APPLICATION OF ARTIFICIAL INTELLIGENCE METHODS FOR ROTOR FAULTS DETECTION OF THE INDUCTION MOTOR

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SUMMARY

The paper deals with rotor fault diagnosis problems of the induction motor using different Artificial Intelligence methods like: neural networks, fuzzy-logic and combined neuro-fuzzy methods. Rotor fault detectors based on these methods were developed. All detectors were trained and tested using measurement data of stator current spectra. The digital signal processor was used for practical realisation of AI-based fault detectors. All detectors were tested in off-line as well as on-line operation. The efficiency of developed neural detectors was evaluated.

Keywords: *induction motors, diagnostics, neural network, fuzzy logic, real time processing*

1. INTRODUCTION

Three phase induction motor is widely used as a main drive for most rotating mechanical loads in the industry due to its ruggedness, low cost and reliability. In such applications the reliability of drive systems is of great importance and the need for fault diagnosis schemes increases significantly nowadays.

Three phase induction motors are the dominant and the preferred machines for most industrial drives. So the diagnostic methods as well as the incipient fault detection of the induction motors is still very important for the exploitation and design of induction motor drives and the problem of fast fault detection and location as well as problem of technical state evaluation is very significant in the industrial practice [1,2,3]. The rotor failures are one of the most frequent electrical faults of IM, especially broken bars of squirrel-cage rotors. The main problem is connected with their destructive character and a tendency to rapid transition. Therefore, early detection of single broken bar during motor operation would eliminate subsequent damage to adjacent bars, reducing repair costs and motor outage time. So current monitoring of the IM state and the early recognition of the growing failure should be performed.

Recently different Artificial Intelligence methods are used for the IM diagnostic problems: neural networks, fuzzy logic and a hybrid method – neuro-fuzzy. These AI methods were applied for the rotor fault detection of the induction motor and three different fault detectors (neural, fuzzy and neuro-fuzzy) were developed. Obtained results were presented and compared in the paper.

2. METHODOLOGY OF THE ROTOR FAULT DETECTION OF INDUCTION MOTOR

Most of recently developed IM faults detection methods based on the analysis of stator current and/or vibration spectra. In the research presented in this paper, the frequency analysis of stator currents and magnitude of Park's vector of the stator phase current was used for the detection purposes [4,6].

In the case of rotor bar failures, the higher harmonics of the stator current occur with characteristic frequency depending on supply frequency f_s and the rotor slip s:

$$f_k=(1\pm 2ks)f_s \tag{1}$$

where: $k = 1,2,3...$

Magnitudes of these harmonics depend on the motor load, fault kind and size but in a non-linear way, what makes impossible the fault detection based on algebraic relations. Thus AI methods are an interesting alternative solution, which enables the development of a fault detector without any complicated algorithmic rules or mathematical models. The magnitudes of harmonics with frequencies described by Eq.1 can be used as input signals for these AI based detectors.

Park's components of stator current vector were calculated from three phase current signals, follows:

$$i_{s\alpha}=\frac{\sqrt{2}}{\sqrt{3}}i_{sA}-\frac{1}{\sqrt{6}}i_{sB}-\frac{1}{\sqrt{6}}i_{sC} \tag{2a}$$

$$i_{s\beta}=\frac{1}{\sqrt{2}}i_{sB}-\frac{1}{\sqrt{2}}i_{sC} \tag{2b}$$

The frequency analysis of the spectrum of the current Park's vector modulus was used for the diagnosis of rotor cage faults. This modulus is the sum of DC component generated mainly by the fundamental component of the motor supply current plus two additional terms, at frequencies of $2sf_s$ and $4sf_s$ [6], which magnitudes depend on the rotor fault extent.

The AI fault detectors presented in this paper, were trained using both signatures simultaneously: magnitudes of slip harmonics of phase current spectrum (f_1, f_2) and magnitudes of frequency components of the current Park's vector modulus (f_3, f_4):

$$f_1 = (1-2s)f_s, \tag{3a}$$

$$f_2 = (1+2s)f_s, \tag{3b}$$

$$f_3 = 2sf_s, \tag{4a}$$

$$f_4 = 4sf_s. \tag{4b}$$

Examples of the line current spectrum and respective Park vector modulus spectrum for the motor with 4 broken rotor bars were presented in Fig. 1.

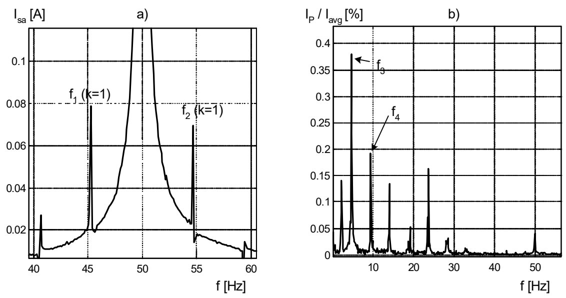

Fig. 1 The stator line current spectrum (a) and Park's vector modulus spectrum (b) for 4 broken rotor bars case

Three fault detectors: neural, fuzzy and neuro-fuzzy were designed and trained for the 1.5kW IM with different failures of changeable cage rotors. These detectors were used for the fault detection and the recognition of fault size (the number of broken bars). The mentioned spectral components (f_1-f_4) were used as input signals of all AI detectors, which were trained using experimental data. These experiments were divided into three stages:

1- measurements of phase currents for the IM with different failures of rotor cages, FFT analysis of phase current and its Park's vector modulus spectra, determination of input signals for detectors;
2- design of the structure for AI detectors, training of neural networks and neuro-fuzzy networks, determination of rule base for fuzzy-logic detector (made off-line using MATLAB);
3- testing of AI detectors working off-line and on-line in the experimental diagnostic system realized using digital signal processor.

For each rotor cage failure five experiments were performed in the same load condition of the motor. The training and testing vectors had the dimension [4x9] and [4x45] respectively.

3. ARTIFICIAL INTELLIGENCE BASED FAULT DETECTORS OF CAGE ROTORS

3.1 Neural fault detector

The neural fault detector had four inputs (magnitudes of components with frequencies $f_1 - f_4$) and one output – the number of broken bars. Different structures of NN were tested, but the best results were obtained for the net 4-25-1 with 25 hidden neurons, with non-linear (sigmoid) activation functions. The output neuron was linear one. The neural network was trained using the average values of suitable harmonics magnitudes obtained in five different measurements for each fault kind.

In case, when learning vector of the NN has little size, effective training of NN is difficult. The NN usually is not able to give correct answer for data different than of learning vector. For this reason the NN was trained with the aid of special algorithm, that schematic diagram was presented in Fig. 2.

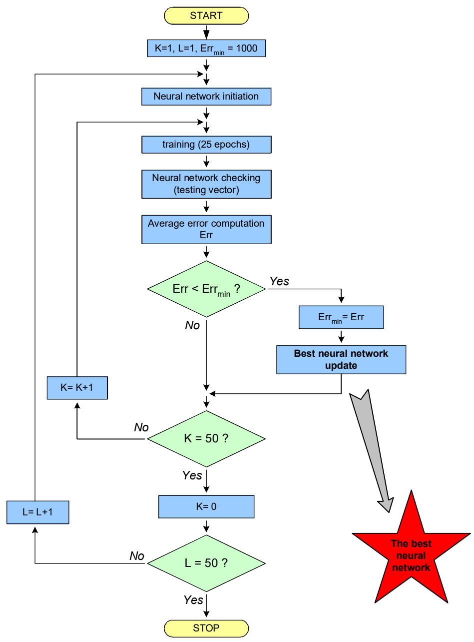

Fig. 2 Flow chart of neural network training algorithm

Numbers K and L in this flow chart indicate iteration counters. Main task of this algorithm is suitable early interrupt of training process, to prevent overtraining of neural network. The Levenberg-Marquardt algorithm was used for NN weights adaptation [5]. For testing other measurement values were used. The NN output information about the number of broken bars was rounded to the integer number. Answers of this detector were presented in Fig. 3.

Obtained results indicate that proposed neural detector recognizes almost perfectly the size of rotor failure: for 45 elements of testing vector, only 2 wrong answers were noticed.

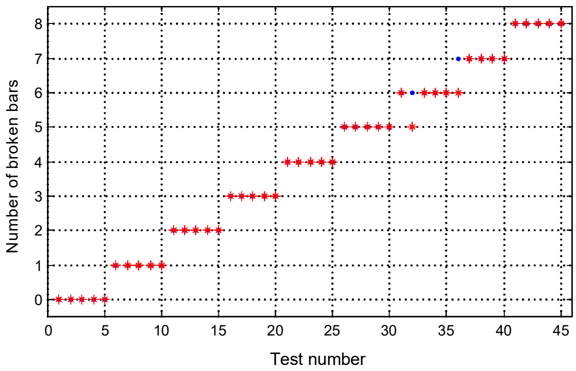

Fig. 3 Answers of neural detector of cage rotor faults for testing vector (dot • means the real failure, sign * means the NN answer)

3.2 Fuzzy-logic fault detector

Fuzzy-logic detector was modelled using Fuzzy Logic Toolbox with MATLAB [5]. Similarly as in the case of NN detector this FL detector had four inputs and one output. For each input nine membership functions were determined: one for each kind of rotor failure. These membership functions were determined arbitrary based on the expert knowledge connected with the range of input signals changes for each fault kind. Rule base was formulated with AND-type implication, i.e.:

IF (Input1 ∈ <one_broken_bar>) AND ... AND (Input4 ∈ <one_broken_bar>) THEN Output=<one_broken_bar>

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IF (Input1 ∈ <nine_broken_bar>) AND ... AND (Input4 ∈ <nine_broken_bar>) THEN Output=<nine_broken_bar>

In the output of the FL detector the number from 0 to 8 was generated, depending on the number of broken bars. In Fig. 4 the rule firing and fuzzy inference for developed FL detector are presented in the case of 4 broken bars.

Presented FL detector was tested for all modelled rotor failures. It worked properly and gave proper answers for all testing vectors. In this approach the expert knowledge is necessary for the determination of membership functions, what not always is possible.

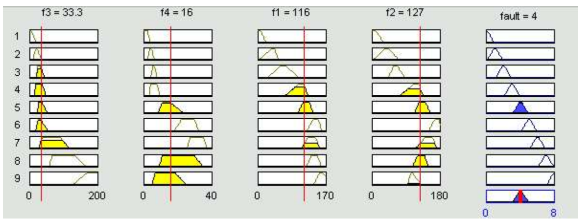

Fig. 4 Rule firing and fuzzy inference for fuzzy-logic detector of the rotor cage of IM with 4 broken bars

3.3 Neuro-fuzzy fault detector

Neuro-fuzzy detector was modelled using ANFIS Toolbox with MATLAB [5]. The input and output signals were the same as for previously described detectors. For each input two trapezoidal membership functions were determined. The network had 16 rules and the same number of output membership functions (Fig. 5).

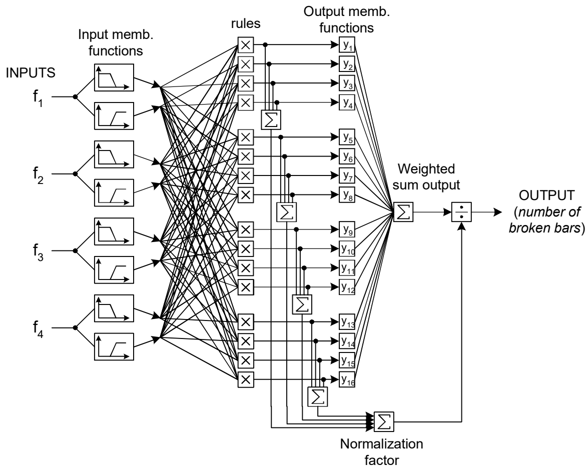

Fig. 5 Neuro-fuzzy network structure for the rotor fault detector

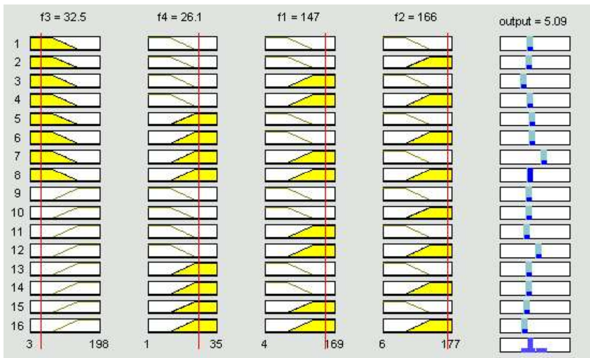

Fig. 6 Rule firing of neuro-fuzzy detector for the rotor cage of IM with 4 broken bars

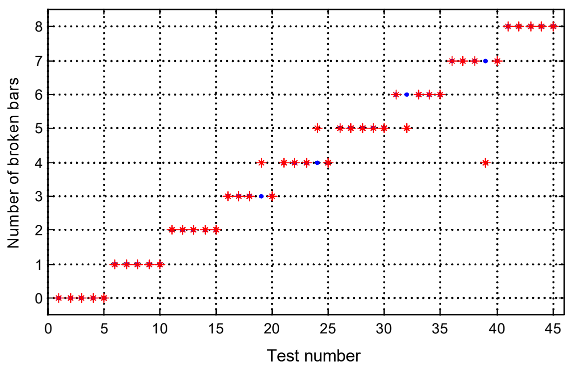

Fig. 7 The answer of neuro-fuzzy detector of cage rotor faults for testing vector (dot • means the real failure, sign * means the NN answer)

The training vector contained two sets of input signals for each kind of the failure. The testing vector was [4x45] – the same as for NN detector. In Fig.6 the rule firing for developed NF detector is presented in the case of 5 broken bars. In the next figure results of testing were demonstrated for this type of fault detector.

This fault detector presents very good performances also; in four cases only the answer of the detector was wrong.

4. TECHNICAL REALISATION OF DSP-BASED FAULT DETECTOR

All experiments were carried out on the laboratory rig with 4-pole 1.5kW induction motor. A mechanical load was provided by DC generator, feeding a variable resistor. The motor was equipped with set of replaceable rotors with broken bars. The set included eight rotors with defect range from 1 to 8 adjacent broken bars. The motor line currents were measured by means of LEM current transducers that were connected to analog inputs of dSPACE DS1102 controller board, equipped with floating point digital signal processor TMS320C31. On-line working fault detector algorithm (Fig.8) was implemented on the controller board, utilizing artificial neural network and neuro-fuzzy methods.

The algorithm was divided into three stages:

- three phase line current recording,
- current signal preprocessing (Park's vector transformation, FFT),
- AI-based detector realization (that was trained off-line before).

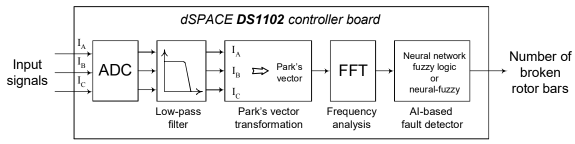

Fig. 8 Scheme of the rotor fault detector realized on DS1102 controller board

During research, rotors with various faults were changed. Individual rotors distinguished different number of adjacent broken rotor bars. During all experiments load torque was constant, equal to nominal value of motor torque.

The experimental results obtained with on-line detector, realized using digital signal processor, were similar to results obtained for the off-line operation. The neural network-based fault detector was found as the best solution of all AI-based methods. It presented the best diagnosis decisions in all simulation and experimental tests.

5. CONCLUSION

Presented experimental results obtained for different AI based fault detectors confirm that neural networks, fuzzy-logic and neuro-fuzzy approach can be effectively used for monitoring and diagnosis of technical state of the induction motors. All these methods enable the development of fault detectors without mathematical modelling of fault type.

One of disadvantages of AI-based rotor fault detectors is poor behavior for the drive with low level mechanical load. To obtain good properties of such fault detectors, constant value of motor torque, equal to its nominal value is necessary.

Researches in the field of AI-based rotor fault detectors working in the wide range of mechanical load torque are being in progress and will be presented in the near future.

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BIOGRAPHIES

Czesław T. Kowalski, M.Sc., Ph.D., has obtained his scientific degrees in 1971, 1983 respectively, at Electrical Engineering Faculty of Wroclaw University of Technology. Since 1983 she has the assistant professor's position at this faculty, in the Electrical Drives Control Chair, in the Institute of Electrical Machines and Drives. He is author and co-author of over 50 scientific papers. His field of interest is mathematical modelling and microprocessor control of electrical drives and power converters, monitoring and diagnosis of the electrical drives using state observers and neural networks.

Marcin Pawlak, M.Sc., has finished his Master Thesis in 1998 and since this year he is an assistant in the Institute of Electrical Machines, Drives and Measurements. His main field of interest is the application of neural networks and microprocessor technique to electrical drives control and diagnosis.

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