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Neural networks application for induction motor faults diagnosis

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Abstract

The paper deals with diagnosis problems of the induction motors in the case of rotor, stator and rolling bearing faults. Two kinds of neural networks (NN) were proposed for diagnostic purposes: multilayer perceptron networks and self organizing Kohonen networks. Neural networks were trained and tested using measurement data of stator current and mechanical vibration spectra. The efficiency of developed neural detectors was evaluated. Feedforward NN with very simple internal structure, used for the detection of all fault kinds, gave satisfactory results, which is very important in practical realization. Experiments with Kohonen networks indicated that they could be used for the initial classification of motor faults, as an introductory step before the proper neural detector based on multiplayer perceptron is used. The obtained results lead to a conclusion that neural detectors for rotor and stator faults as well as for rolling bearings and supply asymmetry faults can be developed based on measurement data acquired on-line in the drive system.

Keywords: Induction motor faults; Neural networks; Monitoring; Diagnosis

1. Introduction

Modern technological processes are characterized by the application of more and more complicated equipment including modern electrical drives. An electrical motor together with a load machine as well as supply and control systems are run to risk of various failures which are independent of the usage of elements and materials characterized by high reliability.

Long time disturbances in technological processes cause big economic loses. The importance of incipient fault detection is a method of cost saving which is realized by detecting potential motor failures before they occur. Currently, motors require to be protected by circuit breakers or fuses that interrupt instantaneous fault currents. However, these devices are intended only as safety devices and they may protect the motor and nearby personnel from injury due to a fault, but will not warn of potential faults before they occur. Incipient fault detection, on the other hand, allows preventative maintenance to be

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scheduled for machines that might not ordinarily be due for service and may also prevent an extended period of downtime caused by extensive motor failure. For this reason, the problem of fast fault detection and location as well as the problem of technical state evaluation are very significant in the industrial practice [2,14].

Diagnostic systems use different procedures in a diagnostic process, starting from heuristic knowledge, through mathematical models to the artificial intelligence methods. The diagnosis of the industrial processes can be performed using different elements of knowledge base like analytical methods, expert systems, neural networks (NN) or fuzzy logic reasoning.

Faults detection using analytical method is not always possible because it requires perfect knowledge of a process model. In the case of a not adequate or imprecise mathematical model false alarms can occur due to estimation errors of the systems state variables or process parameters [13,14].

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 is rather easy to develop and to perform [4]. Neural networks can be applied when the information about the process is obtained by measurements, which later can be used in the training procedures of neural nets. The main advantage of such solution is obtaining on-line information about the kind and the “size” of a fault without developing very complicated mathematical models. Neural detectors can be designed using the data acquired from simulation or experimental tests [4,10,14].

The paper demonstrates diagnosis problems of the induction motors in the case of rotor, stator and rolling bearing faults. For diagnostic purposes artificial intelligence methods based on neural networks were applied. Two kinds of NN were proposed: multilayer perceptron networks and self-organizing Kohonen networks. These networks were trained and tested using the measurement data of stator current and mechanical vibration spectra. The efficiency of the developed neural detectors was evaluated.

2. Basic problems of the induction motor faults

During the operation of induction motors (which at present make about 90% of all electrical motors used in the world) different faults of the electrical and mechanical parts of stator and rotor occur as well as some faults of a loading machine together with coupling devices. The possibility of incipient fault detection of electrical, magnetic and mechanical parts of the a motor has recently become one of the most important problems of induction motors exploitation [1–3,14].

There are three main kinds of faults of induction motors:

1. Winding faults:
   - short-circuits of stator windings,
   - short-circuits of rotor windings, broken rotor bars,
   - broken rings of the rotor.
2. Faults of the magnetic circuit:
   - air-gap asymmetry,
   - stacking clearance.
3. Faults of the motor mechanical system (mainly bearing failures).

All these faults are connected with some particular phenomena: electrical, magnetic and vibroacoustic ones.

The fault statistics of high- and low-voltage induction motors has been changing within the last few years. There is a significant increase of mechanical failures in comparison with electrical and magnetic circuits' failures. It can be demonstrated in the following way (as the percentage of all motor faults) [11]:

- bearing failures: ∼40%,
- stator failures: ∼36%,
- rotor failures: ∼10%,
- other failures: ∼14%.

Condition monitoring schemes have concentrated on sensing specific failure modes in one of three main induction machine components: the stator, the rotor or the bearings.

3. Neural networks application in monitoring and diagnostic problems

The application of the following methods for technical systems fault detection, classification and location is possible:

- the formulation of deterministic and stochastic mathematical models for particular faults—the analytical method,
- the heuristic reasoning based on expert knowledge and experience,
- techniques based on artificial intelligence, especially neural networks and fuzzy logic.

Fig. 1 presents schematic diagrams of the above-mentioned fault detection methods.

Diagnostic systems based on mathematical models usually require good knowledge of the physical phenomena of the plant and lead to very complicated software use. The main idea of methods

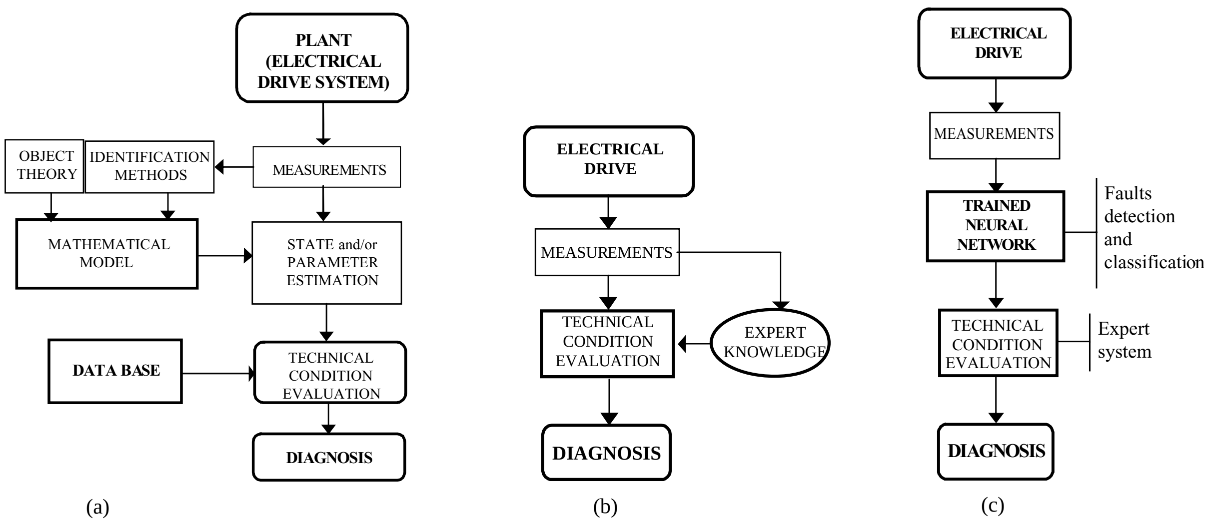

Fig. 1. Schematic diagrams of various methods for faults detection and diagnosis: (a) mathematical model based method, (b) heuristic method, (c) NN based method.

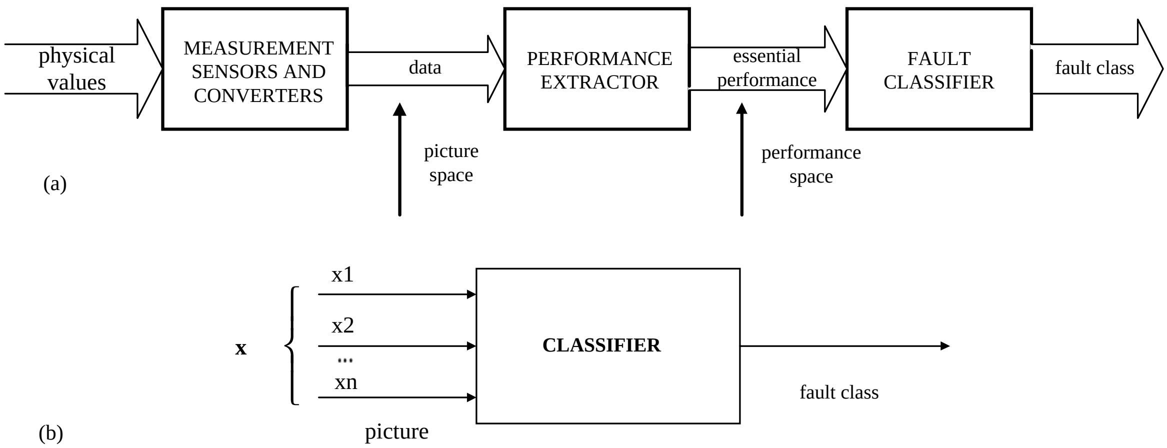

Fig. 2. Recognition and classifier system: (a) general scheme, (b) classifier.

based on mathematical models consists in fault determination, which is based on the comparison of the mathematical model analysis and the expert knowledge about the operation states of the plant (Fig. 1a).

The heuristic reasoning requires an expert presence to perform any diagnostic task. So these two ways are very much dependent on the mathematical models adequacy, measurement errors and expert knowledge.

The connection of the knowledge based on analytical mathematical models and heuristic knowledge, which is realized in the expert systems, enables to obtain significantly greater diagnostic efficiency. But the necessity of a human expert presence and activity is the main disadvantage of these methods, because of the difficulties in automation and spreading out human experience.

The introducing of artificial intelligence methods, especially the neural networks approach, has eliminated the last disadvantage. Intensive research has recently been conducted in the field of NN application in the drive system diagnosis (Fig. 1c). They are used as neural fault detectors and classifiers of the main element of the drive—the electrical machine.

A typical way of NN application in the diagnosis of technical plants consists in the design of a neural classifier of plant’s states based on the collected and actual measurement data. Because the state of the plant can be treated as a specific plant picture, characterized by the set of input/output signals, the diagnosis problem is to recognize and classify the pattern. The main aim of such a task is the plant’s state allocation to one of the previously determined fault categories. A schematic diagram of such a recognition and classifier system is presented in Fig. 2a.

Detectors and converters of input signals change the recognized plant’s picture into signals useful for a suitable conversion performed by a performance extractor and classifier. The main task of the extractor is filtration or data condensation (without any influence on the classification quality). It should be mentioned that this element is not always necessary in the classifier system. The design procedure of a state classifier for a technical plant is connected with the choice of a neural network type, the structure and determination of its weight coefficients in a suitable training procedure. In the following chapters, such a design procedure of the induction motor fault classifier and its training procedure will be presented.

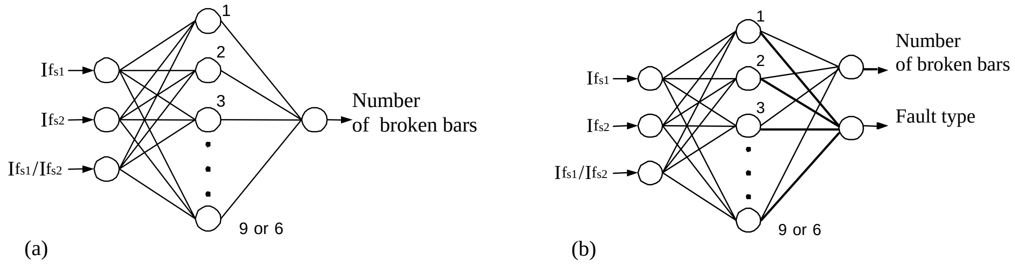

Fig. 3. Structure of rotor fault detectors: (a) with one-output, (b) with two-outputs.

4. Neural detector for rotor faults of the induction motor

The rotor faults cause the asymmetry of the magnetic field of the motor, this in turn results in various additional phenomena, such as a change of the stator current spectrum, additional internal forces and mechanical vibrations, oscillatory components of rotor speed, electromagnetic torque, output power, etc. [13]. These effects are very weak in the initial stage of the rotor fault and only sensitive measurement methods can detect the damage. In practice, the stator current spectral analysis is the most useful one in such cases [6,7,10,13]. Characteristic components with frequency dependent on motor slip s occur in the stator current spectrum in the case of a rotor bar fault. The values of slip harmonics in the spectrum of stator current for various damages of rotor cages (the number of broken bars, fault kind) can be treated as a set of input data for neural network. Based on these data, the neural network modifies its weight coefficients in all hidden layers in the training process. When input values, different from those used in the training procedure yet included in the data set, will be presented to the network, the information about the number of broken bars or fault kind should be given at the network output.

Schematic diagrams of such neural rotor fault detectors are presented in Fig. 3. The slip harmonics obtained from the stator current spectrum were used as input values of neural detectors; at their output the information about the number of damaged rotor bars and fault type (symmetrical or unsymmetrical) is obtained. Tables 1 and 2 present the tests' results for the proposed neural detectors trained with stator current spectra for different rotor faults.

Tests' results for both types of neural detectors indicate that they detect the number of damaged rotor bars and their placement (fault type) almost without errors.

Table 1
Tests' results for neural detector of rotor faults (six neurons in the hidden layer)

Testing vector											
Number of broken bars	0	1	2	2	3	4	4	4	6	8	8
NN responses—real											
Number of broken bars	0.005	1.198	2.007	2.349	3.290	3.939	3.889	4.035	6.2077	8.000	8.003
NN responses—rounding											
Number of broken bars	0	1	2	2	3	4	4	4	6	8	8

Table 2
Tests' results for neural detector of rotor faults (nine neurons in the hidden layer)

Testing vector												
Number of broken bars	0	1	2	3	4	5	2	4	6	8	4	8
Fault type	2	2	2	2	2	2	3	3	3	3	3	3
NN responses—real												
Number of broken bars	−0.013	1.179	2.265	3.311	3.661	4.486	2.071	3.961	6.024	8.044	4.033	7.920
Fault type	2.036	2.147	2.157	2.043	1.991	1.969	3.060	2.904	2.604	2.975	3.103	3.008
NN responses—rounding												
Number of broken bars	0	1	2	3	4	**4**	2	4	6	8	4	8
Fault type	2	2	2	2	2	2	3	3	3	3	3	3

Fault types: 2, unsymmetrical fault; 3, symmetrical fault.

5. Neural detector of rolling bearing faults

Bearing faults cause specific harmonics in the vibration spectrum of a motor, this frequency depends on bearing geometry and kinematics. Motor current spectrum also contains harmonics specific for different types of bearing faults. These symptoms can be used for different monitoring methods of bearings condition. Specific spectral peaks depend on the type of fault, the rotational speed and bearing geometry. Many publications have discussed the use of these frequencies to identity defects in a bearing assembly [8–10,14]. It should be emphasized that, if the defective area is large, harmonics of a special order [8,9] will be present as an indication of defects' severity.

As mentioned in [9,10,14], in addition to the utilization of the vibration spectrum analysis, it is also possible to monitor the state of bearings by performing a stator current spectrum analysis. It should be noted, however, that the current spectrum will also contain other components, which result from, e.g. broken rotor bars, air-gap eccentricity, winding distribution, etc. and the frequency components caused by bearing damage are relatively small compared to the other components. So a sufficient spectral resolution is necessary to use the above calculation for bearing diagnosis purposes. These special vibration and/or current harmonics can be used for the training of neural networks and the design of a neural fault detector.

The main task of a neural detector for rolling bearing faults was the recognition of the bearing state. The detector should assign the bearing to one of these classes: a healthy or damaged bearing. It was assumed that the input signals of this detector consist of harmonics magnitudes of the vibration spectrum and the stator current spectrum.

The tested bearings were divided into two groups:

(a) bearings with a priori known failures, assigned for the training procedure of a neural network: a healthy bearing, a train defect, an outer bearing race defect, a bearing with a damaged rolling element;
(b) bearings assigned for the testing procedure of a neural network: two damaged bearings with unknown failures and one healthy bearing.

The main part of the experimental benchmark was multianalyser PULSE 3560 (Brüel&Kjær). The accelerometer 4397 of Brüel&Kjær was mounted on the motor frame and used as a vibration sensor.

The bearing fault detector was supposed to recognize the bearing state and classify it as one belonging to one of the following groups: healthy or damaged bearings. Two NN types were used for this purpose:

- the feedforward multilayer network trained with back propagation algorithm,
- the self-organizing Kohonen network with two-dimensional feature map.

In both cases, the inputs of the neural network were characteristic magnitudes of the stator current and/or motor vibration frequencies. It was assumed that the input vector has contained maximum 30 elements.

For the feedforward network four types of classifiers were developed:

- the one-output detector for the determination of a bearing condition (good–bad) based on the vibration spectrum,
- the one-output detector for the determination of a bearing condition (good–bad) based on the current spectrum,
- the one-output detector for the determination of a bearing condition (good–bad) based on the vibration and current spectra,
- the three-output detector for the determination of a bearing condition (good–bad) as well as supply asymmetry based on the vibration spectrum.

In the case of feedforward NN training it is necessary to present not only input vectors but also target output. For the one-output detectors these outputs are as follows:

- 0: for a healthy bearing,
- 1: for a damaged bearing.

The bearing condition or the supply asymmetry is represented by the output state of neurons in the output layer of feedforward neural detector. In the case of a three-output detector, each output of NN represents a different condition of the motor: the first output represents a healthy bearing, the second one—a damaged bearing and the third one—supply asymmetry.

Testing the results of the developed NN detectors based on feedforward networks, trained using vibration spectrum are presented in Tables 3–5, for one and three-output detectors, respectively. In these tables, the incorrect answers of neural detectors were marked by bold numbers. In the case of testing healthy and damaged bearings only three bad responses of neural networks were obtained, this gives 85% accuracy of the neural detector presented in Table 3.

For the second detector (Table 4) the results are presented for three bearings only (one healthy and two damaged ones), to achieve better transparency of the table. Additionally, this table presents the responses of the network for two cases of supply asymmetry. In this case the accuracy of the neuron detector was about 93%.

It should be mentioned that in these examples very simple structures of NN were taken into account. For a bigger number of neurons in the hidden layer even better results were obtained. The simplicity of NN is the main condition of practical realization of such neural detectors using digital signal processors. The stator current spectrum was also used for the training of NN detectors. Table 5 presents an example of results obtained for the feedforward one-output detector. In this case the responses of the NN are also good. The obtained accuracy was about 85%.

Moreover, the possibility of the damage classification was tested using an unsupervised, self-organizing neural network. The simple Kohonen two-dimensional feature map was used for bearings failures and

Table 3
Responses of the feedforward NN with five neurons in hidden layer for the one-output NN detector (vibration spectrum used in training)

	Number of bearing																			
	Healthy bearings										Damaged bearings									
	1	2	3	4	5	6	7	8	9	10	1	2	3	4	5	6	7	8	9	10
Actual output	0.03	0.08	0.09	0.04	0.15	0.55	0.32	0.29	0.07	0.12	0.99	0.87	0.72	0.95	1.04	0.38	1.12	0.91	0.46	0.69
Target output	0	0	0	0	0	**1**	0	0	0	0	1	1	1	1	1	**0**	1	1	**0**	1

Table 4
Responses of the feedforward NN with four neurons in hidden layer for the three-output NN detector (vibration spectrum used in training)

	Healthy bearing	Damaged bearing 1	Damaged bearing 2	Supply asymmetry 8%	Supply asymmetry 20%
Neuron 1					
Actual output	0.9463	0.0398	0.4503	0.0196	0.0226
Target output	1	0	0	0	0
Neuron 2					
Actual output	0.1067	1.0280	0.9239	0.0403	0.2652
Target output	0	1	1	0	0
Neuron 3					
Actual output	0.1537	0.0739	0.3441	0.9348	0.7130
Target output	0	0	0	1	1

supply asymmetry recognition. The results obtained for this neural classifier are presented in Fig. 4, in the case when NN was trained and tested using the same vibration spectra as in the case of the three-output feedforward detector. In Fig. 4, the following notation was used:

▲ △—neuron response for training and testing samples of healthy bearings,
● ○—neuron response for training and testing samples of supply asymmetry,
■ □—neuron response for training and testing samples of damaged bearings.

The specific location of responses, suitable for healthy bearings as well as stator supply asymmetry and for damaged bearings, in a different region of Kohonen map is observed, respectively.

It can be seen that the network has well separated the different characteristic regions and thus such network can be used as a pre-processor in a diagnostic system for the clustering of various faults. Then, based on this classification, the other neural network, of perceptron type, can be used for the failure evaluation in the automatic diagnostic system [10,14].

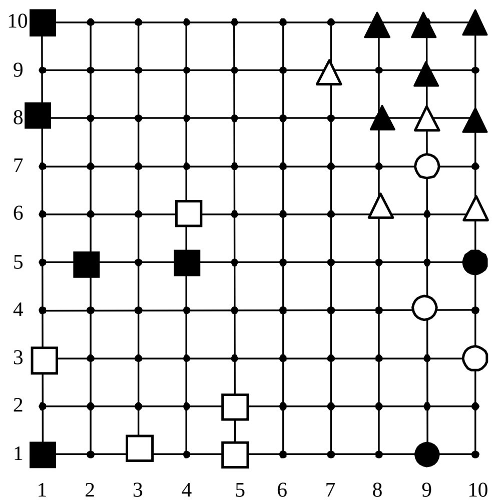

Fig. 4. Two-dimensional Kohonen feature map 10/10.

Table 5
Responses of the feedforward NN with three neurons in hidden layer for the one-output NN detector (stator current spectrum used in training)

	Number of bearing																			
	Healthy bearings										Damaged bearings									
	1	2	3	4	5	6	7	8	9	10	1	2	3	4	5	6	7	8	9	10
Actual output	0.01	0.03	0.19	0.56	0.23	0.09	0.41	0.04	0.06	0.18	0.98	1.10	0.42	1.02	1.24	0.39	1.17	0.90	0.56	0.88
Target output	0	0	0	**1**	0	0	0	0	0	0	1	1	**0**	1	1	**0**	1	1	1	1

6. Neural detector of stator faults based on one-layer perceptron and kohonen network

The detection of stator inter-turn short-circuits during the normal operation of induction motors is a rather difficult task and typical industrial solutions do not exist. The main problem is connected with their destructive character and a tendency to rapid transition. Therefore, early detection of inter-turn shorts during motor operation would eliminate subsequent damage to adjacent coils and the stator core, reducing repair costs and motor outage time [5]. Until recently [1,5,12,13], little work had been done on detecting the onset of an inter-turn short-circuit while machine was operational. Some new techniques for the incipient diagnosis of inter-turn failures were tested, such as the method based on the measurement of negative-sequence impedance or negative-sequence current [3,4,12]. In [11] an axial leakage flux monitoring was used as a method for detecting the occurrence of this type of stator failure at an early stage of its development, as well as to locate the position of the fault in the winding while the motor was operating.

In this paper, the experimental tests were performed for the induction motor with modeled inter-turn short-circuits (maximum 10% of one phase windings could be short-circuit, with the suitable current limitation). Measurement data of the axial leakage flux and mechanical vibration were acquired and then, after suitable pre-processing, used for the neural detector training.

For a detector based on the axial leakage flux measurement, the value of RMS voltage induced in the search coil and its 50 Hz harmonic's magnitude (U_{Ax1}, U_{Ax2}) was measured in search coils placed on both sides of the motor shaft.

For the detector based on vibration spectra, harmonics of measured vibration spectrum with frequency of 100, 200, 225 and 300 Hz were used as an input signal of a neural detector (magnitudes of these harmonics increase when the number of inter-turn short-circuit increase).

Fig. 5 shows the schematic structures of developed neural detectors, and Tables 6 and 7 present testing results of NN trained based on the axial leakage flux measurement, respectively.

The data presented in Tables 6 and 7 show that the neural detector trained based on the axial leakage flux measurement gave better answers. It was probably due to the bigger size of training vector used in this case. All answers of NN detector trained by measurements of axial leakage flux were proper. NN trained using vibration spectra made only one mistake.

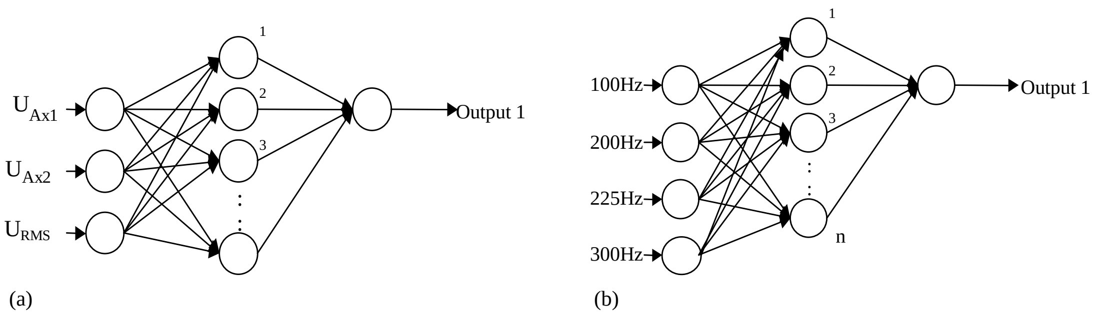

Fig. 5. Structure of neural detectors of stator failures: (a) detector trained by measurements of axial leakage flux, (b) detector trained by measurements of horizontal vibration.

Table 6
Testing results of the neural detector trained based on the measurement of an axial leakage flux (structure according to Fig. 6a, with six hidden neurons)

Target vector								
Number of short-circuit turns	7	21	25	26	30	6	9	11
NN answers—real								
Number of short-circuit turns	6.78	20.9	25.00	26.08	29.88	5.81	8.98	11.11
NN answers—rounding								
Number of short-circuit turns	7	21	25	26	30	6	9	11

Number of training epochs: 8009.

The Kohonen neural network was also tested as a detector of stator inter-turn short-circuits [5,14]. Two-dimensional Kohonen maps were tested for various numbers of neurons: 5×5, 10×10, 15×15 and 20×20. In all cases the rectangle network topology was used.

In the detector based on axial flux measurement, the RMS value of the voltage induced in the measurement coil placed on the motor shaft side and 50 Hz harmonic component of this voltage was used. For the detector based on the vibration measurement and analysis, a two-dimensional input vector was used containing magnitudes of the vibration harmonics' acceleration with the frequency of 100 and 200 Hz. In Fig. 6, the responses of Kohonen network are demonstrated, for training as well as testing vector presented to the network input (1000 training epochs).

The shape △ means training cases, ○ testing cases and numbers mean the number of inter-turn short-circuits. Cases 0, 4, 5, 8, 10, 13, 15, 18, 19, 23, 28, 31, 33 (△) in Fig. 6a were used for NN training, and cases 6, 7, 9, 11, 21, 25, 26, 30 (○) present NN answers to the testing vector. Respectively, in Fig. 6b cases 0, 4, 5, 10, 13, 18, 19, 23, 28, 33 (△) are connected with NN training, and cases 8, 15, 31 (○) to its testing. The analysis of the above Kohonen maps leads to the following conclusions:

- the lack of damage (case 0) is distinctly different from the other cases;
- all damage "sizes" can also be pointed out distinctly, i.e. Fig. 6a shows that damages with up to 13 failure turns are placed in the lower part of Kohonen map, up to 20 failures in the upper left corner, and the biggest failures in the upper right corner.

In the tests performed with Kohonen networks it is clearly seen that this kind of network has clustered the various faults in distinct regions and the three clusters are well separated. This clustering can be used as a pre-processing diagnostic stage which could be followed by the feedforward network which then

Table 7
Testing results of the neural detector trained based on the measurement of horizontal vibration (structure according to Fig. 6b, with eight hidden neurons)

Target vector			
Number of short-circuit turns	8	15	31
NN answers—real			
Number of short-circuit turns	7.76	12.04	30.99
NN answers—rounding			
Number of short-circuit turns	8	**12**	31

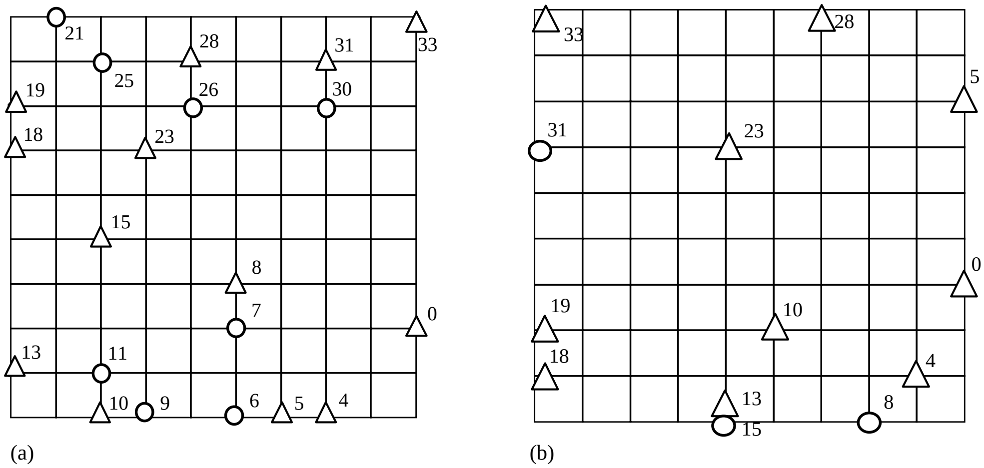

Fig. 6. Responses of the Kohonen network (10 × 10) trained by: (a) the axial leakage flux measurements, (b) vibration spectra (b).

evaluates the fault severities. There is no difference in the quality of failure classification between detector based on the axial flux measurements and detector based on the horizontal vibration measurements.

7. Conclusions

Based on experimental results and numerical simulation of neural networks, the following conclusions can be formulated:

- Application of mechanical vibration, stator current and axial flux spectral analysis based on FFT algorithm gives the proper training and testing data for stator, rotor and bearing faults detectors.
- The appropriate pre-processing of measurement data enables the exclusion of the data, which are less characteristic for a given motor failure. This procedure enables the minimization of a training vector and thus the reduction of NN training time can be obtained.
- Simple NN detectors with one hidden layer and a few neurons enable the recognition of failure type—this is quite important for the practical realization of such detectors.
- The self-organizing Kohonen network can be successively applied for the preliminary classification of failure types and can be used as the preliminary stage of proper NN detector based on multilayer perceptron.

The results of experimental tests show that neural networks can be effectively used for the recognition of stator, rotor, rolling bearings and supply asymmetry faults by appropriate measurements and interpretation of FFT analysis of current and vibration spectra.

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