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Recognition of Acoustic Signals of Synchronous Motors with the Use of MoFS and Selected Classifiers

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This paper proposes an approach based on acoustic signals for detecting faults appearing in synchronous motors. Acoustic signals of a machine were used for fault detection. These faults contained: broken coils and shorted stator coils. Acoustic signals were used to assess the usefulness of early fault diagnostic of synchronous motors. The acoustic signal recognition system was based on methods of data processing: normalization of the amplitude, Fast Fourier Transform (FFT), method of frequency selection (MoFS), backpropagation neural network, classifier based on words coding, and Nearest Neighbor classifier. A plan of study of acoustic signals of synchronous motors was proposed. Software of acoustic signal recognition of synchronous motors was implemented. Four states of a synchronous motor were used in analysis. A pattern creation process was carried out for 28 training samples of noise. An identification process was carried out for 60 test samples. This system can be used to diagnose synchronous motors and other electrical machines.

Keywords: Acoustic measurement, pattern analysis, electrical fault detection, fault diagnosis, acoustic signal processing.

1. INTRODUCTION

FAULT MONITORING of rotating electrical machines using mechanical, acoustic, electrical, and thermal signals is investigated with great interest. The analysis of acoustic signals is an essential strategy for diagnosis. The spectrum analysis of the recorded signals can lead operators to a reliable diagnosis of the motor. Analysis of the signal can also localize the fault of the motor [1].

Technical diagnostics involve assessing the technical condition of a machine by studying the properties of its work processes. The diagnostics is important for mining, metallurgy, processing industry and materials science [2-28]. All rotating electrical machines generate acoustic signals. Modern diagnostic systems can diagnose early failure conditions of motors. These systems are based on the study of various signals such as: magnetic signals, ultrasounds, acoustic signals, images from the camera, vibroacoustic signals, and electric signals [13-28].

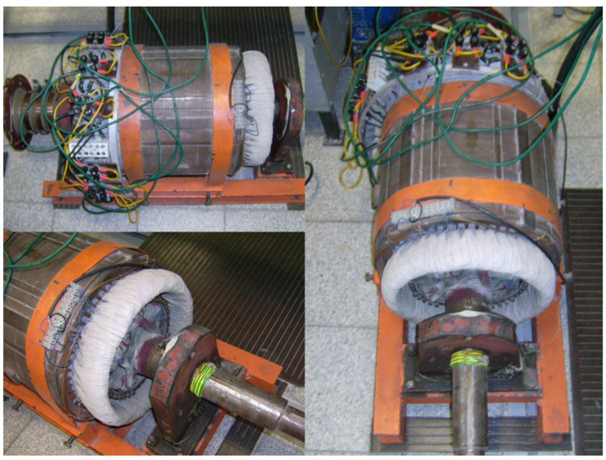

Fig.1. Investigated synchronous motor.

In recent years, the methods of acoustic signal recognition were developed [25-28]. Scientists proposed many methods for preprocessing, data reduction and classification of acoustic signals. In this paper, author proposes the method based on acoustic signals of a synchronous motor (Fig.1.). Results from this research can be used to diagnose electrical, mechanical, hydraulic, and pneumatic machines. Research was conducted using the 50 Hz - 15000 Hz frequency range because higher frequencies are not important for recognition.

2. STUDY OF INFORMATION CONTAINED IN THE ACOUSTIC SIGNAL OF SYNCHRONOUS MOTOR

The greatest difficulties appear when the operator must choose the methods of acoustic signal processing. Acoustic signals of faultless and faulty synchronous motors are different. In order to find these differences, the appropriate signal processing methods must be used. This allows the detection of minute differences of an acoustic signal of a synchronous motor. The plan of study of acoustic signals of synchronous motors was proposed (Fig.2.).

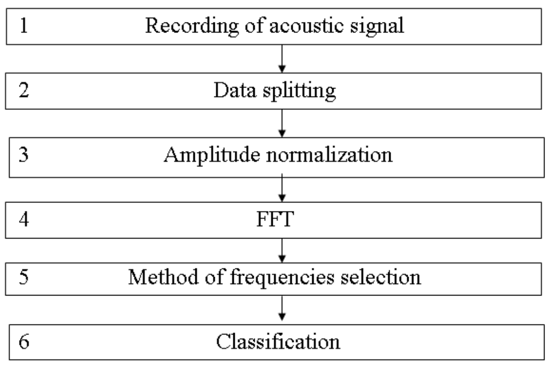

Fig.2. The plan of study of acoustic signals.

3. ACOUSTIC SIGNAL RECOGNITION PROCESS OF SYNCHRONOUS MOTOR

The acoustic signal recognition system had two processes: The process of acoustic signal recognition and the verification process (Fig.3., Fig.4.).

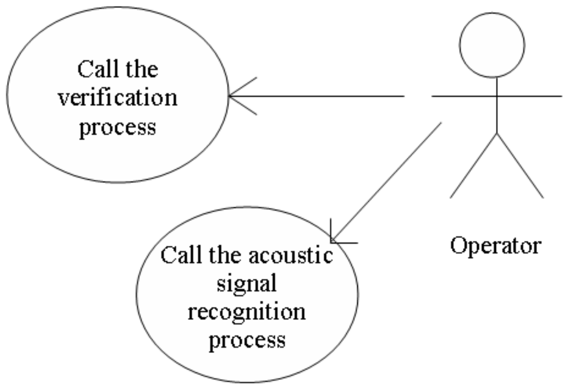

Fig.3. A use case diagram of acoustic signal recognition system.

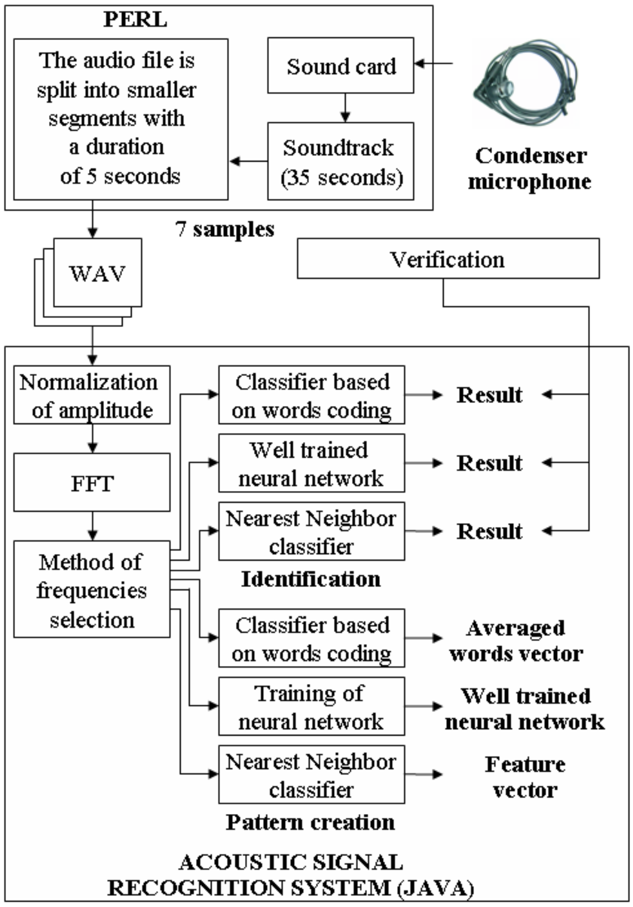

Fig.4. The acoustic signal recognition process with application of MoFS and selected classifiers.

The process of acoustic signal recognition of synchronous motors contained the pattern creation process and the identification process. At the beginning of the pattern creation process acoustic signals were recorded. The soundtrack was split into small samples with a duration of 5 seconds. Next, the signals were normalized. Afterwards the data were converted using the FFT and MoFS. In the pattern creation process 28 feature vectors were created for each type of motor fault. Each vector had 6 features. Nearest Neighbor classifier, neural network and classifier based on words coding used these 28 feature vectors to obtain patterns (trained neural network, averaged words vectors).

The steps of the identification process were similar to the steps of the pattern creation process. In the identification process the audio file was split into smaller segments with a duration of 1-5 seconds. Some changes were also made in the classification step. In this step the Nearest Neighbor classifier calculated the least distance between the test sample and 28 training samples. For this purpose, it used Euclidean distance. In the classification step, neural network was used to identify the acoustic signal. The Manhattan distance was used to obtain output values of neural network. Classifier based on words coding compared new words vector with 4 averaged words vector.

A. *Recording of acoustic signal*

The condenser microphone and the audio sound card were used for recording all of the acoustic signals of the synchronous motor [29]. Acoustic signals were recorded 1 meter away from the motor. The soundtrack was recorded with the following parameters: sampling frequency – 44100 Hz, 16-bit depth. Sampling and quantization were made by the microphone and sound card automatically. Next, acoustic signals were stored on a PC as WAV files.

B. *Data splitting*

Acoustic signal recognition system split the soundtrack into smaller samples in order to analyze them (Fig.5.). It used a program implemented in a Perl scripting language. First, it split data (Fig.6.). Next it created a new wave header.

Fig.5. Soundtrack before data splitting.

Fig.6. Soundtrack file after data splitting.

Afterwards the new wave header was copied and added to each chunk of data. New samples (audio files) were obtained (Fig.7.).

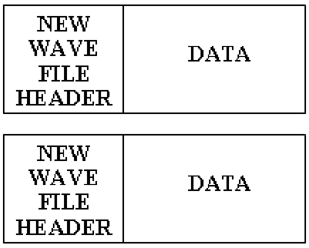

Fig.7. Obtained samples.

These samples were used in the identification process. The smaller sample was more precise in determining a fault, for example: 00:00:50-00:00:51, 00:00:50-00:00:55. The first example (00:00:50-00:00:51) is more precise than the second (00:00:50-00:00:55).

C. *Normalization of amplitude*

The acoustic signal recognition system was based on pattern recognition. Patterns were obtained from samples of noise. Acoustic signals were recorded 1 meter away from the motor. Normalization of amplitude selected the maximum level in raw time waveform. Next it scaled down the amplitude of each point [30]. In this way, all samples were normalized in the range [−1.0, 1.0].

D. *Windowing*

Windowing minimized edge effects. These effects resulted in spectral leakage in the FFT spectrum. In this proposed approach the Hamming window was used. This window was used to avoid distortion of the overlapped window functions [30]. It was defined as:

$$H(i) = 0.53836 - 0.46164 \cos\left(\frac{2\pi i}{l-1}\right) \tag{1}$$

where, l was the length of the window, *H(i)* was the amplitude of the sample, i was the index of the sample.

The window length was 32768 points. It was equaled 0.74 second for sampling frequency 44100 Hz. For this reason, the acoustic signal recognition system can recognize the noise samples of a duration of 0.75 seconds or longer.

E. *FFT*

The FFT transformed data from the time domain to the frequency domain. It was applied instead of discrete Fourier transform. The advantage of this method was shorter calculation times. It used a window size of 2^k. The result of the FFT was an array of coefficients [31]. These coefficients formed amplitudes of frequencies. The number of amplitudes of frequencies was dependent on the window length. The proposed method used window size equal to 32768. Then the number of amplitudes of frequencies was 16384. Next, these coefficients formed feature vectors (Fig.8.).

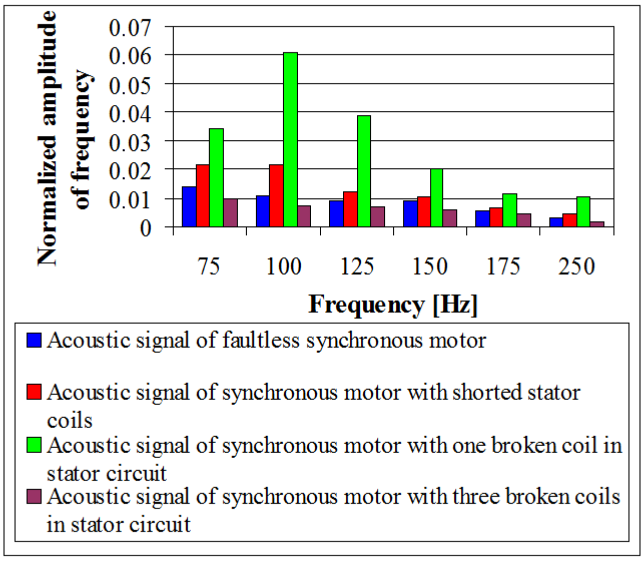

Fig.8. Frequency spectrum of acoustic signals of synchronous motor for 75, 100, 125, 150, 175, 250 Hz.

F. *Method of frequency selection*

The method of frequency selection (MoFS) used the frequency spectrum. The states of motors were dependent on armature current and speed of rotor rotation. They were also dependent on the construction of the electrical motor. For a synchronous motor with electromagnetic excitation the formula was defined as follows:

$$k_c = N_{rotations} \tag{2}$$

where: k_c – a characteristic frequency of early failure state, $N_{rotations}$ – number of rotations of synchronous motor per minute (rpm).

The method of frequency selection was showed as follows:

1) Depending on the rotations of the electrical machine, find the characteristic amplitude of frequency k_c, corresponding to early failure state (equation 2).
2) In the acoustic signal select amplitudes of frequency nk_c, on the basis of the found amplitude of frequency k_c, where n is a positive integer and nk_c <22050.
3) Calculate the difference $||X_{1nkc}|-|X_{2nkc}||$ for the amplitudes of the frequencies nk_c, where $|X_{1nkc}|$ - is the amplitude of the frequency nk_c of the acoustic signal of the first state of machine, $|X_{2nkc}|$ - is the amplitude of the frequency nk_c of the acoustic signal of the second state of machine.
4) Select the amplitudes of the frequencies defined as follows:

$$\| X_{1nkc} | - | X_{2nkc} \| > t \tag{3}$$

where t – threshold of amplitude selection (4), n is a positive integer, $||X_{1nkc}|-|X_{2nkc}||$ – the difference of amplitudes of frequencies nk_c for two different states of the motor. Selecting the parameter t should find a compromise between the number of investigated states, the number of amplitudes of frequencies and the accuracy of the calculations in the classification step. Too many investigated amplitudes of frequencies may cause numerical errors and errors in the classification step. Moreover, the differences between the amplitudes of frequencies may be different values. It can result in a different number of amplitudes for the investigated states of the motor. In this case, select a common characteristic amplitude of frequencies for all investigated states of the motor. Due to the above-mentioned observations it was assumed that the parameter t should be chosen according to (4) and (5). When the number of differences of the amplitudes of frequencies (number s) is greater than 7, the method loops calculation according to (4). Otherwise, the method finishes the calculation of (5).

$$t = \frac{\sum_{s=1}^{s} || X_{1skc} | - | X_{2skc} ||}{s} \tag{4}$$

$$s \leq 7 \tag{5}$$

where t – threshold of amplitude selection, s – number of differences of the amplitudes of frequencies nk_c, (initially $s=n$). When s>7, then in subsequent iterations for s substitute the number of differences of the amplitudes of frequencies that remains after the previous iteration. For such a value of the parameter t the size of the feature space will not cause significant errors in the classification step. Moreover, the number of calculations performed in the following steps of processing will be reduced. Feature vector obtained after the last iteration has 1-7 features ($|X_{kc1}|$, ..., $|X_{kcs}|$), where $|X_{kcs}|$ is the amplitude with the s index for frequency xk_c, x - is a positive integer.

The method of frequency selection for acoustic signals of a synchronous motor was presented (Fig.9.).

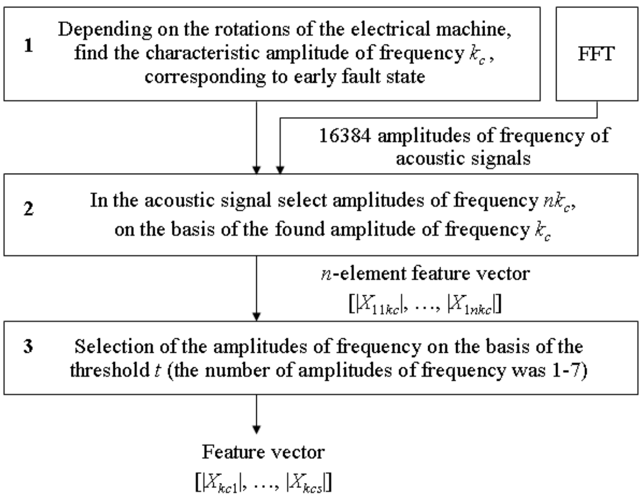

Fig.9. The method of frequency selection (MoFS) for acoustic signals of synchronous motor.

The feature vector ($|X_{kc1}|$, ..., $|X_{kcs}|$) will be used in the next step of processing.

G. Neural network with backpropagation algorithm

Engineers and scientists developed a great variety of feature extraction and classification methods [32-47]. Classification methods are often based on artificial intelligence. This intelligence can be represented by backpropagation neural network [40-47].

There are many possible structures of neural network. The author selected the following structure presented in Figure 10. The pattern creation process used feature vectors (6 amplitudes of frequencies: 75, 100, 125, 150, 175, 250 Hz - see chapter 4) and backpropagation neural network. Neural network used character encoding to convert name of category (class w_n) into the floating-point numbers (ASCII code divided by 128 – vector **z**).

After the training of neural network it was necessary to perform the identification process. Floating point values were obtained on the output of neural network (vector **o**). These 5 values were converted to ASCII characters. In the identification process the value of the output neuron in the output layer was not equal to the exact value of the character in ASCII code divided by 128.

One of the two characters was selected with the use of Manhattan metric (6). This metric calculated the shortest distance.

$$d(\mathbf{o},\mathbf{z}) = \sum_{i=1}^{n} (| o_i - z_i |) \tag{6}$$

where **o** and **z** are following vectors $\mathbf{o}=[o_1, o_2,\ldots, o_k]$, $\mathbf{z}=[z_1, z_2,\ldots, z_k]$.

For example, for the category of recognition "1coil" (acoustic signal of synchronous motor with one broken coil in stator circuit) the following values should have been obtained:

ASCII-CODE (1)/128=49/128=0.3828125
ASCII-CODE (c)/128=99/128=0.7734375
ASCII-CODE (o)/128=111/128=0.8671875
ASCII-CODE (i)/128=105/128=0.8203125
ASCII-CODE (l)/128=108/128=0.84375

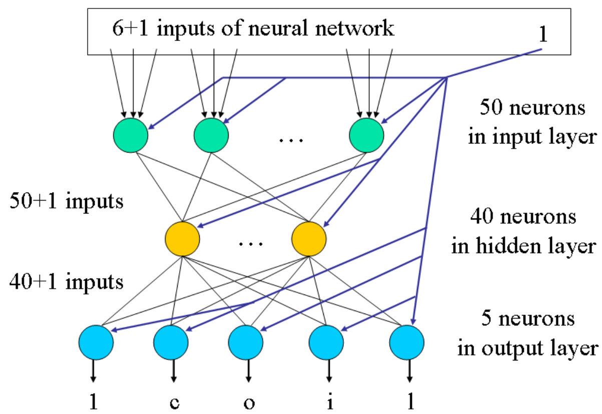

Fig.10. Structure of backpropagation neural network in acoustic signal recognition system.

The test feature vector $\mathbf{h}_{nx}$ was assigned to the class w_n when:

$$d(\mathbf{o},\mathbf{z}_n) = \min_i(d(\mathbf{o},\mathbf{z}_i)) \Rightarrow \mathbf{h}_{nx} \rightarrow w_n \tag{7}$$

where i=1,2,…, K, n=1,2,…, K,
$\mathbf{z}_i$, $\mathbf{z}_n$ were 5-elements vectors having the names of the patterns classes, $\mathbf{h}_{nx}$ was a test feature vector, $\mathbf{o}$ was a 5-elements vector, obtained in output layer in the identification process, K was the number of classes.

H. Classifier based on words coding

Classifier based on words coding was similar to Nearest Mean classifier. It used two phases to recognize the type of fault in the motor. First phase was called "pattern creation process". The second was called "identification process". Samples from training set were used in the pattern creation process. Next samples were processed into the feature vectors $\mathbf{x}_{nx}=[x_1, x_2,\ldots, x_k]$. A feature vector $\mathbf{x}_{nx}$ contained amplitudes of frequencies 75, 100, 125, 150, 175, 250 Hz, so k=6. Next, these vectors were processed into the averaged feature vectors $\mathbf{p}_{1x}, \mathbf{p}_{2x},\ldots, \mathbf{p}_{nx}$ (8),

$$\mathbf{p}_{nx} = \frac{1}{B_n}\sum_{i=1}^{B_n}\mathbf{x}_\mathrm{i} \tag{8}$$

where $\mathbf{p}_{nx}=[p_1, p_2,\ldots, p_k]$ was the averaged feature vector with n index, B_n was the number of the feature vectors from class w_n, feature vector $\mathbf{x}_\mathbf{i}\in w_n$.

The averaged feature vector $\mathbf{p}_{nx}$ was processed into the averaged words vector $\mathbf{q}_{nx}$. The averaged words vector was defined as: $\mathbf{q}_{nx}=[q_1, q_2,\ldots, q_k]$, where $q_1, q_2,\ldots, q_k$ were words. The averaged words vector corresponded to the type of fault of motor. It is very similar to Nearest Mean classifier which used the averaged feature vector. Coordinates $p_1, p_2,\ldots, p_k$ of the averaged feature vector $\mathbf{p}_{nx}$ were processed into words. These words formed the averaged words vector $\mathbf{q}_{nx}$. One word covered a range of values,

$$\begin{gathered} p_k \in [k,2k) \Rightarrow p_k \to q_{i1} \\ p_k \in [2k,3k) \Rightarrow p_k \to q_{i2} \\ \ldots \\ p_k \in [kg,kg+k) \Rightarrow p_k \to q_{ig} \end{gathered} \tag{9}$$

where k was rational number, g was the number of words, q_{ig} was a word with index ig of the averaged words vector, p_k was coordinate with index k of the averaged feature vector.

The proposed classifier used a specified number of words to classify the acoustic signal. This number was equaled 260, because such value was good for recognition. To obtain good results parameter k was selected properly. This parameter was dependent on the number of words.

The identification process used a noise sample form test set. This sample was processed into feature vector $\mathbf{h}_{nx}$. Next sample was processed into the words vector $\mathbf{s}=[s_1, s_2,\ldots, s_n]$, and $s_1, s_2,\ldots, s_n$ were words. Next, words vector $\mathbf{s}$ was assigned to the closest class. The closest class was selected on the base of lexicographical comparison between words vector $\mathbf{s}$ and averaged words vector $\mathbf{p}_{nx}$. Next ASCII codes of two strings were analyzed. It is shown below.

$$\begin{aligned} & s_1 \overset{?}{=} q_1 \\ & s_2 \overset{?}{=} q_2 \\ & \ldots \\ & s_k \overset{?}{=} q_k \end{aligned}$$

There was a problem to select the proper class of recognition. Author proposed the following equation to solve this problem:

$$PVPRW_n = \frac{NPRW}{NALC}100\% \tag{10}$$

where $NPRW$ - the number of properly recognized words, $NALC$ - the number of all lexicographical comparisons (260), $PVPRW_n$ - the percentage value of properly recognized words.

To obtain the proper class of recognition the following formula was proposed:

$$\max(PVPRW_n) \Rightarrow \mathbf{s} \to w_n \qquad n = 1,2,\ldots,\mathrm{K} \tag{11}$$

where $\mathbf{s}$ - the words vector from test set, $PVPRW_n$ - the percentage value of properly recognized words.

Values of the averaged words vector and parameter k were very essential for obtaining good results of acoustic signal recognition. For this reason calculations were carried out for various parameters k.

I. Nearest neighbor classifier

Nearest Neighbor classifier was based on the training set and the test set. Noise samples from training the set were used in the pattern creation process. Next samples were processed into the feature vectors $\mathbf{x}_{nx}=[x_1, x_2,\ldots, x_k]$. Finally, the training set contained feature vectors $\mathbf{x}_{1x}, \mathbf{x}_{2x},\ldots, \mathbf{x}_{nx}$. The test set contained new feature vectors $\mathbf{h}_{1x}, \mathbf{h}_{2x},\ldots, \mathbf{h}_{nx}$.

The method classified feature vectors based on the closest training examples. It contained two steps. The training step involved storing every training feature vector with its label. The identification step for a test feature vector was performed as follows: compute its distance to every training feature vector, next, select the closest training feature vector. In the proposed approach the Nearest Neighbor classifier used feature vectors to identify the type of fault in the motor.

Next, the closest distance was calculated with the help of Manhattan distance. Manhattan distance was defined as the distance between two vectors. For vectors $\mathbf{h}_{nx}$ and $\mathbf{x}_{nx}$ with the length k it was expressed as follows:

$$d(\mathbf{h}_{nx}, \mathbf{x}_{nx}) = \sum_{i=1}^{k}(|\,h_i - x_i\,|) \tag{12}$$

where $\mathbf{h}_{nx}$ and $\mathbf{x}_{nx}$ were feature vectors defined as follows: $\mathbf{h}_{nx}=[h_1, h_2,\ldots, h_k]$, $\mathbf{x}_{nx}=[x_1, x_2,\ldots, x_k]$.

Classes of types of faults of motor were denoted as $w_1, w_2,\ldots, w_n$, where n was the index of the class. The test feature vector $\mathbf{h}_{nx}$ was assigned to the class w_n when $d(\mathbf{h}_{nx}, \mathbf{x}_{nx})$ was the closest distance:

$$\min(d(\mathbf{h}_{nx}, \mathbf{x}_{nx})) \Rightarrow \mathbf{h}_{nx} \rightarrow w_n \quad n = 1, 2, \ldots, \mathrm{K} \tag{13}$$

Results of Nearest Neighbor classifier were dependent on features and selected measure of distance, e.g., Euclidean, Minkowski, Jacquard, cosine distance. The proposed method of classification used Nearest Neighbor with Manhattan distance. Other measures of distances were not analyzed in this paper.

4. RESULTS OF THE ACOUSTIC SIGNAL RECOGNITION

The stator circuit of the synchronous motor contained broken coils and short circuit (Fig.11. – Fig.13.). The following operation parameters of the synchronous motor were measured:

- faultless motor, I_R = 30.9 A, $N_{rotations}$ = 1500 rpm, $I_{excitation}$ ≈ 0 A, U_{RS} = 100 V,
- shorted stator coils (A3-B3) of stator windings of motor, I_R = 31.2 A, $N_{rotations}$ = 1500 rpm, $I_{excitation}$ ≈ 0 A, U_{RS} = 100 V, R_s=2.5 Ω,
- broken coil (B1-B4) of stator windings of motor, I_R = 24 A, $N_{rotations}$ = 1500 rpm, $I_{excitation}$ ≈ 0.3 A, U_{RS} = 100 V,
- broken coils (B1-B4, D1-D4, H1-H4) of stator windings of motor, I_R = 36 A, $N_{rotations}$ = 1500 rpm, $I_{excitation}$ ≈ 0.245 A, U_{RS} = 100 V.

When $N_{rotations}$ was equaled 1500 rpm, then k_c=1500/60= 25 Hz. Method of amplitude selection selected 6 amplitudes of frequencies: 75, 100, 125, 150, 175, 250 Hz.

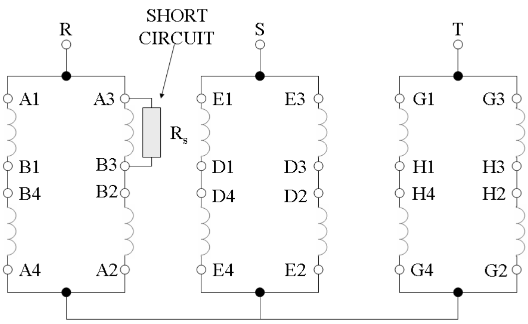

Fig.11. Shorted stator coils (A3-B3) of stator windings of synchronous motor.

Measurements and analysis were carried out for acoustic signals of the faultless synchronous motor, motor with shorted stator coils (A3-B3), motor with one broken coil (B1-B4), and a motor with three broken coils (B1-B4, D1-D4, H1-H4). The pattern creation process was conducted for 28 samples with a duration of 5 seconds for each type of acoustic signal of a synchronous motor. Samples from the test set were used in the identification process. Efficiency of acoustic (electric, thermal) signal recognition was expressed by the equation:

$$ES = \frac{NPIS}{NAS} 100\% \tag{14}$$

where: *ES* – acoustic (electric, thermal) signal recognition efficiency, *NPIS* – number of properly identified samples in the test set, *NAS* – number of all samples in the test set.

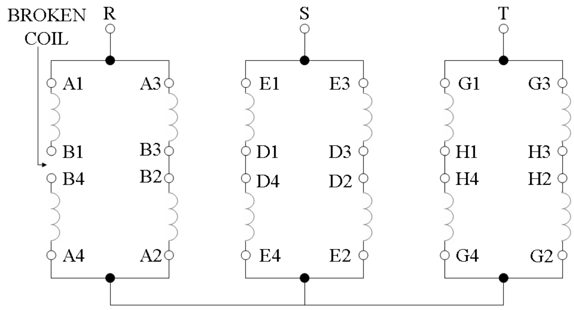

Fig.12. Broken coil (B1-B4) of stator windings of synchronous motor.

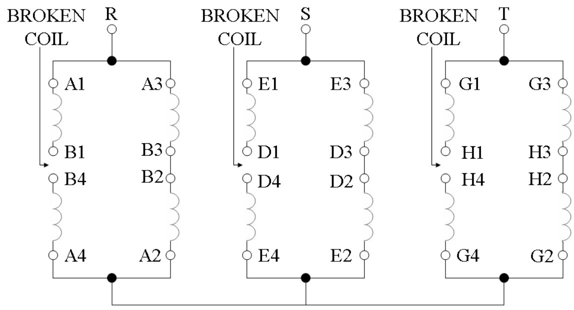

Fig.13. Broken coils (B1-B4, D1-D4, H1-H4) of stator windings of synchronous motor.

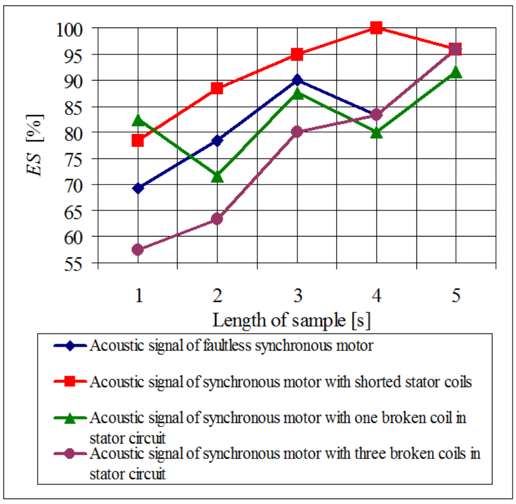

Fig.14. Acoustic signal recognition efficiency of synchronous motor depending on length of sample for MoFS and neural network.

Acoustic signal recognition efficiency of a synchronous motor depending on the length of the sample with MoFS and neural network was presented in Fig.14. This recognition efficiency was in the range of 57.5-100 %.

Acoustic signal recognition efficiency of a synchronous motor depending on the length of the sample with MoFS and classifier based on words coding is shown in Fig.15. This recognition efficiency was in the range of 82.5-100 %.

Acoustic signal recognition efficiency of a synchronous motor depending on the length of the sample with MoFS and Nearest Neighbor classifier was presented in Fig.16. This recognition efficiency was in the range of 93.75-100 %.

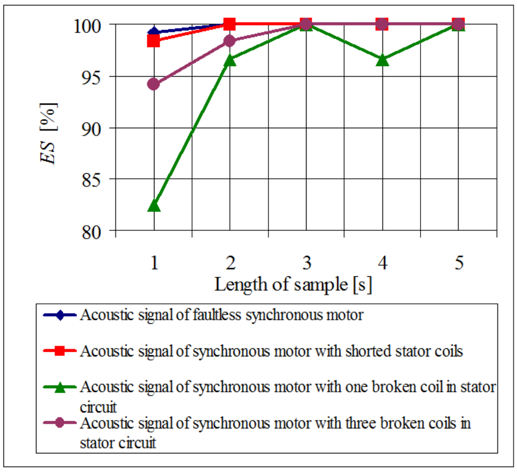

Fig.15. Acoustic signal recognition efficiency of synchronous motor depending on the length of the sample for MoFS and classifier based on words coding.

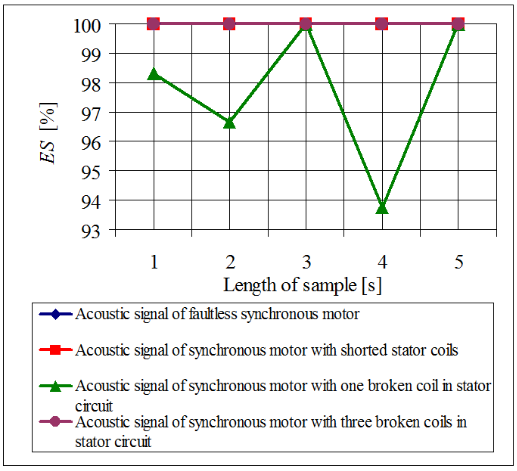

Fig.16. Acoustic signal recognition efficiency of synchronous motor depending on length of sample for MoFS and Nearest Neighbor classifier.

5. VERIFICATION OF THE METHOD

Electric signals and thermal images were used to verify results of acoustic signal recognition (Fig.17.). Methods of recognition of electric and thermal images were implemented.

These methods were discussed in the literature. Verification based on electric signal recognition was carried out. It used excitation current (Fig.18.). This verification method used a digital filter (which passes frequency at 100 Hz), Fast Fourier Transform and the Nearest Mean classifier. Current signal recognition efficiency of the synchronous motor was 100 % , see equation (14).

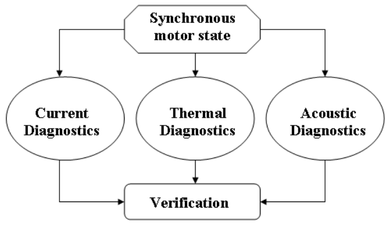

Fig.17. Verification scheme.

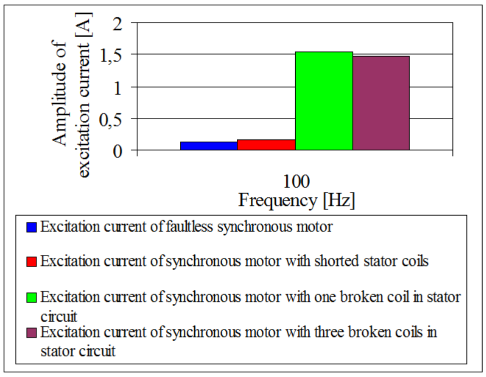

Fig.18. Amplitudes of excitation current of synchronous motor depending on frequency 100 Hz.

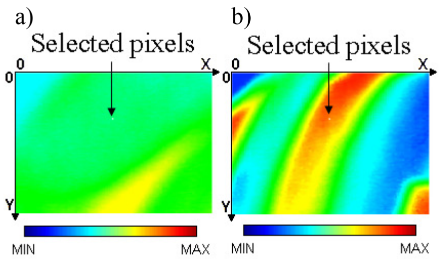

Fig.19. a) Thermographic image of rotating rotor of synchronous motor with no damage, b) Thermographic image of rotating rotor of synchronous motor with damaged rotor bar [48].

Verification based on recognition of thermal images was carried out in the literature [48]. Thermal verification was conducted with application of image cross-section and linear perceptron classifier (Fig.19.).

Thermal signal recognition efficiency of the synchronous motor was 100 %, see equation (14). The obtained results show that the diagnostic method based on acoustic signals is competitive with the diagnostic methods based on thermal and electric signals.

6. CONCLUSIONS

This paper proposes an approach based on acoustic signals for detection of faults appearing in synchronous motors. The proposed method in this paper deals with the analysis of acoustic signals generated by a synchronous motor. Results of the acoustic signal recognition were sufficient enough for MoFS and neural network. Classifier based on words coding and Nearest Neighbor classifier generated good results.

Acoustic signal recognition system was implemented for electrical rotating machines. This system can be used to test electrical rotating machines including synchronous motors.

In the future, new methods of recognition of acoustic signals will be developed. These methods will be supported by other diagnostic methods based on vibrations, thermal, and electrical signals.

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