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Rotor Fault Detection of the Converter-Fed Induction Motor using General Regression Neural Networks

***Abstract**. This paper deals with the application of the General Regression Neural Networks as the rotor fault detectors of the converter-fed induction motors. The major advantages of GRNN application in the considered task are simplified design process and high quality of data classification. Specific fault symptoms of the rotor damages included in the measured stator current spectrum are proposed as elements of the input vectors of the GRNN-based detector. Diagnostic results obtained by the proposed neural detector of rotor faults are demonstrated.*

***Streszczenie.** W artykule przedstawiono zastosowanie regresyjnych sieci neuronowych (GRNN) jako detektorów uszkodzeń wirnika silnika indukcyjnego zasilanego z przekształtnika częstotliwości. Najistotniejszymi zaletami zastosowania modeli GRNN w opisywanej aplikacji są: uproszczony proces projektowania oraz wysoka precyzja klasyfikacji danych. Zaprezentowano również szczegóły związane z generowaniem przesłanek uszkodzeń, będących elementami wektora wejściowego sieci neuronowej. (**Detekcja uszkodzeń wirnika silnika indukcyjnego zasilanego z przekształtnika przy wykorzystaniu regresyjnych sieci neuronowych**).*

Keywords: induction motor, rotor bar faults, fault detection, general regression neural networks
Słowa kluczowe: silnik indukcyjny, uszkodzenia prętów wirnika, regresyjne sieci neuronowe

Introduction

Induction motors (IMs) are nowadays the most widely used in electrical drive systems due to their high reliability, efficiency and safety, and are frequently integrated in commercially available equipment and industrial processes. Thus problems of their condition monitoring is very important. It can provide useful information so that the motor fault, if any, can be fixed at the earliest opportunity, without affecting the industrial process requirement. Therefore, the main goal is to reduce the maintenance costs and to prevent unscheduled downtime of these drive systems.

Recently, needs of the analysis of actual technical condition of IM drives caused the great development of diagnostic methods and techniques, which could be used in the condition monitoring and fault detection [1].

Traditional diagnostic methods of the IM are based on the frequency analysis of the mechanical vibration and stator current signals. Usually the Fast Fourier Transformation (FFT) is used, but in the last decades the Short Time Fourier Transformation (STFT), the Wavelet Transformation (WT) and the High Order Transformation (HOT) are more and more often applied [1-3].

Characteristic harmonics are searched in diagnostic signals, as the faults of each part of electrical machine are showed by different frequency harmonics. The special analyzers of high harmonics or effective computers with high-resolution measurements cards are required for the precise analysis of diagnostic signals. In PWM (Pulse With Modulation) inverter-fed electrical drives, where the frequency control of the rotor speed is realized, additional problem connected with the changeable frequency of the supplying voltage appears, which makes the analysis of diagnostic signal spectrum more difficult [4-5]. Problems erasing in the fault monitoring and detection of the inverter-fed induction motor using traditional methods enforce looking for a new ways of analyzing the technical state of the electrical drive.

Diagnostic systems use different procedures in a diagnostic process, starting from heuristic knowledge, through mathematical models to the artificial intelligence methods [6]. The diagnosis of the industrial processes can be performed using different elements of knowledge base, like analytical methods, expert systems, neural networks or fuzzy logic reasoning. Faults detection using analytical method is not always possible because it requires perfect knowledge of a process model. In case of not adequate or imprecise mathematical model, false alarms can occur due to estimation errors of the systems state variables or process parameters [1]. Human knowledge and experience are used in the case of the application of the heuristic expert system and during the interpretation of measured signals acquired on-line in the diagnosed plant. This solution is much easier and more useful in comparison with analytical methods, but it is difficult for automatic realization.

On the contrary, the application of artificial intelligence methods, like neural networks (NNs) is rather easy to develop and to implement. Neural detectors can be designed using the data acquired from simulation or experimental tests. Neural models are one of the best methods for detecting nonlinear relations between patterns also in the presence of measurements noises and disturbances in analyzed data [7]. The main advantage of such solution is obtaining on-line information about the type and the „size" of a fault, without developing very complicated mathematical models.

Recently implementations of NNs are very popular in diagnostics of electrical machines. It results from very good abilities of NN in the generalization and classification of data, as well as from effective training of the network for solving of complex tasks. NNs work in diagnostics as detectors of damages [6, 8-15].

The most solutions described in technical literature are based on multilayer perceptron MLP [6, 8-12]. One should mark, that the training and testing process of MLP network requires long time and great computing power, which are disadvantageous features appearing at the stage of the NN detectors' design. Moreover the problem associated with the selection of the NN structure appears, having the significant influence on the quality of the diagnostic task realization. So the special algorithms for optimizing the NN structure are applied which much complicate the process of training. Also the training algorithm requires some parameters to be chosen to obtain the proper results.

The other structures of NN were also tested in the fault diagnosis of induction motors (mainly for rotor bars or rolling bearings faults), like Kohonen, RBF networks [6], wavelet artificial neural networks [13], probabilistic neural networks [14], dynamical neural networks [15] and SVM [18]. The most often described application of NNs in diagnostic is feature selection.

In this paper the possibilities of application of general regression neural networks (GRNN) in the detection of rotor bars faults of the converter-fed induction motor drive are tested. This special type of NNs is characterized by very fast training process, realized automatically [16]. Significant simplifying in the design process of GRNNs, combined with good precision of data classification, even in the presence of disturbances in inputs signals, makes them appropriate for diagnostic process of electrical machines. Applications of GRNNs for classification of defects in electrical motors are rarely met in scientific papers. However beneficial properties of such detectors were mentioned earlier in the analysis of symptoms obtained on the base of mechanical vibrations of rotating machines [17].

This paper presents application of GRNN for the rotor faults diagnostics of the converter-fed induction motor, based on stator current analysis. It should be mentioned that diagnostic tests made for the converter-fed induction motor drives, where fault symptoms are disturbed by harmonics resulting from the modulation of the converter, are not very popular in the technical literature. Neural models presented in this paper can detect the damage appearance in the rotor (broken bars) and moreover exact degree of the damage (number of broken bars).

The paper is divided into five sections. After the introduction part, the issues associated with the realization of neural detectors of broken rotor bars of the induction motor are presented. Next the method of data generation with symptoms of motor defects is described. In the third section some basic issues for GRNN are presented. Then the designed detectors of rotor faults are tested basing on the measurement data obtained in the laboratory setup containing the converter-fed induction motor with exchangeable rotors (with different number of broken bars). The short conclusion summarizes the presented approach and obtained results.

Rotor fault symptoms in the stator current

The spectral analysis of the stator current is one of the most often applied methods (MCSA method) of invasion-less detection of the rotor asymmetry caused by broken bars [1-3, 6, 18-20]. Choice of this physical variable allows getting good diagnostic results without the necessity of the expensive measurements and thus without expansion of laboratory setup and additional cost. Magnitudes of harmonic components of the stator current with the following, characteristic frequencies are being observed under the rotor fault:

(1) $$f_p = (1 \pm 2ks) f_s$$

where:
f_s – fundamental frequency of the stator voltage,
s – motor slip, k = 1,2,3...
The value of motor slip is calculated as follows:

(2) $$s = \frac{\omega_s - \omega_m}{\omega_s}$$

where: ω_s – synchronous angular speed, ω_m – the rotor angular speed.

Increasing magnitudes of the components with characteristic frequencies are symptoms of the rotor defect, however evaluation of their level can give an information about degree of damage. One should notice that changes of the load torque can also influence the motor slip value, what causes that load changes disturb analysis of suitable harmonic magnitudes of the stator current. These relations can hamper the diagnostic process of the motor. In a case of tests realized with slight load, slip and fundamental frequencies will cover each other. As a result, the diagnosis of the rotor damages will be incorrect. The solution for this problem is using the Park vector of the stator current as additional signal in the diagnostic procedure [18, 19]. The stator current vector can be described easily by phase currents of the stator winding:

(3) $$\mathbf{i_s} = \sqrt{\frac{2}{3}}(\mathbf{1}i_{sA} + \mathbf{a}i_{sB} + \mathbf{a}^2 i_{sC})$$

where: i_{sA}, i_{sB}, i_{sC} - values of phase stator currents, $\mathbf{a} = e^{j\frac{2\pi}{3}}$, $\mathbf{a}^2 = e^{j\frac{4\pi}{3}}$.

The stator current vector of the induction motor with healthy rotor can be transformed to a stationary coordinate system (α-β) according to equations:

(4-5) $$i_{s\alpha} = \sqrt{\frac{2}{3}}\left(i_{sA} - \frac{1}{2}\left(i_{sB} + i_{sC}\right)\right)$$
$$i_{s\beta} = \frac{1}{\sqrt{2}}\left(i_{sB} - i_{sC}\right)$$

where: I_m^s - magnitude of the stator current.
Modulus of this spatial vector is calculated as:

(6) $$|\mathbf{i_s}| = I_{\max} = \sqrt{i_{s\alpha}^2 + i_{s\beta}^2}$$

For the symmetrical healthy rotor this modulus has constant value. With the assumption that only fundamental component (f_s) of the stator current is analyzed, we obtain:

(7-8) $$i_{s\alpha} = \sqrt{\frac{2}{3}}\left(i_{sA} - \frac{1}{2}\left(i_{sB} + i_{sC}\right)\right) = \frac{\sqrt{6}}{2} I_m \cos\omega_s t$$
$$i_{s\beta} = \frac{1}{\sqrt{2}}\left(i_{sB} - i_{sC}\right) = \frac{\sqrt{6}}{2} I_m \sin\omega_s t$$

In the case of the rotor fault, harmonics with characteristic frequencies appear in the α-β current components, as presented bellow:

(9-10) $$i_{s\alpha} = \sqrt{\frac{3}{2}}\{I_m \cos(\omega_s t - \alpha) + I_{p1}\cos[(1-2s)\omega_s t - \beta_1] + $$
$$+ I_{p2}\cos[(1+2s)\omega_s t - \beta_2]\}$$
$$i_{s\beta} = \sqrt{\frac{3}{2}}\{I_m \sin(\omega_s t - \alpha) + I_{p1}\sin[(1-2s)\omega_s t - \beta_1] + $$
$$+ I_{p2}\sin[(1+2s)\omega_s t - \beta_2]\}$$

where: I_{p1}, I_{p2}- magnitudes of components with frequencies:

(11) $$f_{p1} = (1-2s) f_s \text{ and } f_{p2} = (1+2s) f_s .$$

After substitution of (9) and (10) to (6) we obtain:

(12) $$|\mathbf{i}_s|^2 = \frac{3}{2}\left(\left(I_m\right)^2 + \left(I_{p1}\right)^2 + \left(I_{p2}\right)^2\right) + 3I_m I_{p1}\cos\left(2s\omega_s t - \alpha + \beta_1\right) + $$
$$+ 3I_m I_{p2}\cos\left(2s\omega_s t + \alpha - \beta_1\right) + 3I_{p1}I_{p2}\cos\left(4s\omega_s t + \beta_1 + \beta_2\right)$$

It can be seen that stator current harmonics cause the appearance of other specific components in the modulus of the stator current vector, with frequencies $2sf_s$ and $4sf_s$ respectively. They are very good symptoms of the rotor faults, as these harmonics are much far away from the fundamental current harmonic than slip harmonics (1).
In the diagnostic procedure three main tasks can be distinguished:

- the data acquisition which is focused on getting the database with symptoms of motor defects;

- the classification of the symptoms;
- the diagnosis of the fault type and size.

The above relationships (1) and (12) describing the characteristic frequencies of the stator current in case of rotor damages enable the calculation of fault symptoms for design of the input vectors for detectors based on NNs.

General Regression Neural Networks

In described case, detection of induction motor damages using neural networks is concentrated on analysis of database containing symptoms of faults appearing in internal structure of the machine. It is possible to assume that in analyzed dataset two subsets $\mathbf{X}$ and $\mathbf{Y}$ can be separated. One of them – $\mathbf{X}$ is related to symptoms of faults, the second – $\mathbf{Y}$ corresponds to different degrees of damages in several cases. So it should be noted that, knowing the relationship between the two subsets (described by a function or using some other model), it is possible to determine elements of one of them based on known data set. In the presented situation, it becomes possible to evaluate the symptoms of damage and to obtain clear information about the state of the machine.

In theory of statistics, issues related to searching of data dependencies usually can be realized with regression solutions. For each elements of data set $\{(x_i,y_i)\} \in \Re$ regression model can be described as follows:

$$y_i = f(\beta, x_i) + \varepsilon_{i,} \qquad i = 1....n, \tag{13}$$

where: ε_i error of observation (from normal distribution with zero mean value and with constant variance), f – regression function, β – regression coefficient, n – number of elements in dataset.

One of the examples, most often described in literature, is related to nonparametric regression, where form of the regression function describing dependencies between variables is assumed as not clearly defined [21]. In many solutions this function is estimated by the Naradaya-Watson model [22]. It is assumed that the weights of the estimator for the record x_i from dataset, near the element x from the data space are described by the equation:

$$w_i = \frac{K\left(\frac{x_i - x}{h}\right)}{\sum_{j=1}^{n} K\left(\frac{x_i - x}{h}\right)} = \frac{K(u)}{\sum_{j=1}^{n} K(u)} \tag{14}$$

where: $K(u)$ kernel of the function f, h – width of a window affecting smoothness of the function.

Estimated regression function is determined using following expression:

$$\hat{f} = \frac{1}{n}\sum_{i=1}^{n} w_i(x) y_i . \tag{15}$$

The most popular kernel function is Gaussian curve, however in the literature other characters of applied functions can be found [21]. Some papers show the feasibility of the realization of the regression assumptions with parallel structure of neural network [16]. Several kernels of regression correspond to activation functions in neural network. In the case analyzed in this paper, Gaussian curve is assumed. Data analysis is realized in relation to points from the data space $\mathbf{X}$ (14), which correspond to the centers of activation functions in several neurons. Location of the input elements with respect to the centers of individual neurons is determined using the formula:

$$D_i^2 = (X - X^i)^T (X - X^i) \tag{16}$$

According to above assumption the regression function (14)-(15) is described, in this case, by the equation:

$$\hat{Y}(X) = \frac{\sum_{i=1}^{n} Y^i \exp(-\frac{D_i^2}{2\sigma^2})}{\sum_{i=1}^{n} \exp(-\frac{D_i^2}{2\sigma^2})} \tag{17}$$

where: σ - coefficient shaping the width of the Gaussian function.

Regression neural networks have *feedforward* structure, therefore exist only one fixed direction of the data flow between different layers of neural network (Fig. 1). The structure of network contains connected neurons, arranged in layers: input, output and hidden. Number of nodes in several layers depends on a size of processed data and assumed number of inputs and outputs.

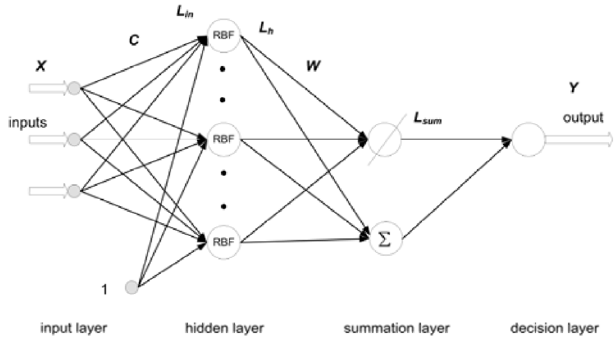


Fig.1. The structure of GRNN neural network

Analyzed NN consists of four layers. Below an algorithm showing software implementation of GRNN and assumed method of weights selection are described. The initial processing step involves the formation of the input vector for the hidden layer. At this stage of neural processing the Euclidean distance between the vector of input values and the centres of radial functions is determined:

$$\upsilon_j(\mathbf{X}) = \left\|\mathbf{X} - \mathbf{C}_j\right\| = \sqrt{\sum_{k=1}^{n}(x_k - c_k)^2}, \quad k = 1,2,3...n \tag{18}$$

where $\mathbf{X} = [x_1, x_2, x_3,...., x_N]^T$ is input vector, $\mathbf{C}_j$ – vector with centers of each neurons.

Next the obtained value is scaled, and achieved results (18) are multiplied by bias value, which is constant for all nodes:

$$\mathbf{L_{in}} = \boldsymbol{\upsilon}\mathbf{b} \tag{19}$$

The level of bias is determined using the following equation:

$$b = (\frac{\sqrt{-\log(0{,}5)}}{\eta}), \tag{20}$$

where: η - scaling coefficient.

The results of the processing described above are input patterns of the activation function calculated according to the equation:

$$\mathbf{L_h} = \mathbf{e}^{-\mathbf{L_{in}^2}} . \tag{21}$$

Achieved results are elements of the output vector of the hidden layer $\mathbf{L_h}$. In summation layer calculations based on vector $\mathbf{L_h}$ and weights values are realized:

$$\mathbf{L_{sum}} = \mathbf{W}\mathbf{L_h} \tag{22}$$

Then, the resulting signals are processed to the decision layer, where following calculation are realized:

$$\mathbf{Y} = \frac{\mathbf{L_{sum}}}{\sum_{q} \mathbf{L_h}} \tag{23}$$

where: q – number of neurons in the hidden layer.

In training process of presented structure of NN, location of centers $\mathbf{C}$ of input neurons and weights values $\mathbf{W}$ of summation layer are determined. For this purpose, in this application the following method was used for determination of the parameters of the neural network:

- the centers of radial neurons are obtained by rewriting the values of the input training data,
- the weights are taken as the output values from the data set used for training.

It should be noted a very short duration of the whole process (*one-pass training method*), in contrast to the algorithms used for training of classical NNs, mostly based on calculation of the derivatives of the objective function according to the weights. In addition, there is no necessity of initial weight values selection, often assumed as random numbers; it means full repeatability of the results.

Generation of input vectors for GRNN

In the diagnostic process of the IM the following stages can be distinguished:

- measurements of physical quantities using special sensors,
- preprocessing of measurement data for fault symptoms extraction,
- classification of the obtained data and fault detection with NN.

The converter-fed induction motor of 3kW nominal power and nominal speed n_N = 1400rev/min was tested. The DC motor mechanically coupled with the tested IM was used as a loading machine. For research purposes the testing IM was equipped with suitable number of specially prepared rotors with artificial faults. In the Fig. 2 the illustrations of the squirrel cage rotors with damaged rotor bars are shown.

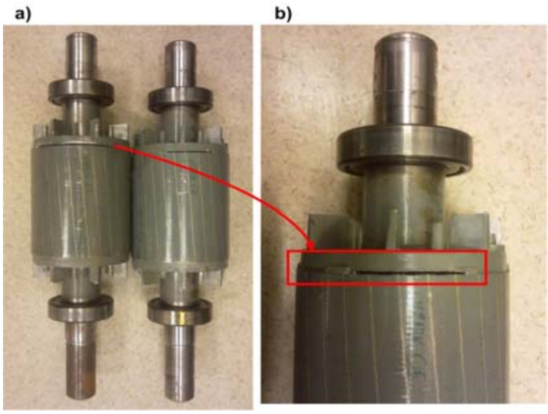


Fig.2. Rotors with different number of broken bars (8 and 4) (a) and zoom of the 8 broken rotor bars (b) prepared using spark erosion machine

The converter-fed drive system has been controlled using simple scalar U/f_s method. Measurement data have been acquired for different supply frequency reference values (reference speed) in the range (5–50 Hz) and five values of the load torque T_L in the range (0–1.25)T_{LN}. Measurements were performed using LEM current sensors and NI PXI-4461 data acquisition card.

For stator current data processing the FFT transform has been applied. Providing the right resolution for frequency is necessary for correct separation of characteristic components in the stator current spectrum. In the analyzed case the measurements were made with the following resolution: df = 0.048 (219 samples in the time sequence 20.97s) in the range of 25kHz.

Based on realized measurements and data processing the following diagnostic symptoms of the rotor fault have been proposed:

- f_s – supply frequency,
- I_{max} – magnitude of the stator current vector,
- s_{l1} – left slip component close to 1st harmonic of the stator current,
- s_{r1} – right slip component close to 1st harmonic of the stator current,
- s_{l5} – left slip component close to 5th harmonic of the stator current,
- s_{r5} – right slip component close to 5th harmonic of the stator current,
- s_{l7} – left slip component close to 7th harmonic of the stator current,
- s_{r7} – right slip component close to 7th harmonic of the stator current,
- s_{lr1} – sum of components s_{l1} and s_{r1},
- s_{lr5} – sum of components s_{l5} and s_{r5},
- s_{lr7} – sum of components s_{l7} and s_{r7},
- p_1, p_2 – fault components extracted from the modulus of the stator current spatial vector, related to its magnitude I_{max},
- p_{12} – sum of components p_1 and p_2.

All slip harmonics were related to the magnitude of the fundamental harmonic of the stator current.

Five different input vectors (set 1 – set 5) for NN were formed, based on those diagnostic symptoms. These vectors contained following sets of signals, respectively:

- set 1: f_s, I_{max}, s_{l1}, s_{r1}, p_1
- set 2: f_s, I_{max}, s_{l1}, s_{r1}, s_{lr1}, p_1, p_2
- set 3: f_s, I_{max}, s_{l1}, s_{r1} s_{l5}, s_{r5}, s_{l7}, s_{r7}
- set 4: f_s, I_{max}, s_{l1}, s_{r1}, s_{l5}, s_{r5}, s_{l7}, s_{r7}, p_1, p_2
- set 5: f_s, I_{max}, s_{l1}, s_{r1}, s_{lr1}, s_{l5}, s_{r5}, s_{lr5}, s_{l7}, s_{r7},s_{lr7}, p_1, p_2, p_{12}.

Results

Data sets for training and testing purposes of GRNN detectors were obtained from experimental measurements of the motor with exchangeable rotors, with different degree of damages. An extensive database, containing 900 records, with 14 diagnostic features each (shown above) was created. The data sets were divided into three parts; two of them were used for training process, the third was used for testing of the designed detectors. So, resulting training sets contained 600 input records; while testing sets had 300 records. Designed neural detectors were tested according to the cross-validation method. GRNNs were trained repeatedly, for all combinations of subsets of teaching data; in every case the last part of data was used in the process of testing. At the output of the network the number of broken rotor bars should be given.

To compare the achieved results, a percentage effectiveness of the detected number of broken rotor bars in the examined number of measured samples was appointed. The quality assessment was taken from the average value of the calculated effectiveness of the fault type detection.

Table 1. The quality of the broken bar detection by GRNN for different input vectors and sets of training data; results obtaining for testing data

$\sigma = 1$				
	Training data_12	Training data_13	Training data_23	mean value[%]
set1	29.7	28.3	26.7	28.2
set2	27.7	29.0	29.3	28.7
set3	83.7	88.3	85.3	85.8
set4	86.7	91.0	87.0	88.2
set5	84.7	92.0	86.3	87.7

In the Table 1 testing results for all combinations of training subsets, used in training and testing process of the designed GRNN are presented. For detectors with the greatest efficiency a graphical presentation of achieved results is shown in Fig. 3. The direct results given by GRNN-based detector are shown in Fig. 3a, while in Fig. 3b the rounded values are presented.

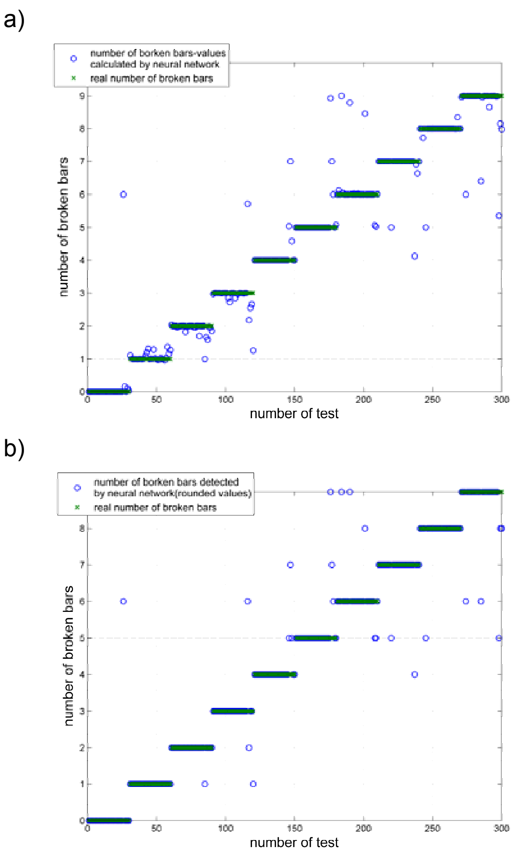


Fig.3. Graphical presentation of GRNN detector results for data-set 5 (σ = 1) (for testing data): direct NN calculation results (a), rounded results (b)

Best results were obtained for the most extended input vectors of GRNN – set 4 and set 5. In the case of set 1 and set 2, satisfying accuracy of correct detections was not obtained, because the input vector did not contain the sufficient information about fault symptoms describing the rotor damage.

Due to almost negligible difference in the accuracy obtained with those two last sets of NN input vectors (set 4 and set 5), it could be said, that the shorter vector (set 4) is enough and should be used for the detector based on GRNN, due to a greater simplicity of the NN structure.

It should be mentioned that a very good accuracy of the fault level detection with GRNN was obtained in the presence of the load torque change and inverter supply of the IM, even for the incipient fault (one or two faulted rotor bars) This last issue is especially important, because in the case of electrical drives supplied by converters, fault symptoms connected with characteristic harmonics of the stator current are disturbed by harmonics connected with the converter modulation.

For evaluation of generalization abilities of designed GRNN detectors, analogical results are presented in Table 2, but these are obtained for training data. Generally, it is possible to observe better results than before, but it is important that calculations of GRNN-based detectors for different testing data are very accurate also.

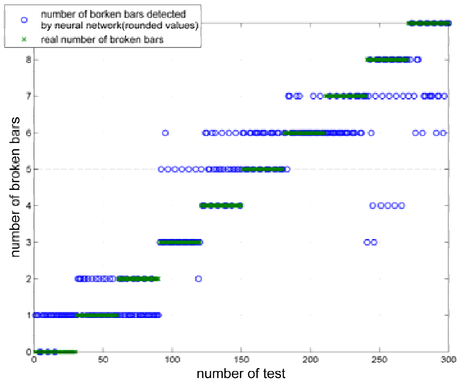
Table 2. The quality of the broken bar detection by NN for different input vectors and sets of teaching data, results obtained for training data

$\sigma = 1$				
	Training data_12	Training data_13	Training data_23	mean value[%]
set1	27.5	28.67	29.83	28.67
set2	30.0	30.33	31.83	30.72
set3	96.5	96.67	97.33	96.83
set4	98.67	97.5	98.33	98.17
set5	100.0	99.67	99.67	99.78

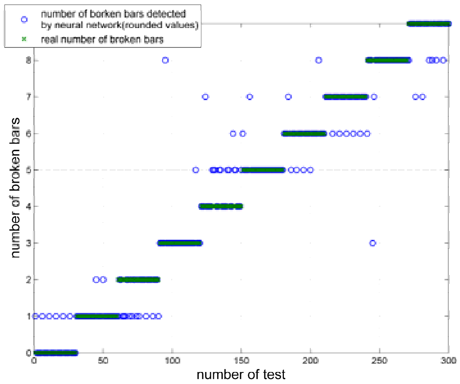
Results presented in Fig. 3 are obtained for the GRNN parameter σ = 1. This parameter highly influences the detection quality. So in the next stage of tests, the influence of this spread parameter σ on the detection quality was checked, and the obtained results for the data set 4 are shown in Fig. 4.

Basing on these results it can be concluded that the reducing of the σ value causes the increase in the accuracy of the fault detection. It is caused by the fact that for smaller σ values a greater number of networks input values exist, for which neurons in the radial layer are operating in the range of greater changes of the output value; so the greatest effectiveness of the network action is obtained. In the other way, with reducing of the parameter σ the most accurate calculations in pattern layer are obtained for bigger compatibility between the input data and centers of the radial functions. In such case the activation function is very steep. The precision of detection, realized by NN is increasing, but on contrary – the generalization abilities are lowering. Concluding, in presented tests selected value of parameter σ should be chosen depending on the obtained precision of the detection and also in a context of the generalization properties. The similar tests with different σ values were carried out for the input vector from the set 1, which is minimal from the point of view of the information used in NN training.

a)



b)



c)

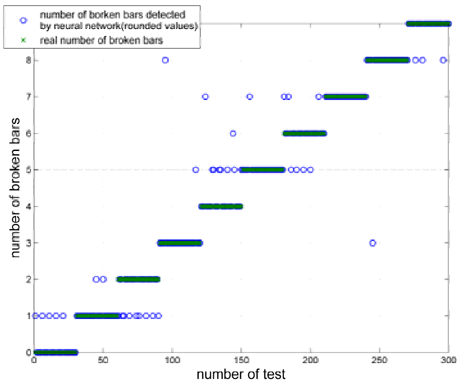


Fig.4. Graphical presentation of GRNN detector results for data set 4 and chosen σ values (for testing data): (a – σ =0.5, b – σ =0.1, c – σ =0.05); rounded values

In the case of GRNNs their structure considerably depends on the dimension of training data. Based on a smaller input vector and simplified topology of NN, the reconstruction of the output data is more difficult. Therefore for the NN with the smaller structure better fitting to training data is required. Results for neural detectors with this minimal input vector information and with different values of spread parameter σ are presented in the Table 3. With increasing σ value, simultaneous increase of the detection quality of neural detectors working with the shortest input vector (set 1) is simultaneously observed. The interesting phenomenon was observed for the detector developed for the spread parameter $\sigma = 0.01$. During the test algorithm returned the warning about dividing by zero. This error in neural calculations for small values of spread parameter σ is resulting from the specific structure of GRNN. Input values of radial neurons are Euclidean distances between input and centers scaled by the value $0.8326/\sigma$.

Table 3. The quality of the broken bars detection by GRNN with minimal input vector and different σ value

Training data_12, set1	
σ=1	29.7
σ=0.5	45.3
σ=0.1	81.3
σ=0.05	87.0
σ=0.01	67.7 (Warning: division by zero)

If the value of σ is very small, then values of biases are very big. Scaling the input signal of nodes in the pattern layer in such a way causes that output values of individual neurons are accepting nulls. In the summation layer dividing by sum of output values from previous layer is realized, and then the warnings about errors in calculation are appearing. Thus the proper selection of the spread coefficient is important issue and suitable compromise between this value and size of the input vector must be done in the case of GRNN application for fault diagnosis of the induction motors.

Another issue, important for practical implementation of the presented diagnostic method, can be observed for all graphical presentations shown in Fig. 3 and Fig. 4. Besides very high diagnostic efficiency, there is no indication of a "healthy rotor" for existing broken bar cases.

Conclusions

In this paper a new idea of using GRNN structure for rotor fault detection of converter-fed induction motor is proposed and results of practical implementation are presented. There are many papers presenting classical MLP neural networks in diagnostics of electrical machines. However just a few works propose the application of GRNN in the field of rotating machines, not for the electrical faults of induction motors. Presented high quality results and simplified design process lead to the conclusion that GRNN networks can be an alternative to classical MLP networks, widely used before in the diagnostic task of the induction motors.

A simplified process of the detector design and training is a most valuable advantage for this type of NN. The only design parameter is the spread s of the RBF activation function. The suitable choice of this value is very important from the point of view of the detector accuracy. Even for very short input vector (like in data set 1) and thus simple structure of NN, a good accuracy can be obtained, when spread s takes a very small value. But on the other hand, for very small s coefficient some errors, related to the precision of calculations, are observed. So, from the practical point of view is better to choose the more extended input vector of the GRNN-based fault detector and use bigger value of the spread factor.

Very good results for the rotor fault classification of the induction motor in the presence of the load changes and converter supply harmonics are obtained. A possibility of detecting the degree of damage (number of broken rotor bars) is an additional advantage of the proposed GRNN-based detectors.

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