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Research and application of artificial neural network to diagnostics of stator winding short-circuit of slip-ring induction motor

Streszczenie. *W artykule przedstawiono zastosowanie sztucznej sieci neuronowej (SSN) do diagnostyki zwarcia uzwojenia stojana z obudową silnika. Zgromadzono zbiór pomiarów przyspieszeń drgań maszyny dla różnych wartości rezystancji, przez którą zwierano uzwojenie z obudową. Rozpatrzono cztery wartości rezystancji oraz cztery wartości momentu obciążenia silnika. Z widma częstotliwościowego przyspieszeń drgań maszyny stworzono zbiór zwierający wartości amplitud o częstotliwościach: 100, 200, 300, 400, 500, 600 Hz. Tak przygotowany zbiór wartości amplitud przyspieszeń drgań uzupełniony o wartości skuteczne prądów fazowych oraz wartość momentu obciążenia posłużył do wytrenowania sztucznej sieci neuronowej. Natomiast odpowiedzią sieci była wartość rezystancji zwarcia uzwojenia stojana z obudową. (**Badania i zastosowanie sztucznej sieci neuronowej do diagnostyki zwarcia uzwojenia stojana w silniku indukcyjnym pierścieniowym**).*

Abstract*. The paper presents an application of an artificial neural network (ANN) to diagnostics of short-circuit between one phase of the stator winding and the motor housing. A set of machine vibration acceleration measurements for different values of resistance, through which winding and the housing was short-circuited, was gathered. Four resistance values and four load torque values were examined. From the frequency spectrum of machine vibration accelerations a set containing the amplitudes values of the frequencies: 100, 200, 300, 400, 500, 600 Hz was chosen. Thus prepared set of the vibration accelerations amplitudes supplemented with RMS phase currents and the load torque values was used to train the artificial neural network. The network response was the value of the short-circuit resistance between the stator winding and the motor housing.*

Słowa kluczowe: sztuczna sieć neuronowa, diagnostyka, silnik indukcyjny, zwarcie
Keywords: artificial neural network, diagnostics, induction motor, short-circuit

Introduction

Because of the many practical applications of three-phase induction motors the technical diagnostics plays a very important role. In particular, it is important to detect early the damage and switch off the machine before major failure occurs. In such cases the methods of on-line diagnostics are very popular. They are based on continuous monitoring of the machine operation, which allows detecting the gradually developing damages. One of on-line diagnostics methods is the study of the induction motor vibration spectrum [5, 8, 9].

Formulation of appropriate relationship between the type and degree of damage and the diagnostic signal is a very complex issue [2, 6]. The main task is to collect a set of measurement results or the results of computer simulations for many types of different damages and then separation and analysis of diagnostic signals. Recognition of types of damages from the results of diagnostic signal analysis is a very difficult task. One of the methods which helps in the identification of the type and degree of damage is the use of artificial neural networks [4, 3, 1].

This paper presents an application of an artificial neural network (ANN) to diagnostics of short-circuit between one phase of the stator winding and the motor housing. A set of machine vibration acceleration measurements for different values of resistance, through which winding and the housing was short-circuited, was gathered. Four resistance values and four load torque values were examined. From the frequency spectrum of machine vibration accelerations a set containing the amplitudes values of the frequencies: 100, 200, 300, 400, 500, 600 Hz was chosen. Thus prepared set of the vibration accelerations amplitudes supplemented with RMS phase currents and the load torque values was used to train the artificial neural network. The network response was the value of the short-circuit resistance between the stator winding and the motor housing.

Selected measurement results

Measurements of vibration accelerations were performed at three-phase induction motor with the following rated parameters: voltage 380 V, star connected, 50 Hz, 2.2 kW power, the stator phase current 4.6 A, cosφ 0.88, 82% efficiency, speed 1400 rev / min, rotor voltage 72 V, rotor current 19 A. To obtain the possibility of modelling different internal damages of the induction motor, the special new stator winding was prepared.

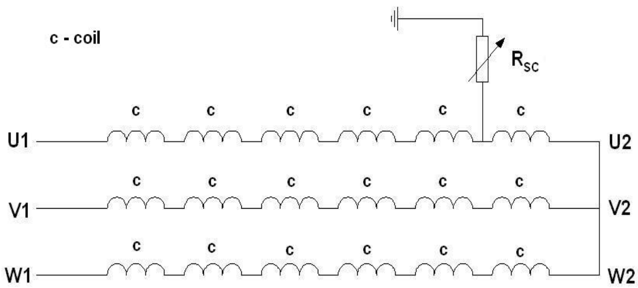

Fig. 1. Terminal board wiring diagram for simulation of a short-circuit between one phase and the motor casing

Many internal points of this winding were connected with the terminals of the external board. Terminal board wiring diagram for simulation of a short-circuit between one phase and the motor casing is shown in Figure 1. In order to obtain various degrees of damage severity the variable resistor is used.

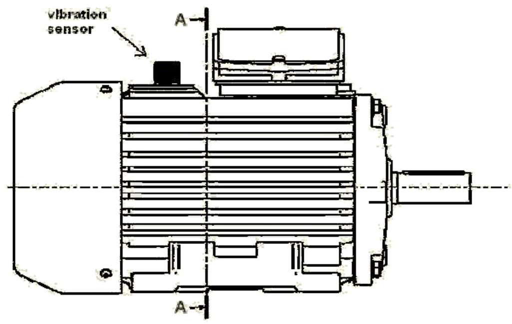

Fig. 2. Placement of the vibration sensor

Measurements were made with the motor mounted on a rigid foundation at commutator test bench in order to allow the adjustment of the load torque. Vibration was measured with a multimeter Svan 914A. The sensor was placed in the vertical axis of the motor (Fig 2).

Measured amplitudes of vibration accelerations (APD) were analyzed. This allowed better visualization of the high-frequency vibration components. In addition, also the currents in the different phases of the motor (IA, IB, IC), the short-circuit current (IA0) and load torque (T) were measured. Figure 3 presents the frequency spectrum of the motor vibration accelerations at rated load torque in case of health motor, i.e. the value of resistance RSC is infinitive. Figures 4-7 show the frequency spectrum of the motor vibration accelerations in case of faulty motor. In order to eliminate the speed and the rotor flux harmonics the fault-tolerant controller based on the indirect rotor field oriented control can be applied [7].

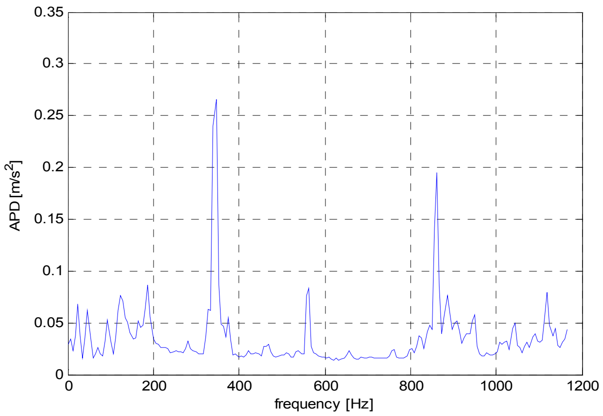

Fig. 3. Vibration spectrum of the health motor, T=13Nm

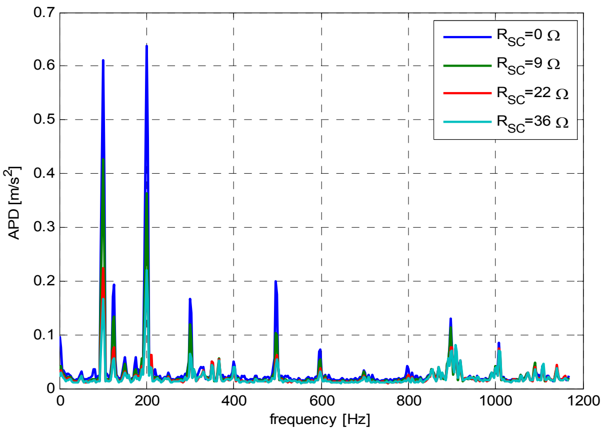

Fig. 4. Vibration spectrum of the motor T=0Nm

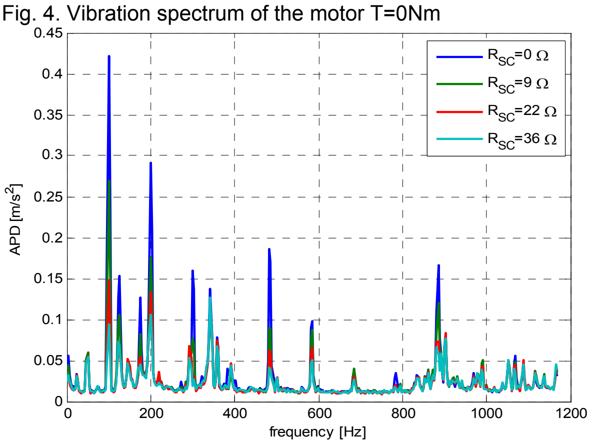

Fig. 5. Vibration spectrum of the motor T=4Nm

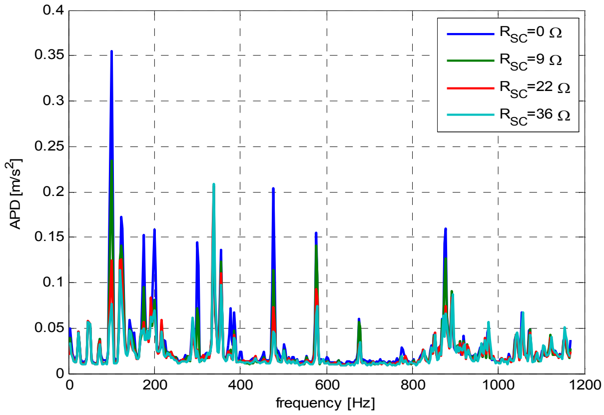

Fig. 6. Vibration spectrum of the motor T=6.5Nm

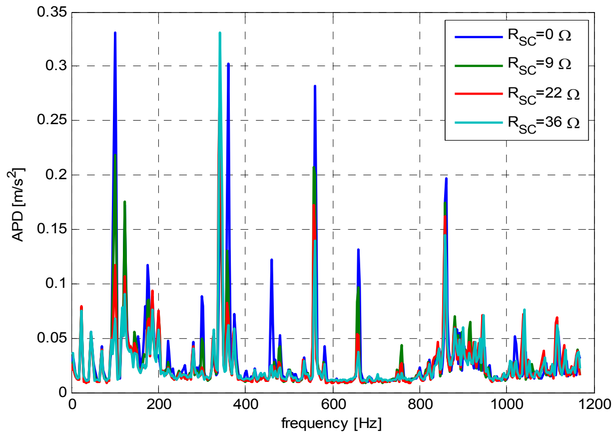

Fig. 7. Vibration spectrum of the motor T=13Nm

Artificial neuron network multiple-layer perceptron (ANN MLP)

In order to determine the degree of the winding damage the one-way artificial neural network multiple-layer perceptron (ANN MLP) with back-propagation was developed. The structure of the network includes 10 neurons in the input layer, and one neuron in the output layer. The neurons in the input layer use a non-linear activation function of the hyperbolic tangent, and in the output layer a linear activation function. ANN MLP structure is shown in Figure 8.

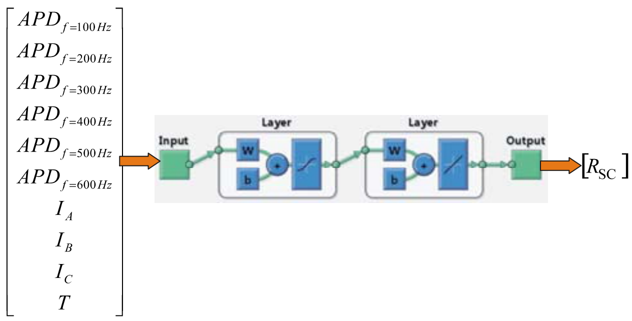

Fig. 8. Structure of the artificial neuron network

The ANN MLP was trained using the data set containing the following groups of parameters: (1) the amplitudes of vibration accelerations (APD) with frequencies f = (100, 200, 300, 400, 500, 600) Hz, (2) the value of effective stator phase currents, (3) torque values. Based on the measured data an input vector was created containing 16 groups of data. The expected result was the value of short-circuit resistance RSCin ohms.

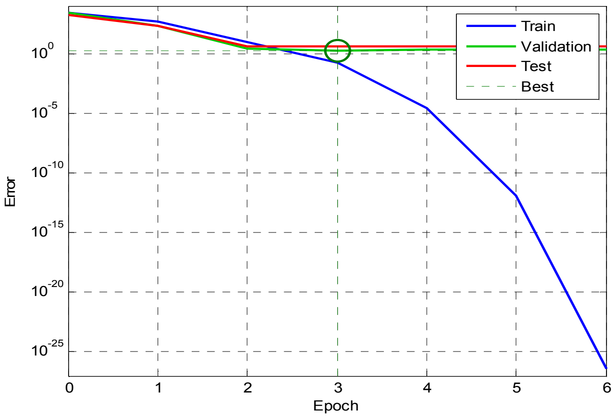

Fig. 9. ANN MLP Learning process

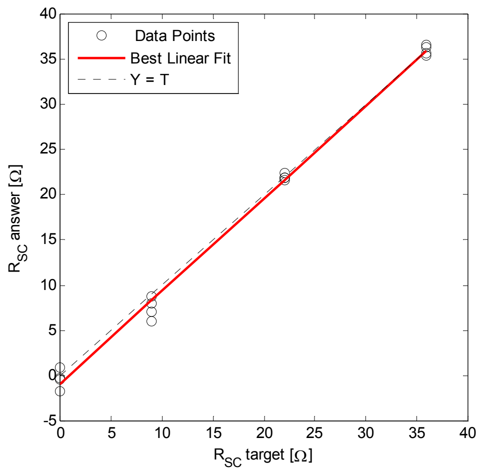

Fig. 10. ANN MLP fit degree

Developed ANN MLP was trained using the Levenberg-Marquardt algorithm. A measure of the ANN MLP fitness was an error calculated as the difference between the expected value and the response of the ANN MLP for the selected input data. If the error is greater than the setup value the network parameters are modified. Then the test is repeated and network response error is calculated. The learning process is repeated as long as the error is larger than assumed. One cycle of the learning process is called an epoch. The process of learning in the various epochs are shown in Figure 9. The degree of fit can be assessed on the basis of ANN MLP response linear regression as a function of the expected value, Figure 10.

Radial basis artificial neuron network (ANN RB)

For the problem under consideration the ANN RB has two layers. The neurons in first layer have radial basis transfer function and linear transfer function in the second layer. This type of the ANN is Radial Basis Artificial Neural Network (ANN RB). The structure of ANN RB is presented in Fig. 10 . The radial basis transfer function can be expressed as follows

$$\varphi(\mathbf{x})=\varphi(\|\mathbf{x}-\mathbf{c}_i\|)=\exp\left(-\frac{\|\mathbf{x}-\mathbf{c}_i\|^2}{2\sigma_i^2}\right) \tag{1}$$

where $\mathbf{c}_i$ – center, σ_i – spread.

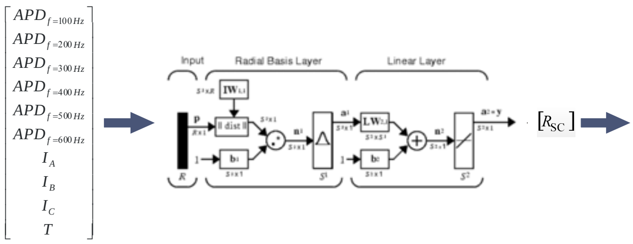

Fig.10. The structure of ANN RB

The classification problem is realized as a sum of radial basis functions. This sum can be expressed as follows

$$f(x)=\sum_{i=1}^{n} w_i\varphi(\|\mathbf{x}-\mathbf{c}_i\|) \tag{2}$$

The training process of ANN RB is a procedure of modifying the weights and biases of each neuron in the network. The procedure ends when the minimum of the objective function of the following form

$$E=\sum_{i=1}^{p}\left[\sum_{j=1}^{n} w_j\varphi(\|\mathbf{x}-\mathbf{c}_i\|)-d_i\right]^2 \tag{3}$$

is achieved.

The application of RBNN ANN RB in diagnosing faults in rotor of electrical machines can be found in [4].

Selected results of ANN MLP and ANN RB testing

Trained ANN MLP and ANN RB were tested with a set of samples that have been involved in training of the network. The results of testing ANN MLP and ANN RB are shown in Table 1 and Table 3, respectively. The difference between the expected value and the ANN response was a measure of the learning effectiveness of the ANN. Error of the damage detection is defined as the difference between the real value of resistance and the network response. The results of ANN MLP and ANN RB are shown in Table 2 and Table 4, respectively. The ANN is trained better when these differences are smaller. In the ideal case, a perfectly trained network, the difference is equal to zero.

Table 1. ANN MLP response

	Expected value	R_{SC} = 0 Ω	R_{SC} = 9 Ω	R_{SC} = 22 Ω	R_{SC} = 36 Ω
T=0 Nm	ANN response	0.00323	6.487	22.894	35.966
T=4 Nm		0.00400	9.032	22.448	36.557
T=6.5 Nm		0.00842	5.641	22.010	35.803
T=13 Nm		0.03375	9.077	22.899	35.998

Table 2. ANN MLP response error

	Expected value	R_{SC} = 0 Ω	R_{SC} = 9 Ω	R_{SC} = 22 Ω	R_{SC} = 36 Ω
T=0 Nm	ANN response error	0.323 %	-27.922 %	4.064 %	-0.0944 %
T=4 Nm		0.400 %	0.356 %	2.036 %	1.547 %
T=6.5 Nm		0.842 %	-30.231%	1.000 %	-0.547 %
T=13 Nm		3.375 %	0.856 %	4.086 %	-0.00556 %

Table 3. ANN RB response

	Expected value	R_{SC} = 0 Ω	R_{SC} = 9 Ω	R_{SC} = 22 Ω	R_{SC} = 36 Ω
T=0 Nm	ANN response	1.421e-13	9.000	22.000	36.000
T=0.4 Nm		8.527e-14	8.999	22.000	36.000
T=0.65 Nm		8.527e-14	9.000	22.000	36.000
T=1.3 Nm		8.527e-14	9.000	22.000	36.000

Table 4. ANN RB response error

	Expected value	R_{SC} = 0 Ω	R_{SC} = 9 Ω	R_{SC} = 22 Ω	R_{SC} = 36 Ω
T=0 Nm	ANN response error	1.421e-11 %	1.224e-9 %	0 %	2.763e-11 %
T=4 Nm		8.527e-12%	-8.882e-11 %	9.043e-11 %	2.763e-11 %
T=6.5 Nm		8.527e-12 %	1.007e-10%	0 %	0 %
T=13 Nm		8.527e-12 %	1.007e-10%	4.522e-11 %	2.763e-11 %

Summary

The paper presents the results of vibration accelerations measurements of the machine at short-circuit between one phase of the stator winding and the motor housing. An artificial neural network was developed to determine the damage degree of the windings (controlled short-circuit resistance value) based on the frequency of vibration amplitudes.

Based on the obtained results it can be concluded that the developed ANN is able to determine the tendency of the stator winding damage worsening. Unfortunately, ANN MLP is not able to accurately determine the degree of the damage. The second type of network (ANN RB) is very suitable for the presented issue of machine faults .

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