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RECOGNITION OF ACOUSTIC SIGNALS OF INDUCTION MOTORS WITH THE USE OF MSAF10 AND BAYES CLASSFIER

Condition monitoring of deterioration in the metallurgical equipment is essential for faultless operation of the metallurgical processes. These processes use various metallurgical equipment, such as induction motors or industrial furnaces. These devices operate continuously. Correct diagnosis and early detection of incipient faults allow to avoid accidents and help reducing financial loss. This paper deals with monitoring of rotor electrical faults of induction motor. A technique of recognition of acoustic signals of induction motors is presented. Three states of induction motor were analyzed. Studies were carried out for methods of data processing: Method of Selection of Amplitudes of Frequencies (MSAF10) and Bayes classifier. Condition monitoring is helpful to protect induction motors and metallurgical equipment. Further researches will allow to analyze other metallurgical equipment.

Keywords: Fault, Acoustic signal, Induction motor, Diagnostics.

1. Introduction

Condition monitoring of deterioration in the metallurgical equipment is essential for faultless operation of the metallurgical processes. These processes use various metallurgical equipment, such as induction motors or industrial furnaces. These devices operate continuously in ironworks. Correct diagnosis and early detection of incipient faults allow to avoid accidents and help reducing financial loss. Induction motors faults include: stator faults, rotor electrical faults and failure of electronic components of motor.

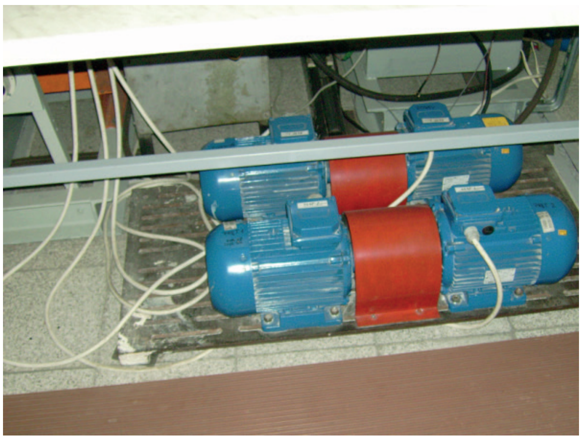

Fig. 1. Induction motors

A good diagnostic method should take the minimal measurements from induction motor and extract proper diagnosis using pattern recognition. Scientists developed methods of condition monitoring of electrical motors and various devices [1-20]. Many data processing methods (such as FFT, Wavelets, classifiers) were developed in the literature [21-26]. Data processing methods are associated with diagnostic methods. This paper deals with monitoring of electrical faults of rotor of induction motors (Fig. 1). A technique of recognition of acoustic signals of induction motors is presented in the paper.

2. Process of recognition of acoustic signal of induction motor

Processing of acoustic signal of induction motor is not an easy problem. Faultless induction motor and faulty induction motor generate very similar acoustic signals. Acoustic signal recognition system of induction motors was implemented to recognize these small differences between signals. This system uses a process of recognition of acoustic signal of induction motor (proposed technique). This process include a pattern creation process. The results of the pattern creation process are feature vectors (processed training samples). The first step of the pattern creation process of induction motor is recording of acoustic signal. Capacitor microphone (OLYMPUS TP-7) and sound card were used for this purpose [27, 28]. Other capacitor microphone would be also good for recording. Afterwards soundtracks are divided. Next divided data are sampled and normalized. Afterwards signals are converted through the FFT, MSAF10 and Bayes classifier. These vectors are used in training step (Fig. 2).

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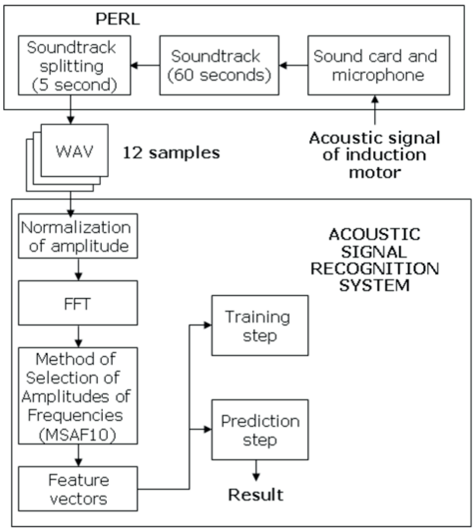

Fig. 2. Process of acoustic signal recognition of induction motor with the application of MSAF10 and Bayes classifier

Moreover process of recognition of acoustic signal of induction motor include an identification process. The identification process uses test samples to diagnose the state of the motor. Steps of the identification process are following: soundtrack splitting, sampling, normalization and feature extraction. These steps are the same for the pattern creation process. There is a prediction step at the end of the identification process. In this step feature vectors of training samples are compared with feature vector of test samples. These comparisons use a priori probability.

2.1. Method of selection of amplitudes of frequencies MSAF10

Author proposes method of selection of amplitudes of frequencies of acoustic signals of induction motors called MSAF10. This method is based on differences between amplitudes of states of induction motor. The acoustic signal is dependent on the state, rotor speed and construction of motor. Steps of MSAF10 are following:

1. Calculate spectrum of frequency of acoustic signal for each state of induction motor.
2. Calculate differences between spectra of frequencies of states of induction motor: **x-y**, **x-z**, **y-z**. The spectrum of frequency of acoustic signal of faultless induction motor is defined as **x**. The spectrum of frequency of acoustic signal of induction motor with faulty rotor bar is denoted as **y**. The spectrum of frequency of acoustic signal of induction motor with two faulty rotor bars is defined as **z**.
3. Calculate absolute values of differences between spectra of frequencies of states of induction motor: |**x-y**|, |**x-z**|, |**y-z**|.
4. Select 10 maximum amplitudes of the frequencies for each difference between states of induction motor: $\max_1$|**x-y**|, ..., $\max_{10}$|**x-y**|, $\max_1$|**x-z**|, ..., $\max_{10}$|**x-z**|, $\max_1$|**y-z**|,..., $\max_{10}$|**y-z**| and determine corresponding frequencies.
5. Find common frequencies (1-10) and then determine (for these frequencies) the amplitudes of spectrum for each state of induction motor.

The method of selection of amplitudes of frequencies of induction motor MSAF10 was presented in Fig. 3.

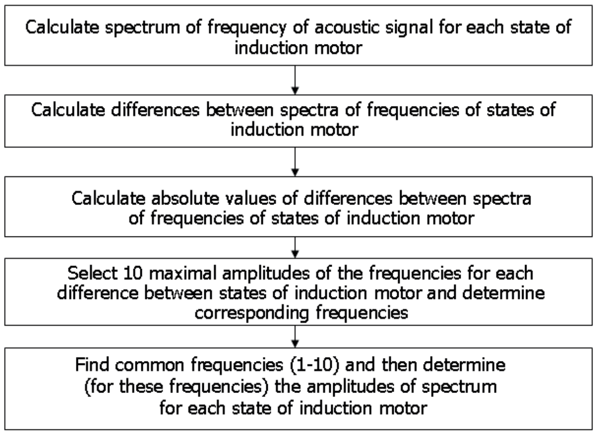

Fig. 3. Block scheme of MSAF10

Differences between spectra of frequencies for 3 states of induction motor with rotor speed 1400 rpm were shown in figures 4-6.

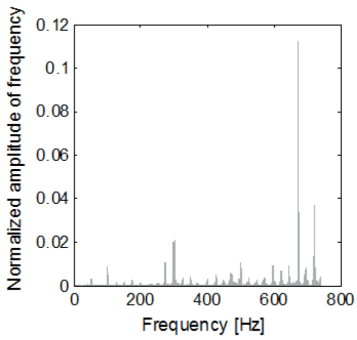

Fig. 4. Difference between spectra of frequencies of acoustic signal of faultless induction motor and induction motor with faulty rotor bar (|x-y|)

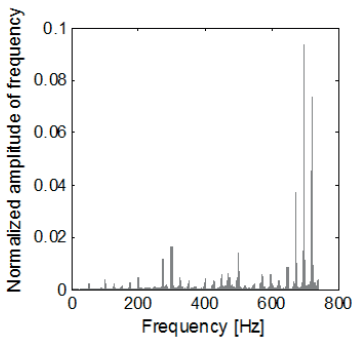

Fig. 5. Difference between spectra of frequencies of acoustic signal of faultless induction motor and induction motor with two faulty rotor bars (|x-z|)

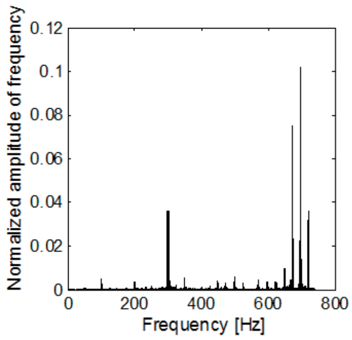

Fig. 6. Difference between spectra of frequencies of acoustic signal of induction motor with faulty rotor bar and induction motor with two faulty rotor bars (|y-z|)

Selected amplitudes of frequencies formed the feature vectors (Fig. 7). In the classification step these feature vectors were used by Bayes classifier.

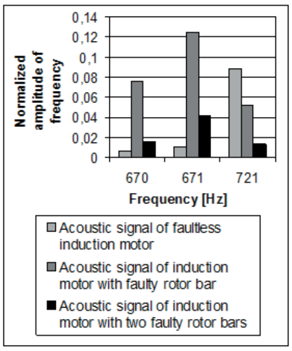

Fig. 7. Selected amplitudes of frequencies for 3 states of induction motor (670, 671, 721 Hz). These amplitudes of frequencies were selected by MSAF10

2.2. Bayes classifier

Many classification methods were developed in the literature [29-45]. Author selected Bayes classifier [6]. Bayes classifier is useful method for classification of feature vectors. This classifier uses parameters associated with a posterior probability. Posterior probability is defined as:

$$p(n_j \mid m) = \frac{p(m \mid n_j)\, p(n_j)}{p(m)}, \tag{1}$$

where $p(n_j \mid m)$ - probability of instance m being in class n_j (Posterior probability); $p(m \mid n_j)$ - probability of generating instance m given class n_j; $p(n_j)$ - probability of occurrence of class n_j; $p(m)$ - probability of instance m occurring.

The classifier used two steps: training step and prediction step. These steps used feature vectors. In the prediction step, new test samples were analyzed. Samples were classified according to the higher posterior probability [6].

3. Results of acoustic signal recognition

Parameters of soundtracks were: sampling frequency - 44.1 kHz, bit depth - 16-bit, number of channels - single channel, sound file format - WAVE PCM. The analysis was conducted for three induction motors. Each of induction motor has following parameters: P_N = 0.55 kW, U_N=220/380 V (Δ/Y), I_N=2.52/1.47 A (Δ/Y), n_N = 1400 rpm, where P_N - motor power, U_n - nominal stator voltage, I_n - nominal stator current, n_N - rotor speed. Following motor faults were prepared: faultless induction motor, induction motor with one faulty rotor bar (Fig. 8), induction motor with two faulty rotor bars.

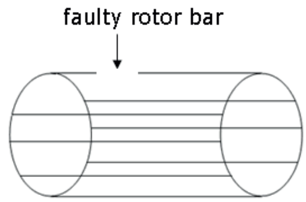

Fig. 8. Squirrel-cage of induction motor with faulty rotor bar

15 five-second training samples were converted into 15 feature vectors. Next classifier used these feature vectors in the training step. New 72 test samples were converted into 72 feature vectors. Afterwards classifier used 72 feature vectors in the prediction step. Efficiency of acoustic signal recognition was expressed by following relation:

$$E = \frac{NCITS}{NTS} 100\% , \tag{2}$$

where: $NCITS$ – number of correctly identified test samples used in the prediction step, NTS – number of test samples used in the prediction step, E – efficiency of acoustic signal recognition.

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

Where $TEASR$ - Total efficiency of acoustic signal recognition, E_1 - efficiency of acoustic signal recognition of faultless induction motor, E_2 - efficiency of acoustic signal recognition of induction motor with 1 faulty rotor bar, E_3 - efficiency of acoustic signal recognition of induction motor with 2 faulty rotor bars.

Table 1 showed efficiency of acoustic signal recognition of induction motor depending on type of signal. The best results were obtained for acoustic signal of faultless induction motor and acoustic signal of induction motor with 1 faulty rotor bar. It was equal 95.83 %. Total efficiency of acoustic signal recognition of acoustic signal of induction motor was equal 93.05 %.

TABLE 1

Results of acoustic signal recognition of induction motor with application of MSAF10 and Bayes classifier

Type of acoustic signal	Efficiency of acoustic signal recognition [%]
Faultless induction motor	95.83
Induction motor with 1 faulty rotor bar	95.83
Induction motor with 2 faulty rotor bars	87.5

	Total efficiency of acoustic signal recognition [%]
Induction motor	93.05

4. Conclusions

Acoustic signal recognition system of induction motors was presented. This system used technique based on FFT, MSAF10 and Bayes classifier. These methods were good for analyzing acoustic signals of induction motor faults. Total efficiency of acoustic signal recognition of induction motor was 93.05 % for 3 classes. The additional analyses should be performed for other motors with different operational parameters and sizes. Condition monitoring is helpful to protect induction motors and metallurgical equipment. Further researches will allow to analyze other metallurgical equipment.

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REFERENCES

[1] B. Bedkowski, M. Baranski, Electrical machine with permanent magnets as a vibration sensor - a test stand model, 2014 International Conference on Electrical Machines (ICEM), 1590-1593 (2014).

[2] D. Pleban, Definition and Measure of the Sound Quality of the Machine, Archives of Acoustics **39**, 1, 17-23 (2014).

[3] L. Jedlinski, J. Caban, L. Krzywonos, S. Wierzbicki, F. Brumercik, Application of vibration signal in the diagnosis of IC engine valve clearance, Journal of Vibroengineering **17**, 1, 175-187 (2015).

[4] B. Bedkowski, J. Madej, The innovative design concept of thermal model for the calculation of the electromagnetic circuit of rotating electrical machines, Eksploatacja i Niezawodnosc – Maintenance and Reliability **17**, 4, 481–486 (2015).

[5] I. El-Thalji, E. Jantunen, A summary of fault modelling and predictive health monitoring of rolling element bearings. Mechanical Systems and Signal Processing **60-61**, 252-272 (2015).

[6] A. Glowacz, A. Glowacz, Z. Glowacz, Recognition of Thermal Images of Direct Current Motor with Application of Area Perimeter Vector and Bayes Classifier, Measurement Science Review **15**, 3, 119-126 (2015).

[7] J. Barglik, A. Smalcerz, R. Przylucki, I. Dolezel, 3D modeling of induction hardening of gear wheels, Journal of Computational and Applied Mathematics **270**, 231-240 (2014).

[8] M. Michalak, M. Sikora, J. Sobczyk, Analysis of the longwall conveyor chain based on a harmonic analysis, Eksploatacja i Niezawodnosc – Maintenance and Reliability **15**, 4, 332-336 (2013).

[9] A. Glowacz, Recognition of Acoustic Signals of Loaded Synchronous Motor Using FFT, MSAF-5 and LSVM, Archives of Acoustics **40**, 2, 197-203 (2015).

[10] E. Kupiec, W. Przyborowski, Magnetic equivalent circuit model for unipolar hybrid excitation synchronous machine, Archives of Electrical Engineering **64**, 1, 107-117 (2015).

[11] T. Wegiel, M. Sulowicz, D. Borkowski, A distributed system of signal acquisition for induction motors diagnostic, 2007 IEEE International Symposium on Diagnostics for Electric Machines, Power Electronics & Drives, Cracow, Poland, 261-265 (2007).

[12] C. Wang, YG. Zhang, Fault Correspondence Analysis in Complex Electric Power Systems, Advances in Electrical and Computer Engineering **15**, 1, 11-16 (2015).

[13] YG. Zhang, ZP. Wang, A Novel Approach to Fault Detection in Complex Electric Power Systems, Advances in Electrical and Computer Engineering **14**, 3, 27-32 (2014).

[14] K. Pietrucha-Urbanik, Failure analysis and assessment on the exemplary water supply network, Engineering Failure Analysis 57, 137-142 (2015).

[15] H. Saavedra, JR. Riba, L. Romeral, Detection of Inter-turn Faults in Five-Phase Permanent Magnet Synchronous Motors, Advances in Electrical and Computer Engineering **14**, 4, 49-54 (2014).

[16] DY. Ning, Y. Gong, Shocking fault component of abnormal sound signal in the fault engine extract method based on linear superposition method and cross-correlation analysis, Advances in Mechanical Engineering **7**, 8, (2015).

[17] M. Irfan, N. Saad, R. Ibrahim, VS. Asirvadam, An on-line condition monitoring system for induction motors via instantaneous power analysis, Journal of Mechanical Science and Technology **29**, 4, 1483-1492 (2015).

[18] G.M. Krolczyk, J.B. Krolczyk, S. Legutko, A. Hunjet, Effect of the disc processing technology on the vibration level of the chipper during operations, Tehnicki Vjesnik-Technical Gazette **21**, 2, 447-450 (2014).

[19] P. Hreha, A. Radvanska, L. Knapcikova, G.M. Krolczyk, S. Legutko, J.B .Krolczyk, S. Hloch ,P. Monka, Roughness Parameters Calculation By Means Of On-Line Vibration Monitoring Emerging From AWJ Interaction With Material, Metrology and Measurement Systems **22**, 2, 315-326 (2015).

[20] A. Glowacz, W. Glowacz, Simulation language for analysis of discrete-continuous electrical systems (SESL2), 26th IASTED International Conference on Modelling, Identification and Control Location: Innsbruck, Austria, 94-99 (2007).

[21] M. Duspara, K. Sabo, A. Stoic, Acoustic emission as tool wear monitoring, Tehnicki Vjesnik-Technical Gazette 21, **5**, 1097-1101 (2014).

[22] K. Stepien, Research on a surface texture analysis by digital signal processing methods, Tehnicki Vjesnik-Technical Gazette **21**, 3, 485-493 (2014).

[23] K. Stepien, W. Makiela, A. Stoic, I. Samardzic, Defining the criteria to select the wavelet type for the assessment of surface quality, Tehnicki Vjesnik-Technical Gazette 22, 3, 781-784 (2015).

[24] W. Glowacz, Z. Glowacz, Diagnostics of separately excited DC motor based on analysis and recognition of signals using FFT and Bayes classifier, Archives of Electrical Engineering **64**, 1, 29-35 (2015).

[25] A. Glowacz, W. Glowacz, Sound recognition of dc machine with-application of FFT and backpropagation neural network, Przeglad Elektrotechniczny **84**, 9, 159-162 (2008).

[26] C. da Costa, M. Kashiwagi, M.H. Mathias, Rotor Failure Diagnosis of Induction Motors by Wavelet Transform and

Fourier Transform in Function of the Load, International Conference on Computer Science and Artificial Intelligence (ICCSAI 2014), 109-113 (2015).
[27] M. Kundegorski, P.J.B. Jackson, B. Ziolko, Two-Microphone Dereverberation for Automatic Speech Recognition of Polish, Archives of Acoustics **39**, 3, 411-420 (2014).
[28] Z. Kulka, Advances in Digitization of Microphones and Loudspeakers, Archives of Acoustics **36**, 2, 419-436 (2011).
[29] J. Roj, A. Cichy, Method of Measurement of Capacitance and Dielectric Loss Factor Using Artificial Neural Networks, Measurement Science Review **15**, 3, 127-131 (2015).
[30] D. Valis, K. Pietrucha–Urbanik, Utilization of diffusion processes and fuzzy logic for vulnerability assessment, Eksploatacja i Niezawodnosc–Maintenance and Reliability **16**, 1, 48-55 (2014).
[31] D. Valis, L. Zak, O. Pokora, P. Lansky, Perspective analysis outcomes of selected tribodiagnostic data used as input for condition based maintenance, Reliability Engineering & System Safety 145, 231-242 (2016).
[32] P. Augustyniak, M. Smolen, Z. Mikrut, E. Kantoch, Seamless Tracing of Human Behavior Using Complementary Wearable and House-Embedded Sensors, Sensors 14, 5, 7831-7856 (2014).
[33] M. Izadbakhsh, A. Rezvani, M. Gandomkar, Dynamic response improvement of hybrid system by implementing ANN-GA for fast variation of photovoltaic irradiation and FLC for wind turbine, Archives of Electrical Engineering **64**, 2, 291-314 (2015).
[34] S. Jun, O. Kochan, Investigations of Thermocouple Drift Irregularity Impact on Error of their Inhomogeneity Correction, Measurement Science Review **14**, 1, 29-34 (2014).
[35] M. Marzec, R. Koprowski, Z.Wrobel, Methods of face localization in thermograms, Biocybernetics and Biomedical Engineering **35**, 2, 138-146 (2015).
[36] T. Hachaj, Pattern Classification Methods for Analysis and Visualization of Brain Perfusion CT Maps, Computational Intelligence Paradigms in Advanced Pattern Classification, Book Series: Studies in Computational Intelligence **386**, 145-170 (2012).
[37] J. Jaworek-Korjakowska, R. Tadeusiewicz, Determination of border irregularity in dermoscopic color images of pigmented skin lesions, Annual International Conference of the IEEE Engineering in Medicine and Biology Society, 6459-6462 (2014).
[38] L. Brocki, K. Marasek, Deep Belief Neural Networks and Bidirectional Long-Short Term Memory Hybrid for Speech Recognition, Archives of Acoustics **40**, 2, 191-195 (2015).
[39] JB. Krolczyk, An attempt to predict quality changes in a ten-component granular system, Tehnicki Vjesnik-Technical Gazette **21**, 2, 255-261 (2014).
[40] E. Nawarecki, S. Kluska-Nawarecka, K. Regulski, Multi-aspect Character of the Man-Computer Relationship in a Diagnostic-Advisory System, Human-computer systems interaction: Backgrounds and applications 2. Pt 1, Book Series: Advances in Intelligent and Soft Computing **98**, 85-102 (2012).
[41] K. Regulski, D. Szeliga, J. Kusiak, Data exploration approach versus sensitivity analysis for optimization of metal forming processes, Material Forming Esaform 2014, Book Series: Key Engineering Materials **611-612**, 1390-1395 (2014).
[42] YB. Li, MQ. Xu, Y. Wei, W.H. Huang, Bearing fault diagnosis based on adaptive mutiscale fuzzy entropy and support vector machine, Journal of Vibroengineering **17**, 3, 1188-1202 (2015).
[43] XQ. Wang, Y.F. Li, T. Rui, H.J. Zhu, J.C. Fei, Bearing fault diagnosis method based on Hilbert envelope spectrum and deep belief network, Journal of Vibroengineering **17**, 3, 1295-1308 (2015).
[44] L. Saidi, J. Ben Ali, F. Friaiech, Application of higher order spectral features and support vector machines for bearing faults classification, ISA Transactions **54**, 193-206 (2015).
[45] R. Tadeusiewicz, Place and Role of Intelligent Systems in Computer Science, Computer Methods in Materials Science **10**, 4, 193-206 (2010).

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