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

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.

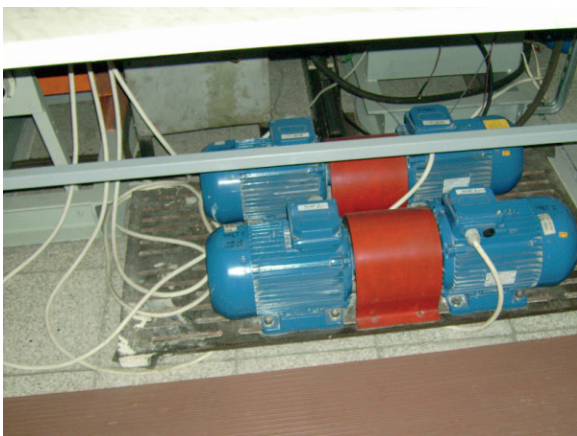


Fig. 1. Induction motors

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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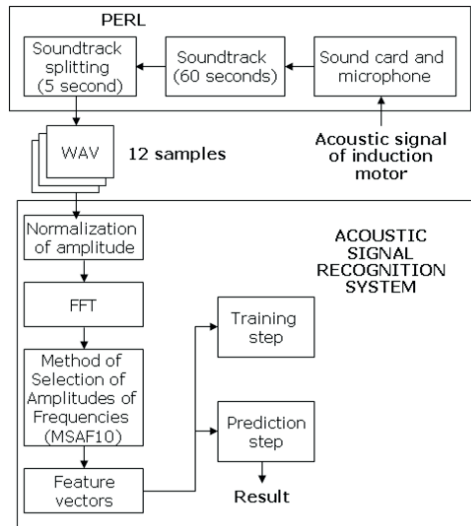


Fig. 2. Process of acoustic signal recognition of induction motor with the application of MSAF10 and Bayes classifier

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.

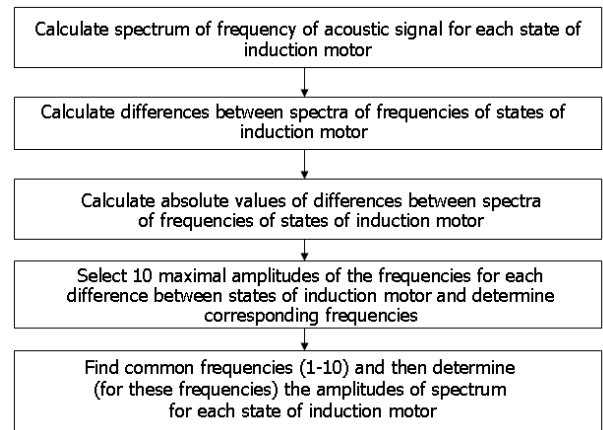


Fig. 3. Block scheme of MSAF10

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

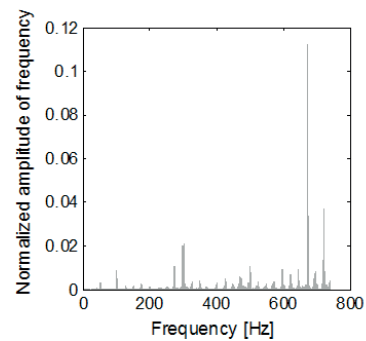


Fig. 4. Difference between spectra of frequencies of acoustic signal of faultless induction motor and induction motor with faulty rotor bar ($|x-y|$)

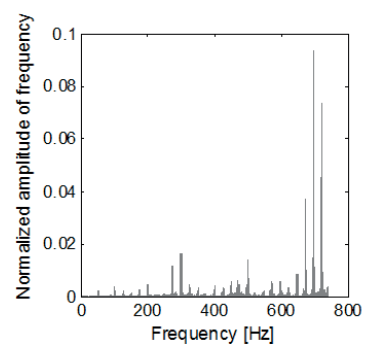


Fig. 5. Difference between spectra of frequencies of acoustic signal of faultless induction motor and induction motor with two faulty rotor bars ($|x-z|$)

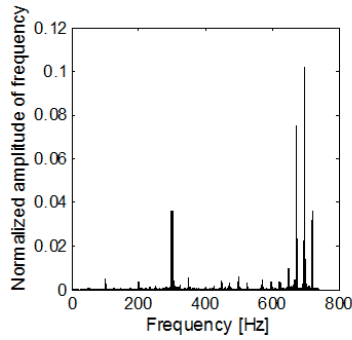


Fig. 6. Difference between spectra of frequencies of acoustic signal of induction motor with faulty rotor bar and induction motor with two faulty rotor bars ($y-z$)

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

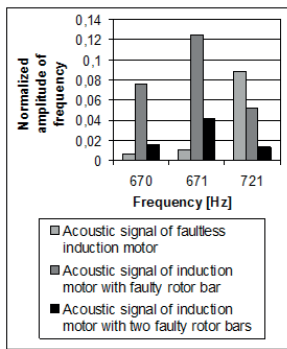


Fig. 7. Selected amplitudes of frequencies for 3 states of induction motor (670, 671, 721 Hz). These amplitudes of frequencies were selected by MSAF10

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:

$$p(n_j | m) = \frac{p(m | n_j)p(n_j)}{p(m)}, \quad (1)$$

where $p(n_j | m)$ - probability of instance m being in class n_j (Posterior probability); $p(m | n_j)$ - 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.

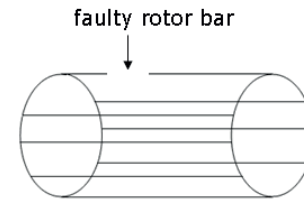


Fig. 8. Squirrel-cage of induction motor with faulty rotor bar

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:

$$E = \frac{NCITS}{NTS} 100\% , \quad (2)$$

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.

$$TEASR = \frac{E_1 + E_2 + E_3}{3} , \quad (3)$$

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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