Diagnostics of Synchronous Motor Based on Analysis of Acoustic Signals with the use of Line Spectral Frequencies and K-nearest Neighbor Classifier

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In industrial processes electrical motors are serviced after a specific number of hours, even if there is a need for service. This led to the development of early fault diagnostic methods. Paper presents early fault diagnostic method of synchronous motor. This method uses acoustic signals generated by synchronous motor. Plan of study of acoustic signal of synchronous motor was proposed. Two conditions of synchronous motor were analyzed. Studies were carried out for methods of data processing: Line Spectral Frequencies and K-Nearest Neighbor classifier with Minkowski distance. Condition monitoring is useful to protect electric motors and mining equipment. In the future, these studies can be used in other electrical devices.

Keywords: acoustic signal, pattern analysis, synchronous motor, diagnostics.

1. Introduction

Condition monitoring of synchronous motors decreases the cost of maintenance and the risk of unexpected failures of machine. In this monitoring, maintenance or machine replacement based on previous records or statistical estimates of motor failures. Usually, the information about machine are provided by condition monitoring systems. An important element of diagnostics is having an accurate means of condition assessment. Condition monitoring also uses measurements taken while a motor is operating. On the basis of measurements operator determines the state of motor. Measurements can be performed with the use of various sensors. Various signal processing methods can be applied to extract characteristic features of selected signal (SIN *et al.*, 2003).

Synchronous motors are constructed of steel, aluminium and copper elements. Many researchers have discussed thermal and mechanical properties of materials (BOGUCKA, 2014; DUDA, 2013; GLUCHOWSKI *et al.*, 2014; GOLANSKI, SLANIA, 2013; GRONOSTAJSKI *et al.*, 2013; KULCZYK *et al.*, 2014; KULESZA *et al.*, 2013; MADEJ, 2013; MAMALA, SCIEZOR, 2014; MUSIAL, 2013; SZYSZKIEWICZ *et al.*, 2013; TOMCZAK *et al.*, 2013; STUBNA *et al.*, 2014). Thermal and mechanical properties of materials are very important for the diagnostics. Many diagnostic and visualization methods were developed by researchers (BIENIAS *et al.*, 2013; CZMOCHOWSKI *et al.*, 2014; GIRTLER, SLEZAK, 2013; GLOWACZ *et al.*, 2014a; 2014b; GOGOLA *et al.*, 2013; JAKLINSKI, 2013; SMALCERZ, 2013; TASINKEVYCH *et al.*, 2012; TU *et al.*, 2014). Electrical signals are often used in diagnostics of electrical machines (DUDZIKOWSKI, CIURYS, 2010; GLOWACZ, GLOWACZ, 2007; GLOWACZ, 2013; GLOWACZ, KOZIK, 2012; 2013; GLOWACZ, ZDROJEWSKI, 2009; GWOZDZIEWICZ, ZAWILAK, 2011; KOZLOWSKI, 2009; LIN *et al.*, 2013; ORLEWSKI, SIWEK, 2010). In this paper, research concerns with acoustic signals of selected synchronous motor. The results of research can be used to improve the diagnostics of synchronous motors in industry.

2. Process of acoustic signal recognition of synchronous motor

The process of acoustic signal recognition of synchronous motor contains two processes. The first of them is a pattern creation process. In this process training samples are converted into feature vectors. The second is an identification process (Fig. 1). In this process test samples are used to obtain the state of motor.

At the beginning of the pattern creation process acoustic signals of synchronous motor are recorded. After that data are divided. Next divided data are sam-
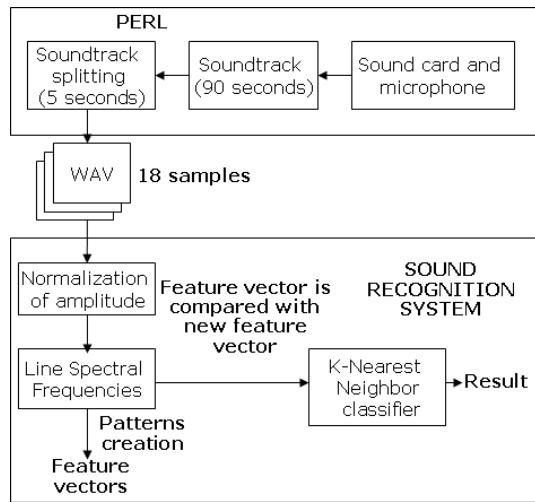
Fig. 1. Process of sound recognition of synchronous motor with the use of Line Spectral Frequencies and K-Nearest Neighbor classifier.

pled and normalized. Afterwards signals are converted through the Line Spectral Frequencies. The pattern creation process uses 10 feature vectors. Steps of identification process are similar to the pattern creation process. Soundtrack splitting, sampling, normalization and feature extraction are the same for both processes. Significant change occurs in the classification. In this step, feature vectors are compared with each other. Feature vectors of training samples are compared with feature vector of test sample.

2.1. Line Spectral Frequencies

Line spectrum frequency (LSF) method was proposed by Itakura (1975). It was used for robust representation of the coefficients of linear predictive speech models. In this paper author investigates performance of LSF for acoustic signal recognition of synchronous motor. Linear predictive analysis of acoustic signal assumes that a short stationary segment of sound is represented by a linear time invariant all pole filter. It can be defined as follows:

$$H(z) = \frac{1}{A(z)}, \tag{1}$$

where $H(z)$ is a p-th order model of the vocal tract. LSF method refers to the p-th order inverse filter $A(z)$. This filter can be represented by two polynomials $P(z) = A(z) - z^{p+1}A(z^{-1})$ and $Q(z) = A(z) + z^{p+1}A(z^{-1})$. It is expressed as follows:

$$H(z) = \frac{1}{A(z)} = \frac{2}{P(z) + Q(z)}. \tag{2}$$

These polynomials have $p/2$ zeros on the unit circle. Phases of the zeros are interleaved in the range $[0; \pi]$. These p zeros create the LSF features of the linear predictive model. The formant frequencies depends on the

zeros of $A(z)$. LSF features can be used to model sound related information in the sound spectra (Bozkurt *et al.*, 2010; Morris, Clements, 2002). On the basis of the literature author decided to use LSF method for sound of synchronous motor. Training and test samples of sound were converted through LSF method. After these calculations following feature vectors were obtained (Figs. 2, 3).
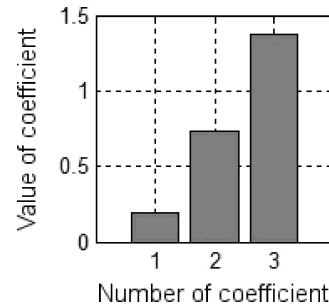

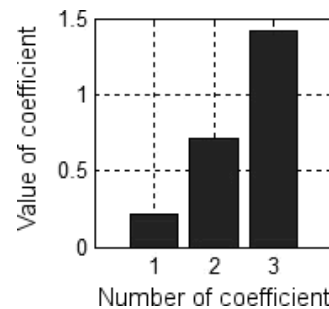Fig. 2. LSF coefficients of acoustic signal of faultless synchronous motor.

Fig. 3. LSF coefficients of acoustic signal of synchronous motor with shorted stator coils.

2.2. K-Nearest Neighbor Classifier

Different methods of classification of the signals were presented in the literature (Duan, Zhou, 2014; Glowacz, Glowacz, 2012; Hachaj, Ogiela, 2011, 2013; Jaworek, Augustyniak, 2011; Kantoch *et al.*, 2011; Kantoch, Augustyniak, 2012; Knap *et al.*, 2014; Meo *et al.*, 2013; Michalak *et al.*, 2013; Mikulik, Zajdel, 2009; Ogiela *et al.*, 2007; Oleksy, Szymanski, 2010; Rojek, Studzinski, 2014; Roj, 2013; Skowronek, Wozniak, 2013; Smolen *et al.*, 2012; Su, Fu, 2014; Uygur *et al.*, 2014; Valis, Pietrucha-Urbanik, 2014; Zuber *et al.*, 2014). In this paper K-Nearest Neighbor Classifier was applied. This classifier used feature vector calculated in the earlier step. Each vector in training set has n attributes. These attributes are formed as an n-dimensional vector: $\mathbf{x} = [x_1, \ldots, x_n]$. Next these n attributes are considered to be the independent variables. Vectors also have another attribute, denoted by p. This attribute is the dependent variable. Value of attribute depends on the other n attributes x. Attribute p is an identifier of the class.

A set of M vectors are given together with their corresponding classes: $x(i)$, $p(i)$ for $i = 1, 2, \ldots, M$. This set is referred to the training set. In the identification process vectors from test set are used. These vectors have n attributes. These attributes are formed as an n-dimensional vector: $\mathbf{y} = [y_1, \ldots, y_n]$. The problem is to find the class that this vector $\mathbf{y}$ belongs to. This can be done in the following way:

1. identify k vectors in the training set whose independent variables x are similar to y,

2. use these k vectors in the training set to classify test vector into a class v.

This method is called K-Nearest Neighbor classifier. The most important step of this method is to find similarity between vectors. The good idea is to use distance function (MING LEUNG, 2007). In this approach Minkowski distance was chosen. Minkowski distance is the measure of distance between two selected vectors. Two vectors with the same lengths are given: $\mathbf{y} = [y_1, y_2, \ldots, y_n]$, $\mathbf{x} = [x_1, x_2, \ldots, x_n]$. In this case Minkowski distance is defined as follows:

$$d(\mathbf{y}, \mathbf{x}) = \left(\sum_{i=1}^{n} \left(|y_i - x_i| \right)^r \right)^{1/r}. \qquad (3)$$

One of the cases of K-Nearest Neighbor classifier is $k = 1$. In this case vector in the training set is closest to y and set $v = p$. Variable p is index of the class of the nearest neighboring vector. Using a nearest neighbor method to classify vectors can be very helpful when there are large number of vectors in training set. K-Nearest Neighbor classifier uses a majority decision rule to classify the test vector. It compares the number of k nearest neighbors (feature vectors of training set) and selects the class that has the most of them. The advantage of such rule is that, it reduces the risk of over-fitting due to noise in the training data. Usually parameter k is equal odd number in units or tens (MING LEUNG, 2007).

3. Results of acoustic signal recognition

Sound card and OLYMPUS TP-7 microphone were used to record acoustic signals. Parameters of audio file were: format – WAVE PCM, sampling frequency – 44100 Hz, number of bits – 16, number of channels – 1. Short circuit and broken coils were located in the stator circuit of synchronous motor (Fig. 4). Operational parameters of synchronous motor were following:

- acoustic signal of faultless synchronous motor, $nrotations = 1500$ rpm, $U_{RS} = 100$ V, $I_R = 30.9$ A, $I_w \approx 0$ A,

- acoustic signal of synchronous motor with shorted stator coils, $nrotations = 1500$ rpm, $R_z = 2.5$ Ω, $U_{RS} = 100$ V, $I_R = 31.2$ A, $I_w \approx 0$ A.
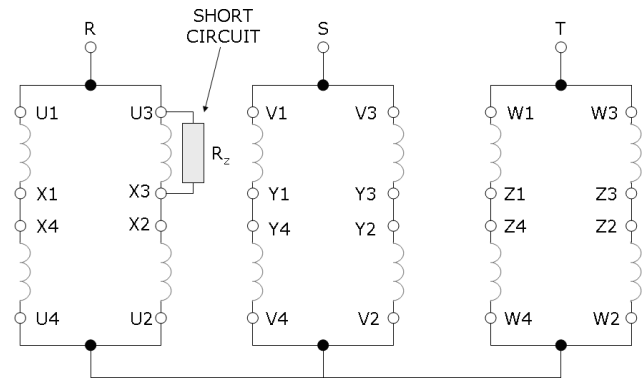

Fig. 4. Scheme of stator winding for the synchronous motor with shorted stator coils (U3-X3).

Moreover synchronous motor operated in open-loop control. In open-loop control feedback loop is not employed. Variations of the system are not detected or corrected. Investigations were conducted for acoustic signal of faultless synchronous motor and acoustic signal of synchronous motor with shorted stator coils (U3-X3).

The pattern creation process was conducted for 5 training samples with a duration of five seconds for each category of acoustic signal. Next 36 test samples were used in the identification process. On the basis of the pattern recognition system should determine the state of synchronous motor correctly. Efficiency of acoustic signal recognition is expressed by following relation:

$$E = \frac{NCITS}{NTS} \, 100\%, \qquad (4)$$

where $NCITS$ – number of correctly identified test samples in the identification process, NTS – number of test samples in the identification process, E – efficiency of acoustic signal recognition.

Figure 5 shows efficiency of acoustic signal recognition of synchronous motor depending on the number of Line Spectral Frequencies coefficients. The best results
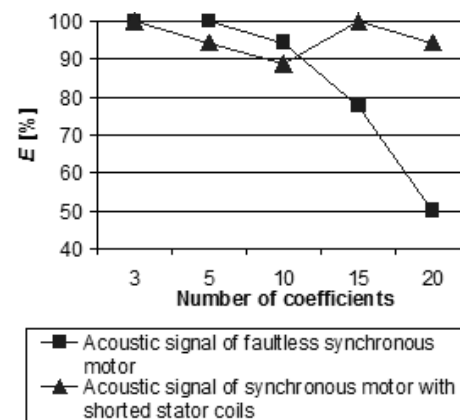

Fig. 5. Efficiency of acoustic signal recognition of synchronous motor depending on the number of LSF coefficients.

were obtained for 3 coefficients. The best recognition results were obtained using the normalization of the amplitude. Parameter r was 4.0. Efficiency of acoustic signal recognition of faultless synchronous motor was 100%. Efficiency of acoustic signal recognition of synchronous motor with shorted stator coils was 100% (Fig. 5). Results of diagnostic system was verified by Matlab.

Figure 6 illustrates efficiency of acoustic signal recognition of synchronous motor depending on parameter k. The best results were obtained for parameter $k = 1, 3, 5$.
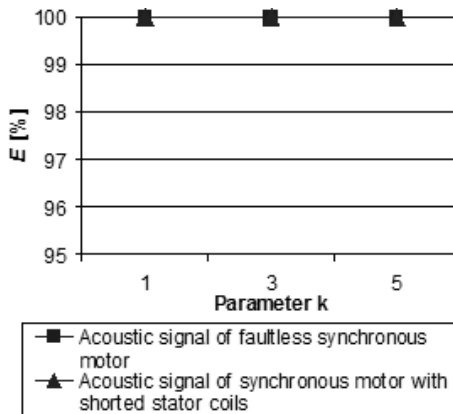

Fig. 6. Efficiency of acoustic signal recognition of synchronous motor depending on parameter k.

4. Conclusions

In this paper, acoustic signal recognition system was analyzed for synchronous motor. Methods of data processing were used for synchronous motor. Results of researches were very good for Line spectrum frequency method and K-Nearest Neighbor classifier with Minkowski distance. Efficiency of acoustic signal recognition of synchronous motor was 100% for 3 coefficients.

A limitation of proposed method is that it can be useful for electric motors with the same parameters and size. Condition monitoring is useful to protect electric motors and mining equipment. In the future, these researches can be used in other electrical devices.

Acknowledgments

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