Article citation info:
GLOWACZ A. Recognition of acoustic signals of induction motor using FFT, SMOFS-10 and LSVM. Eksploatacja i Niezawodnosc – Maintenance and Reliability 2015; 17 (4): 569–574, http://dx.doi.org/10.17531/ein.2015.4.12.

Adam GLOWACZ

RECOGNITION OF ACOUSTIC SIGNALS OF INDUCTION MOTOR USING FFT, SMOFS-10 AND LSVM

ROZPOZNAWANIE SYGNAŁÓW AKUSTYCZNICH SILNIKA INDUKCYJNEGO Z ZASTOSOWANIEM FFT, SMOFS-10 I LSVM*

A correct diagnosis of electrical circuits is very essential in industrial plants. An article deals with a recognition method of early fault detection of induction motor. The described approach is based on patterns recognition. Acoustic signals of specific induction motor are analyzed patterns. Acoustic signals include information about motor state. The analysis of the patterns was conducted for three states of induction motor using Fast Fourier Transform (FFT), shortened method of frequencies selection (SMoFS-10) and Linear Support Vector Machine (LSVM). The results of calculations suggest that the method is efficient and can be also used for diagnostic purposes.

Keywords: *acoustic signal, induction motor, feature extraction, classification.*

Prawidłowa diagnostyka obwodów elektrycznych jest bardzo istotna w zakładach przemysłowych. Artykuł zajmuje się metodą rozpoznawania stanów przedawaryjnych silnika indukcyjnego. Opisane podejście jest oparte na rozpoznawaniu wzorców. Sygnały akustyczne określonego silnika indukcyjnego są badanymi wzorcami. Sygnały akustyczne zawierają informację o stanie silnika. Analiza wzorców została przeprowadzona dla trzech stanów silnika indukcyjnego używając FFT, skróconej metody wyboru częstotliwości (SMoFS-10) i liniowej maszyny wektorów wspierających (LSVM). Wyniki obliczeń sugerują, że metoda jest skuteczna i może być również zastosowana dla celów diagnostycznych.

Słowa kluczowe: *sygnał akustyczny, silnik indukcyjny, ekstrakcja cech, klasyfikacja.*

1. Introduction

The induction motors are used in various industries such as: mining, fuel, metallurgical. These motors have low maintenance and low price. To reduce maintenance costs scientists analyze mechanical properties of materials [18, 20, 25, 30].

They also develop early fault detection methods [1, 5, 6, 10-15]. Especially non-invasive methods are developed such as: acoustic, vibrations, thermal, magnetic [3, 14, 19, 27, 28, 29, 35, 36, 38]. Non-invasive methods are capable to diagnose early faults without disassembly the induction motor. Many of them used patterns recognition and signal processing to identify type of fault.

Incipient faults of motors may change into damages and may stop the production line. The stopped production line causes losses of resources and production time. It increases the cost of operation and maintenance.

This article deals with a recognition method of early faults of induction motor. Proposed method uses Fast Fourier Transform (FFT), shortened method of radio frequencies selection (SMoFS-10) and Linear Support Vector Machine (LSVM).

2. Proposed approach of recognition of acoustic signal of induction motor

The proposed approach of recognition of acoustic signal of induction motor contained two processes: a pattern creation process and an identification process. These processes were needed for proper recognition of acoustic signal (Fig. 1).

The first of them recorded acoustic signal of motor with the help of a sound card and a microphone [22]. Acoustic signal was converted

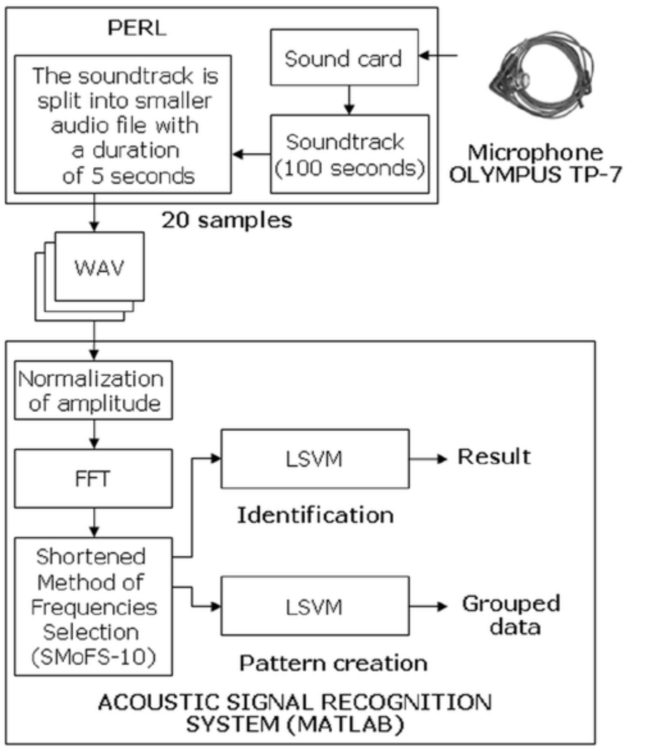

Fig. 1. Process of recognition of acoustic signal of induction motor using FFT, shortened method of frequencies selection (SMoFS-10) and Linear Support Vector Machine

(*) Tekst artykułu w polskiej wersji językowej dostępny w elektronicznym wydaniu kwartalnika na stronie ***www.ein.org.pl*** to soundtrack. Next this signal was converted into smaller audio files with a duration of 5 seconds. After that amplitudes of audio files (recorded acoustic signal) were normalized. Next the radio frequency spectra were calculated by FFT algorithm [8]. These spectra were processed by the shortened method of radio frequencies selection (SMoFS-10). The results of this method were feature vectors containing specific amplitudes of radio frequencies. The shortened method of frequencies selection (SMoFS-10) was discussed in chapter 2.2. Next step was grouping of data. For this purpose, Linear Support Vector Machine (LSVM) algorithm was used. The same methods as above were used in the identification process. Calculated feature vectors were recognized by Linear Support Vector Machine algorithm.

The described approach was based on patterns recognition. Patterns of acoustic signals of specific induction motor were analyzed. For this reason, there were two databases of patterns: training database and test database. The training database of patterns was used in the pattern creation process. All training samples and their classes were known. The test database of patterns was used in the identification process. All test samples were known, but their classes were unknown. Proposed method identified the correct class.

2.1. Measurement and preprocessing of acoustic signals of induction motor

The sound card and the microphone OLYMPUS TP-7 were applied to record acoustic signal of induction motor. Parameters of recorded soundtrack were following: 16-bit depth, number of channels – single channel, sampling rate – 44100 Hz, WAVE PCM audio file. Obtained soundtrack was converted into smaller audio files with a duration of 5 seconds. Afterwards amplitudes of audio files were normalized. Normalization of amplitude divided each point of the signal by maximum value. In that way signals were comparable in the range <-1, 1>. Next the radio frequency spectra were calculated by FFT algorithm. Obtained radio frequency spectra were used by shortened method of frequencies selection SMoFS-10.

2.2. Shortened method of frequencies selection (SMoFS-10)

The shortened method of frequencies selection (SMoFS-10) was based on the radio frequency spectrum. The method had following steps:

1) Calculate the difference of the radio frequency spectra of two states of motor $||F_1|-|F_2||$, where $|F_1|$ - is the radio frequency spectrum of acoustic signal of the first state of motor, $|F_2|$ - is the radio frequency spectrum of acoustic signal of the second state of motor.
2) Select the radio frequencies, which meets following criterion:

$$||F_1|-|F_2||>t \tag{1}$$

where t – threshold of selection of amplitudes of radio frequencies (formula 1), $||F_1|-|F_2||$ – the difference of amplitudes of radio frequencies for two different states of the motor.

Parameter t should be selected properly. This parameter depends on number of analyzed states and number of selected radio frequencies. Too little number of analyzed radio frequencies can cause errors. The differences between the selected radio frequencies can have different values (for example the first difference has maximum amplitude for frequencies 100, 200, 300 Hz; the second difference has maximum amplitude for frequencies 150, 200, 250 Hz; the third difference has maximum amplitude for frequencies 150, 225, 275 Hz in that case states 1 and 3 do not have common radio frequencies). For this reason, the parameter t is selected according to formulas 2 and 3. If the number of radio frequencies (number s) is greater than 10, the method will do loop calculation (formula 3). If the number of radio frequencies is smaller or equal to 10 it finishes its calculations.

$$t = \frac{\sum_{s=1}^{s} ||F_1|-|F_2||}{s}, \tag{2}$$

$$s \le 10, \tag{3}$$

where t – threshold of selection of amplitudes of radio frequencies (it depends on s and analyzed acoustic signal), s – natural number, number of radio frequencies (initially s=16384, 16384 is the number of all frequencies after usage of FFT algorithm). The amplitudes of selected radio frequencies of acoustic signals of motor are used to create feature vectors. SMoFS-10 method gives feature vector with 1-10 features, where a feature is the amplitude of radio frequency. The feature vector may have 2 features or 8, depending on the analyzed signals and the parameter s (for SMoFS-10 s = 10). Optimalization of parameters s and t depends on the number of analyzed states, their types, disturbances and the type of machine.

Difference between spectrum of acoustic signal of faultless induction motor and spectrum of acoustic signal of induction motor with faulty rotor bar was showed in figure 2.

Selected radio frequencies for differences between spectra of acoustic signals of induction motor were presented (Fig. 3-5). Two radio frequencies were common for analyzed states of induction mo-

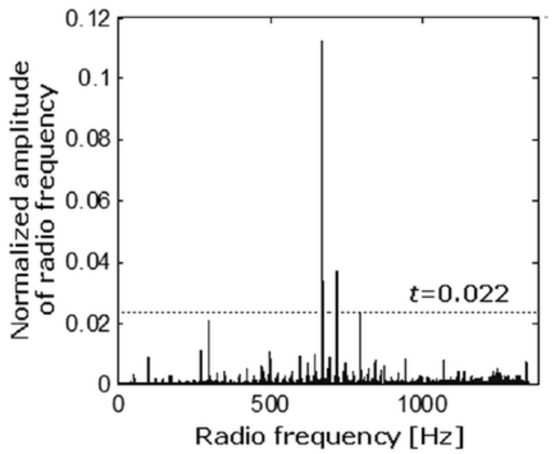

Fig. 2. Difference between spectrum of acoustic signal of faultless induction motor and spectrum of acoustic signal of induction motor with faulty rotor bar

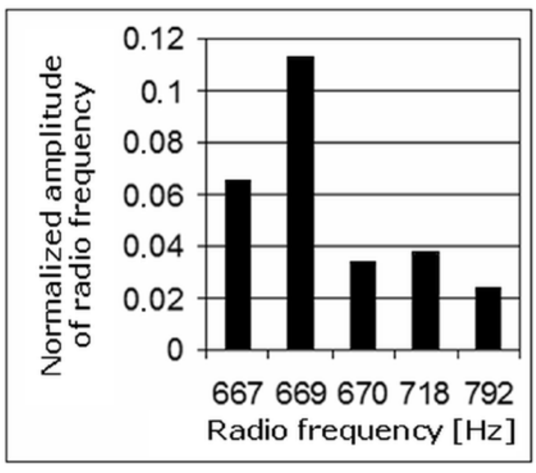

Fig. 3. Selected radio frequencies for difference between spectrum of acoustic signal of faultless induction motor and spectrum of acoustic signal of induction motor with faulty rotor bar with the use of SMoFS-10

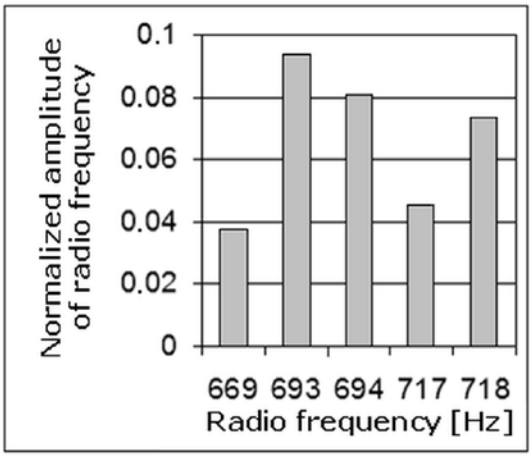

Fig. 4. Selected radio frequencies for difference between spectrum of acoustic signal of faultless induction motor and spectrum of acoustic signal of induction motor with two faulty rotor bars with the use of SMoFS-10

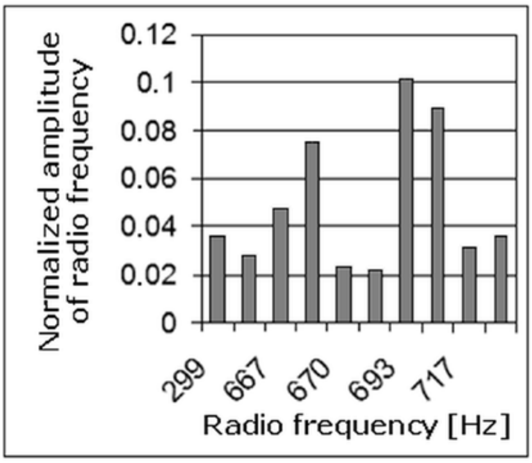

Fig. 5. Selected radio frequencies for difference between spectrum of acoustic signal of induction motor with faulty rotor bar and spectrum of acoustic signal of induction motor with two faulty rotor bars with the use of SMoFS-10

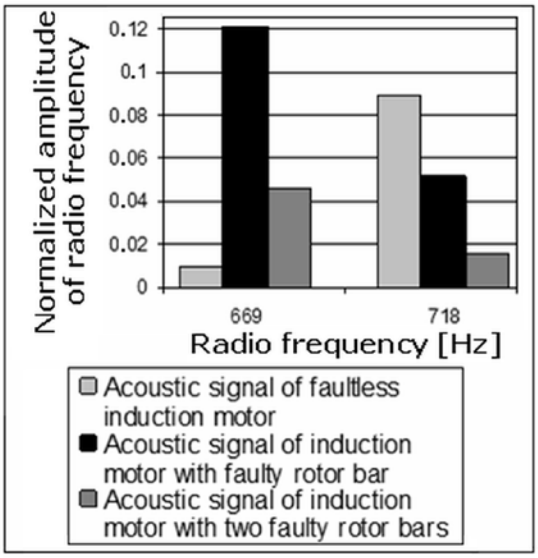

Fig. 6. Selection of common radio frequencies for 3 states of induction motor (669 and 718 Hz) with the use of SMoFS-10

tor: 669 and 718 Hz (Fig. 6). Selected amplitudes of frequencies 669 and 718 Hz were used to form feature vector.

2.3. Linear Support Vector Machine

Last step of signal processing was classification. Scientists proposed many methods of classification in the literature [2, 4, 7, 9, 16, 17, 21, 23, 26, 31-34]. Linear Support Vector Machine (LSVM) classified feature vectors by finding the best hyperplane that separated all vectors of one class from those of the other class. The considered hyperplane had the largest margin between the two classes [24, 37]. There were two more hyperplanes parallel to the separating hyperplane. They cut through the closest training examples (support vectors) on either side. These hyper-planes were called "support hyperplanes". They contained support vectors. A set of vectors $\mathbf{x}_i$ with their categories y_i were training examples.

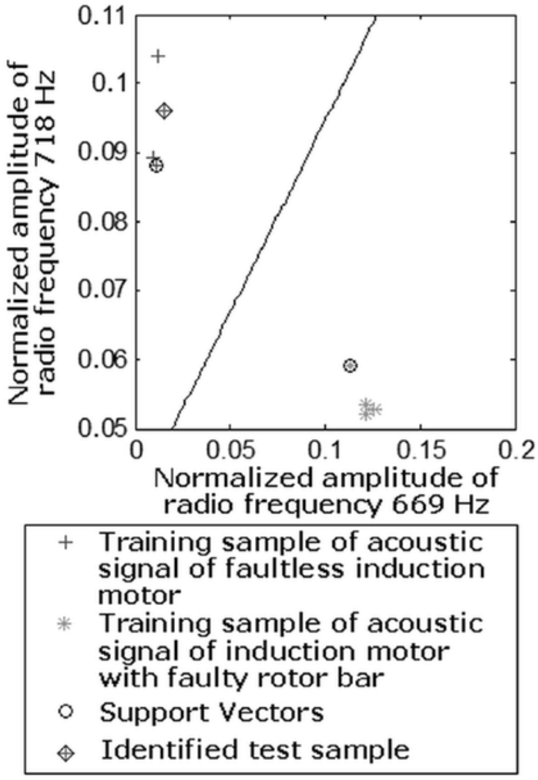

Fig. 7. Identification of test sample (acoustic signal of faultless induction motor) with the use of SMoFS-10, LSVM and training samples of acoustic signal of faultless induction motor and acoustic signal of induction motor with faulty rotor bar

A hyperplane was defined by following formula:

$$\langle \mathbf{w},\mathbf{x} \rangle + b = 0, \qquad (4)$$

where $\mathbf{w} \in R_d$, $\mathbf{x}_i \in R_d$, R_d (datapoints), $y_i = \pm 1$, $\langle \mathbf{w},\mathbf{x} \rangle$ was the inner product of $\mathbf{w}$ and $\mathbf{x}$, b was real.

Solution of this problem was to find $\mathbf{w}$ and b that minimize $||\mathbf{w}||$ for all training examples $(\mathbf{x}_i, y_i)$,

$$y_i(\langle \mathbf{w},\mathbf{x}_i \rangle + b) \geq 1. \qquad (5)$$

More about Linear Support Vector Machine could be found in literature [24, 37]. Identification of test sample of acoustic signal of faultless induction motor was showed (Fig. 7, 8).

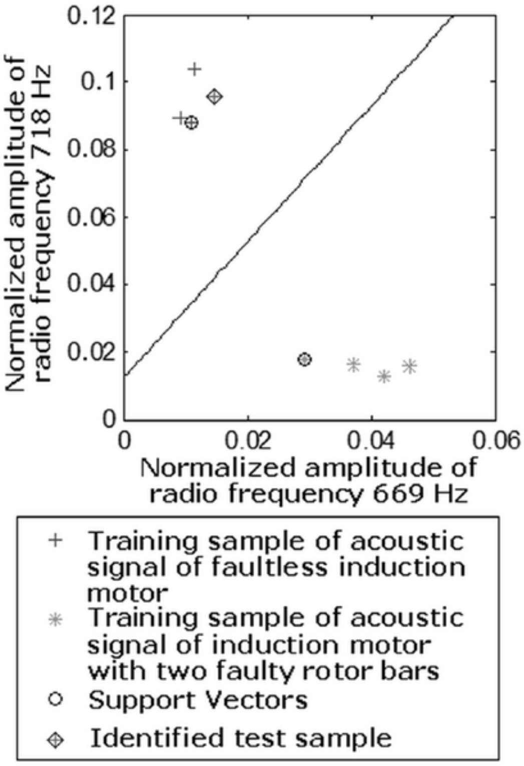

Fig. 8. Identification of test sample (acoustic signal of faultless induction motor) with the use of SMoFS-10, LSVM and training samples of acoustic signal of faultless induction motor and acoustic signal of induction motor with two faulty rotor bars

3. Analysis of acoustic signals of three phases induction motors

Three loaded three phases induction motors were used in analysis. These motors were the same. Open loop control system was used for these motors. Each of them had operational parameters: U_N=220/380 V (Δ/Y), I_N=2.52/1.47 A (Δ/Y), P_N = 0.55 kW, n_N = 1400 rpm, where U_n - nominal stator voltage, I_n - nominal stator current, P_N - motor power, n_N - rotor speed.

The first motor was faultless induction motor. The second motor was induction motor with faulty rotor bar. The third motor was induction motor with two faulty rotor bars (Fig. 9).

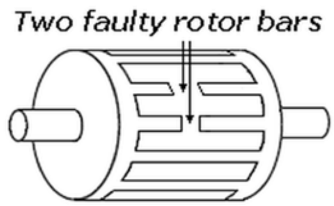

Fig. 9. Squirrel-cage rotor of three phases induction motor with two faulty rotor bars

In the pattern creation process 12 five-second training samples were processed by proposed method of acoustic signal recognition. These training samples were used to group data.

The identification process used 60 samples (20 samples for each class). These samples were used to evaluate efficiency of recognition of acoustic signal. This efficiency was defined as:

$$E = \frac{NoPITS}{NoTS} 100\% \ , \tag{6}$$

where *NoPITS* – number of properly identified test samples of specific class used in the identification process, *NoTS* – number of test samples of specific class used in the identification process, *E* – efficiency of recognition of acoustic signal of specific class.

$$TEoRoAS = \frac{E_1 + E_2 + E_3}{3} \ , \tag{7}$$

where *TEoRoAS* - Total efficiency of recognition of acoustic signal, E_1 - efficiency of recognition of acoustic signal of faultless induction motor, E_2 - efficiency of recognition of acoustic signal of induction motor with faulty rotor bar, E_3 - efficiency of recognition of acoustic signal of induction motor with two faulty rotor bars.

Table 1 presented efficiency of recognition of acoustic signal of three phases induction motor depending on state of induction motor. It also presented total efficiency of recognition of acoustic signal of induction motor.

On the basis of table 1 it can be noticed that *E* was in the range of 90-100 % and *TEoRoAS* was 96.66 %.

Table 1. Results of recognition of acoustic signal of three phases induction motor with the use of SMoFS-10 and LSVM

State of induction motor	*E* [%]
Faultless motor	100
Motor with faulty rotor bar	90
Motor with two faulty rotor bars	100
	TEoRoAS [%]
3 analyzed states of motor	96.66

4. Conclusions

Paper presented method of recognition of acoustic signal of three phases induction motor. This method contained methods of processing such as: FFT, SMoFS-10 and LSVM. SMoFS-10 was also new method of feature extraction. Analysis of acoustic signals showed that proposed solution was good to recognize state of induction motor. Total efficiency of recognition of acoustic signal of induction motor was equal to 96.66 % for 3 analyzed states of motor. Presented method can be used for early diagnostics of specific induction motors (the same size, operational parameters). It can be used for other electric motor when the patterns are properly selected. Moreover method based on acoustic signal can be used together with diagnostics methods based on thermal signals and stator current signals. In this way, it can improve the diagnostics of electrical motors.

Acknowledgments

This work has been financed under AGH researcher grant in 2015 (Adam Glowacz).

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Adam GLOWACZ
AGH University of Science and Technology
Faculty of Electrical Engineering, Automatics
Computer Science and Biomedical Engineering
Department of Automatics and Biomedical Engineering
al. A. Mickiewicza 30, 30-059 Kraków, Poland
e-mail: adglow@agh.edu.pl