2(37), No. 2, 2017 DOI: 10.5277/PED170209

APPLICATION OF NEURAL NETWORKS TO DETECT ECCENTRICITY OF INDUCTION MOTORS

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Abstract: The possibility of using neural networks to detect eccentricity of induction motors has been presented. A field-circuit model, which was used to generate a diagnostic pattern has been discussed. The formulas describing characteristic fault frequencies for static, dynamic and mixed eccentricity, occurring in the stator current spectrum, have been presented. Teaching and testing data for neural networks based on a preliminary analysis of diagnostic signals (phase currents) have been prepared. Two types of neural networks were discussed: general regression neural network (GRNN) and multilayer perceptron (MLP) neural network. This paper presents the results obtained for each type of the neural network. Developed neural detectors are characterized by high detection effectiveness of induction motor eccentricity.

Keywords: *neural network, general regression neural network, multilayer perceptron, eccentricity, induction motor*

1. INTRODUCTION

Diagnostics and monitoring can influence the exploitation costs of the whole electrical drive. Detection of damages in initial phase leads to appropriate action, thus preventing their expansion to other motor components. In addition, efficient diagnosis may be important in complex industrial drives where motor failure can result in downtime of the whole system. Application so-called invasionless methods of damage detection of induction motors (IM) seems to be especially advantageous. Methods based on the analysis of stator current or mechanical vibrations are the most often applied because of their high effectiveness. The essential problem in the issue of diagnostics is a correct evaluation of the obtained symptoms of damages. A review of the detection methods of induction motor eccentricity using stator current analysis has been presented elsewhere [1].

In the last years, implementations of neural networks (NN) in IM diagnostics have been often appearing, due to their very good generalization abilities and classification of data as well as effective NN training for the solving complex tasks. Those models are

Manuscript received: October 18, 2017; accepted: November 22, 2017.

one of the best methods for detecting nonlinear relations between patterns also in the presence of measurements noises and disturbances in the analyzed data. Fault symptoms are introduced as inputs of such structures, however at the output the information about the defect appearance and often degree of the motor damage is obtained. Solutions with classical multilayer perceptrons (MLP) have often been presented [2]. Training of the models is time consuming and may require a considerable computing power, being an obstacle, especially at the stage of the neural detector design. Moreover, the problem of an important significance for the quality of the diagnostic task realization arises, associated with the selection of the NN structure. For the NN structure optimization, special algorithms should be used, which complicates the training process. Apart from that, preparing the MLP network for fault detection tasks requires the selection of many parameters of the NN model and a training method [2–5]. Other structures of NN were also tested in the fault diagnosis of induction motors, like Kohonen or RBF networks [2, 4, 6].

In this paper, the possibilities of application of the general regression neural networks (GRNN) and multilayer perceptrons in the detection of the IM eccentricity are tested. GRNN is characterized by very fast training process, realized automatically [7]. This special type of NNs is applied for prediction, modelling, classification, and data analysis [8]. Significant simplification in the process of GRNN design, combined with good precision of data classification, even in the presence of disturbances in inputs signals, predisposes this kind of NN for diagnostic process of electrical motors. Applications of GRNN for defect classification in electrical motors are rarely met in scientific papers. In this paper, the MLPs have been used to detect the type and degree of eccentricity. Various structures of neural detectors were investigated.

2. SYMPTOM VECTOR GENERATION

Approximately 80% of mechanical damages of induction motors leads to eccentricity. It should also be noted that the eccentricity can occur during the production of the machine or during the installation process. Monitoring of eccentricity makes a lot of problems because it must be carried out during normal motor operation (on-line), non-invasive, so as not to change the balance of forces acting on the machine. Detection of the eccentricity is a very important part of monitoring and diagnosis of the IM.

In this work, the field-circuit modelling is applied to the mathematical modelling of various types of eccentricities [5, 9, 10]. Spectral analysis of the phase current of the IM model with different levels of static, dynamic and mixed eccentricities, allowed obtaining testing and learning data set for developed neural networks.

Eccentricity of the electrical machines is a state when an unsymmetrical air gap appears between the stator and the rotor [5]. Slight crossing of tolerance limits of the length of the air crack can lead to the friction between the rotor and stator and in consequence to the stator or the rotor damage. It can also intensify the influence of other negative phenomena such as power asymmetry, damage of the rotor or stator circuits, overloading motor operation, etc. There are three types of eccentricity: static, dynamic and a mixed one. Asymmetry of the air gap can disturb current transients, which is a result of characteristic changes in mutual magnetic couplings between the motor windings. In the case of induction motors, an additional frequencies appear in the spectrum of the stator current, described by the equation:

$$f_e = f_s\left(\left(kN_r \pm n_d\right)\frac{1-s}{p_b} \pm n_w\right) \tag{1}$$

where: f_s – nominal frequency of the stator supply, s – motor slip, k = 1, 2, 3, ..., N_r – the number of rotor slots, $n_d = 0$ for static eccentricity, n_d = 1, 2, 3 ... in the case of dynamic eccentricity, p_b – the number of motor winding poles, n_w = ±1, ±3, ±5, ±7, – harmonic order.

Moreover, the simultaneous occurrence of static and dynamic eccentricity in the stator current spectrum is connected with new components with frequencies close to the supply frequency:

$$f_{ed} = \left|f_s \pm kf_r\right| \tag{2}$$

The spectral analysis of the stator current cannot be successfully applied to all types of squirrel-cage induction motors. The main reason is that, only those machines that have a suitable combination of the number of rotor slots can generate characteristic high frequency components in the stator current spectrum. To be able to observe the characteristic harmonics for static and dynamic eccentricities, the number of rotor slots N_r and the number of motor winding poles p_b must satisfy the following relation [11]:

$$N_r = 2p_b\left[3\left(m \pm q\right)\right] \pm k \tag{3}$$

where: $m \pm q$ = 0, 1, 2, 3, …, and k = 1 or 2.

Experimental modelling of eccentricity in the real machine or in a laboratory is very difficult, so for the generation of diagnostic symptoms the mathematical field-circuit model of the tested motor was used. The nominal parameters of tested machine (Sh-90L-4) are: power P_N = 1.5 kW, speed n_N = 1410 rpm, electromagnetic torque M_N = 10.16 N·m, voltage U_N = 400 V, current I_N = 3.5 A, power coefficient $\cos\varphi = 0.79$, number of the rotor cage bars N_r = 26. This model was constructed using the Maxwell 2D software (transient module). The geometry of the field-circuit model with a part of the discretization grid is presented in Fig. 1. In the field part of the model, the static, dynamic and mixed eccentricities were taken into account (by the appropriate moving of the stator and/or rotor along the x-axis). In any case, the center of the rotation remained unchanged in the origin of the x-y coordinate system.

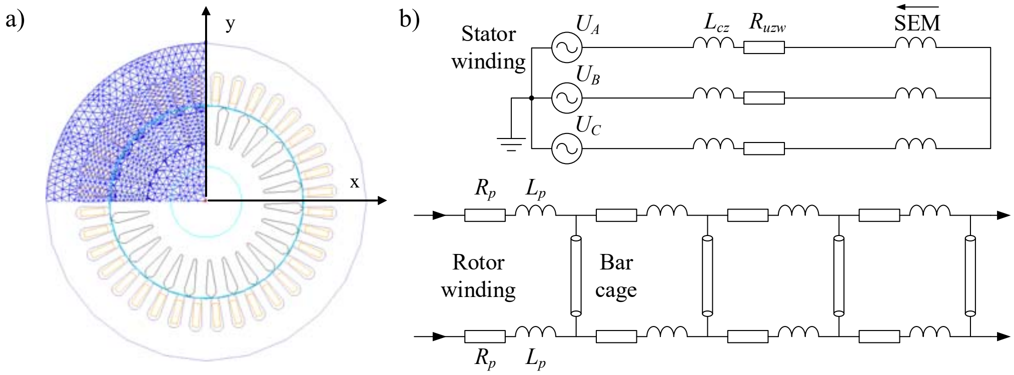

Fig. 1. The geometry of the IM field-circuit model with a part of the discretization grid (a), and scheme of the circuit part (b)

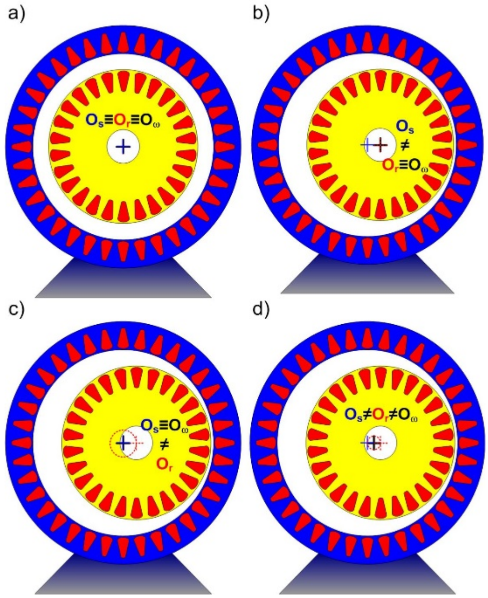

Fig. 2. Coaxial and eccentric position of the rotor in the stator hole:
a) motor without eccentricity, b) static eccentricity, c) dynamic eccentricity, d) mixed eccentricity

Figure 2 shows the coaxial and eccentric position of the rotor in the stator hole, where: O_s – axis of the stator symmetry, O_r – axis of the rotor symmetry, O_ω – axis of the rotor rotation.

Preliminary analysis of the stator current spectrum allowed determining which characteristic components are the best for NN training (the amplitude of those components varied linearly upon increasing eccentricity). In Figure 3, an exemplary spectra of stator current with the IM eccentricity obtained by the field-circuit modelling are presented.

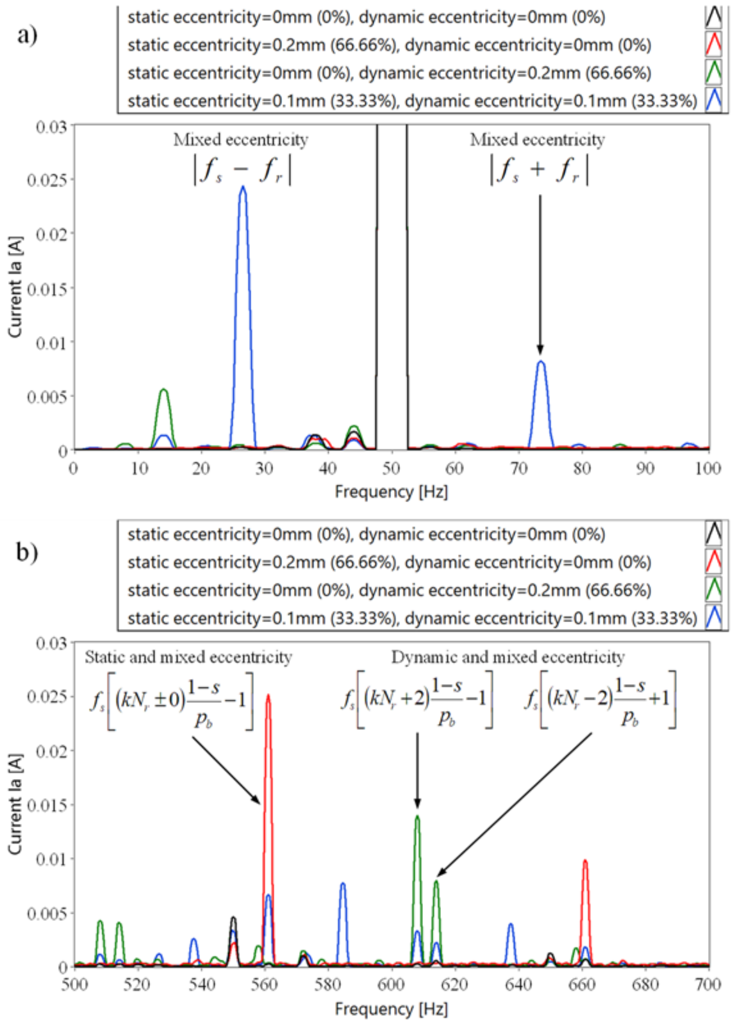

Fig. 3. Spectra of the stator current for Sh-90L-4 motor (nominal load) without and with different types of eccentricity: (a) low-frequency band, (b) high-frequency band

3. NEURAL NETWORKS

In the preceding section, techniques used for fault symptoms generation have been presented. Based on the described methods, a large database of those symptoms was acquired. Direct analysis of the obtained results is difficult due to large number of data. In the paper, the analysis related to the fault detection is conducted by the NN.

Neural networks are models with structures and operating principles inspired by biological nerve cells. Their typical features are: adaptive abilities, parallel data processing, approximation, generalization of data, classification and prediction. Properties of neural networks dedicate them to applications in many fields of science and engineering. Increase of real hardware implementation of NN is connected with progress in microprocessor techniques, digital signal processors and FPGA platforms.

3.1. GENERAL REGRESSION NEURAL NETWORK

The application of GRNN for detection of induction motors eccentricity has been presented taking into account their good ability to approximate and generalize measurement data sets [10]. These models are parallel implementation of statistical rules in the structure of artificial neural networks. A basic task for regression is finding relations between output variables **Y** and input variables **X**, based on data containing representative set of elements for the analyzed field. If we assume that **X** is a vector containing known inputs, it is possible to define the following scalar function [7]:

$$D_i^2 = (\mathbf{X} - \mathbf{X}^i)^T (\mathbf{X} - \mathbf{X}^i) \tag{4}$$

The parameter D_i^2 gives the information about the difference between two vectors. Using this factor, the estimate of vector **Y** can be calculated:

$$\hat{\mathbf{Y}}(\mathbf{X}) = \frac{\sum_{i=1}^{N} \mathbf{Y}^i \exp\left(-\frac{D_i^2}{2\sigma^2}\right)}{\sum_{i=1}^{N} \exp\left(-\frac{D_i^2}{2\sigma^2}\right)} \tag{5}$$

where: σ – the width of sample probability for each sample $\mathbf{X}^i$, $\mathbf{Y}^i$ (smoothing parameter).

The GRNNs have feed-forward topology that means that there is one fixed way of signal propagation between several layers in the network (Fig. 4). This structure contains neurons grouped in layers (input, output and hidden). There are no connections between neurons in the hidden layer, therefore executing parallel calculations is possible. This feature is very important in a hardware implementation of the NN (e.g., using FPGA) [12]. In the regression theory, final equations describing the estimate value of output parameters use an exponential function, however in the process of the design and realization other activation functions, like sigmoid or radial basis functions (RBF) can be used.

Neural network presented in Fig. 4 consists of four layers. The former one is the input layer, where the input vector is created for the next one. The next layer is called a pattern layer.

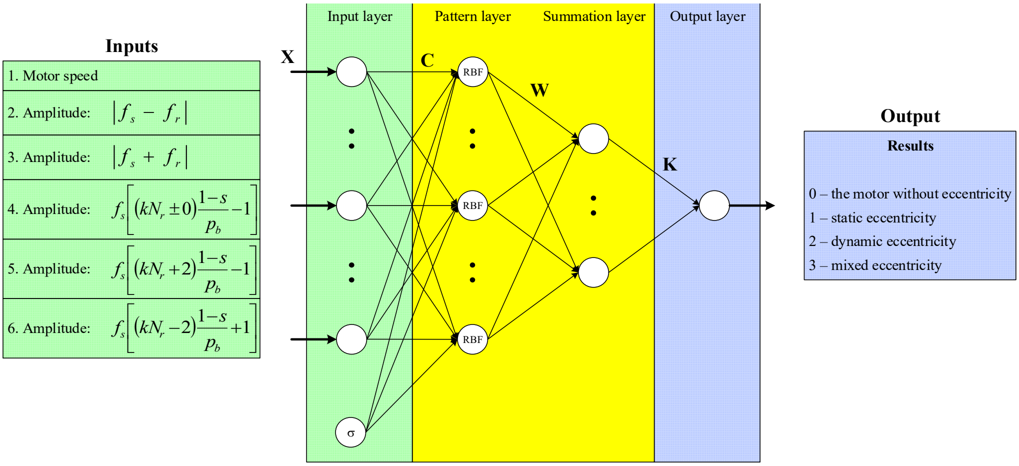

Fig. 4. Structure of general regression neural network

At this stage of neural processing, the Euclidean distance between input vector values and centers of radial basis functions is calculated:

$$\upsilon_j(\mathbf{X}) = \left\|\mathbf{X} - \mathbf{C}_j\right\| = \sqrt{\sum_{k=1}^{n}(x_k - c_k)^2}\,,\; k = 1, 2, 3, \ldots, n \tag{6}$$

where $\mathbf{X} = [x_1, x_2, x_3, \ldots., x_N]^{\mathrm{T}}$ is the input vector, $\mathbf{C}_j$ – a vector related to the center of each neuron.

Next parameters $\upsilon_j(\mathbf{X})$ are scaled by multiplication of their values by bias values. Vector of biases has constant values for each neuron:

$$b_i = b = \frac{\sqrt{-\log(0.5)}}{\sigma} \tag{7}$$

If the distance between the input vector and the RBF centers is equal to σ, the output of the pattern layer will be equal to 0.5. This is the average of possible values of the activation function. In this way, the input signal for radial basis function is obtained. This activation function is described by the following formula:

$$a = \mathrm{e}^{-n_1^2} \tag{8}$$

Next, the output signals of neurons in the pattern layer are introduced to the third summation layer. In this part of neural processing, the following calculations are performed:

$$n_2 = \frac{\sum_q a_{1,q} W_q}{\sum_q a_{1,q}} \tag{9}$$

In the last stage of computation, the obtained results are scaled by the K coefficient and introduced to a linear output neuron. K is a constant determined by the Parzen window. This parameter is independent of the input data [7].

Neural model described above results from the mathematical background presented in [7]. Such structure of NN requires a special training algorithm however, exact method of structure and parameters selection is rather simple and fast to develop. The selection of parameters for GRNN is different than that for multilayer perceptrons (MLP). There is necessity to select centers in radial layer and weight values in the summation layer. For this purpose, a one-pass learning method is applied. Values of centers in radial neurons are obtained by rewriting the values of inputs learning data, however weights in the summation layer are set to the output training data. Number of nodes in the input and output layer depends on the size of processing data in training process. One should emphasize very short duration of the whole process, in contrast to the classical MLP networks. Moreover, under such design procedure, a full repetitiveness of achieved results is possible, and the problem associated with random initial values of weights does not exist. Next advantage of applying such a structure of GRNNs and the method of their training is no necessity to make decision about the structure, which is important for correct realization of a given task.

For optimizing the topology of the MLP networks special algorithms are often applied which are complicated and usually require extending of the training process. It causes that the time of calculations is much longer and the process needs more computing power. In the case of the MLP networks, a necessity of initial processing of data based on linear scaling is often necessary. This operation is introduced for the adaptation of the input data to the range of activation function with significant changeability.

In the case of the GRNN, the Euclidean the distance between the input data and the centers of radial function is only counted. The centers are equal to input training data, so the compared values are similar. In the designing process for specific structure of the described NN networks and their training algorithm, just the parameter σ is chosen. In calculations inside the network, this parameter influences the calibrating of data introduced to radial nodes. Therefore it acts as the shaping factor of radial functions. In the GRNN, large matrices must be transformed during the computation process. For this reason, read-only-memory and look-up table are used in hardware application, so they often are called memory-based neural network. Properties resulting from the specific structure and parameters of GRNN predispose them to applications in classification and approximation of data.

3.2. MULTILAYER PERCEPTRON

The most frequently used neuron architecture in practical applications is unidirectional, it is also defined as multi-layer perceptron (MLP) [13]. The MLP network structure (Fig. 5) includes neurons connected with each other and grouped into layers (input and output layer and also hidden layers which do not have any direct connection with external signals). In addition to this, there are no connections between neurons in the same layer. Activation functions of input and output neurons are linear, while in the hidden layers, the hyperbolic tangent was used. In Figure 5, two different cases regarding the objective of the network are shown. They will be described in details in the following sections.

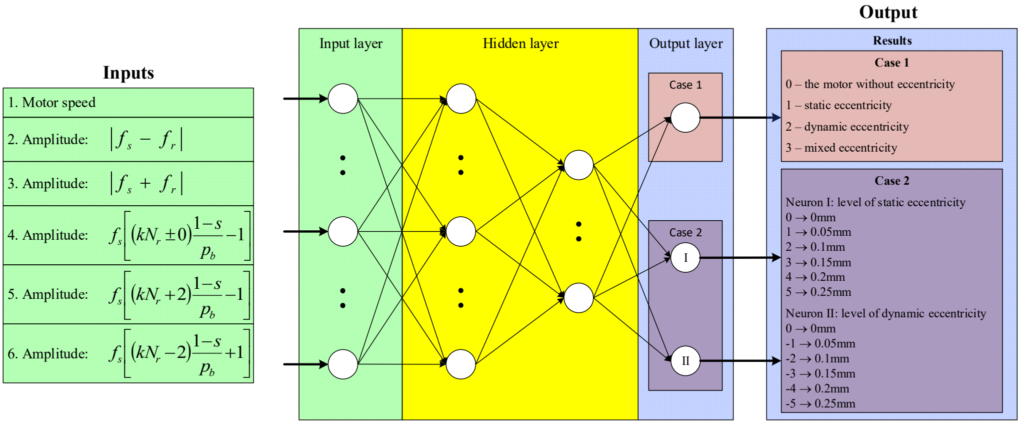

Fig. 5. Sample structure of neural network with one or two neurons in the output layer

The output signal of a particular neuron is given by the following equation:

$$y_j = f\sum_{i=1}^{N}\left(w_{ij}x_i(t) + w_{0j}\right) \tag{10}$$

$$f(u) = \mathrm{tgh}(\beta u) \tag{11}$$

where: f – the activation function, w_{ij} – weighting factors, x_i – input signals, β – correction factor for the shape of the activation function, u – activation function argument, w_{0j} – bias value.

The values of the weight connection coefficients were selected using the Levenberg –Marquardt algorithm [13].

4. RESULTS OF THE TEST

The diagnostic process consists of the following stages: registration of the relevant physical quantities of the prepared motor model (field-circuit model), processing of the obtained data to extract the fault features, and classification of symptoms in the final stage using the developed neural network. The simulations and calculations associated with the detectors have been carried out in the Matlab–Simulink. Designed neural estimators were tested with the data not used in the training process. Tested motor was unsymmetrical (in one or two phase windings the current value was different). The training vector contains information from phase A and B, for tests – magnitudes of components from phase C were used. The NN output values present the information about eccentricity occurrence and on the type of the motor eccentricity (0 – the motor without eccentricity, 1 – static eccentricity, 2 – dynamic eccentricity and 3 – mixed eccentricity). The input vector of the NN was formed with magnitudes of components described by equations (1) for $n_d = 0$ and $n_w = -1$, $n_d = 2$, and $n_w = -1$, $n_d = -2$ and $n_w = 1$, $k = 1$. Additionally, elements calculated according to the formula (2) for $k = 1$ and the motor speed were introduced into this input vector (Figs. 4, 5). It should be mentioned that during the tests, six different values of the load torque were applied (nominal and five values less than nominal).

4.1. GENERAL REGRESSION NEURAL NETWORK

The tests were made for different values of the σ parameter, and show σ influence on calculation results of the GRNN networks. Table 1 contains several tested values of the σ parameter and the corresponding detection quality. Quality of the detection is calculated as a percentage of correct indications for 120 sets of tested samples. Proper selection of the σ parameter for the GRNN is one of the most important issues in the design process of these neural detectors. Best results are obtained for $\sigma = 0.00044$, quality of the detection was 95.83% in this case. This value of the σ parameter was determined experimentally.

Table 1. Percentage values of the detection quality of the IM eccentricity by GRNN for different σ

σ	Quality of the detection [%]
0.1	25.0
0.01	32.5
0.001	75.8
0.0001	68.3
0.00044	95.8
0.00001	15.0

Finding the correct σ values is very easy in this case with the application of a simple searching algorithm. Using this algorithm, the implementation of the whole design process of the GRNN detectors, including training and tests, takes about 4 s. It should be marked that additional scaling of the input data was not introduced. This is often applied problem during the implementation of the MLP neural networks for calculation performed with real data (e.g. high values of motor speed).

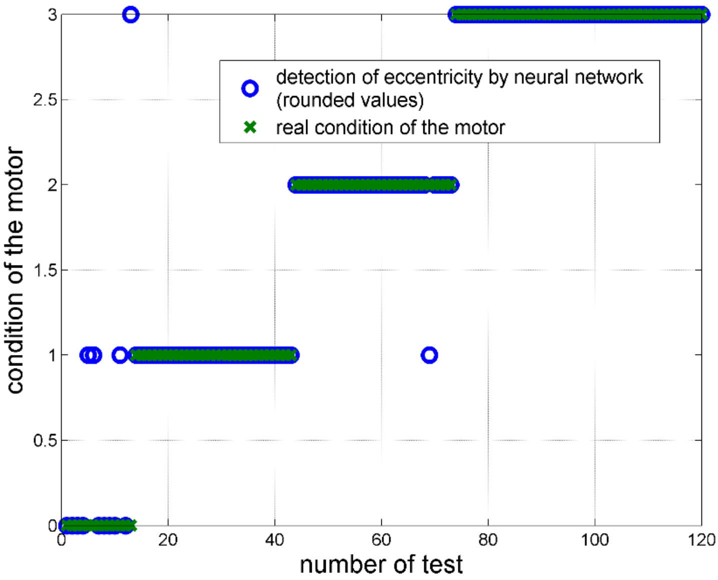

Fig. 6. Graphical presentation of the GRNN detectors results

In Figure 6, the graphical presentation of the results for the best detector is presented ($\sigma = 0.00044$). Type of the damage (0 – the motor without eccentricity, 1 – static eccentricity, 2 – dynamic eccentricity and 3 – mixed eccentricity) is indicated at the NN output. Figure 6 presents the output values rounded to integer numbers. The precision of the eccentricity detection is very high, even in the case of the eccentricity type detection.

4.3. MULTILAYER PERCEPTRON

The use of the MLP networks to detect eccentricities has also been investigated in this study. For this purpose, the structures with one (Table 2) and two (Table 3) hidden layers were tested. Teaching and testing were performed with the same learning and testing vectors for the GRNN networks. Before beginning the learning process, the motor speed was divided by 10^7. In order to average the results, 30 learning and testing series were performed. The results are summarized in Tables 2 and 3, respectively.

The best average effectiveness of 30 tests of neural networks with one hidden layer was obtained for network of 6-9-1 structure. It was about 82%. Highest efficiency of 93.3% has been reached for a network of 6-5-1 structure. The average time needed to teach the network varied from about 3 s for the 6-3-1 network to about 8 s for a network containing 17 neurons in the hidden layer.

Table 2. Detection effectiveness of induction motor eccentricity
by the MLP neural networks with one hidden layer

Effectiveness of 30 learning and testing series, %	Neural network structure							
	6-3-1	6-5-1	6-7-1	6-9-1	6-11-1	6-13-1	6-15-1	6-17-1
Lowest	60.8	61.7	68.3	67.5	71.7	65.8	65.8	67.5
Highest	92.5	93.3	91.7	91.7	90.0	90.0	86.7	92.5
Average	73.4	76.2	81.6	82.4	81.4	79.5	79.1	80.1

Table 3. Detection effectiveness of induction motor eccentricity
by the MLP neural networks with two hidden layers

Effectiveness of 30 learning and testing series, %	Neural network structure					
	6-5-3-1	6-7-5-1	6-9-7-1	6-11-9-1	6-13-11-1	6-15-13-1
Lowest	35.8	69.2	72.5	58.3	52.5	45.8
Highest	94.2	95.0	95.0	95.0	91.7	93.3
Average	86.6	86.5	85.4	80.9	77.3	75.0

The use of neuron detectors with two hidden layers improves the eccentricity detection rate by only a few percent. The best average efficiency detection of approximately 87% was obtained for the network of 6-5-3-1 structure. The highest detection efficiency of 95% was achieved for three structures: 6-7-5-1, 6-9-7-1 and 6-11-9-1. Taking into account the lowest, highest and average effectiveness of 30 learning and testing series, the neural network of 6-9-7-1 structure has the efficiency of detecting eccentricity at 73–95%. The average learning time of detectors with two hidden layers varies from about 5 s to about 10 s depending on the number of neurons. Figure 7 shows the result of testing the neural network of the 6-7-5-1 structure. The efficiency of the neural detector was very high and was 90%.

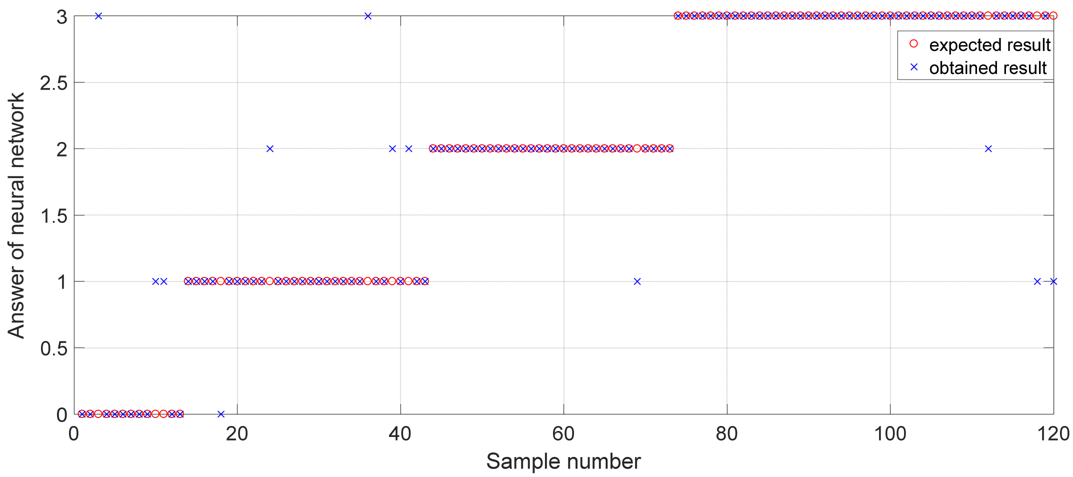

Fig. 7. Sample testing result of 6-7-5-1 neural network structure

The use of two neurons in the output layer allows one to detect the type of the eccentricity as well as to assess its level. The eccentricity levels connected to the respective output neurons are shown in Fig. 5. Table 4 summarizes the results obtained for a network with one hidden layer, and Table 5 for that with two hidden layers.

Table 4. Detection effectiveness of induction motor eccentricity by the MLP neural networks with one hidden layer and two neurons in the output layer [%]

Effectiveness of 30 learning and testing series, %	Neural network structure													
	6-3-2		6-5-2		6-7-2		6-9-2		6-11-2		6-13-2		6-15-2	
	I	II	I	II	I	II	I	II	I	II	I	II	I	II
Lowest	60.0	35.8	78.3	75.0	82.5	75.8	77.5	76.7	83.3	73.3	76.7	70.8	80.8	71.7
Highest	85.8	78.3	92.5	86.7	93.3	91.7	93.3	91.7	95.8	91.7	96.7	92.5	95.0	90.0
Average	79.1	71.5	87.6	83.1	88.5	85.5	88.9	85.7	90.4	85.1	90.0	81.4	90.2	80.9
Lowest	26.7		67.5		68.3		70.8		65.0		63.3		68.3	
Highest	68.3		80.8		85.8		86.7		90.8		89.2		85.0	
Average	59.9		75.1		78.1		79.3		80.3		77.4		77.3	

Table 5. Detection effectiveness of induction motor eccentricity by the MLP neural networks with two hidden layers and two neurons in the output layer [%]

Effectiveness of 30 learning and testing series, %	Neural network structure											
	6-5-3-2		6-7-5-2		6-9-7-2		6-11-9-2		6-13-11-2		6-15-13-2	
	I	II	I	II	I	II	I	II	I	II	I	II
Lowest	20.0	20.0	86.7	70.8	81.7	74.2	78.3	72.5	73.3	68.3	70.8	50.0
Highest	95.8	92.5	98.3	93.3	98.3	91.7	95.8	89.2	95.8	90.8	93.3	83.3
Average	88.2	84.9	92.6	85.7	91.6	84.7	89.0	82.0	87.6	76.8	85.2	71.9
Lowest	15.0		67.5		70.8		68.3		63.3		46.7	
Highest	89.2		90.0		90.0		85.8		86.7		80.8	
Average	79.0		82.1		81.8		78.9		73.7		69.5	

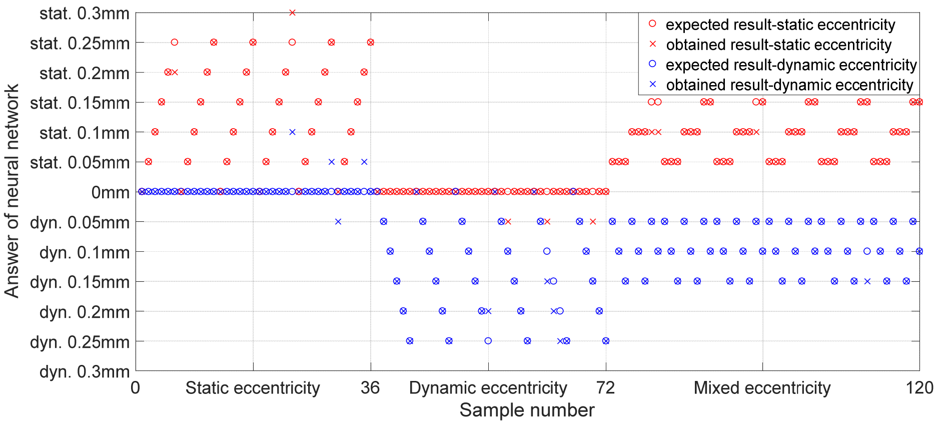

Fig. 8. Sample testing result of 6-7-5-2 neural network structure

The use of two neurons in the output layer does not improve the average efficiency of neural detectors, which was about 80% for 6-11-2 and 82% for 6-7-5-2 and 6-9-7-2 structures. The effectiveness of the assessment of static or dynamic eccentricity levels of the detectors is high and is over 80%. The average teaching time of tested detectors with two output neurons varied from about 4 s to 25 s depending on the number of neurons.

The neural network shown in Fig. 8 has a very high efficiency of 87.5%. Effectiveness of individual output neurons is also high, about 93% for neuron I and 92.5% for neuron II.

5. CONCLUSION

Neural detectors of eccentricity of induction motors have been presented. General regression neural networks and multilayer perceptron were applied. Using field-circuit modelling of the motor with different types of eccentricity, the necessity of creating a database with long-term experiments and measurements on real objects has been eliminated. Such an approach gives also a possibility to generate a very large number of diagnostic patterns necessary for training and testing neural detectors. GRNN networks can be the alternative to classical MLP networks. A simplified process of the detector design is an advantage for this type of neural networks. During the design process, a necessity to make a decision only about the value of the spread parameter of the activation function exists. Very good results for classification of the faults are obtained. A possibility of detecting the type and level of the eccentricity are additional advantages of the proposed detectors.

REFERENCES

[1] EWERT P., WOLKIEWICZ M., *Detection methods overview of induction motor eccentricity using stator current analysis*, Scientific Papers of the Institute of Electrical Machines, Drives and Measurements of the Wrocław University of Technology, Studies and Research, 2015, 35, 151–160 (in Polish).

[2] KOWALSKI C.T., ORLOWSKA-KOWALSKA T., *Application of neural networks for the induction motor faults detection*, Trans. of IMCAS Mathematics and Computers in Simulation, 2003, 63(3–5), 435–448.

[3] BOUZID M.B.K., CHAMPENOIS G., BELLAAJ N.M., SIGNAC L., JELASSI K., *An effective neural approach for the automatic location of stator interturn faults in induction motor*, IEEE Trans. Ind. Electron., 2008, 55(12), 4277–4289.

[4] AWADALLAH M.A., MORCOS M.M., *Application of AI tools in fault diagnosis of electrical machines and drives. An overview*, IEEE Trans. En. Conv., 2003, 18(2), 245–251.

[5] NANDI S., TOLIYAT H.A., LI X., *Condition monitoring and fault diagnosis of electrical motors. A review*, IEEE Trans. En. Conv., 2005, 20(4), 719–729.

[6] KOWALSKI C., KAMIŃSKI M., *Rotor fault detector of the converter-fed induction motor based on RBF neural network*, Bull. Polish Acad. Sci., Techn. Sci., 2014, 62(1), 69–76.

[7] SPECHT D.F., *A general regression neural network*, IEEE Trans. Neural Netw., 1991, 2(6), 568–576.

[8] CARDOSO G. Jr., ROLIM J., ZURN H.H., *Application of neural network modules to electric power system fault section estimation*, IEEE Trans. on Power Delivery, 2004, 19(3), 1034–1041.
[9] FAIZ J., EBRAHIMI B.M., AKIN B., TOLIYAT H.A., *Comprehensive eccentricity fault diagnosis in induction motors using finite element method*, IEEE Trans. Magn., 2009, 45(3), 1764–1767.
[10] EWERT P., KAMIŃSKI M., KOWALSKI C., *Eccentricity detection of the induction motors using general regression neural networks*, 10th International Conference on Modeling and Simulation of Electric Machines, Converters and System, ELECTRIMACS 2011, Paris, France, 2011, 1–6.
[11] ILAMPARITHI T., NANDI S., *Comparison of results for eccentric cage induction motor using finite element method and modified winding function approach*, Joint International Conference on Power Electronics, Drives and Energy Systems (PEDES), 20–23 December 2010, 1–7.
[12] LAZARO J., ARIAS J., MARTIN J.L., DE ALEGRIA I.M., ANDREU J., JIMENEZ J., *An implementation of a general regression network on FPGA with direct Matlab link*, Proc. IEEE of International Conference on Industrial Technology IEEE-ICIT 2004, 2004, 3, 1150–1155.
[13] VAS P., *Artificial intelligence-based electrical machines and drives. Applications of Fuzzy, Neural, Fuzzy-Neural and Genetic Algorithm Based Techniques*, Oxford University Press, 1999.