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Recognition of Acoustic Signals of Loaded Synchronous Motor Using FFT, MSAF-5 and LSVM

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This article discusses a system of recognition of acoustic signals of loaded synchronous motor. This software can recognize various types of incipient failures by means of analysis of the acoustic signals. Proposed approach uses the acoustic signals generated by loaded synchronous motor. A plan of study of the acoustic signals of loaded synchronous motor is proposed. Studies include following states: healthy loaded synchronous motor, loaded synchronous motor with shorted stator coil, loaded synchronous motor with shorted stator coil and broken coil, loaded synchronous motor with shorted stator coil and two broken coils. The methods such as FFT, method of selection of amplitudes of frequencies (MSAF-5), Linear Support Vector Machine were used to identify specific state of the motor. The proposed approach can keep high recognition rate and reduce the maintenance cost of synchronous motors.

Keywords: acoustic signal, fault detection, loaded synchronous motor, signal processing, pattern recognition.

1. Introduction

The synchronous motor is type of AC motor which is a constant-speed motor (Fig. 1). These motors are used in many applications where synchronization of angular position of the rotating elements is required, for example in gas and oil pumps, rolling machines. The performance of the electrical machine depends on both the structure of magnetic circuit as well as the type of material and its treatment (Krolczyk *et al.*, 2014; Nadolny, Kaplonek, 2014; Tokarski *et al.*, 2012).

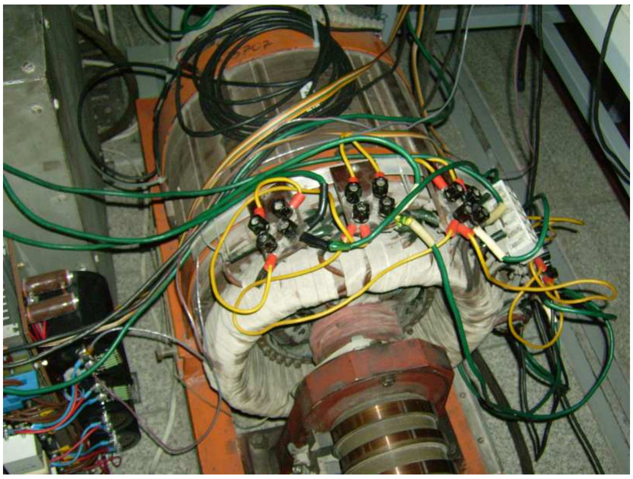

Fig. 1. Investigated synchronous motor.

In the literature diagnostic signals of different physical nature: electric, thermal, vibro-acoustic are used to fault detection (Abramov *et al.*, 2014; Bicek *et al.*, 2015; Czopek, 2012; Glowacz, 2010; 2014; Glowacz, Glowacz, 2007; Glowacz *et al.*, 2012a; 2012b; 2014; 2015; Gornicka, 2014; Idziak, Rawicki, 2010; Koscielny, Syfert, 2014; Kudelcik *et al.*, 2011; Li *et al.*, 2015; Pleban *et al.*, 2013; Pribil *et al.*, 2014; Rusinski *et al.*, 2014; Sebok *et al.*, 2011; Smolnicki *et al.*, 2013; Sulowicz *et al.*, 2010; Wu *et al.*, 2010; Zhao *et al.*, 2014). The electrical signals are a good source of information on of all types disturbances taking place during operation (Glowacz, Zdrojewski, 2007; Glowacz, Kozik, 2013; Glowacz *et al.*, 2015). On the other hand method based on electric signals is an invasive method of diagnostic. Acoustic signals of incipient failures of electric motors have a lot of disturbances and they are difficult to process. However, the method based on acoustic signals is non-invasive and inexpensive but little known.

It is essential to study the incipient failures of motor. Undetected, they may turn into failure and cause production shutdowns. These shutdowns may lead to wasting production time and raw resources.

This paper discusses selected incipient faults such as broken stator coils and shorted stator coil. They are mechanical faults caused by natural degradation of motor equipment. Detection of such faults is a diagnostic task. A new method of diagnostic based on acoustic signals is proposed in this paper.

2. Proposed method of recognition of acoustic signal of loaded synchronous motor

The proposed method of recognition consists of 6 steps of processing (Fig. 2). First one is recording of acoustic signal. To achieve that, OLYMPUS TP-7 microphone, a sound card and PC computer are used. The second step is splitting recorded soundtrack into small samples. The third step of processing is normalization of the amplitude. Next, data is converted by the FFT method. After that obtained spectrum of frequency is processed by the method of selection of amplitudes of frequencies (MSAF-5). The last step of processing is a classification. The classification contains 2 substeps – the pattern creation and the identification. The patterns (processed training samples) are created in the pattern creation. Test samples are compared in the identification.

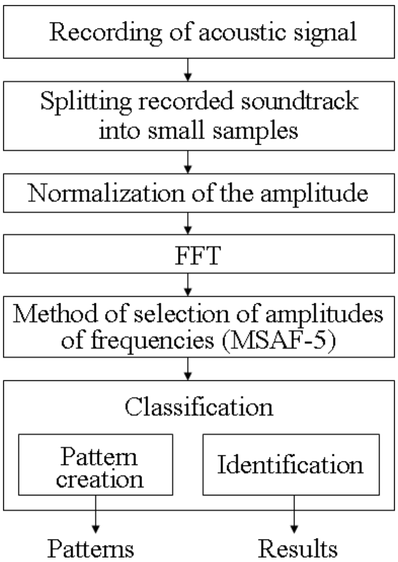

Fig. 2. Recognition of acoustic signal of synchronous motor using FFT, MSAF-5 and LSVM.

2.1. Recording of acoustic signal

Acoustic signals were recorded with the use of OLYMPUS TP-7 microphone, a sound card and PC computer. The parameters of WAVE PCM format of the sound samples were: sampling frequency – 44.1 kHz, number of channels – single channel, 16-bit depth.

2.2. Preprocessing

A preprocessing of acoustic signal includes splitting recorded soundtrack into small samples, normalization of the amplitude, FFT. The recorded soundtrack was split into 5-seconds sound samples. The normalization of the amplitude divided each point of the discreet signal by maximum value. The FFT method is well described in the literature (Glowacz, Glowacz, 2008). The FFT method creates vector of 16384 elements as window size equals 32768 (32768/44100 = 0.743, duration of 0.743 s).

2.3. Method of selection of amplitudes of frequencies (MSAF-5)

The proposed method of selection of amplitudes of frequencies MSAF-5 uses differences between amplitudes of acoustic signals of loaded synchronous motor. Different states and incipient faults of the loaded synchronous motor generates characteristic acoustic signals. Steps of proposed approach MSAF-5 are presented below:

1. Calculate the frequency spectrum of acoustic signal for each incipient failures and healthy state of loaded synchronous motor. The spectrum of frequency of acoustic signal of healthy loaded synchronous motor is denoted by vector $\mathbf{d} = [d_1, d_2, ..., d_{16384}]$. The spectrum of frequency of acoustic signal of loaded synchronous motor with shorted stator coil is denoted by vector $\mathbf{f} = [f_1, f_2, ..., f_{16384}]$. The spectrum of frequency of acoustic signal of loaded synchronous motor with shorted stator coil and broken coil is denoted by vector $\mathbf{g} = [g_1, g_2, ..., g_{16384}]$. The spectrum of frequency of acoustic signal of loaded synchronous motor with shorted stator coil and two broken coils is denoted by vector $\mathbf{h} = [h_1, h_2, ..., h_{16384}]$.
2. Calculate differences between spectra of frequencies of incipient failures and healthy state of loaded synchronous motor: $\mathbf{d}-\mathbf{f}$, $\mathbf{d}-\mathbf{g}$, $\mathbf{d}-\mathbf{h}$, $\mathbf{f}-\mathbf{g}$, $\mathbf{f}-\mathbf{h}$, $\mathbf{g}-\mathbf{h}$.
3. Calculate absolute values of differences between spectra of incipient failures and healthy state of loaded synchronous motor: $|\mathbf{d}-\mathbf{f}|$, $|\mathbf{d}-\mathbf{g}|$, $|\mathbf{d}-\mathbf{h}|$, $|\mathbf{f}-\mathbf{g}|$, $|\mathbf{f}-\mathbf{h}|$, $|\mathbf{g}-\mathbf{h}|$.
4. Choose 5 maximum amplitudes for each difference between spectra of frequencies of incipient failures and healthy state of loaded synchronous motor: $\max_1 |\mathbf{d}-\mathbf{f}|$, ..., $\max_5 |\mathbf{d}-\mathbf{f}|$, $\max_1 |\mathbf{d}-\mathbf{g}|$, ..., $\max_5 |\mathbf{d}-\mathbf{g}|$, $\max_1 |\mathbf{d}-\mathbf{h}|$, ..., $\max_5 |\mathbf{d}-\mathbf{h}|$, $\max_1 |\mathbf{f}-\mathbf{g}|$, ..., $\max_5 |\mathbf{f}-\mathbf{g}|$, $\max_1 |\mathbf{f}-\mathbf{h}|$, ..., $\max_5 |\mathbf{f}-\mathbf{h}|$, $\max_1 |\mathbf{g}-\mathbf{h}|$, ..., $\max_5 |\mathbf{g}-\mathbf{h}|$.
5. Find common amplitudes of frequencies (1–5) for each state of loaded synchronous motor.
6. Choose these amplitudes and create feature vector.

The method of selection of amplitudes of frequencies of loaded synchronous motor MSAF-5 is showed in Fig. 3.

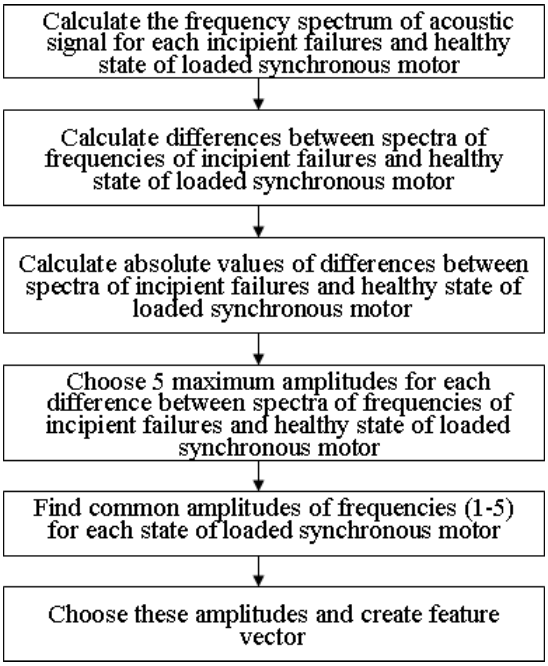

Fig. 3. Steps of MSAF-5.

Differences between spectra of frequencies for incipient failures and healthy state of loaded synchronous motor with rotor speed 1500 rpm are shown in Figs. 4–9.

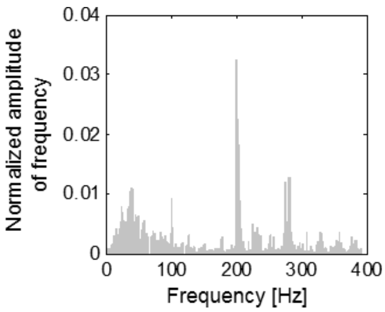

Fig. 4. The difference between spectra of frequencies of acoustic signal of healthy state of loaded synchronous motor and acoustic signal of loaded synchronous motor with shorted stator coil ($|\mathbf{d}-\mathbf{f}|$).

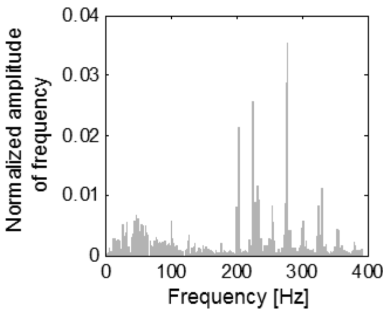

Fig. 5. The difference between spectra of frequencies of acoustic signal of healthy state of loaded synchronous motor and acoustic signal of loaded synchronous motor with shorted stator coil and broken coil ($|\mathbf{d}-\mathbf{g}|$).

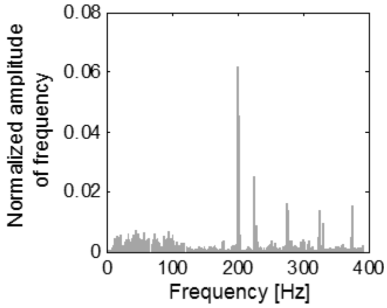

Fig. 6. The difference between spectra of frequencies of acoustic signal of healthy state of loaded synchronous motor and acoustic signal of loaded synchronous motor with shorted stator coil and two broken coils ($|\mathbf{d}-\mathbf{h}|$).

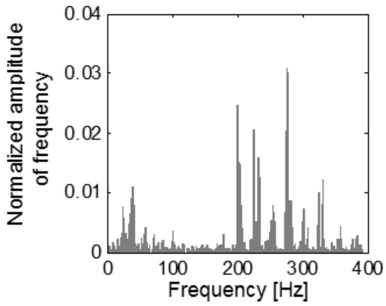

Fig. 7. The difference between spectra of frequencies of acoustic signal of loaded synchronous motor with shorted stator coil and acoustic signal of loaded synchronous motor with shorted stator coil and broken coil ($|\mathbf{f}-\mathbf{g}|$).

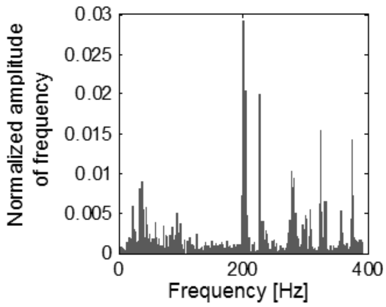

Fig. 8. The difference between spectra of frequencies of acoustic signal of loaded synchronous motor with shorted stator coil and acoustic signal of loaded synchronous motor with shorted stator coil and two broken coils ($|\mathbf{f}-\mathbf{h}|$).

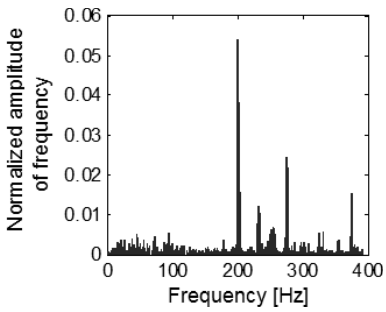

Fig. 9. The difference between spectra of frequencies of acoustic signal of loaded synchronous motor with shorted stator coil and broken coil and acoustic signal of loaded synchronous motor shorted stator coil and two broken coils ($|\mathbf{g}-\mathbf{h}|$).

Analysis of 4 states of loaded synchronous motor was conducted for frequency 202 Hz (Fig. 10).

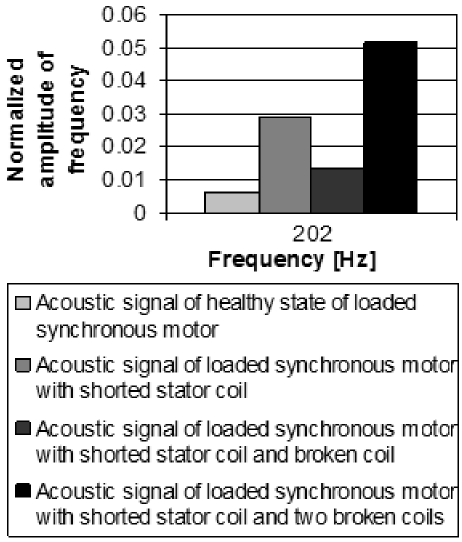

Fig. 10. Selected amplitude of frequency 202 Hz for incipient failures and healthy state of loaded synchronous motor. This amplitude of frequency was selected by MSAF-5.

Common frequencies of incipient failures and healthy state of loaded synchronous motor formed feature vectors (in this case – amplitude of frequency 202 Hz). Next, these vectors were used by Linear Support Vector Machine classifier.

2.4. Linear Support Vector Machine Classifier

A classification of data is a difficult task in machine learning. Many classification methods were discussed in recent literature (Augustyniak *et al.*, 2014; Czech *et al.*, 2014; Dudek-Dyduch *et al.*, 2009; Hachaj, Ogiela, 2011; 2013; Igras, Ziolko, 2014; Jakubiec *et al.*, 2007; Jaworek-Korjakowska, Tadeusiewicz, 2014; Jun, Kochan, 2014; Khan, Kannan, 2014; Krolczyk, 2014; MathWorks, 2014; Mazurkiewicz, 2014; Turchenko *et al.*, 2006; Valis, Pietrucha-Urbanik, 2014; Valis *et al.*, 2014; Zuber *et al.*, 2013). A Linear Support Vector Machine classifier (LSVM) analyzed data and recognized patterns. This classifier was described as a classification problem in (Cristianini, Shawe-Taylor, 2000; MathWorks, 2014; Suykens *et al.*, 2002). This classifier found the best hyperplane that separated feature vectors of the first class from vectors of the second class. Separating hyperplane was used for classification. This hyperplane had two more hyperplanes. Hyperplanes were parallel to separating hyperplane. Support vectors (nearest training examples) were cut by these two hyperplanes.

A group of classes r_i with their vectors $\mathbf{p}_i$ was tested. A separating hyperplane was defined as follows:

$$\langle \mathbf{k}, \mathbf{p} \rangle + c = 0, \tag{1}$$

where $\mathbf{k} \in R_d$, $\mathbf{p}_i \in R_d$, R_d (datapoints), c – real number, $r_i = \pm 1$, $\langle \mathbf{k}, \mathbf{p} \rangle$ – the inner product of $\mathbf{k}$ and $\mathbf{p}$. Finding $\mathbf{k}$ and c that minimize $||\mathbf{k}||$ for all training examples $(\mathbf{p}_i, r_i)$ was the solution of the considered classification problem.

$$r_i(\langle \mathbf{k}, \mathbf{p}_i \rangle + c) \geq 1. \tag{2}$$

The LSVM classifier was described in more detail in (Cristianini, Shawe-Taylor, 2000; MathWorks, 2014; Suykens *et al.*, 2002).

3. Analysis of acoustic signal of loaded synchronous motor

The loaded synchronous motor rotated at rotor speed of 1500 rpm. A load resistance was equal 1 Ω. Broken coils and short circuit were prepared in the stator circuit of the loaded synchronous motor (Figs. 11–13). A shorted resistance was equal 0.85 Ω. Other operating parameters depended on states of the motor. These parameters are presented below:

- healthy loaded synchronous motor, $I_{obc} = 10$ A, $I_T = 44.9$ A, $U_{RS} = 150$ V,
- loaded synchronous motor with shorted stator coil (U3-X3), $I_{obc} = 10$ A, $I_T = 42.7$ A, $U_{RS} = 150$ V, $I_{zw} = 42.5$ A,
- loaded synchronous motor with shorted stator coil and broken coil (U3–X3, Y1–Y4), $I_{obc} = 10$ A, $I_T = 47.2$ A, $U_{RS} = 150$ V, $I_{zw} = 38.8$ A,
- loaded synchronous motor with shorted stator coil and two broken coils (U3–X3, Y1–Y4, Z1–Z4), $I_{obc} = 10$ A, $I_T = 32.3$ A, $U_{RS} = 150$ V, $I_{zw} = 32$ A,

where I_{obc} – current load, I_T – the current of phase T, U_{RS} – the voltage between phases R and S, I_{zw} – current of short circuit.

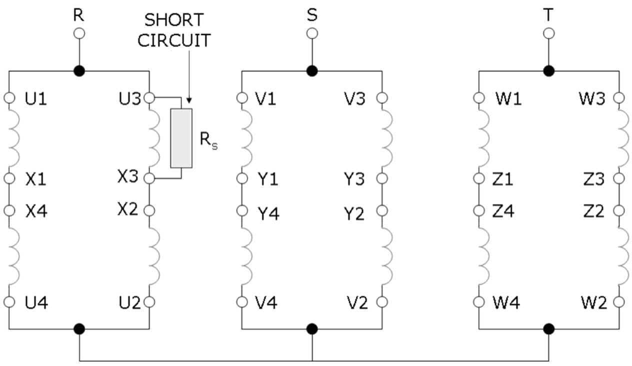

Fig. 11. Shorted stator coil (U3–X3) of loaded synchronous motor.

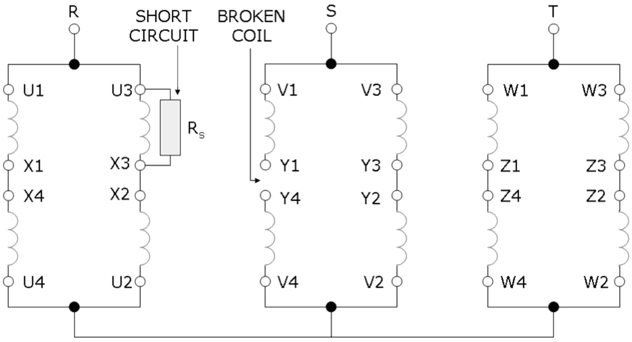

Fig. 12. Shorted stator coil and broken coil (U3–X3, Y1–Y4) of loaded synchronous motor.

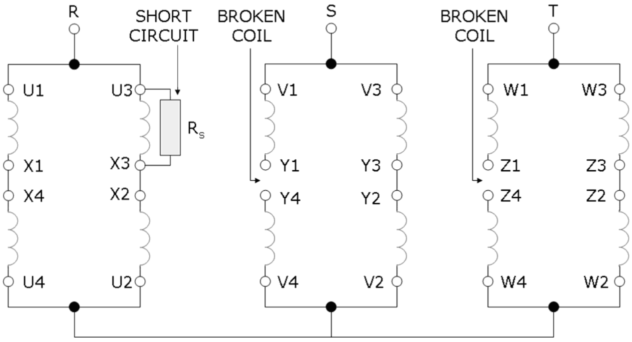

Fig. 13. Shorted stator coil and two broken coils (U3–X3, Y1–Y4, Z1–Z4) of loaded synchronous motor.

The method of selection of amplitudes of frequencies (MSAF-5) selected frequency 202 Hz – 1 feature (Fig. 10). Measurements and analysis were conducted for acoustic signals of incipient failures and healthy state of loaded synchronous motor. Incipient failures were as follows: motor with shorted stator coil (U3–X3), motor with shorted stator coil and broken coil (U3–X3, Y1–Y4), motor with shorted stator coil and two broken coils (U3–X3, Y1–Y4, Z1–Z4). 16 training and 120 test 5-second samples were used in the analysis.

Efficiency of acoustic signal recognition was analyzed. For this purpose the following formula (3) was introduced:

$$EASR = \frac{NPRTS}{NATS} 100\%, \tag{3}$$

where $EASR$ denoted efficiency of acoustic signal recognition, $NPRTS$ denoted number of properly recognized test samples, $NATS$ denoted number of all test samples.

Next, total efficiency of acoustic signal recognition ($TEASR$) was analyzed. For this purpose the following formula (4) was introduced:

$$TEASR = \frac{EASR_1 + EASR_2 + EASR_3 + EASR_4}{4}, \tag{4}$$

where $TEASR$ denoted total efficiency of acoustic signal recognition, $EASR_1$ denoted efficiency of acoustic signal recognition of healthy loaded synchronous motor, $EASR_2$ denoted efficiency of acoustic signal recognition of loaded synchronous motor with shorted stator coil (U3–X3), $EASR_3$ denoted efficiency of acoustic signal recognition of loaded synchronous motor with shorted stator coil and broken coil (U3–X3, Y1–Y4), $EASR_4$ denoted efficiency of acoustic signal recognition of loaded synchronous motor with shorted stator coil and two broken coils (U3–X3, Y1–Y4, Z1–Z4).

The efficiency of acoustic signal recognition of loaded synchronous motor depending on considered states is presented in Table 1. It also presents total efficiency of acoustic signal recognition of loaded synchronous motor.

Table 1. Results of recognition of acoustic signal of loaded synchronous motor using FFT, MSAF-5 and LSVM.

State of loaded synchronous motor	$EASR$ [%]
Healthy loaded synchronous motor	100
Loaded synchronous motor with shorted stator coil (U3–X3)	96.77
loaded synchronous motor with shorted stator coil and broken coil (U3–X3, Y1–Y4)	87.09
loaded synchronous motor with shorted stator coil and two broken coils (U3–X3, Y1–Y4, Z1–Z4)	96.77
	$TEASR$ [%]
4 analyzed states of loaded synchronous motor	95.16

The results presented in Table 1 were very good. The analyzed efficiency of acoustic signal recognition ($EASR$) was in the range of 87.09–100%. The total efficiency of acoustic signal recognition ($TEASR$) was equal 95.16%.

4. Conclusions

In this article a system and a method of recognition of acoustic signal of loaded synchronous motor were proposed. The proposed approach uses acoustic signals generated by loaded synchronous motor. Studies include following states: healthy loaded synchronous motor, loaded synchronous motor with shorted stator coil, loaded synchronous motor with shorted stator coil and broken coil, loaded synchronous motor with shorted stator coil and two broken coils. The proposed approach based on FFT, MSAF-5 and LSVM classifier was used to identify specific state of the motor. The results of analysis were good. The total efficiency of acoustic signal recognition ($TEASR$) was equal 95.16%.

Proposed approach can be used to advise on condition of synchronous motors. Moreover, it is inexpensive approach to protect rotating electrical machines.

Acknowledgments

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