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FAULT DIAGNOSIS OF THREE PHASE INDUCTION MOTOR USING CURRENT SIGNAL, MSAF-RATIO15 AND SELECTED CLASSIFIERS

A degradation of metallurgical equipment is normal process depended on time. Some factors such as: operation process, friction, high temperature can accelerate the degradation process of metallurgical equipment. In this paper the authors analyzed three phase induction motors. These motors are common used in the metallurgy industry, for example in conveyor belt. The diagnostics of such motors is essential. An early detection of faults prevents financial loss and downtimes. The authors proposed a technique of fault diagnosis based on recognition of currents. The authors analyzed 4 states of three phase induction motor: healthy three phase induction motor, three phase induction motor with 1 faulty rotor bar, three phase induction motor with 2 faulty rotor bars, three phase induction motor with faulty ring of squirrel-cage. An analysis was carried out for original method of feature extraction called MSAF-RATIO15 (Method of Selection of Amplitudes of Frequencies – Ratio 15% of maximum of amplitude). A classification of feature vectors was performed by Bayes classifier, Linear Discriminant Analysis (LDA) and Nearest Neighbour classifier. The proposed technique of fault diagnosis can be used for protection of three phase induction motors and other rotating electrical machines. In the near future the authors will analyze other motors and faults. There is also idea to use thermal, acoustic, electrical, vibration signal together.

Keywords: Fault, current, electrical signal, induction motor, diagnostics, classification

1. Introduction

A degradation of metallurgical equipment is normal process depended on time. Some factors such as: operation process, friction, high temperature can accelerate the degradation process of metallurgical equipment. Three phase induction motors are common used in the metallurgy industry, for example in conveyor belt. The diagnostics of such motors is essential. The early detection of faults prevents financial loss and downtimes. In the literature researchers developed methods of fault detection based on acoustic [1-13], thermal [14-20] and vibration signals [21-29]. An acoustic signal is difficult to process because microphone records many sounds from environment. Measurements of temperature are possible when motor is hot. Electrical signals are very good for a recognition for example MCSA (Motor Current Signature Analysis). These kinds of signals do not have many disturbances. The recognition of electrical signals of motors was also described in the literature [30-40]. However more analyses are needed in this topic, to develop more effi-

cient methods of fault diagnosis . There are also possibility to diagnose materials such as steel [41] or properties of materials [42]. In this paper the authors analyzed 4 three phase induction motors (Fig. 1).
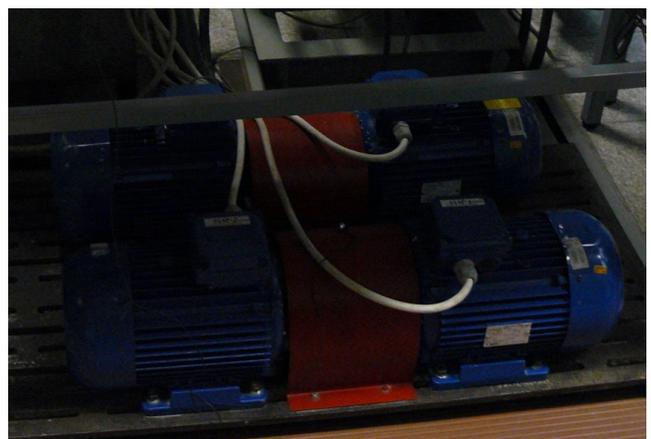

Fig. 1. Four analyzed three phase induction motors

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The authors proposed a technique of fault diagnosis based on recognition of currents.

2. Technique of fault diagnosis based on recognition of current signal

The proposed technique of fault diagnosis was based on recognition of current signal. It included a pattern creation process and identification process (Fig. 2).
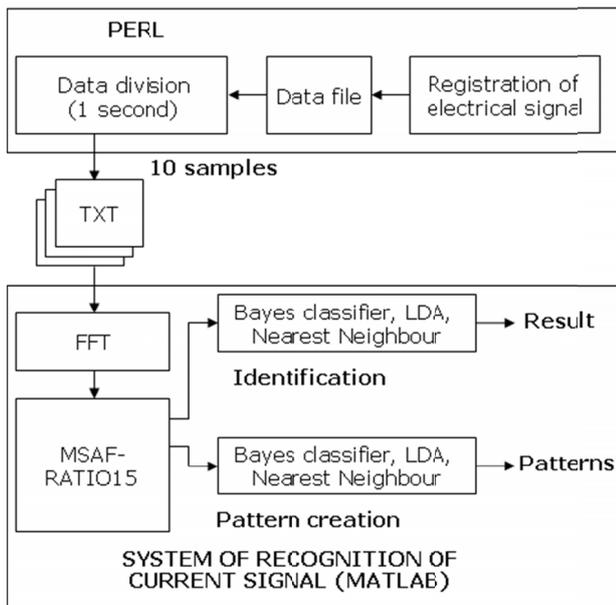

Fig. 2. Technique of fault diagnosis based on recognition of current signal with the use of MSAF-RATIO15 and Bayes classifier, LDA, Nearest Neighbour classifier

Both processes were similar. At the beginning of both processes an electrical (current) signal was recorded. This was done by data acquisition card and a computer. Next obtained signals were divided, converted through windowing (windows size 20000) and the FFT method. Next feature extraction with the use of MSAF-RATIO15 was performed for pattern creation process. The last step of pattern creation process was formulation of patterns – feature vectors. Performing of MSAF-RATIO15 was not necessary for identification process, because all frequencies were calculated in pattern creation process. A test sample was processed and new feature vector was obtained. This vector was compared with patterns with the use of Bayes classifier, Linear Discriminant Analysis (LDA) and Nearest Neighbour classifier.

2.1. Method of selection of amplitudes of frequencies MSAF-RATIO15

MSAF-RATIO15 (Method of Selection of Amplitudes of Frequencies – Ratio 15% of maximum of amplitude) was an original feature extraction method. Figure 3 showed block diagram of MSAF-RATIO15.
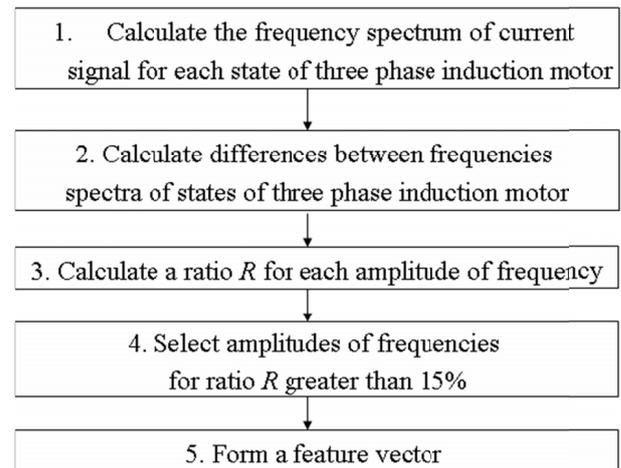

Fig. 3. Block diagram of MSAF-RATIO30-EXPANDED

Specific steps of MSAF-RATIO15 were following:

1) Calculate the frequency spectrum of current signal for each state of three phase induction motor. Frequency spectrum of current signal of healthy three phase induction motor was a vector **htpim**=[$htpim_1$, $htpim_2$, ..., $htpim_{16384}$]. Frequency spectrum of current signal of three phase induction motor with 1 faulty rotor bar was the vector **tpim1frb**=[$tpim1frb_1$, $tpim1frb_2$, ..., $tpim1frb_{16384}$]. Frequency spectrum of current signal of three phase induction motor with 2 faulty rotor bars was the vector **tpim2frb**=[$tpim2frb_1$, $tpim2frb_2$, ..., $tpim2frb_{16384}$]. Frequency spectrum of current signal of three phase induction motor with faulty ring of squirrel-cage was the vector **tpimfrsc**=[$tpimfrsc_1$, $tpimfrsc_2$, ..., $tpimfrsc_{16384}$].

2) Calculate differences between frequencies spectra of states of three phase induction motor: |**htpim – tpim1frb**|, |**htpim – tpim2frb**|, |**htpim – tpimfrsc**|, |**tpim1frb – tpim2frb**|, |**tpim1frb – tpimfrsc**|, |**tpim2frb – tpimfrsc**|.

3) Calculate ratio R for each spectrum of frequency. The ratio was expressed by formula (1):

$$R = (100\%)A_i/A_{max}, \qquad (1)$$

where A_i, A_{max} were based on differences between frequency spectra of training samples, A_i – amplitude of frequency with index i, A_{max} – maximum amplitude in the spectrum of frequency, R =15% for MSAF-RATIO15.

4) Select amplitudes of frequencies for ratio R greater than $(15\%)A_{max}$. Next select common amplitudes of frequencies for all analyzed differences.

5) Form a feature vector.

Differences of frequencies spectra of current signals of three phase induction motor |**htpim – tpim1frb**|, |**htpim – tpim2frb**|, |**htpim – tpimfrsc**|, |**tpim1frb – tpim2frb**|, |**tpim1frb – tpimfrsc**|, |**tpim2frb – tpimfrsc**| were showed in (Figs. 4-9) (rotor speed 1400 rpm).

Selected amplitudes of frequencies formed feature vectors. These vectors contained frequencies 26, 51, 76 Hz. Next obtained vectors were used for classification.
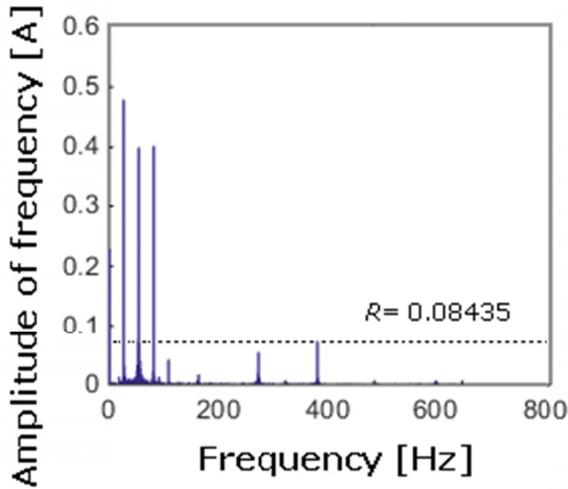
Fig. 4. Difference between spectra of frequencies of current signal of healthy three phase induction motor and three phase induction motor with 1 faulty rotor bar (|htpim – tpim1frb|)

Fig. 7. Difference between spectra of frequencies of current signal of three phase induction motor with 2 faulty rotor bars and three phase induction motor with 1 faulty rotor bar (|tpim2frb – tpim1frb|)

Fig. 5. Difference between spectra of frequencies of current signal of healthy three phase induction motor and three phase induction motor with 2 faulty rotor bars (|htpim – tpim2frb|)
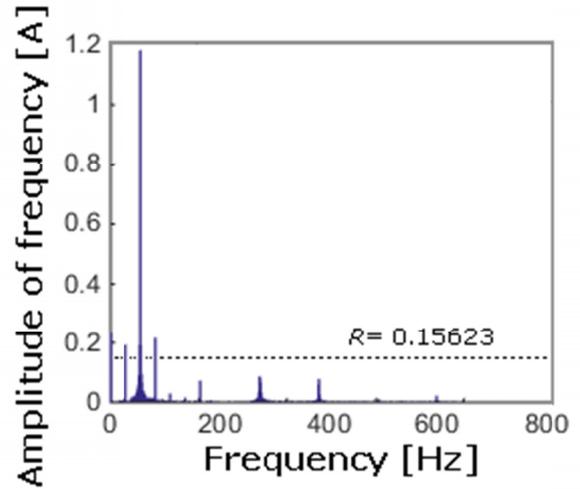

Fig. 8. Difference between spectra of frequencies of current signal of three phase induction motor with 2 faulty rotor bars and three phase induction motor with faulty ring of squirrel-cage (|tpim2frb – tpimfrsc|)
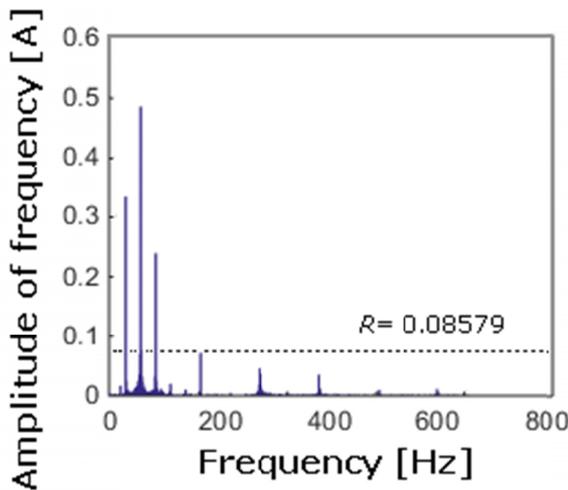

Fig. 6. Difference between spectra of frequencies of current signal of healthy three phase induction motor and three phase induction motor with faulty ring of squirrel-cage (|htpim – tpimfrsc|)
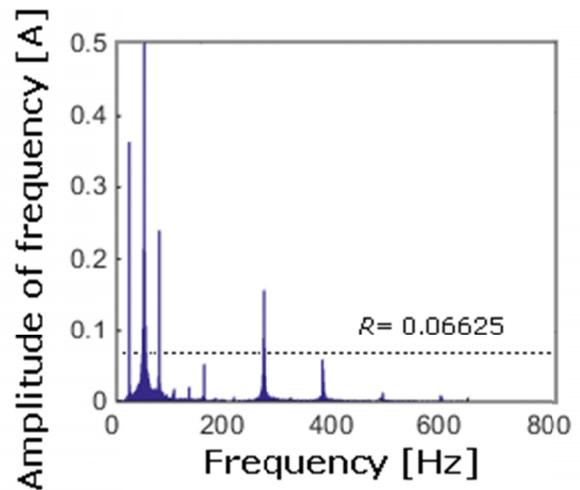

Fig. 9. Difference between spectra of frequencies of current signal of three phase induction motor with 1 faulty rotor bar and three phase induction motor with faulty ring of squirrel-cage (|tpim1frb – tpimfrsc|)
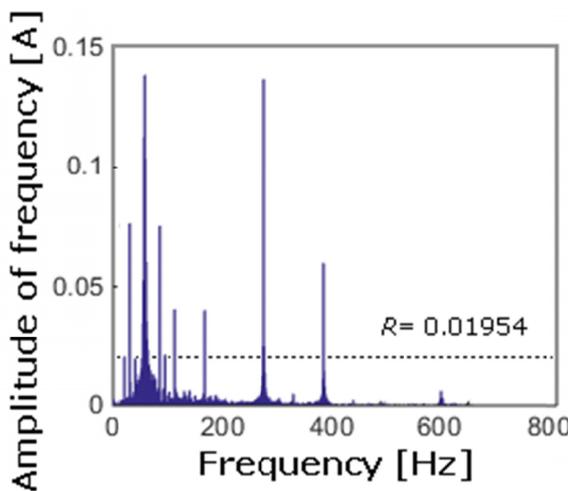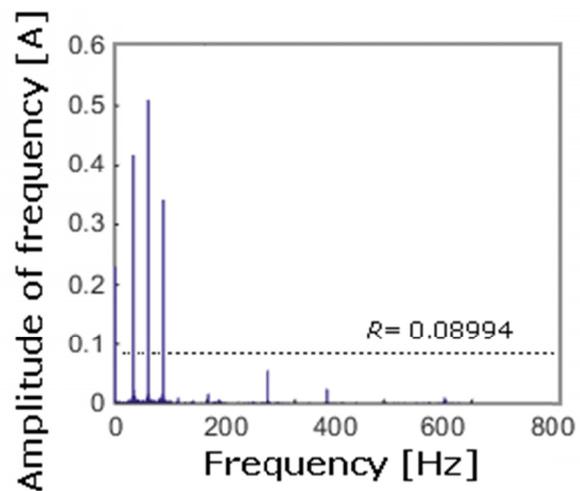
2.2. Bayes classifier

Classification methods were discussed in many articles by many researchers [43-52]. Neural networks were often used for classification problems [53-58]. Statistical data analysis was also described [59]. One of classification methods was Naive Bayes classifier. It was well described in the literature [48,60]. This classifier used a posterior probability, which was expressed by (2):

$$p(v_j \mid z) = \frac{p(z \mid v_j) p(v_j)}{p(z)} \qquad (2)$$

where $p(v_j)$ – probability of occurrence of class v_j, $p(z)$ – probability of instance z, $p(z \mid v_j)$ – probability of generating instance z given class v_j, $p(v_j \mid z)$ – probability of instance z being in class v_j.

Classifier calculated the posterior probability for all training feature vectors (patterns) and marked patterns with respect to their category. Next it classified test feature vectors (test samples) according to the higher probability $p(v_j \mid z)$.

2.3. Linear Discriminant Analysis

Linear Discriminant Analysis (LDA) was a classification method. It was well described in the literature [61,62]. LDA maximized the component axes for class-separation and created the best hyperplane between training points (training feature vectors). After performance of pattern creation process new test samples were classified. The result of classification was depended on distance between new feature vector and the calculated hyperplane. More information about LDA was available in the literature [61,62].

2.4. Nearest Neighbour classifier

The Nearest Neighbour classifier was common used classification method [48,63,64]. It was used in many applications such as: robotics, pattern recognition, databases, coding theory, plagiarism detection, spell checking. The application of such classifier for fault detection of three phase induction motor was interesting. The Nearest Neighbour classifier used training and test samples. After performance of pattern creation process new test samples were classified by distance function. The authors decided to use Manhattan distance (3):

$$M(\mathbf{htpim}, \mathbf{tpim1frb}) = \sum_{i=1}^{3} |(htpim_i - tpim1frb_i)| \qquad (3)$$

where feature vectors $\mathbf{htpim}=[htpim_{26}, htpim_{51}, htpim_{76}]$ and $\mathbf{tpim1frb}=[tpim1frb_{26}, tpim1frb_{51}, tpim1frb_{76}]$. The calculations were performed for 4 feature vectors: $\mathbf{htpim}$, $\mathbf{tpim1frb}$, $\mathbf{tpim2frb}$, $\mathbf{tpimfrsc}$.

There was a possibility of use other distance functions such as: Euclidean, Minkowski, Chebyshev, cosine, Jacquard.

The results of mentioned distance functions were very similar. More information about the Nearest Neighbour classifier was available in the literature [48,63,64].

3. Analysis of proposed technique

Measurements of current signals were performed by data acquisition card and computer. Each of four three phase induction motor had power 550W and rotor speed $r_s = 1400$ rpm.
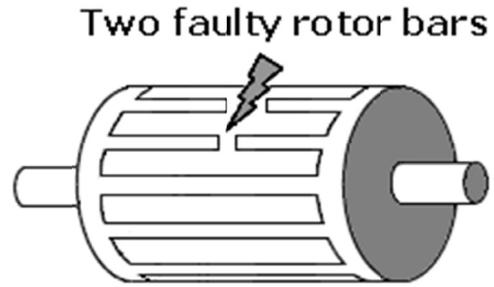

Fig. 10. Squirrel-cage of three-phase induction motor with two faulty rotor bars

The authors analyzed 4 states of three phase induction motor: healthy three phase induction motor, three phase induction motor with 1 faulty rotor bar, three phase induction motor with 2 faulty rotor bars (Fig. 10), three phase induction motor with faulty ring of squirrel-cage.

Feature vectors contained amplitudes of frequencies 26, 51, 76 Hz (see section 2.1). The training set had 12 one-second samples (vectors). The test set had 40 one-second samples. Efficiency of current signal recognition was defined as (4):

$$E_C = \frac{N_{ip}}{N_a} \cdot 100\% \qquad (4)$$

where: E_C – efficiency of current signal recognition, N_{ip} – number of test samples identified properly, N_a – number of all test samples.

The authors analyzed 3 classifiers: Bayes classifier, LDA and Nearest Neighbour classifier. The results of all classifiers were the same. Efficiency of current signal recognition was equaled 100% for 4 states of three phase induction motor (Tab. 1).

TABLE 1

Results of current signal recognition of three phase induction motor with the application of MSAF-RATIO15

Type of current signal	Efficiency of current signal recognition [%]
Healthy three phase induction motor	100
three phase induction motor with 1 faulty rotor bar	100
three phase induction motor with 2 faulty rotor bars	100
three phase induction motor with faulty ring of squirrel-cage	100

4. Conclusions

The technique of current signal recognition was presented for three phase induction motor. This technique used the original method of feature extraction MSAF10. The authors analyzed 3 classifiers: Bayes classifier, LDA and the Nearest Neighbour classifier. The results of all classifiers were very good (100%). The proposed technique of fault diagnosis can be used for protection of three phase induction motors and other rotating electrical machines. It is essential for metallurgy industry. In the near future the authors will analyze other motors and faults. There is also idea to use thermal, acoustic, electrical, vibration signals together.

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