ARCHIVES OF ELECTRICAL ENGINEERING VOL. 64(1), pp. 29-35 (2015)

DOI 10.1515/aee-2015-0004

Diagnostics of separately excited DC motor based on analysis and recognition of signals using FFT and Bayes classifier

WITOLD GLOWACZ, ZYGFRYD GLOWACZ

AGH University of Science and Technology
Department of Automatics and Biomedical Engineering
A. Mickiewicza 30, 30-059 Kraków, Poland
e-mail: {wglowacz/glowacz}@agh.edu.pl

(Received: 30.10.2014, revised: 22.12.2014)

Abstract: In this article results of diagnostic investigations of separately excited DC motor were presented. In diagnostics were applied a Fourier analysis method based on the fast Fourier transform (FFT) and a recognition method using Bayes classifier. In training process a set of the most important frequencies has been determined for which differences of corresponding signals in two states are the largest. Three categories of signals have been recognized in identification process: faultless state, state of the rotor broken one coil and state of the rotor shorted three coils.

Key words: DC motor, diagnostic investigations, FFT, Bayes classifier

1. Introduction

Diagnostic tests are used to detect possible damages in electric circuits of DC and AC motors [2, 7, 10, 12, 13, 17, 20, 21]. For this purpose the relevant methods of analysis and recognition of measuring signals are used [1, 3, 4, 14-16, 18, 22, 23]. Diagnostic signals that contain information about the state of the motor can be electric, acoustic, mechanical, thermal and other quantities [6, 8, 9, 11, 19]. The basic electrical signals in the diagnostics are currents and voltages in electrical circuits of the motor. Current signals are often used in diagnostics because of the lower sensitivity on the external disturbances in comparison with the voltage signals. This paper presents the results of diagnostics of separately excited DC motor, which uses two signals: the excitation current and the armature current. In the research the method of analysis based on the fast Fourier transform (FFT) and the method of recognition using Bayes classifier [5] have been applied.

2. Bayes classifier

The classifier is based on Bayes theorem described by formula (1):

$$P(C_i \mid X) = \frac{P(C_i)\,P(X \mid C_i)}{P(C_1)\,P(X \mid C_1) + \ldots + P(C_n)\,P(X \mid C_n)}, \tag{1}$$

where: $P(C_i)$ – the probability of the event (category) C_i, $P(C_i \mid X)$ – the probability of the event (category) C_i under the condition that event (signal) X occurred, $P(X \mid C_i)$ – the probability of the event (signal) X under the condition that event (category) C_i occurred.

In the statistical methods presented in 1973 by Richard O. Duda and Peter E. Hart, deciding to assign an unknown signal to the class, we consider the probability of belonging of objects to classes and the costs of misclassification. Bayes classifier assigns a signal to the class for which the posterior probability is highest.

Therefore $X = \{X_1\}$ is assigned to the class ω^L, if there is a relationship (2):

$$P(\omega^L | X_1) \quad \rangle \quad P(\omega^j | X_1), \quad \text{for each } j \in \{1, 2, ..., \mathrm{C}\}, \ \ j \neq \mathrm{L}, \tag{2}$$

when we identify signals in n-dimensional feature space, i.e. $X=\{X_1, X_2,\ldots,X_n\}$, we can use a simple Bayes classifier.

In this classifier is assumed the mutual independence of the features. The probability density distribution of the n-dimensional feature vector is defined by formula (3):

$$p(X\omega^j) = \prod_{i=1}^{n} p(X_i | \omega^j). \tag{3}$$

Another generalization of the Bayes classifier is based on taking into account that not all of the wrong decisions in recognizing an object are the same "expensive" (i.e. have the same negative consequences). In order to take into account this fact, a cost (mistakes) function is introduced. Based on this function and the posterior probability function a risk classifier is defined.

The purpose of this classifier is to minimize the risk function.

3. Measurements of diagnostic signals

The object of the research was separately excited DC motor made by BOBRME KOMEL in Katowice (Fig. 1). This machine allows to implement one broken coil of the rotor and three or six shorted coils of the rotor. The motor had the following data: P_N = 13 kW, U_N = 75 V, I_N = 200 A, U_{fN} = 220 V, n_N = 700 rpm, p = 2, N_r = 42, K = 126.

The motor had a simple loop winding in the rotor and was powered by a voltage generator. Another voltage generator, working on the external resistance, was used as the load for the motor.

The measurements were performed in the laboratory conditions using data acquisition card with sampling frequency of 20 kHz and recording time of 10 s.

The following signals were recorded: the speed of the rotor, the armature voltage, the armature current, the excitation voltage, the excitation current, the current in the rotor shorted coils. For the purpose of the learning and identification processes a multivariate registrations of loaded motor were carried out in following states: faultless state, the state of the one broken coil of the rotor, the state of the three shorted coils of the rotor, the state of the six shorted coils of the rotor, the state of the one broken coil and the three shorted coils of the rotor, the state of the one broken coil and six shorted coils of the rotor, for rotor speeds: 700 rpm, 600 rpm, 500 rpm, 400 rpm.

From the registered quantities as diagnostic signals the excitation current and the armature current were selected.

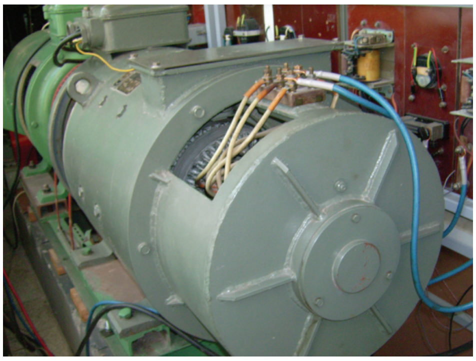

Fig. 1. Separately excited DC motor

4. Analysis and recognition of diagnostic signals

The recorded signals were divided into samples with a length of 0.2 s, 0.4 s, 0.6 s, 0.8 s, 1 s, 1.2 s, 1.4 s, 1.6 s, 1.8 s 2 s. Then FFT analysis of signals was conducted. The results of the FFT analysis of the excitation current and the armature current for a rotor speed of 700 rpm is shown in Figures 2-7.

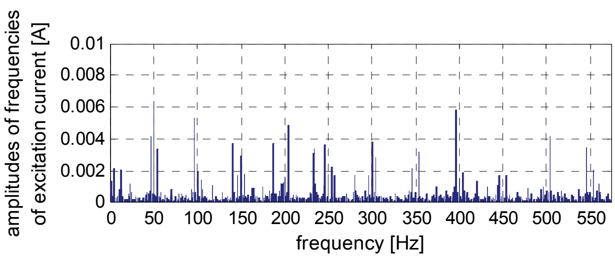

Fig. 2. Frequency spectrum of the excitation current in the faultless state

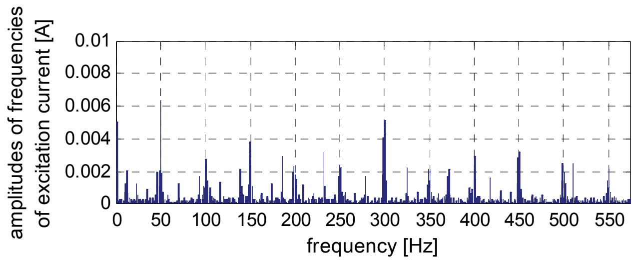

Fig. 3. Frequency spectrum of the excitation current in the state of the one broken coil of the rotor

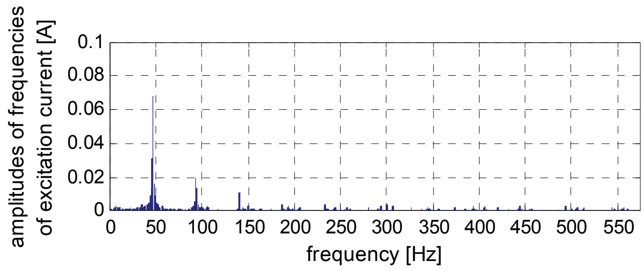

Fig. 4. Frequency spectrum of the excitation current in the state of the three shorted coils of the rotor

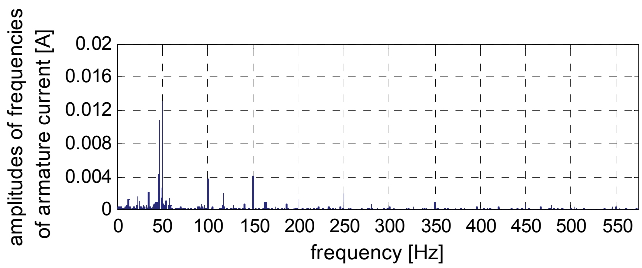

Fig. 5. Frequency spectrum of the armature current in the faultless state

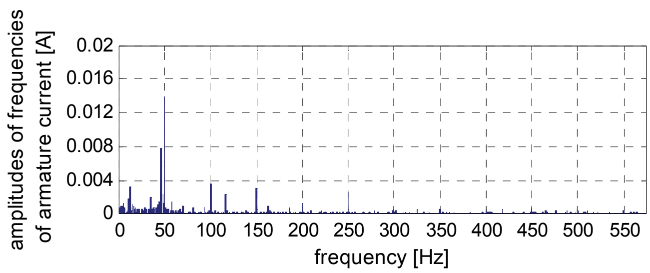

Fig.6. Frequency spectrum of the armature current in the state of the one broken coil of the rotor

For each signal sample length a set of the most important frequencies was defined for which the signal differences corresponding to the motor in two states are the biggest. In learning and identification processes the feature vectors of diagnostic signals for frequencies belonging to the set of the most important frequencies were created. Components of the feature vectors were amplitudes of frequencies of the excitation current and the armature current for three states: the faultless state, the state of the one broken coil of the rotor and the state of the three shorted coils of the rotor.

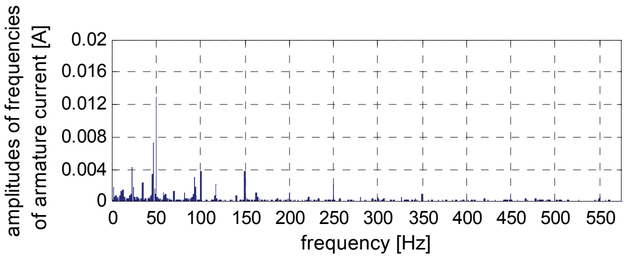

Fig. 7. Frequency spectrum of the armature current in the state of the three shorted coils of the rotor

In learning and identification processes the Bayes classifier was used.

The efficiency of the signal recognition of the motor was defined by the formula (4):

$$E_{ns} = \frac{N_{np}}{N_{nw}} \cdot 100\%, \tag{4}$$

where E_{ns} – the efficiency of the signal recognition of the motor for *n*-second signal samples, N_{np}, N_{nw} – numbers of successful diagnosis and all diagnoses for *n*-second motor signal samples in the states: faultless state, the state of the one broken coil of the rotor and the state of the three shorted coils of the rotor.

The efficiency of the state recognition of the motor was defined by the formula (5):

$$E_n = \frac{E_{nb} + E_{np} + E_{nz}}{3}, \tag{5}$$

where: E_n – efficiency of the state recognition of the motor for n-second signal samples, E_{nb}, E_{np}, E_{nz} – efficiencies of the signal recognition of the motor for n-seconds signal samples in the states: faultless state, the state of the one broken coil of the rotor and the state of the three shorted coils of the rotor.

Efficiencies of the signal recognition of the motor were as follows:

1) in the faultless state:
   a) the excitation current: E_{ns} = 100%,
   b) the armature current: E_{ns} = 100%,
2) in the state of the one broken coil of the rotor:
   a) the excitation current: E_{ns} = 100%,
   b) the armature current: E_{ns} = 100%,
3) in the state of the three shorted coils of the rotor:
   a) the excitation current: E_{ns} = 100%,
   b) the armature current: E_{ns} = 100%.

The efficiencies (E_n) of the state recognition of the motor based on the excitation current and the armature current were equal to 100%.

5. Conclusions

The applied methods of analysis and recognition allow to determine the state of the separately excited DC motor, e.g. the state without faults, the state of the one broken coil of the rotor and the state of the three shorted coils of the rotor, on the basis of diagnostic samples of the excitation current and armature current. In the laboratory conditions the efficiencies of motor state recognition based on the excitation current and the armature current were 100%. The efficiencies of state recognition of this motor in the industry conditions are assumed to be lower.

Acknowledgments
This work has been partly supported by AGH University of Science and Technology, grant No. 15.11.120.445 (Witold Glowacz) and grant No. 11.11.120.354 (Zygfryd Glowacz).

References

[1] Demenko A., *Circuit models of systems with the electromagnetic field* (in Polish). Wyd. Politechniki Poznańskiej, Poznań (2004).
[2] Drozdowski P., Duda A., *Fault detection of induction motors due to the effects of magnetic saturation*. Zeszyty Problemowe – Maszyny Elektryczne 100(I): 33-38, Katowice, (2013).
[3] Dudek-Dyduch E, Tadeusiewicz R, Horzyk A., *Neural network adaptation process effectiveness dependent of constant training data availability.* Neurocomputing 72(13-15): 3138-3149 (2009).
[4] Dudzikowski I, Ciurys M., *Analysis of operation of a car starter with BLDC motor.* Przegląd Elektrotechniczny, 86(4): 166-169 (2010).
[5] Flasiński M., *Introduction to Artificial Intelligence* (in Polish). PWN, Warszawa (2011).
[6] Gieras J., Gieras I., *Electrical Energy Utilization.* Publishing House Adam Marszalek (1998).
[7] Glinka T., *Investigations of electrical machines in the industry* (in Polish). Katowice, ed. I (1998), II (2002).
[8] Głowacz A., *Sound recognition of induction motor with the use of discrete Meyer wavelet transform and classifier based on words.* Przegląd Elektrotechniczny 89(6): 152-154 (2013).
[9] Głowacz A., Głowacz A., Głowacz Z., *Diagnostics of Direct Current generator based on analysis of monochrome infrared images with the application of cross-sectional image and nearest neighbor classifier with Euclidean distance.* Przegląd Elektrotechniczny 88(6): 154-157 (2012).
[10] Głowacz A., Głowacz W., Głowacz Z., *Recognition of armature current of dc motor with application of FFT and Euclidean distance.* Zeszyty Problemowe – Maszyny Elektryczne 84: 179-182, Katowice, (2009).
[11] Głowacz W., *Diagnostics of induction motor based on Spectral Analysis of Stator Current with Application of Backpropagation Neural Network.* Archives of Metallurgy and Materials 58(2): 561-564 (2013).
[12] Głowacz Z, Kozik J., *Detection of synchronous motor inter-turn faults based on spectral analysis of park's vector.* Archives of Metallurgy and Materials 58(1): 19-23 (2013).

[13] Kowalski Cz. T., *Monitoring and fault diagnosis of induction motors using neural networks* (in Polish). Prace Naukowe Instytutu Maszyn, Napędów i Pomiarów Elektrycznych Politechniki Wrocławskiej 57(18), Wrocław (2005).
[14] Łukaniszyn M., *Basis of electromagnetism* (in Polish). Oficyna Wydawnicza PO, Opole (2003).
[15] *MathWorks*, MATLAB and Simulink for Technical Computing (2014).
[16] Noga M., Gołębiowski L., Gołębiowski M., Mazur D., *Synchronous motor control with internal permanent magnets IPMS taking into account the limitations* (in Polish). Zeszyty Problemowe – Maszyny Elektryczne 82: 55-62, Katowice (2009).
[17] Retana R., Paweletz A., Herzog H., *Analysis and Detection of Short Circuits in Fractional Horsepower Commutator Machines, Energy Conversion*. IEEE Transactions on 23(2): 484-491 (2008).
[18] Skomorowski M., *Selected aspects of pattern recognition* (in Polish). Wydawnictwo Uniwersytetu Jagiellońskiego, Kraków (2013).
[19] Sobczyk T.J., *Frequency analysis of faulty machines – possibilities and limitation*. Proceedings of SDEMPED, Cracow, pp. 121-125 (2007).
[20] Sułowicz M., Borkowski D., Węgiel T., Weinreb K., *Specialized diagnostic system for induction motors*. Przegląd Elektrotechniczny, 86 (4), pp. 285-291 (2010).
[21] Szymański Z., *Application of the Magnetic Field Distribution in Diagnostic Method of Special Construction Wheel Traction Motors, Studies in Applied Electromagnetics and Mechanics*. Advanced Computer Techniques in Applied Electromagnetics 30: 449-456 (2008).
[22] Zakrzewski K., Tomczuk B., Koteras D., *Simulation of forces and 3D field arising during power autotransformer fault due to electric arc in HV winding*. IEEE Transactions on Magnetics 38(2): 1153-1156 (2002).
[23] Zawilak J., Zawilak T., *Medium-power synchronous motors excited permanent magnets* (in Polish). Zeszyty Problemowe – Maszyny Elektryczne 100(I): 5-8, Katowice (2013).