DEVELOPMENT OF A DECISION BOX OF DIAGNOSTIC SYSTEM FOR ELECTRIC DRIVES

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The paper describes a diagnostic system for electromechanical equipment with a decision-making block based on a neural network. An asynchronous gear drive was used as a control object. Decision making was carried out on the basis of a comprehensive analysis of vibration data (from the gear drive) and the current consumption of the induction motor. Vibration velocity, vibration acceleration and current in the phases of the stator winding of the drive electric motor are distinguished as diagnostic signs. The work shows the possibility of increasing the efficiency of diagnostics of electromechanical equipment by using complex analysis with the use of an intelligent decision-making unit. Analysis of the results of the neural network operation with the received vibration and current data showed that with a smaller number of iterations (training time) (by 40 %), 97.9 % of correct answers and a lower error value (by 12 %) were obtained.

KEYWORDS

Current, vibration, neural network, diagnostics, electric drive.

1 INTRODUCTION

With the increasing automation of modern production (Industry 4.0), the requirements for its reliability are increasing. Therefore, diagnostics (control of technical condition) of equipment is becoming the most promising and rapidly developing aspect of modern mechanical engineering. At present, the theoretical foundations for assessing the technical state of electric drive systems are insufficiently developed due to the complexity of the physical processes occurring in such systems, the complexity of the mathematical formalization of the description of these processes and defects, with the limited measured diagnostic parameters, with measurement errors. Due to the above-mentioned reasons, there are no descriptions of the regularities between the diagnostic parameters and the states of electric drives. Therefore, it is not possible to systematically solve the problems of diagnosing and assessing the residual resource, planning maintenance and repair.

In industry, an asynchronous electric drive is widely used due to a number of advantages: high reliability, low cost. In engineering practice, it is the use in the field of production technology and production technologies such as turning, milling, drilling, etc. [Kolesnyk 2020, Sentyakov 2020, Peterka 2013, Vopat 2014]. The main purpose of the research is to improve the efficiency of diagnosing the states of an electric drive through the use of an integrated approach based on the analysis of information of different physical nature (vibration and current consumption) generated by individual drive elements. In an electric drive, electrical processes occur, which are characterized by electric current, and mechanical processes, which are characterized by vibration. Therefore, the choice of these diagnostic parameters is obvious.

In work [Stepanov 2014] such diagnostic features as the coefficients of the wavelet transformation of vibration (using the example of vibration velocity) and the current consumed by the drive motor are investigated. As a supplement, the vibration velocity spectra are also considered.

The modern level of development of hardware and software allows high-quality data collection and processing, as well as displaying information and making decisions about the state of the equipment. One of the promising directions in the development of means for monitoring the technical condition of equipment is the use of neural networks [Stepanov 2013].

The detection and diagnosis of motor faults based on a metacognitive network of random vector functional relationships is discussed in [Sayed-Mouchaweh 2018]. The book [Saad 2019] covers various issues related to motor condition monitoring, signal processing and conditioning, instrumentation and measurements, faults for induction motors failures, new trends in condition monitoring, and the fault identification process using motor currents electrical signature analysis. For detection of the various faults usually affecting motors, several techniques have been proposed and used successfully [Isermann 2006, Murcinkova 2013, Costa 2016]. However, a good understanding of the mechanical and electrical properties of the motor in healthy and faulty conditions significantly influences the accuracy and reliability of the online condition monitoring methods.

Methods of diagnostics on fuzzy logic and neural networks are considered in [Kuric 2021, Bozek 2021, Nikitin 2020a]. It is shown that these methods give good results for finding defects in motors. The various issues of diagnostics of electric motors are considered in [Peterka 2020, Turygin 2018, Thomson 2017, Nikitin 2020b, Lekomtsev 2021]. Diagnostic methods based on the current signature analysis of the electric motor are discussed in [Luo 2017, Qiu 2020]. The diagnosis of bearing in electric motors is discussed in [Ojaghi 2018, Cui 2017]. Fault-Tolerant electrical machines and drives is discussed in [Mustafa 2017]. The pioneer studies of such systems are fault diagnosis studies.

On the basis of existing research, modern methods of diagnostics of the technical condition of electromechanical equipment have been studied. The standards for vibration control are also considered. It was revealed that the following trends can be traced in the field of diagnostics:

1. Development has received the diagnosis of electric drives only for one type of diagnostic parameters (vibration of equipment) without taking into account the interaction of electrical and mechanical elements of the equipment.

2. Most modern diagnostic systems have the ability to collect signals from additional sensors (temperature, current, etc.) in addition to vibration sensors. However, their use is limited only to the output of the overall level of such a signal.

3. At the same time, there is a need to improve the efficiency of diagnostics and to eliminate errors and false alarms by introducing an integral (complex) assessment of the technical condition.

The authors concluded that the analysis of vibration, as the most common type of diagnostic parameters, in some cases may not be enough. One of such cases is diagnostics of electric drives. For these units, the necessity of the complex use of mechanical and electrical parameters has been substantiated.

Thus, in this work, the task is to improve the efficiency of the diagnostic process for electric drives using an intelligent decision-making unit based on vibration and current sensors.

2 LABORATORY BENCH AND RECORDING EQUIPMENT

A laboratory stand (asynchronous drive with a worm gear, Fig. 1) was used as an object of diagnostics. The power of the asynchronous electric motor is P = 0.18 kW. Rotation speed n = 1350 rpm. Worm gear MCh-40M-31.5-47.6-51-5-1S-U3. Load on the output shaft of the worm gear M = 32 N·m. In laboratory conditions, the following malfunctions were identified and reproduced: reduction of the contact patch of the gear transmission, misalignment of the gear transmission, grazing in the engagement zone, grazing on the drive motor shaft, rotor imbalance, loosening of the foundation (fastening), lack of lubrication.

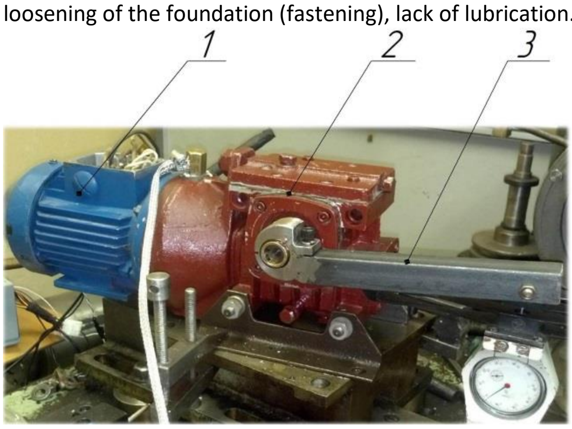


Figure 1. Laboratory bench: 1 - asynchronous motor; 2 - worm gear; 3 - loading device

To obtain diagnostic information at both stands, the following sensors were used: vibration transducer AR2019, current sensors LEM LA-55P.

Tab. 1 and Tab. 2 shows the technical parameters of the sensors used: vibration transducer AR2019 and current sensors LEM LA-55P.

Parameter of Vibration transducer AR2019	Value
Noise level, RMS (1 Hz–10 kHz), g	< 0.005
Frequency response (flatness ± 1 dB), Hz	5-30000
Working temperature range, °C	-40...+125
Maximum impact (peak value), g	± 10000
Amplitude range, g	± 7000
Transverse sensitivity	< 5 %
Axial sensitivity, mV/g	0.5 ± 10 %

Table 1. Technical parameters of the AR2019 vibration transducer

Parameter of LEM LA-55P current sensor	Value
Rated value of the measured current, A	50
Response time, ns	50
Output, mA	25

Measurement range, A	±100
Bandwidth, kHz	200
Working voltage, V	±15 (±5 %)
Working temperature, °C	-40...+85
Accuracy, at rated current in the primary winding, T = 25 °C, ± 15V (± 5 %) – power supply	±0.65 %

Table 2. Technical parameters of the AR2019 vibration transducer and the LEM LA-55P current sensor

The current sensors were installed in the electric motor control unit (for two phases), and the vibration sensor was installed at the control point on the gear reducer in accordance with GOST R ISO 13373-1-2009.

Vibration transducer AR-2019 needs external power supply. The connection diagram of the sensor to the equipment and the matching device is shown in Figures 2 and 3.

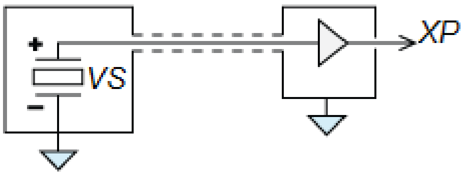


Figure 2. Connection diagram of the AP2019 to the recording equipment: VS - vibration transducer, XP - output from the matching device

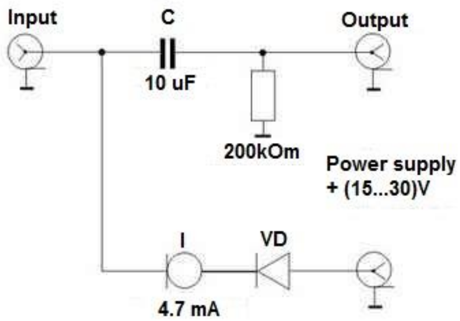


Figure 3. Diagram of the matching device for the AP2019 sensor

The terminator output connects to the NI SCB-68 connector block. LEM LA-55P current sensors are installed on the stator windings of the drive motor. The sensor circuit and its connection are shown in Figure 4.

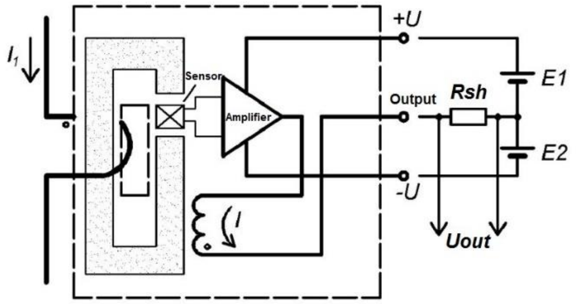


Figure 4. LEM LA-55P sensor connection diagram

A resistor of 100 Ohm is selected as Rsh.

The calculation of the coefficients of the discrete wavelet transform was carried out using the developed software in the LabView environment (data collection and processing unit). The reliability of the calculation was confirmed in the MatLab software environment using the Wavelet Toolbox.

3 DEVELOPMENT OF THE ARCHITECTURE OF THE DECISION BOX

As part of the research, work was carried out to select the optimal architecture of the neural network classifier and it was concluded that the best results in training and testing are achieved precisely on the basis of a 3-layer neural network with the number of neurons on the input layer – 80, on the intermediate layer – 1000 and on the output – 8.

Based on the application of the basic principles of building decision-making systems, a model for recognizing the technical states of electromechanical equipment has been developed on the basis of a 3-layer neural network classifier (Fig. 5) with a nonlinear activation function of computational elements in a layer (bipolar sigmoid) and a learning algorithm based on backpropagation based error. The proposed model is capable of developing a decision on the state of the object for various combinations of diagnostic features that were not previously encountered in the training sample, and thereby increasing the reliability of recognizing the technical condition of the equipment.

The developed architecture includes an input layer (80 neurons, labeled X_1, ..., X_i, ..., X_n), an intermediate layer (1000 neurons, labeled Z_1, ..., Z_j, ..., Z_m) and an output layer (8 neurons, labeled Y_1, ..., Y_k,..., Y_p). The input layer receives information about the current state of diagnostic features (the number of neurons is equal to the number of diagnostic features), data is processed on the intermediate layer, and a larger number of neurons ultimately lead to more accurate results and a decrease in the performance of the network as a whole. At the output layer, decisions about the state of the object are issued (the number of neurons is equal to the number of recognizable states of the equipment).

Neurons representing the network outputs (designated $Y_1,\ldots, Y_k,\ldots, Yp$) and hidden neurons can have an offset of 1 (Fig. 5). These biases serve as weights on the connections (*v*, *w*) emanating from neurons, the output of which always appears 1. During the learning process, the signals propagate in the opposite direction, where the network response error is calculated and the weighting coefficients *v* and *w*. The output signal *Y* takes on a maximum value in%, which corresponds to a specific technical condition of the equipment (the probability of this condition).

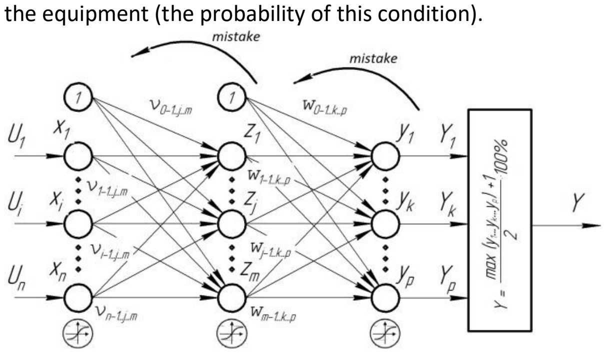


Figure 5. Neural network architecture

The decision box was implemented as a separate environment with the ability to load data from the data collection subsystem.

The training was built on the basis of the error back propagation algorithm (Fig. 5).

On one laboratory bench in each experiment, a certain type of defect or malfunction was created by changing either the position of the worm wheel or replacing it (5 wheels were made). After testing with a gear reducer, the reducer worm wheel was replaced (5 gear wheels were replaced). In each experiment, about 1000 measurements were carried out.

4 DECISION BOX TRAINING

Training and testing of the developed network was carried out on the basis of experimental data obtained at the laboratory bench when simulating defects. The training sample included 20 features (general level and Daubechies wavelet coefficients db-8 – root-mean-square values (hereinafter - RMS) and their maximum values (max)) for each information flow (vibration acceleration, vibration velocity and two electric current of phases), supplemented with a noise component (10-200 % of the standard deviation (hereinafter – SD) for vibration acceleration and vibration velocity and 10-300 % of SD for current). With such a sample, the neural network was trained (about 40000 iterations), the result of which is shown in Tab. 3.

Parameter	Value
Number of hidden layers	1
The number of neurons on the hidden layer	1000
Vibration noise, % of RMS	200
Noise current, % of RMS	300
Total iterations	40473
Total correct answers	39674
Total errors	799
Percentage of correct answers, %	98
Mean square error	0.071
Number of neurons on the input layer	80
The number of neurons on the output layer	8

Table 3. Neural network training results

Also, a statistical estimate of the root mean square error (MSE) was carried out, defined as the mean square value of the differences between the desired output value ti and the values Yi actually obtained at the network outputs for each example i, averaged over n tests. Formula (1) characterizes this error:

$$MSE = \sqrt{\frac{\sum_{i=1}^{n}(t_i - Y_i)^2}{n}}, \qquad (1)$$

where ti is the required response from the neural network; Yi is the answer received as a result of the neural network; n is the total number of neural network tests.

The noise component during training affects the sensitivity of the neural network as a whole. The selected noise values ultimately affect the ultimate reliability of the network's responses, as well as the learning rate. For example, in the case of “rotor imbalance” malfunction, the RMS of the wavelet coefficient d6 of the current of the first phase was 0.682 with an RMS of 0.003. By increasing the RMS value by 300 % (adding a noise component), the network sensitivity also changes (downward), but the recognition accuracy increases (during testing). However, this approach yields good results only with a small number of recognizable output states. In the context of this work, an increase in the noise component is acceptable.

To further substantiate the presence of a connection between mechanical and electrical parameters, we present the results of training a neural network (of the same architecture: one hidden layer with 1000 neurons) when only vibrational (Tab. 4) and only current parameters are supplied to its input (Tab. 5).

It can be seen from the results obtained that this architecture of the neural network shows good results during training when only vibration data is supplied to the input (Tab. 4). However, when comparing these learning results with the results obtained on the parameters of vibration and current (Tab. 3), we can conclude that with a smaller number of iterations (training time), we get approximately the same percentage of correct answers and a smaller error value.

Parameter	Value
Vibration noise, % of RMS	200
Total iterations	64487
Total correct answers	62941
Total errors	1546
Percentage of correct answers, %	97.6
Mean square error	0.081

Table 4. Results of training the neural network when the parameters of vibration acceleration and vibration velocity are fed into the input

Parameter	Value
Noise current, % of RMS	300
Total iterations	1114867
Total correct answers	897312
Total errors	217555
Percentage of correct answers, %	80.5
Mean square error	0.5

Table 5. The results of training the neural network when the current parameters are fed to the input (phase 1 and phase 2)

In fig. 6 shows the effectiveness of training an artificial neural network using various input data: "all data" hereinafter – SD both vibration (vibration acceleration and vibration velocity) and current data (phase 1 current, phase 2 current) are fed to the neural network input.

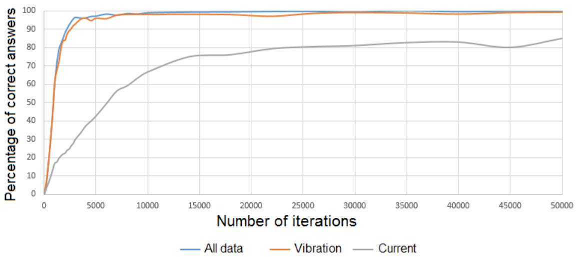


Figure 6. The effectiveness of training an artificial neural network

It can be seen from the presented graph that when only current data is supplied to the input, the training efficiency drops sharply. However, if we compare training with the use of only vibration data, with training with complex data, we can conclude that when the values are 70% or more, the current parameters have a significant effect on the training duration.

Consequently, the training of the neural network is carried out most efficiently with an increase in the number of input parameters. The positive dynamics during training can also be explained by the presence of the same reaction of the controlled parameters of vibration and current to the occurrence of defects and malfunctions.

5 DECISION BOX TESTING

When testing the trained network, the values of diagnostic signs (80 values) obtained in laboratory conditions were fed into the input. The test results are shown in table 6. A change in the noise component of the training sample strongly affects the final reliability of the network solutions. The selected value for this component led to the best test results (average confidence about 99 %).

An important result when testing a neural network was the identification of diagnostic features (wavelet coefficients), which are the most sensitive (informative) to changes in the technical state of electrical equipment. In the studies carried out, the value of the selected controlled traits has been substantiated.

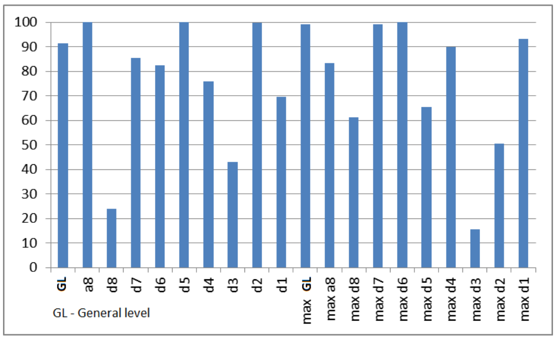
Input data	Number of tests	Validity of decisions, %
Working condition	2121	100
Reduction of the contact patch of the gear train	1067	99.6
Gear misalignment	1067	98.9
Grazing in the engagement zone	1063	100
Grazing on the asynchronous motor shaft	1062	100
Rotor imbalance	1063	100
Looseness of fastening	1056	100
Lack of lubrication	1137	97.9

Table 6. Results of testing the neural network after training

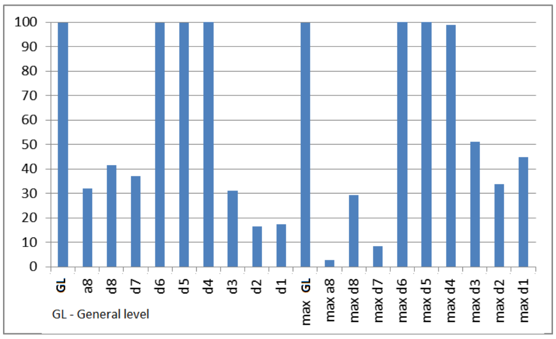
In view of the fact that the training set included 20 features supplemented by a noise component of 10-200 % of the standard deviation for vibration acceleration and vibration velocity and 10-300 % of the standard deviation for the current, in table 5 the best results in comparison with table 2-4 were obtained. This manipulation allows to increase the range of diagnostic signs for troubleshooting. In the future, with an increase in the number of faults, it is necessary to adjust the training sample in order to achieve better results during testing.

If a signal is sent to one of the neurons of the output layer and pass it through all the hidden layers to the input layer, the numerical characteristics of the input neurons in relation to this output neuron is given. This allows, as a result of the work of the decision-making unit, to select the most sensitive diagnostic signs for assessing the technical condition with the level of confidence in these results (in %).

For example, for the diagnosis “Lack of gear lubrication” (Fig. 7), the most informative are the wavelet coefficients a8, d5, d2 and the peak values of the general level and coefficients d7, d6 of vibration acceleration (99-100 %), as well as general level, coefficients d6, d5, d4, peak values of the general level and coefficients d6, d5, d4 of the current of the first phase (99-100 %).



(a)



(b)

Figure 7. An example of the selection of sensitive (the level of confidence is indicated on the ordinate axis, in %) diagnostic signs in the absence of lubrication of the gear transmission in the decision block: a) from the vibration acceleration signal, b) from the current signal of the first phase

6 CONCLUSIONS

As a result of the analysis, a method was developed for selecting the most informative diagnostic signs for diagnosing electric drives with a reliability level of results close to 100 %, obtained from the output of the decision box. The architecture of a neural network has been developed, which consists of 80 input neurons, 1000 intermediate and 8 output neurons. Analysis of the results of the neural network operation with the obtained vibration and current data showed that with a smaller number of iterations (training time) (by 40 %), approximately the same percentage of correct answers and a lower error value (by 12 %) were obtained.

Thus, on the basis of the study carried out, the urgent scientific and technical problem of developing a decision-making block, characterized by a joint analysis of mechanical and electrical parameters, has been solved. Thus, the efficiency of the technical condition monitoring is increased in the form of an increase in the reliability indicator up to 97.9 %.

For automated processing of experimental research results and subsequent practical implementation, a unified information and measurement system has been developed, which includes a hardware platform and software products for collecting and processing data, as well as a decision-making unit based on a neural network, including a laboratory stand for research malfunctions of the electric drive.

The results of the study showed the possibility of increasing the efficiency of diagnostics through the use of an integrated approach (increasing the number of diagnostic signs), which speeds up the adjustment (by 1.5 times), reduces the magnitude of the error and increases the reliability of the decisions.

Thus, based on the analysis of the wavelet coefficients of current and vibration acceleration, reliable detection of such defects as defects of the mechanism as a whole (loosening of fastening and grazing), malfunctions of motors (imbalance of the rotor of an induction motor, grazing of the rotor), malfunctions of the gear transmission (misalignment, reduction of the contact patch, lack of lubrication) is provided. This paper shows the possibility of increasing the efficiency of diagnosing an asynchronous electric drive by using complex analysis using an intelligent decision-making unit.

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