental version of the pump respectively for the value of discharge pressure p_t: 0, 2, 4, ..., 30 [MPa] and the frequency f: 25÷20k [Hz] have been obtained in the analysis. Table 1 shows exemplary acoustic measurements of a gear pump after tooth root undercutting for pt = 12 MP [9].

Table 1. Acoustic measurements of a gear pump after tooth root undercutting for p_t = 12 MPa

f [Hz]	number of microphone								Thirds				Octaves	
	1	2	3	4	5	6	7	8	Lmj	Smj	KAj	LAj	Lmj	LAj
	-1.48	-0.15	-0.20	0.33	0.16	-0.10	0.26	0.42						
25	84.1	81.8	62.5	46.8	65.4	83.8	82.4	78.1	80.1	15.4	-44.7	35.4		
31,5	62.3	60.0	54.9	40.0	56.8	63.7	60.3	62.0	60.1	8.0	-39.3	20.8	80.2	40.9
40	58.9	49.4	58.5	55.7	52.9	51.8	46.4	53.7	54.7	4.3	-34.6	20.1		
50	70.8	67.8	74.2	74.9	73.0	66.0	65.3	62.2	71.1	5.0	-30.2	40.9		
63	71.7	76.4	76.1	75.2	71.9	66.0	78.4	59.6	74.4	6.8	-26.2	48.2	77.1	50.9
80	75.4	73.0	67.1	69.8	64.9	63.8	68.7	69.0	70.1	3.8	-22.5	47.6		
100	69.9	64.8	60.9	61.9	65.4	65.1	60.8	62.8	64.6	2.7	-19.1	45.5		
125	74.6	73.3	75.1	66.6	71.0	66.2	68.5	70.0	71.5	3.3	-16.1	55.4	75.0	58.9
160	69.8	69.1	70.5	69.5	68.6	74.1	71.9	75.1	71.8	2.8	-13.4	58.4		
200	81.8	71.1	76.8	74.0	69.4	78.2	76.5	74.0	76.3	3.8	-10.9	65.4		
250	83.0	72.6	79.8	76.3	73.0	80.2	79.5	75.9	78.4	3.5	-8.6	69.8	81.2	72.6
315	77.1	68.8	73.4	70.6	75.0	72.6	74.0	65.7	73.0	3.5	-6.6	66.4		
400	83.4	80.6	80.2	69.9	69.7	79.6	73.2	74.2	78.2	5.2	-4.8	73.4		
500	84.2	81.3	80.5	71.4	70.8	80.6	74.4	75.1	79.0	4.9	-3.2	75.8	81.9	78.7
630	65.4	67.1	69.4	71.3	73.8	68.2	70.4	71.8	70.5	3.4	-1.9	68.6		
800	60.7	60.9	63.9	62.5	64.1	63.1	69.5	63.8	64.6	3.3	-0.8	63.8		
1 k	61.8	63.4	65.9	63.5	63.1	63.4	71.7	65.7	66.2	3.8	0	66.2	71.4	71.4
1,25 k	68.8	68.8	71.2	69.7	67.8	66.5	65.8	66.6	68.4	1.8	0.6	69.0		
1,6 k	72.5	69.3	68.9	68.1	70.8	70.8	67.1	65.4	69.3	1.9	1	70.3		
2 k	72.3	72.0	72.2	70.4	69.6	72.9	71.1	71.3	71.5	0.9	1.2	72.7	74.8	76.0
2,5 k	70.2	69.2	70.3	69.2	67.1	68.3	69.3	67.3	68.9	1.0	1.3	70.2		
3,15 k	66.2	68.5	67.4	65.9	65.9	66.9	65.0	66.0	66.5	1.1	1.2	67.7		
4 k	69.4	69.8	69.7	68.2	66.0	68.9	67.7	67.4	68.4	1.1	1	69.4	71.6	72.6
5 k	67.5	65.1	65.2	65.4	62.5	63.5	64.3	63.0	64.6	1.2	0.5	65.1		
6,3 k	67.7	64.0	63.1	64.9	63.5	62.5	66.1	63.8	64.6	1.5	-0.1	64.5		
8 k	68.6	65.5	65.2	64.3	63.2	65.2	64.2	64.4	65.1	1.1	-1.1	64.0	69.3	68.2
10 k	65.5	65.6	63.5	63.1	64.3	63.8	62.9	61.9	63.8	0.9	-2.5	61.3		
12,5 k	66.1	63.0	63.2	62.4	61.7	61.9	60.8	62.7	62.8	1.1	-4.3	58.5		
16 k	59.6	57.7	56.3	58.3	56.3	54.9	55.0	55.2	56.8	1.4	-6.6	50.2	63.9	57.3
20 k	53.2	51.4	49.8	49.3	49.0	47.3	47.7	47.6	49.6	1.6	-9.3	40.3		

Figure 4 presents the value of the acoustic pressure level L_m, corrected acoustic pressure level L_A, acoustic power level L_p and corrected acoustic power level L_{pA} in the function of discharge pressure p_t at a constant rotational speed of a pump shaft n = 1500 rpm.

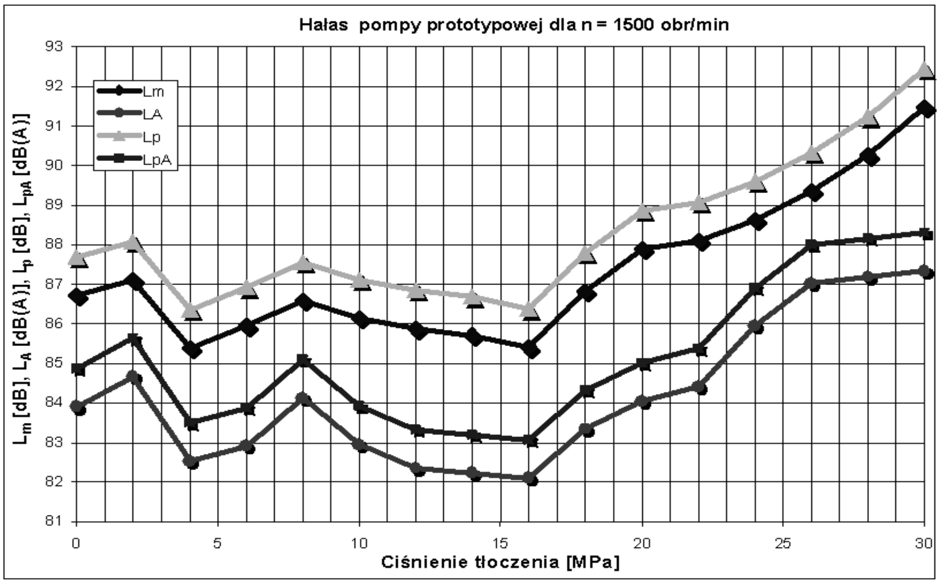


Fig. 4 The noise of the gear pump after tooth root undercutting for nominal rpm.

Figures 5 present a tertian and an octave spectrum of the gear pump after tooth root undercutting for nominal discharge pressure and nominal rotational speed.

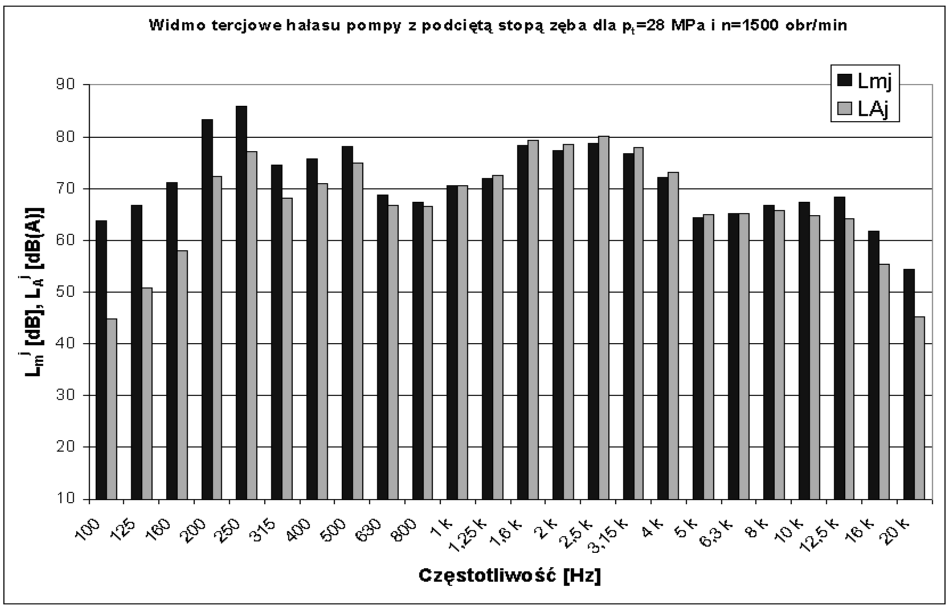


Fig. 5. The tertian spectrum of an experimental unit for nominal pressure and rotational speed.

Figures 6 compare a corrected level of the acoustic pressure L_A, and the corrected level of the acoustic power L_{pA} of an experimental unit and pump PZ4-32 TKs 186. In both pumps the teeth of wheels grinding has been made before and after nitriding.

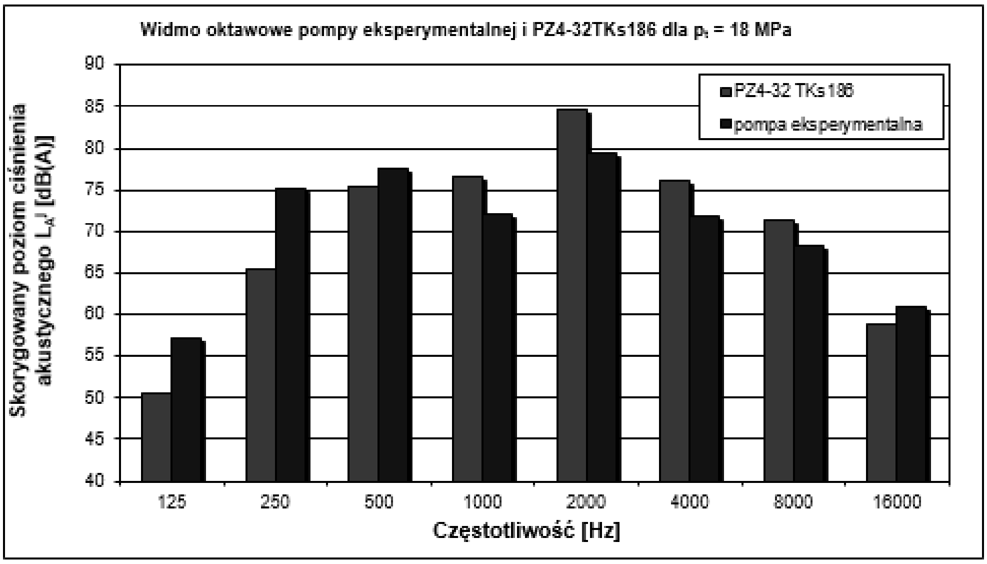


Fig 6. An octave spectrum of an experimental pump and PZ4-32 TKs-186 for pt =18 MPa.

Table 2. Comparison of octaves of the centre frequency equal to 2k Hz for an experimental pump and PZ4 TKs 186.

p_t [MPa]	Pompa badawcza $L_{A(1)}^{2000}$	PZ4-32 TKs 186 $L_{A(2)}^{2000}$	ΔL_A^{2000}	$10\log\left(10^{0,1L_{A(2)}^{2000}} - 10^{0,1L_{A(1)}^{2000}}\right)$
6	74,7 [dB]	79,5 [dB]	4,8 [dB]	77,8 [dB]
12	74,8 [dB]	79,5 [dB]	4,7 [dB]	77,7 [dB]
18	78,2 [dB]	83,6 [dB]	5,4 [dB]	82,1 [dB]
24	81,0 [dB]	83,0 [dB]	2,0 [dB]	78,7 [dB]
28	82,9 [dB]	83,6 [dB]	0,7 [dB]	75,3 [dB]

4. Application of neural network to the recognize the acoustic properties

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 [6, 13, 14].

The present study is limited to the analysis of the acoustic properties of a gear pump with tooth root relief, in particular with the use o game graphs and neural networks.

Figure 7 presents a graph showing the correctness in the scope of the layout of the acoustic pressure level – with taking into consideration all microphones – depending on the value of frequency and the discharge pressure. It is possible to observe an empirical reduction in the level of acoustic pressure in all microphones with the increase in frequency and decrease in discharge pressure.

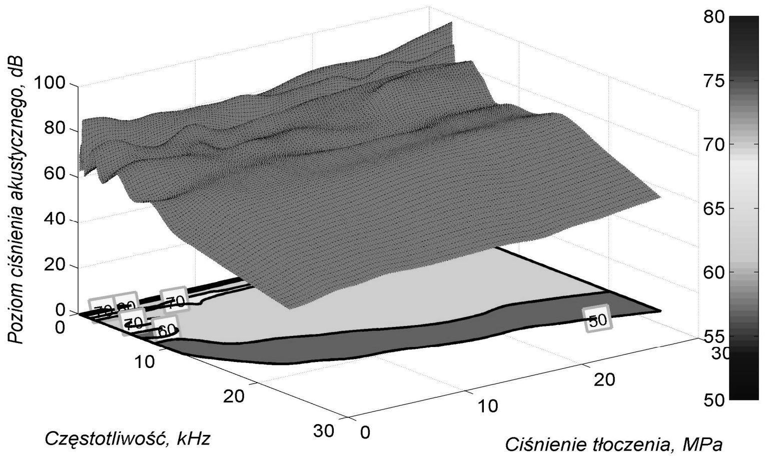


Fig 7. The layout of acoustic pressure of 8 microphones depending on the frequency value and the discharge pressure

Figure 8 presents a tertian spectrum of the pump noise with taking into values of particular 8 microphones depending on the frequency and the level of acoustic pressure.

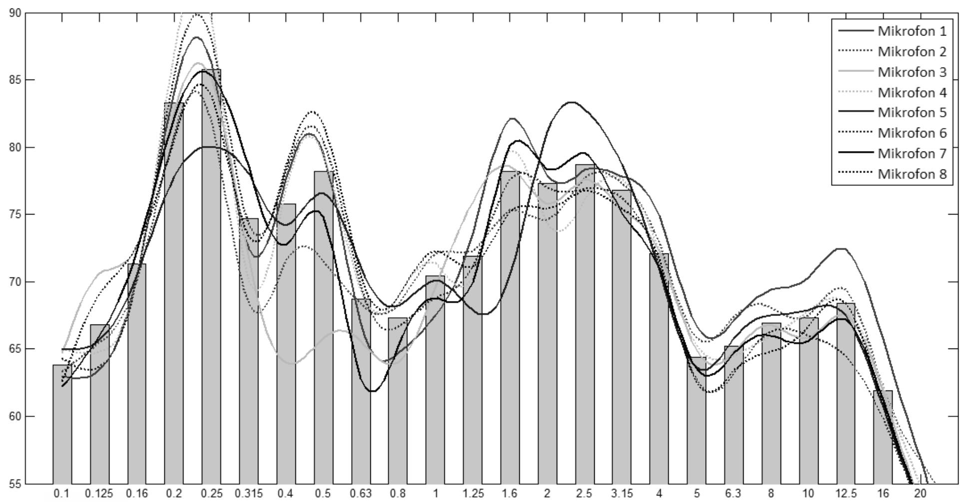
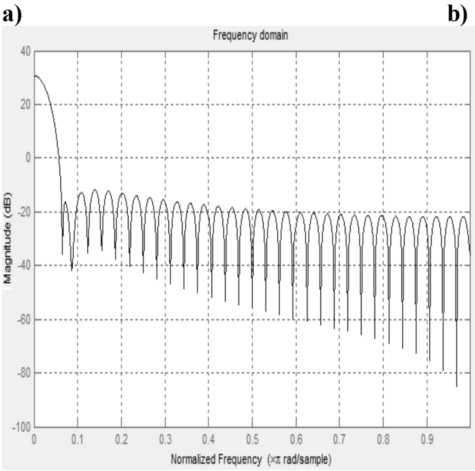


Fig 8. The tertian spectrum of the pump noise with taking into consideration values for particular 8 microphones depending on the frequency and the discharge pressure

In a typical attitude to the computer-based analysis of signals, it is assumed that there is a hierarchy of three data processing levels [13, 14]. In the scope of each of them, there are three stages of processing:

1) an analysis in time – acquisition of a signal tone and the useful signal detection,
2) a spectrum analysis – transformation of signal frames (windows) in the frequency domain,
3) speech signal parametrization – designation of vectors (numerical) properties of signal frames / windows.

Figure 9 presents preliminary signals processing without a filter for 8 microphones in the whole range of values of discharge pressure that is 2-30 MPa.

a) 

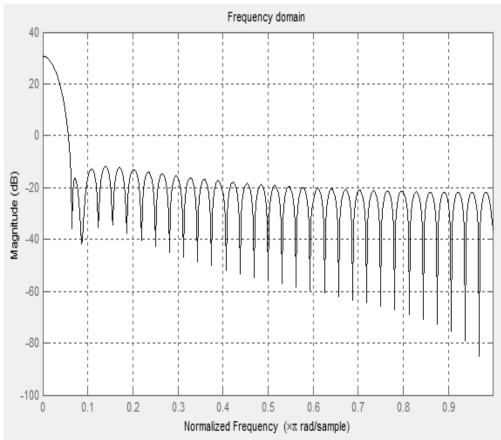
b) 

Fig. 9. Initial processing of the signals for the two examples microphones: a)1, b)8

A method of analysing a frequency spectrum has been chosen as a parametrisation method. A signal sample u(n) can be presented as a linear combination of samples for n>0.

$$\tilde{u}(n) = -\sum_{p=1}^{p} a_p u(n-p) \tag{1}$$

where:

a_p - prediction rates, *p=1, 2, ..., P, P*- prediction row

$\tilde{u}(n)$ - *n* sample estimator – the difference between $u(n)$ and $\tilde{u}(n)$ will be a prediction error *e(n).*

$$\mathrm{e}(n) = u(n) - \tilde{u}(n) = u(n) + \sum_{p=1}^{P} a_p u(n-p) \tag{2}$$

The method using this rule is called the Burg method, the implementation of which is included among others in the range "Signal Processing Toolbox" of the Matlab programme. Next, we create a signal spectrograms. In Matlab spectrogram command divides the signal into overlapping segments, windows each segment and forms the columns with their discrete Fourier transforms [1].

The figure 10 shows the spectrogram for 2 examples microphones.

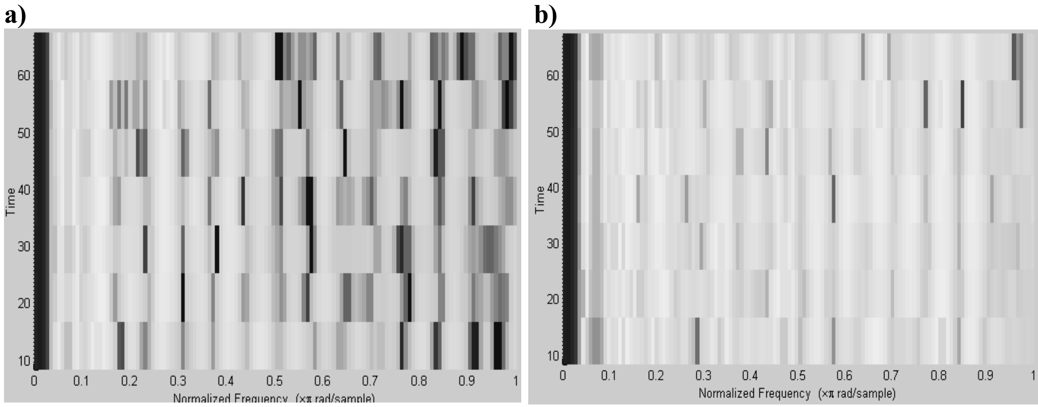


Fig. 10 The spectra of acoustic signals of two microphones a) 1 b) 8

Neural networks are composed of single objects or indirect layers, playing a key role in the input signal processing into the final result. In the training process, it is essential to obtain such neuron weights on the sets of input and output data so that for a given input data set the same input data are obtained out of the training set.

The most popular network training algorithm is the backpropagation algorithm. A multi-layer neural network of the Feed- Forward Backpropagation Network (F-F - BP) type (Figure 11) , in which each neuron had a sigmoidal activation function, was applied in the article aimed at recognising acoustic characteristics.

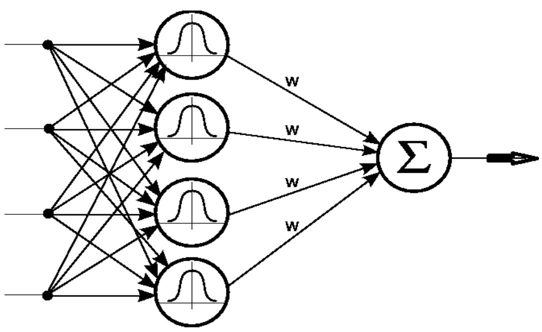


Fig 11. Topology of the neural network used

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 have been tested for the training procedure: **GDA** (Gradient Descent with Adaptive Learning Rate Backpropagation) and **RPROP** (Resilent Backpropagation) [12].
The weight correction process of particular neurones for this algorithm takes place according to the dependence described by the formula below:

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

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

where:

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

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

a, b- stałe, $n_{\max}=50$, $n_{\min}=10^{-6}$

Figure 12 presents the efficacy of recognising analysed acoustic characteristics by the training procedure **GDA** and **RPROP.**

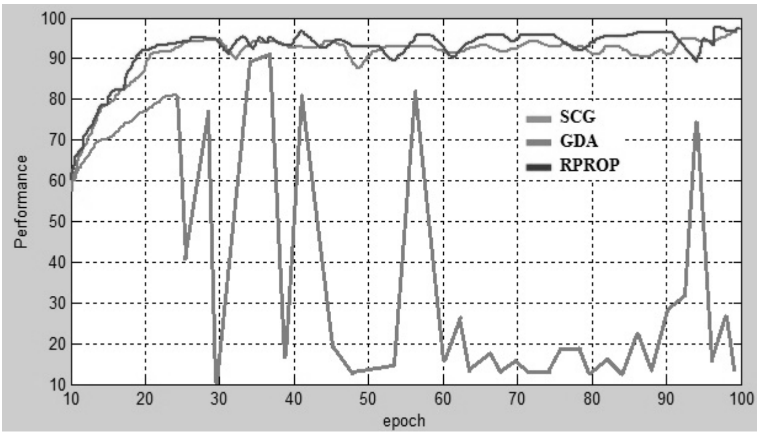


Fig 12. Comparison of the effectiveness of the recognition of acoustic signals, depending on the type of training algorithm

A parameter which can be used to build the training and testing SSN vectors was the use of results of the time and frequency analysis with the use of the Short Time Fourier Transform **(STFT)**. Figure 13 presents the total efficiency of acoustic signals recognition of eight analysed microphones.

The last stage was an appropriate choice of the size of the hidden layer of the applied classification tool.

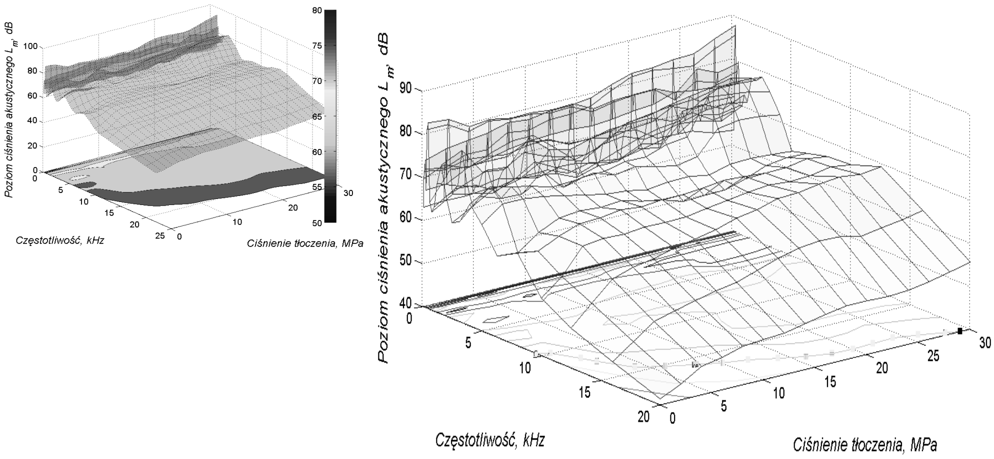


Fig 13. The total efficiency of the recognition of the analysed acoustic signals by SSN depending on the level of acoustic pressure Lm, frequency kHz and discharge pressure for 8 microphones.

6. Conclusions

The aim of calculations was to determine such a structure of the adopted SSN architecture, which, apart from reaching a satisfactory total efficiency of recognition (SKUT > 90%), would be characterised by a relatively short time of required patterns acquisition. The most favourable results from the point of view of data processing time-consumption are obtained for LNWU in the range from 20 to 70. The classification is an important stage in the analysis of acoustic properties. The obtained results connected with the application of SSN and induction tree classifiers to the efficient identification of acoustic signals on the basis of among others frequency and time-frequency analysis indicators showed that there is a potential possibility of using the suggested classifiers during the construction of the computerised expert system (SE). The adopted architecture of the neural network could form one of the most important elements of the SE that is to be formed in the future that is its inference mechanism. The task of the SSN presented in the paper would be to constantly compare the measured and correctly parameterised acoustic signals from eight microphones with the indicators collected in the data base based on the acoustic empirical studies of the gear pump after tooth undercutting.

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