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ROTOR DIAGNOSTICS OF INDUCTION MOTORS BY MEANS OF NEURAL NETWORKS

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Abstract - The investigation results presented in the paper are related to diagnostics of induction rotor's cages. The virtual tool shown in the paper was created for investigations as an instrument to measure, to present and to register the stator's current spectrum characteristics. The neuron classifier was constructed to create an instrument enabling to assign the induction motor under test to one of two groups – faultless or defective, and to prove the effectiveness of applying the neuron network in conjunction with the stator's current spectrum analysis to find out damage in the rotor's cage. Two options are described: Kohonen self-organizing feature maps and unidirectional multi-layer perceptrons (MLP). Both the networks have successfully solved the stator's current spectra classification problem assigned to it, and also the technical diagnostics of the rotor's cage condition.

Keywords: motor, neural network

1. BASIC INFORMATION

The neural networks have appeared to be a convenient tool, useful for carrying out a great number of different practical tasks. They successfully find application to an exceptionally wide range of diagnostic problems.

The aim of this paper is to point out the usefulness of the neural networks in diagnostics of induction motors.

Failures occurring in rotor's cages are caused not only by the manufacturer of the motors, but also by their users. However, the reasons for the failures in both cases can vary:

- in the former the cause lies in incorrect execution of cages
- in the latter, heavy or frequent startings occurring in course of operation, which cause some thermal, dynamic, and electrodynamic effects can result in fatigue cracking of bars.

Damages caused to the rotor's cage of an induction motor by operational use can be indicated by:

- variation in the electrodynamic moment characteristic: $M = f(\omega_m)$
- more intensive vibrations of bearings
- current fluctuations in motor
- temperature increment

Magnetic flux Φ_1 excited by the stator's winding, generates a flow in the rotor's asymmetric winding. The flow is characterized by two components [1] :

- positive-sequence component $\theta_2^{(1)}$ rotating in compliance with flux Φ_1 and cooperating with the flux while generating the motor's electromagnetic torque (useful torque),
- negative-sequence component $\theta_2^{(2)}$ rotating at angular velocity in relation to the stator

$$\omega = \omega_m - s\omega_{1m} = (1-s)\omega_{1m} - s\omega_{1m} = (1-2s)\omega_{1m} \tag{1}$$

(where: s - slip, ω_{1m} - angular velocity of the magnetic flux Φ_1)

and exciting in the magnetic circuit its own flux $\Phi_2^{(2)}$ which induces current $I_1^{(2)}$ of frequency equal to *(1-2s)*f_1 (f_1 - fundamental frequency of the supply voltage) in the stator's winding shorted by network.

The interaction of flux $\Phi_2^{(2)}$ with flow $\theta_1^{(2)}$ excited by current $I_1^{(2)}$ flowing within the stator's winding generates an electromagnetic braking torque.

The torque has an effect on the resultant characteristic of the electromagnetic torque in function of the motor's rotational velocity. When the number of damaged bars is significantly large, the mechanical characteristic of the motor M=f(ω_m) can be so deformed that the motor is unable to perform its task.

The diagnostics of the rotor's winding can be carried out [2]:

- in course of the motor's starting or during its regular operation by separating and registering the signal generated by the damaged rotor,
- by fulfilling some particular conditions of the motor's operation during which the damage in the rotor's winding is indicated by the diagnostic signal,
- using the bare rotor to find out the damaged bar, or to check the quality of the aluminium filling in slots.

Under conditions of operational use the most appropriate methods, in general, are those which make it possible to carry out the diagnostics at normal work. One of them is based on the stator's current spectrum analysis under steady state (operational) conditions.

The above method takes advantage of separating the stator's current component $I_1^{(2)}$ excited by asymmetric winding of the rotor. Frequency and amplitude of this component depend on slip s.

The author's sphere of interest is the diagnostics of induction motors by use of spectral analysis of measured electric current supplying a motor. The investigation results are related to diagnostics of rotor's cages.

2. THE CURRENT MEASUREMENTS

Making use of the LabVIEW [4,5] environment it was possible to work out a program which can be applied to measurements, presentation and registration of the stator's current spectrum characteristics taking account of the measurement needs occurring in testing induction motor rotors by use of neuron networks.

The investigated motors have parameters:

- Power 1,1kW
- Current 2,9 A
- Voltage 3 x 380 V
- Rated rotational speed 1400 RPM
- Number of cage's bar : 22

The LabVIEW is a system of software of general use equipped with a built-in set of libraries containing routines for servicing the equipment of data acquisition. The system takes advantage of graphical software language G. The program worked out in this environment is called virtual instrument (VI for short). All LabVIEW VIs have a front panel and a block diagram

The front panel is an interactive software and enables the user to put in entry data by use of the keyboard and the mouse and their two-, or three-dimensional visualization. The block diagram is the graphical source code area. The virtual tool "Pomiar.VI" created for investigations is an instrument used to measure, to present and to register the stator's current spectrum characteristics.

It can be divided into four basic parts:

- Card service
- Signal spectrum analysis
- Visualization of the measured results
- Registration of the results in file

DAQ card type NI 6024E was used. Parameters of the card are: 200 kS/s, 12-bit.

To reach the expected results– resolution of FFT and speed of measurements - it was sufficient to use parameters:

- sampling rate – 1000 S/s,
- frame size – 16384.

Blackman-Harris window gave the best results in interpretation of the spectra.

On account of a low level of the slip components their isolation is practically impossible when using the linear scale. For this reason it is necessary to apply the logarithmic scale.

A typical result of the current spectrum analysis is given in Fig.1.

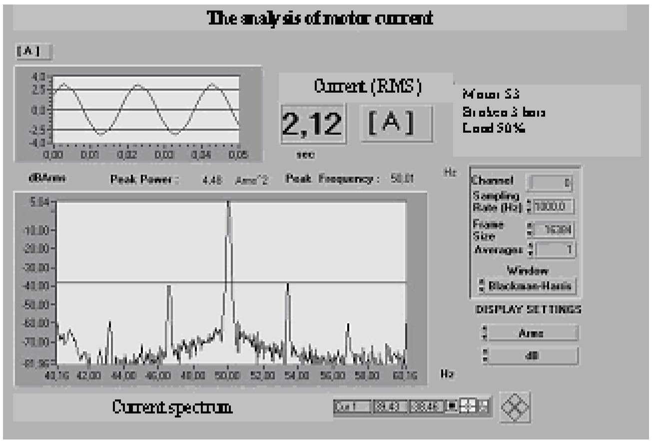

Fig. 1 View of the front panel of "Pomiar.VI" program

The magnitude of the damage is determined by the difference between the fundamental component and the modulating one. Thus, in the case of a faultless motor it varies from 45 to 50 dB, and if the winding of the rotor is faulty it amounts to about 40 dB and gradually declines along with the rising number of the damaged bars.

For the purpose of creating properly working neuron networks it was necessary to have an appropriate number of real characteristics of the stator's current spectra. During the laboratory tests, using program "Pomiar.VI" in LabVIEW environment there were obtained 55 characteristics for the stator's current spectra applying various degrees of motor's loading (idle run was neglected). Each of the obtained spectral characteristics ranging from 0 to 500 Hz had at its disposal 8192 points. If a neural network was constructed taking advantage of the whole set of characteristics, the number of the entry neurons determined by the number of the spectral lines would also have to reach 8192. It has been assumed that the data carrier related to the technical condition of the rotor cage is the interval between 40 Hz and 60 Hz, and since components of slip frequencies for a faulty motor appear at 40-50 Hz and 50-60 Hz intervals, the interval of 50-60 Hz amounting to 170 points has been taken for the analysis. The number of points in this interval was still too high to construct a correctly operating neuron network. The problem was solved in the following way. One spectral line of the utmost value was chosen from each consecutive tenth. Such a procedure reduced the number of points to seventeen (for each spectrum), at the same time retaining satisfactory resolution reaching 0.6 Hz.

The information system created in this way, regarding 55 spectra, has randomly been divided into two sets: 43 spectra have been assigned to the learning set, while 12 spectra, to the testing part. The investigation included faultless and defective motors, as specified below:

- motor S1 – defective
- motor S2 - faultless
- motor S3 – defective
- motor S4 – faultless

Fig. 2 presents the learning data, signal spectrum for successive measurements while load in motor S1 is rising, Fig. 3. illustrates similar spectrum for motor S2.

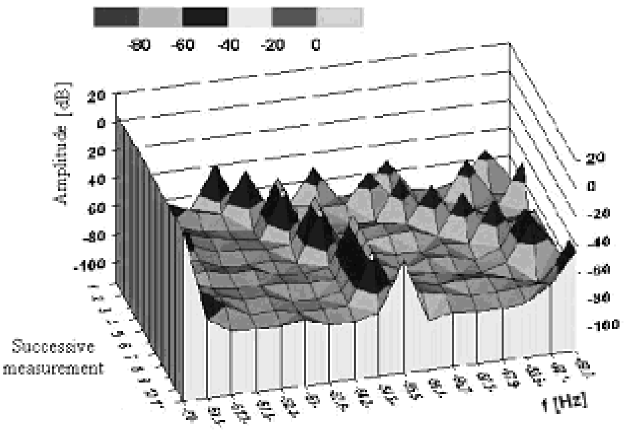

Fig. 2 Stator's current spectra characteristics of motor S1 used for training set

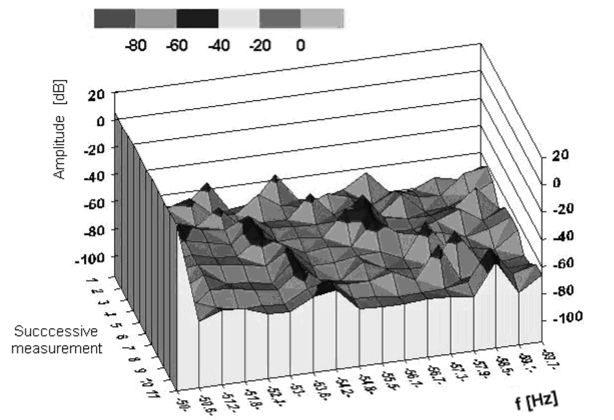

Fig. 3 Stator's current spectra characteristics of motor S2 used for training set

3. THE NEURON NETWORKS

The aim of the constructed neuron classifier was to create an instrument enabling to assign the induction motor under test to one of two groups – faultless or defective, and to prove the effectiveness of applying the neuron network in conjunction with the stator's current spectrum analysis to find out damage in the rotor's cage.

Use has been made of the following types of neuron networks [6]:

- Kohonen self-organizing feature maps
- unidirectional multi-layer perceptrons (MLP)

3.1 The Kohonen network

The Kohonen network is a neuron model carrying out non-standard classification. It consists of two layers, the input layer, where the number of neurons is determined by the structure of the data set, in this case including 17 inputs, and the output layer in which the number of neurons is determined by the user. In the case under consideration the network has 25 neurons in the output layer.

Learning of the Kohonen network was carried out without a teacher, which means, that the learning process was entirely based on the input variables. The learning time is determined by the number of epochs (for this network 500). The learning rate – 0.999 is responsible for the technique of modifying the neuron scales. The large values of this parameter cause a fast modification of the weighing coefficients. The learning radius 3.0 defines the dimensions of the area surrounding the victorious neuron and the neurons that are subjected to modification.

Learning of the network began with a random initiation of the output neuron weights. This procedure was followed by inputting successive spectral characteristics of the stator's current with various loads to the inputs using different motors (effective and damaged).

In each case there was chosen such an initial neuron whose weights were to the utmost degree close to the output values of the vector (this neuron is called the victorious neuron). On determining the victorious vector its weights were so modified as to correspond to the input vector. Similarly, the weights of the neurons neighboring with the victorious one were updated.

The learning procedure performed repeatedly resulted in the creation of a model functioning as a topological map of Fig.4., enabling to test the induction motor stator's current spectrum characteristics.

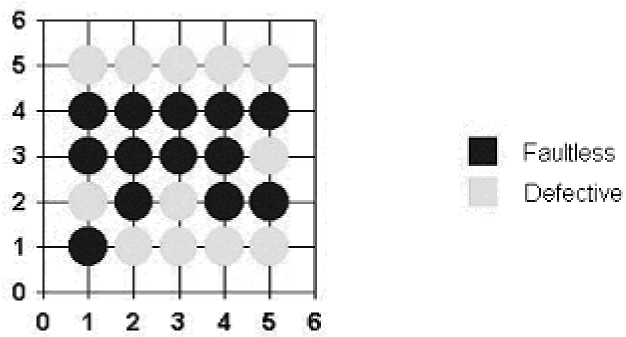

Fig. 4 Diagram of the created Kohonen network

The neurons in the figure in darker colour react to the characteristics of a faultless motor, whereas the neurons in lighter color react to a defective motor. Depending on, which neuron wins, the neuron network will produce a diagnosis : "faultless" or "defective".

3.2 Neuron network of MLP type.

The neuron network of MLP (Multilayer Perceptrons} type is an example of the so called standard classification. The problem of standard classification consists in assigning each test characteristic of the stator's current spectrum to one of two classes:

- defective motor
- faultless motor

However the assignment of respective characteristics to either of the classes is known prior to the accomplishment of the task. In order to solve the problem of classifying the spectra, an MLP network has been designed. The concept of the solution is illustrated in Fig. 5.

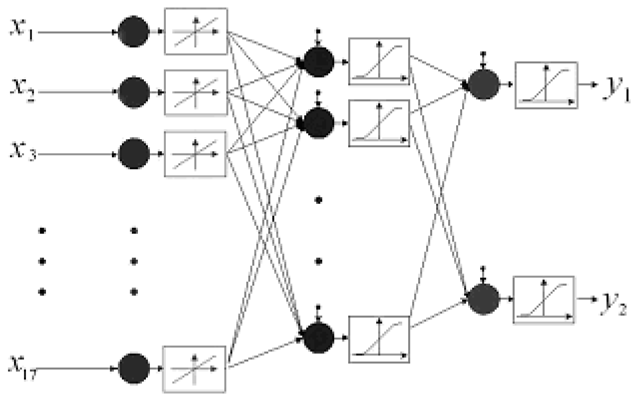

Fig. 5. Diagram of the MLP-type neuron network

The assumed number of neurons within the input layer (amounting to 17) is equal to the number of the input variables – each variable suits one line neuron responsible for putting into the network appropriately transformed values of variables (related to the stator's current spectrum interval under testing).

The network learning was of iterative nature, which means that in consecutive iterations (called learning epochs) the weights and threshold values were modified so as to reduce the value of the global network error. After completing each epoch, the diagram of the network error was updated, which is illustrated in Fig. 6 where it is possible to note the value of error determined by means of the learning set of data.

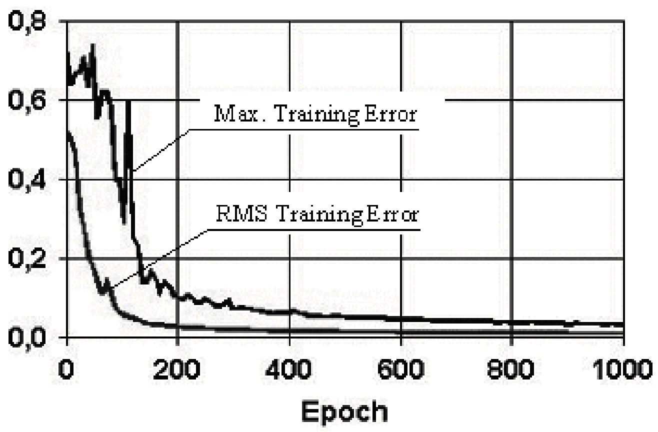

Fig. 6. Diagram of error variations in course of the MLP network learning process

The diagram of the learning error makes it possible to visually check the shaping of the network error calculated by use of the learning set. It can be noted that in course of learning the magnitude of the error is diminishing.

4. INVESTIGATION RESULTS

The Kohonen network created on the basis of the learning set has successfully solved the stator's current spectra classification problem assigned to it, and hence also the technical diagnostics of the rotor's cage condition. Out of 43 spectra of the presented networks in course of the learning process, 41 characteristics were properly classified by the network. Two mistakes were made in the case of faultless motors. They were connected with the direction of teaching the network. In the presented solution, the network reaction should always be correct for defective motors, possible mistakes can arrive in faultless motor investigations. In the set of tests including 12 spectra (three for each motor tested) there did not occur any error in the Kohonen neural network in classifying the motors to appropriate groups (faultless or defective).

The MLP network correctly recognized all of the 43 spectra of the networks presented during the learning process, and like the Kohonen network, did not make a mistake in the test set classifying correctly all the twelve spectra and thus proving its usefulness for induction motors diagnostics.

The standard version of LabVIEW environment is not equipped with neural network module. In the described solution, DataEngine (MIT GmbH) software was used for building the neural networks.

At this stage of creating the diagnostic system, the neural network was not put into VI, which can be done in the future, after an expected development of the system. The direction of planned development is widening the range of recognizing the faults of induction motors - also of mechanical type.

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