DIAGNOSTICS OF AUTOMATED TECHNOLOGICAL DEVICES

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Automated technological devices need diagnostics. At present, it is possible and necessary to use a wide range of sensors, computing systems and artificial intelligence methods based on neural networks, fuzzy inference systems in diagnostic systems. This paper proposes three models of information processes for diagnosing mechatronic systems - parallel, sequential and combined. To diagnose the nodes of mechatronic systems showed that it is necessary to combine neural networks and fuzzy logic. For a fuzzy inference system, it is proposed to use such parameters as the value of the diagnostic parameter, the trend of this parameter, and the value of the node operating time. Examples of diagnostics of such units of mechatronic systems as bearings and electric drives based on a neural network and fuzzy logic are given. Experiments have been carried out confirming the correctness of the reliability of the diagnostic model.

KEYWORDS

diagnostic, technological devices, mechatronic systems, neural network, Computer Numerical Control, Artificial Intelligence

1 INTRODUCTION

Brushless direct current (BLDC) motors belong to the type of electric motors, which is gaining popularity fast, thanks to its great performance and the progress of the microprocessor control development. The presented paper discusses the new PWM (Pulse-width modulation) switching strategy, which is based on sensor control of the rotor position. This strategy ensures that the torque ripple in BLDC motor is minimized [Abramov 2015]. The methodology for tuning the parameters in BLDC motor drive system and diagnosis for the BLDC motor faults detection including the wavelets and state estimation are described in [Abramov 2014a]. Stator winding faults and bearing faults, that cause most of the motor failures, are examined [Abramov 2014b].

A new method, presented in [Basseville 1993], is oriented on the parameters, which are operated under constant movement. The usage of quadratic time-frequency representations provided an identification in motors that operate in the terms (conditions) the continually changing [Cowan 2013].

Three algorithms are presented for the identification of the faults of the BLDC motors are presented three algorithms. These algorithms are able to trace and discover rotor faults in transient or non-stationary current signals [Zhang 2010, Frank 1990, Hammer 2010].

In papers [Aldrich 2013, IME 2012, Isermann 2006, Lee 2007, Luo 2017] is presented the union of diagnostic systems and control systems too. From the view of economic, thanks of increased reliability are the efficiency of the diagnostics systems higher, reduced number of rejections, accidents reduction, decrease of downtime of expensive equipment, increase of the service life and reduction of repair and maintenance costs.

2 MODELS OF INFORMATION PROCESSES FOR DIAGNOSTICS OF MECHATRONIC SYSTEMS

The Mechatronic Object Diagnostic System is a set software and hardware components that consists of multiple sensors, analog-to-digital converters, a computing device that processes information and operates based on the technical condition [Nikitin 2010, Felkaoul 2017, Saitaev 2014]. Accordingly, information process models and hardware models for systems diagnosing mechatronic objects are considered [Stepanov 2014a, Stepanov 2014b, Stepanov 2013]. Analysis of existing diagnostic models of MS makes it possible to conclude that there are no formulas for models, information processing algorithms and decision making [Tiwari 2018, Toro 2018]. The diagnosis of automated technological devices, MS and their components are an urgent task [Trefilov 2019, Turygin 2018, Guan 2015]. Use of modern methods such as machine learning for state prediction [Peterkova 2017 & 2018].

There are several information processes in the diagnostic system. The first information process determines how the diagnosis is organized. Determines the intervals, sequence of diagnostic modules, nodes, and MS elements. The second information process is used to decide on the technical condition of modules, nodes and MS elements based on AI methods.

Information process models, for determining the method of diagnostics

Three models of MS diagnostic methods are proposed: parallel, sequential and combined.

1. *Model of parallel MS diagnostics.* All nodes and MS elements are diagnosed simultaneously. The technical condition monitoring is continuous. This method requires maximum cost - each node and feature has its own diagnostic microsystem. A parallel way of organizing the diagnostic process is recommended when there is a threat to human health and life. High reliability is required because there are nodes and elements with high rates of deterioration processes.
2. *Model of sequential MS diagnostics.* All nodes and MS elements are diagnosed, one by one. Regular monitoring of the technical condition is implemented. Nodes and elements have integrated sensors to measure diagnostic parameters. There is one regulator for information processing that processes information at certain diagnostic intervals. This method requires minimal costs. However, it is necessary to calculate the intervals of diagnosis of nodes, elements and to determine the sequence of their diagnosis.
3. *Model of combined MS diagnostics*. the most critical nodes and elements of the MS are diagnosed simultaneously and the rest - at certain intervals of diagnosis. The criterion of minimum economic losses during MS operation must be used as a target function in the selection of the method of organizing the diagnostic process. Economic losses consist of equipment downtime, STOP in product manufacturing, and diagnostic system costs.

Model of information process on technical state of mechatronic systems

In order to properly decide on the technical state of MS, it is necessary to analyse the information provided by sensors. The following diagnostic parameters are used: electrical current, voltage, power and temperature fields, vibroacoustic parameters, spatial position accuracy, firmness, performance parameters, time periods (intervals). Diagnostic parameters have distinct physical characteristics; therefore, only mathematical apparatus is needed for their analysis. Neural networks, fuzzy logic, and genetical algorithm are suitable as such devices.

The NN that consists of modules corresponding to each MS node can be used to diagnose MS. These modules process the information based on the parameters obtained from the diagnostics. We know these NN layers [Stepanov 2014]:

- input layer,
- hidden layer, in which are the received data processed, the scales are assigned in the learning process [Turygin 2018, Enguang 2015],
- output layer.

Each input layer module contains a precise number of neurons. The number of neurons of the preceding layer is the same as the number of neurons of the hidden layer [Stepanov 2014]. Every module that has its own input layer has no reference to other modules. Each module is necessarily connected to the output layer separately. The output data is a matrix whose rows correspond to the state of a diagnosed node and the columns correspond to defects in that node.

So far, Anti-friction bearings in MS with integrated microprocessors have been developed and used, which measure the angular position and the rotational speed. It is possible to create electric propulsion that, in addition to MS, will have integrated the diagnostic system for detecting a defect of windings, rotor, mechanical gears, powerful semiconducting devices.

The main methods used for fault detection of an electrical drive in MS are: vibration diagnostics, analysis of motor´s actual electrical current, measurement of electromagnetic field of motor with measuring coils, chemical analysis, temperature, torque and power measurement, infrared measurement, acoustic noise measurement, radiofrequency measurement, measurement of partial discharges. The most common methods of these are vibration diagnostics, analysis of the motor´s actual electrical current and temperature analysis due to simplicity, high accuracy, and reliability. In many cases, the vibration methods are effective in detecting defects of electrical engines. However, vibration sensors, such as accelerometers, are installed on expensive devices where the cost of continuous condition monitoring is justified.

The NN with the reverse error propagation algorithm is used for diagnostics of MS. Errors in robots, manipulators, machining centres and CNC (Computer Numerical Control) machines [Pokorny 2012], AC (Automation Cell) [Calvo 2014], located in the following subsystems, are considered as an example of errors in MS. The mechanical subsystem´s defects are listed as:

- robots, mobile manipulators,
- regals, columns, sliding tables,
- universal spindle units, crankshafts, and driveshafts,
- gearboxes, starter couplings, brake coupling,
- cooling systems, lubricants.

Defects of electrical and electromechanical subsystems are specified in the following list:

- propulsion engines, generators,
- electrical cabinets with electrical equipment,
- other elements of the subsystems.

Hydraulic (tire) defects are mentioned as follows:

- hydraulic (pneumatic) cylinders, hydraulic engines,
- hydraulic pumps,
- control devices.

Defects of CNC technological equipment and tools

To measure diagnostic parameters force sensors are used to diagnose instrument, temperature sensors, current and voltage sensors for electric motors, sensors, and vibration sensors. Figure 1 shows a block diagram of a hybrid intelligent diagnostic system that represents a software and hardware complex. The knowledge database (rules) contains a set of rules "If ... then ... ". The decision subsystem uses the knowledge database to process the information, the database contains.

The decision subsystem provides the interface with the operator and operation in real-time. The hybrid intelligent diagnostic system software is based on algorithms for processing the information and deciding on the state/status of MS elements and nodes. Algorithms are based on intelligent data analysis algorithms. Such algorithms, called Data mining [Zidek 2016, Nemeth 2017, Nemeth 2019], enable the determination of the technical state and predict its change by the following tasks:

- The simulation of complex non-linear variations between I&O data,
- The identification of trends,
- Operating with loud signals and incomplete data,
- The actualization of the model, when new data becomes available,
- The identification of abnormal data.

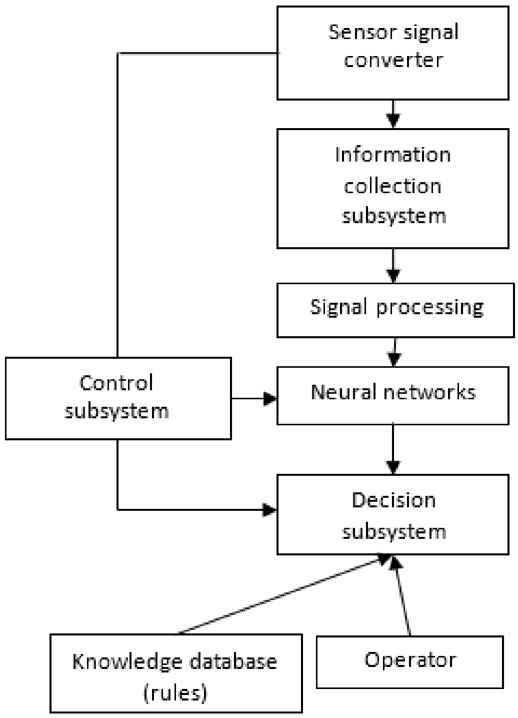

Figure 1. Block diagram of a hybrid intelligent diagnostic system

To solve the problems of intelligent diagnostics, it is necessary to integrate NN with fuzzy logic [Rezoug 2012, Janglova 2004, Mohd 2013]. For example, in the diagnosis of the machine spindle unit, axial and radial loads and speeds have a large impact on vibration and noise. Under the influence of load, the bearing clearance/voltage, the stiffness and the temperature in the bearings increases. The bearings clearance/voltage and the thermal deformation of the spindle is affected by the temperature change.

Therefore, four parameters: axial and radial load, temperature and rotation speed affecting the rules of using NN – x_1, x_2, x_3, x_4. Each rule uses its NN. Generally, we can write: "If $X = \{x_1, x_2, x_3, x_4\}$ is A_s, then y_s is output belonging to the NN S, where A_s is a fuzzy set of the conditional part of each rule. Each NN S has n inputs for diagnostic parameters and own scales. Figure 2 shows a model of a NN of fuzzy inference.

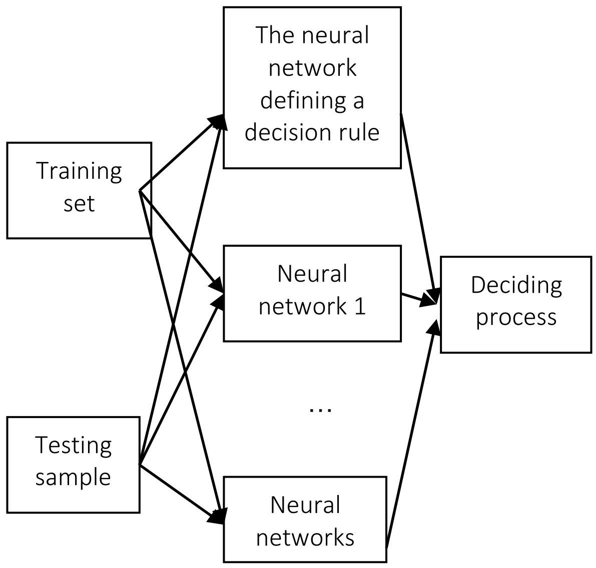

Figure 2. Model of a neural network of fuzzy inference

The NN model of fuzzy inference is crucial for propose of following algorithm for deciding on the technical state of MS:

Step 1. The creation of training and test samples. The training sample is created on a database acquired in different modes of MS operation.

Step 2. Cluster the training file. The training file is divided into r classes.

The *N*-dimensional entrance space is divided into r subspace. A decisive rule is set for each subspace.

Step 3. Training of the NN defining the decision rule. For each input vector $X_i \in R_s$ there is a subspace for decision rule M_i. R_s is a subspace for decision rule. After training and testing, the NN is able to determine the level to which each input vector and to which class of subspace Rs belongs. In this algorithm, it is possible to modify membership functions as a result of obtaining new data from experts to obtain more reliable results.

Step 4. NN *S* learning. The training set with input vector $X_i \in R_s$ and output value y_s is fed to NN *S*, a model of NN.

Step 5. Decision making.

The Gaussian function is selected as the term of membership functions of the linguistic variable *M*. The Gaussian function is quite simple, differentiable and defined only by two parameters. These reasons reduce the computing complexity of the algorithm. Linguistic variables *z*, *s* functions are chosen for the functions of expressions *L*, *H*.

There was chosen Mamdani fuzzy inference (MFPID), because of its good parameter settings. In the Figure 3 we show the example of terms *L*, *M*, *H* functions of I&O variables.

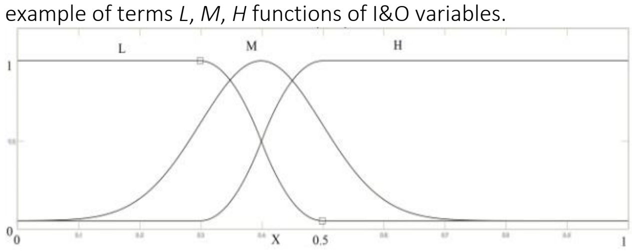

Figure 3. The example of terms L, M, H functions

When three linguistic variables are used with three terms combined with two logical operations AND, OR, 7 rules are possible. The mentioned rules, as shown below, reflect the dependence of the technical condition on the quantity of parameters, adequately the development of the resource too:

If (x is L) and (d is L) and (t is L) then (z is L)
If (x is M) and (d is L) and (t is L) then (z is M)
If (x is L) and (d is M) and (t is L) then (z is M)
If (x is L) and (d is L) and (t is M) then (z is M)
If (x is H) then (z is H)
If (d is H) then (z is H)

For a given input vector using NN *S*, the output value is calculated.

Thus, using the presented algorithm, which uses a fuzzy inference NN model, the technical state of MS elements and nodes is determined.

Sensor signals inform about the modes of operation of the MS. At present, there are no rules for network selection. Rosenblatt's perceptron network is suitable because it has an error propagation algorithm and allows us to minimize multilayer perceptron error. To select type of neurons, it is necessary to estimate the time to calculate the threshold activation function and the ability to differentiate this function. At each iteration of the backbone network, scales of the NN are modified to improve the solution of one example.

For a given input vector using NN *S*, the output value is calculated. Thus, using the presented algorithm, which uses a fuzzy inference NN model, the technical state of MS elements and nodes is determined. There are currently no network selection rules and types of neurons.

Rosenblatt's perceptron network is suitable because it has a back-propagation algorithm to minimize multilayer perceptron error.

In order to use the reverse error propagation method, the transmission function of neurons must be differentiable. Therefore, exponential sigmoidity is selected as the activation function. It is necessary to select the number of neurons and layers. If there are too few neurons or layers in the network, the network will not be able to learn, and the error will remain large during network operation. If there are too many neurons or layers, the network speed will be low, will needed a lot of memory and the network will be retrained. This means that the output vector will transmit insignificant and irrelevant details on the output e.g. will not be able to learn. Scaling is used to prepare the input and output data to bring the data to an acceptable extent. There is no general rule on how many hidden layers should be. Usually, there are *1-3* hidden layers. The more nonlinear problems, the more hidden layers should be. Using NN, the known stages of problem-solving of MS are emphasized:

- Data preparation and normalization,
- Choice of network topology,
- Experimental selection of network characteristics,
- Experimental selection of learning parameters,
- Proper network training,
- Checking the adequacy of training,
- Parameter settings,
- Final training,
- Publishing the network for future use.

3 NEURAL NETWORK FOR ANTI-FRICTION BEARNINGS DIAGNOSTICS

As an example, the development of a NN for bearing assemblies diagnostics that are common nodes in MS. The Rosenblatt perceptron network with Widrow-Hoff teaching algorithm was chosen for the diagnostics of MS bearing assemblies. This network allows minimizing multilayer perceptron error.

Four layers were chosen for the bearing assemblies' diagnosis experiment: one input, two hidden layers for the weight attribution and calculation of the output parameters taking into account weights, one output. Then, after learning the network, three layers will be used:

1. Input,
2. Hidden layer,
3. Output.

Informative parameters of the bearing unit are input – it is the frequency and amplitude of vibrations determined by spectrum. The error frequency of bearing assemblies' various elements was given by known terms. The input parameter can be the temperature of bearing circles/rings, but the temperature can be increased by relatively serious errors. In the case of initial errors, the temperature of bearing assemblies does not increase, therefore it is not considered as a diagnostic feature in this example. The Rosenblatt perceptron Network is a normal perceptron having a training sample consisting of input vectors, each having its own target vector. Components of input vector are represented as the continuous scope of values; the target vector components are binary values (*0* or *1*). After training, at the input, the network receives a set of continuous inputs and generates the required output as a vector with binary components. As is widely known, a defect in various states does not need to be a unique value but is within a range that requires a continuous field of output target values.
The maximum frequency of the vibration acceleration signal for single row radial ball bearing 6-180605 with double seals is *850.9 Hz*. Table 1 shows the frequency of manifestations of various bearing defects.

Table 1. Manifestation frequency of various bearings defects/frequency of manifestation of various bearing defects

Indication of frequencies at which bearing defects occur	Frequency of rotation of bearing parts	Frequency of manifestation of various bearing defects, (Hz)
f_{kl}	Frequency of bearing cage rotation	98.18
f_{vt-vok}	Frequency of anti-friction element rolling on the outer ring	589.09
f_{vt-vnk}	Frequency of anti-friction element rolling on the inner ring	850.90
f_{vt}	Frequency of anti-friction element rotation	638.18

For experiments, the MMA6233Q sensor with a frequency range of up to *900 Hz* was chosen. It has a built-in amplifier, low-pass filter with high sensitivity and a wide range of accelerations. During the experiments, the PCS500 digital oscilloscope was used to acquire an online frequency spectrum. The sensitivity of the MMA6233Q sensor is *120 mV* / g. On the PCS500, the *1*-volt digital oscilloscope display corresponds to a vibration acceleration of *8.33 g*. The DREMEL 300 electric drive was used as the motor for turning the inner ring of the bearing. Figure 4 shows a photograph of an experimental test bench consisting of an electric drive (1), a bearing (2), a vibration acceleration sensor (3), a digital oscilloscope (4), a personal computer (5).
Figure 5 shows the error-free carrier signal spectrum 6-180605 – of rotational speed error at 11250 min-1. We can see that there are clear peaks at 100 and 200 Hz. These frequencies are harmonics of the industrial frequency of 50 Hz and are caused by interference from the 50 Hz network.

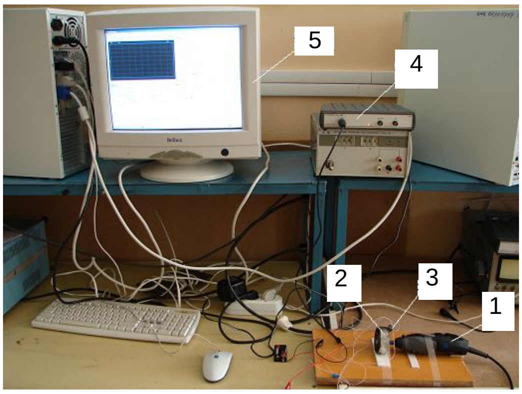

Figure 4. Experimental stand
1 – electric drive, 2 – bearing, 3 – vibration acceleration sensor, 4 – digital oscilloscope, 5 – personal computer

There are also peaks at a frequency of *75Hz* and a second harmonic frequency of *150 Hz*. Other apparent vibration peaks are not observed, the average vibration level is negligible at *0.5 V*, indicating good bearing condition.

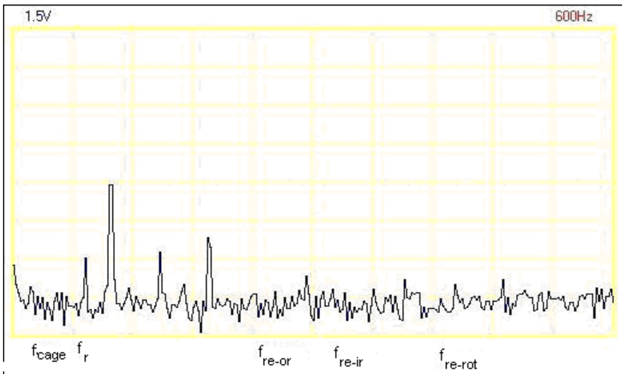

Figure 5. The error-free carrier signal spectrum 6-180605 at 11250 rpm

Figure 6 demonstrates the signal spectrum of the same bearing with artificial damage in form of transverse grooves on the outer ring. Defects of this type are reflected in the spectrum as peaks in the high-frequency field. By comparing the defected bearing with the defect-free bearing, it was discovered that the spectrum of the defected bearing increases overall vibration level by *0.7 ... 0.8 V* and there are wide peaks at *250 Hz*, which agrees to rolling frequency of anti-friction elements on the outer ring and at *340 Hz*, which agrees to rolling frequency of anti-friction elements on the inner ring.

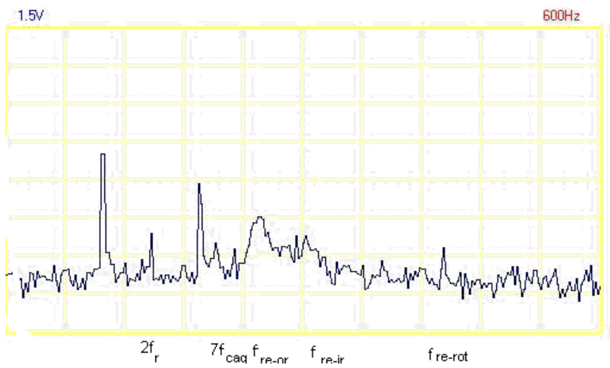

Figure 6. The 6-180605 carrier signal spectrum 6-180605 at 11250 rpm with defect

Figure 7 illustrates the spectrum of bearings for defect 6-180605 with an increased radial load. In this graph, the amplitudes of the spectral components increased at frequencies that are multiples of *50 Hz*, at a separator rotation frequency of *0.78 ... 0.8 V* at the rotor frequency and at its second harmonic frequency.

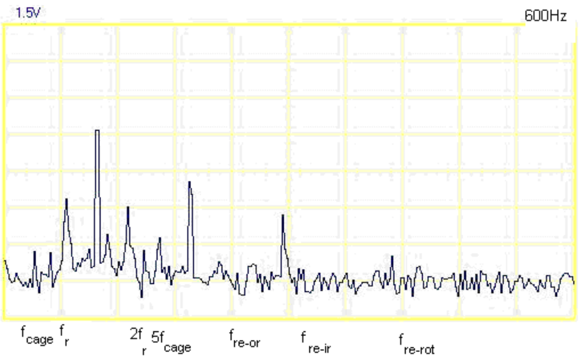

Figure 7. The carrier signal spectrum 6-180605 at 11250 rpm under radial load

Figure 8 shows the signal spectrum of bearing 6206 at *7800 rpm* without error. This spectrum also shows peaks at a frequency that is a multiple of *50 Hz*, *100 Hz*, and *150 Hz*. The average vibration amplitude corresponds to a level of *3 V*.

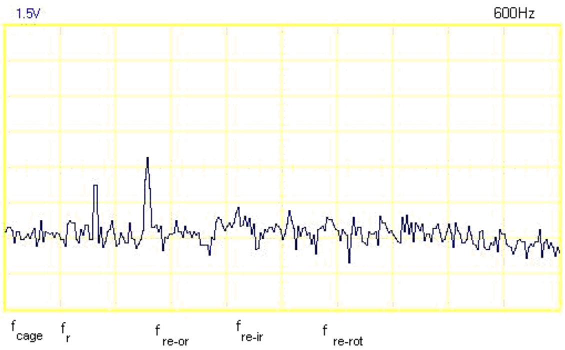

Figure 8. The carrier signal spectrum 6-180605 at a rotational speed of 180 rpm without error

The spectrum of the same bearing with a defect is demonstrated in Figure 9. The defect is damage to the outer ring in the form of transverse furrows. When comparing the defect-bearing spectrum with the defect-free bearing spectrum, an increase in vibration amplitude of *0.7 ... 0.8 V* is observed at a frequency of *270 Hz* of anti-friction element rolling frequency along the inner ring. The harmonic rotational frequencies of the bearing cage and outer ring will be recorded.

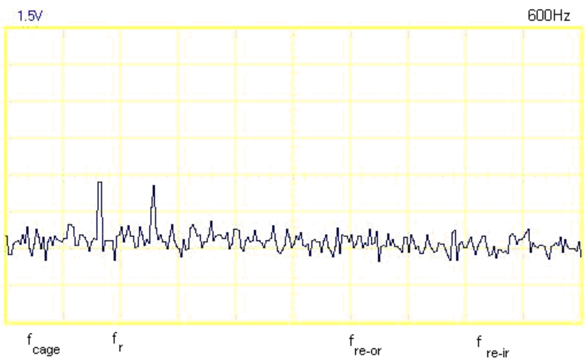

Figure 9. The 6-180605 carrier signal spectrum at 7800 rpm with defect

The signal spectrum of bearing 6206 without defect at *14400 rpm* is illustrated in Figure 9. This spectrum also shows peaks at a frequency that is a multiple of *50 Hz*, *100 Hz*, and *150 Hz*. The average vibration amplitude corresponds to a level of *3 V*.

Figure 11 illustrates the spectrum of the same bearing as in Figure 9 but with defect. When comparing the defect-bearing spectrum with the defect-free bearing spectrum, an increase in the overall vibration level is observed at frequencies from 360 Hz to *0.7 ... 0.8 V*, with the maximum peak decreasing to the *510 Hz*, the rolling frequency of the outer ring anti-friction elements. The amplitude increased by *2 ... 2.5 V*.

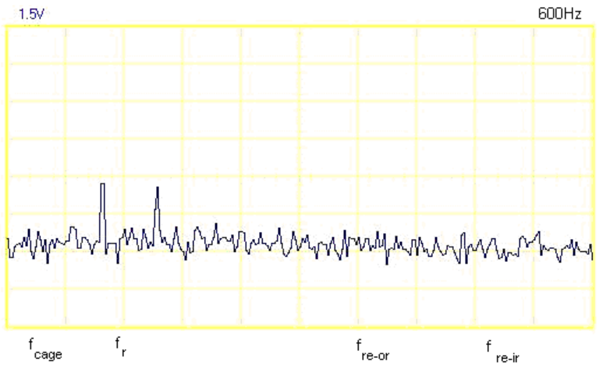

Figure 10. The carrier signal spectrum 6-180605 at 14400 rpm without defect

When errors are present, the amplitude increases by an average of *0.75 V* throughout the frequency spectrum, the vibration level increases by *1.5 ... 2 V* at the rotational frequencies of the outer and inner ring anti-friction elements. While under the radial load the amplitude increases at rotor speed and at the industrial frequency of *50 Hz* the peaks appear at the rotational speed of the separator.

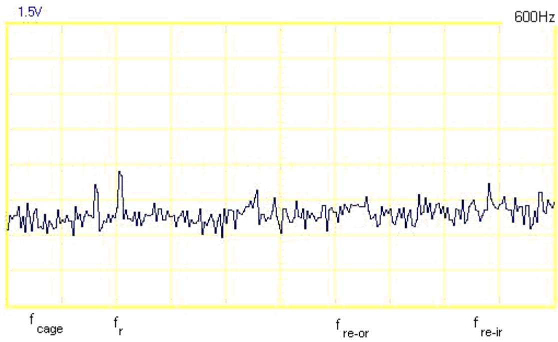

Figure 11. The carrier signal spectrum 6-180605 at 14400 rpm with defect

The NN modelling was performed in the MATLAB. The input data in all examples are presented in the form of a two-dimensional vector, including frequency and corresponding amplitude:

- bearing cage rotation frequency,
- the bearing balls noise frequency on the outer ring,
- the bearing balls noise frequency on the inner ring,
- the rotational frequency of the anti-friction elements.

The NN input data of bearing 6-180605 are shown in table 2. The target vector is a value that is the product of the logical addition of the binary values *0* and *1*, characterizing the absence of an error or its presence in the bearing components (bearing cage, outer ring, inner ring, anti-friction elements). Therefore, the expression *0v0v0v0 = 0* means the absence of any defects and expression equal to *1* corresponds to the presence of a defect in the bearing.

Figure 12 demonstrates the training sample of NN in MATLAB for bearing 6-180605.

Table 2. The NN input data for the bearing 6-180605

The neural network inputs			
Frequency		Amplitude	
		Defect-free	With defect
f_{lk}	0.050	0.250	0.500
5	0.250	0.210	0.470
7	0.375	0.246	0.530
$f_{lk\text{ - }vok}$	0.420	0.250	0.750
$f_{lk\text{ - }vnk}$	0.550	0.250	0.500
f_{vt}	0.730	0.250	0.330

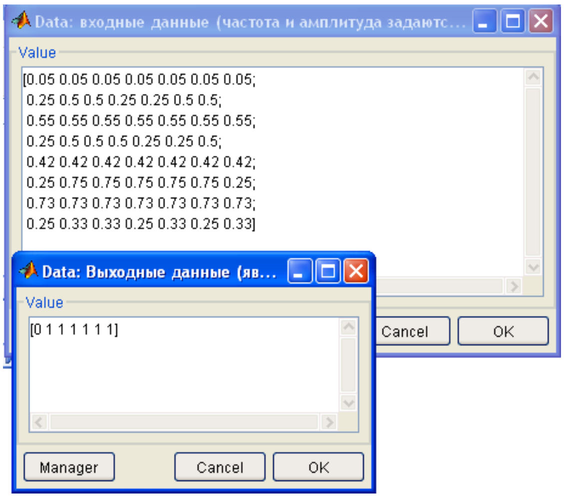

Figure 12. Training NN sample of the bearing 6-180605, output data

Figures 13 to 16 demonstrate the training and testing of the NN. The target vector is a value that is the product of the logical addition of the binary values 0 and 1 that characterize the absence of the error or its presence in the supporting structural elements.

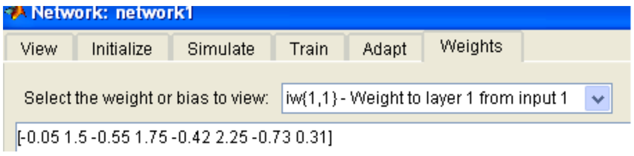

Figure 13. The scales of NN for the bearing 6-180605

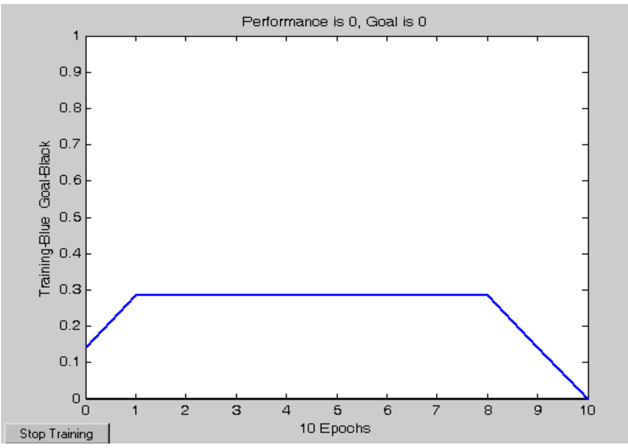

Figure 14. Neural network learning curve for the bearing 6-180605

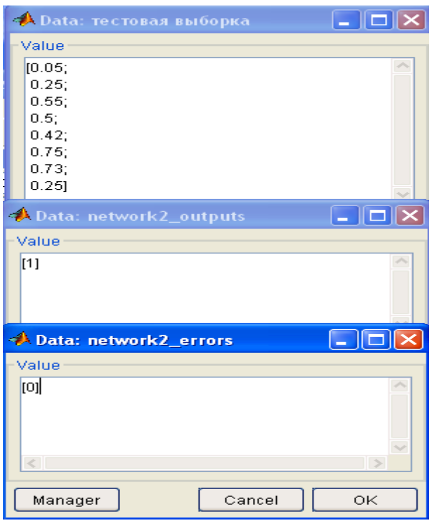

Figure 15. Neural network results for the bearing 6-180605

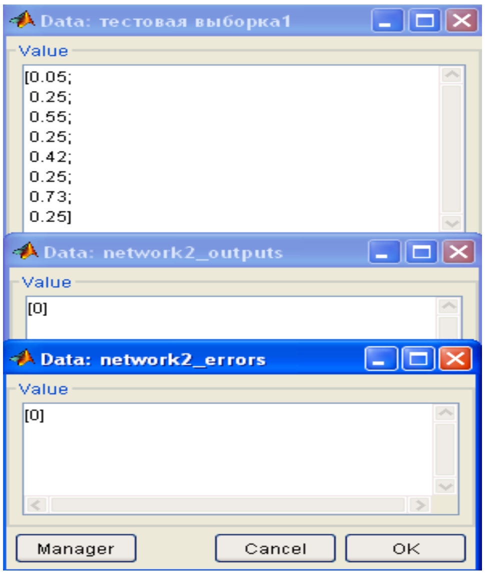

Figure 16. Neural network results for the bearing 6-180605

4 CONCLUSIONS

The most important prospects for the development of automated technology systems are intellectualization, increased reliability, and modular design. Diagnostics of technological systems increases their level of intellectualization and reliability. By analysing a method based on the analysis of methods of diagnostics of technological systems, it was concluded that the following diagnostic methods should be used for their diagnostics: by means of vibrations, temperature and electric current and by methods of AI. Analysis of the current state of algorithms and software products of automated diagnostic systems revealed a tendency to create diagnostic programs based on modular AI methods. Analysis of diagnostic equipment for technology systems has shown that the development of small diagnostic devices based on a microcontroller or processor for processing digital signals with excellent computational capabilities and a standard operating system for express-diagnostics that have a connection to an in-depth diagnostics server, the trends in diagnostics are calculated: parameters, calculation of residual lifetime of MS, data archiving. Continuous diagnostic systems are recommended for diagnosing critical propulsion of technological systems in order to prevent accidents that can lead to human casualties, technological disasters or significant economic damage. It should be noted that diagnosis is dependent on the use of all types of sensors that are capable of measuring both electrical and non-electrical quantities.

1. On the spectrum of a bearing 6-180605 with a defect, the general vibration level increases by 0.7–0.8 V and wide peaks are observed at a frequency of 250 Hz, which corresponds to the rolling frequency of the rolling bodies along the outer ring, and 340 Hz, which corresponds to the rolling frequency of rolling bodies along the inner ring.
2. On the spectrum of bearing 6206 with a defect, an increase in the amplitude of vibrations is observed by 0.7–0.8 V at a frequency from 270 Hz, which belongs to the frequency of rolling of rolling elements along the inner ring. The harmonics of the rotational speeds of the separator and the outer ring become noticeable.
3. In the presence of defects, the amplitude increases by an average of 0.75 V over the entire frequency spectrum, the vibration level increases by 1.5 ... 2 V at the frequencies of rotation of the rolling elements along the outer ring and the inner ring, with a radial load, the amplitude at the rotor

speed increases and industrial frequency of 50 Hz, and peaks appear at the speed of the separator.

4. The performed investigations show the possibility of application of artificial neural networks for detection of automated technological devices state according to diagnostic features. Neural networks and fuzzy logic are perspective mathematical apparatus for creation of systems of diagnosis of automated technological devices.
5. We got the results that both fuzzy logic and neural networks are suitable for diagnosing automatic devices. For the diagnosis of automatic devices with the help of neural networks, a certain set of data is required for serviceable and defective training devices. To diagnose automatic devices using fuzzy logic, it is necessary to draw up rules that determine the state of devices based on the values of the diagnostic parameters, their trends, taking into account the current operating mode and the exhausted resource.
6. The results can be used in practice to create smart automatic devices that will report on their technical condition, the presence of defects and predict the residual life of the work.

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