A Cyber-physical System of Diagnosing Electric Drives of Building Robots

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Abstract-

This article studies the development of a cyber-physical system for diagnosing and forecasting the technical condition of electric drives in robots used for construction. The structure of the cyber-physical system is described and the defect statistics for asynchronous drives submitted. Additionally, a critical analysis of existing diagnostic methods, the selection of the optimal set of diagnostic parameters and existing methods for measuring and analyzing the parameters used for the drives adopted in construction robots for is described. Herein, a method capable of distinguishing a faulty state from a load change based on wavelet transformation and neural networks (diagnosing the technical condition of robot drives) is proposed. Finally, we provide the simulation and experimental results of the proposed method.

Keywords –

Cyber-physical system, building robots, electric drives, diagnosing of technical conditions, forecasting, wavelet transformation, neural networks classification

1 Introduction

Increasing the requirements for reliability and efficiency of construction robots entails the need for constant monitoring of the technical condition of all actuators with further optimization of the operating mode of individual components and hence of all equipment as a whole. This can be achieved by using a technical condition monitoring system built into the robot's end-effectos, which continuously measures parameters with sensor system, analyzing the information obtained and determining the current technical condition, forecasting the development of defects, and optimizing the parameters of the object's operation mode. Implementation of this approach to improving the functioning efficiency of the equipment assumes the integration of computing resources into physical processes, i.e. application of cyber-physical systems [1]. In such systems, sensors, mechanical equipment and information systems are connected during all stages of the life cycle and interact with each other using standard Internet protocols in order to predict and adapt to changes in operating conditions and technical condition of the equipment. The structural scheme of the cyber-physical predicting diagnosing system of the construction robot is shown in Figure 1.

The cyber-physical prediction diagnosis system has five levels: connection, conversion, cloud, cognition and configuration [2].

At the "Connection" level, sensors are selected and installed, which can be designed for self-connection and self-monitoring of the state of the object.

At the "Conversion" level, data from devices with autonomous connection and sensors measure the characteristics of critical problems and methods for analyzing the information that will be used to determine possible selected malfunctions.

Storage and processing of large amounts of diagnostic information is carried out in cloud servers. This will allow the information flow and communication between the drives of various construction robots. Based on that, the optimization of the technological process starts taking into account the state of a separate actuating element.

At the "Cognition" level, the results of diagnosing and forecasting are determined, which are presented to users and transferred to the mathematical model of the object for further optimization of the object mode operation.

The application of the cyber-physical approach is to develop a diagnostic platform. The forecasting systems will significantly improve the reliability of the construction robots. Information links between the robots at the construction site through the Internet protocol will allow optimizing the entire construction process, depending on the technical condition of each drive of the executive equipment. This will maximize performance and minimize the likelihood of failure.

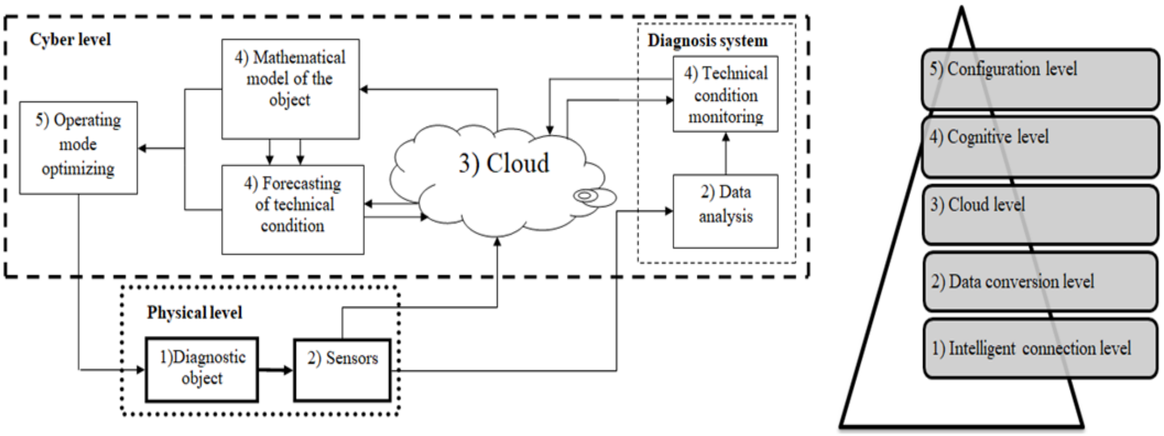

Figure 1. Cyber-physical system of the technical condition prediction diagnosis for electrical equipment

2 "Connection" level organization

The main component powering up the end-effectors of the robots is the electric drives of direct and alternating current (e.g. see Figure 2), which operate in a short-time mode and must have a high overload capacity and dust and waterproof design criteria known as IP standards.

The main type of drives used in construction robotics is a medium power asynchronous drive with a squirrel-cage rotor. The available statistics give the following data on the relative damage of the nodes of such engines (e.g. see Table 1) [3, 4].

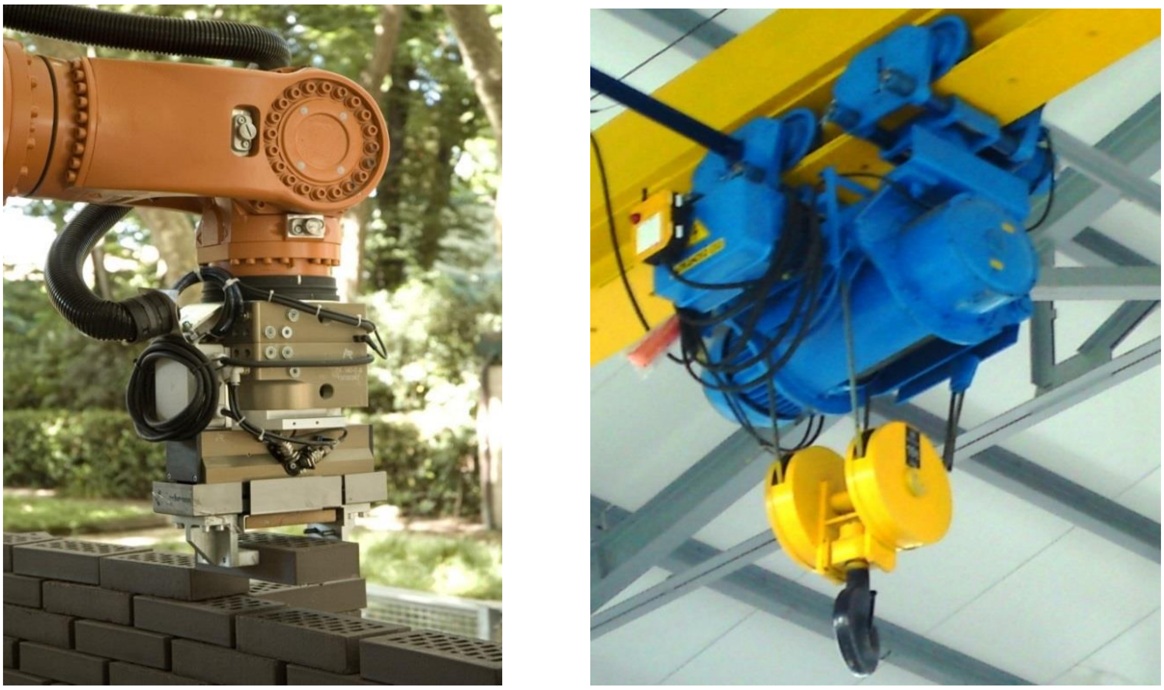

Figure 2. Electric drives in building robots

This figure shows that all engine failures of the aforementioned type are of mechanical or electrical origin. Thus, multi-parameters diagnostics methods are used that assume control of thermal, electrical and mechanical defects at the operating voltage [5]. In this case, the following applies:

- direct electrical control methods with galvanic connec-tion to the terminals of the motor leads (measurements or harmonics, or pulsations, or pulses of the supply current and voltage);
- methods of monitoring with the installation of sensors on the motor housing that fix electromagnetic or sound waves:

Table 1 Medium voltage motors typical defects

Fault	Percentage failure in operation
Discharge an sparking in current wire	40
Discharge and sparking in insulator. Heating of the terminal box	20
Insulation damage in stator winding	15
Sparking in magnet core. Heating of the defect zone	10
Heating of bearing	9
Discharge in cable insulation	4
Sparking in the squirrel cage	2

measurements of partial discharges, sound waves or capacitive currents to the ground while monitoring vibration;
- method of remote control: thermal imaging measurements of the temperature of the engine and bearing surfaces.

Joint use of these methods makes it possible to determine the technical state, but at the present time, the analysis of diagnostic information is currently done manually by troubleshooting experts, which is very not cost effective.

Hence, it is necessary to choose a list of diagnostic parameters that allow determining all possible classes of defects, having accepted sensitivity features over the changes in the values of structural parameters, minimum composition, accessibility for monitoring, measurement and software analysis without operator's involvement, cost and time effectiveness and sufficient degree of segregation when recognizing individual defects.

Construction robots operate in complex non-deterministic conditions with high alternating loads in conditions of high humidity and dust; their drives are often installed on a mobile base, which imposes significant requirements for the choice of methods and means of diagnosis such as:
- minimum composition of the measured parameters;
- the absence of complex bulky measuring equipment installed on the drive housing, which can affect the operation of process equipment;
- the ability to automatically analyze the measured parameters.

The most common diagnostic parameters for asynchronous drives are a partial discharge, supply and capacitive current, vibration and temperature [6]. A comparative analysis of the adequacy of methods based on the control of these parameters [7, 8], taking into account the limiting requirements, allows to make the following conclusions:
- the diagnostic of mechanical defects in medium power engines, instead of vibration analysis, harmonic analysis of motor feed currents (MCSA technology), harmonic analysis of capacitive currents to ground (CTG technology) can be used;
- as for the diagnostic of electrical defects, it is advisable to combine harmonic analysis of supply and capacitive currents in the ground circuit.

Analysis of the majority of electrical and mechanical faults of the asynchronous drive can be detected by monitoring the supply and capacitive current, which can be measured without the use of special sensors.

3 "Conversion" level organization

The analysis of current supply harmonics (MCSA-Technology) consists in the decomposition of the signal using Fourier transform and amplitude analysis at characteristic frequencies. Each fault has its own characteristic frequencies, including sub-harmonics, harmonics and intera-harmonics between the spectral lines of the reverse frequency - f_{rot}. For example, if there are harmonics of the reverse frequency (f_{rot}, $3f_{rot}$, $5f_{rot}$), there will be misalignment or no parallelism of the motor shafts and the mechanism. With several simultaneous defects of the shafting line, half and quarter harmonics appear (¼f_{rot}, ½f_{rot}, f_{rot}, 1,5f_{rot}). With the stator winding, the stator windings fob, $2f_{rot}$, $3f_{rot}$, etc.

The analysis of the harmonics of capacitive currents (CTG-Technology) studies the capacitive currents to ground. In the case of vibration, the capacities change with frequencies proportional to the vibration of the active part in the engine [9, 10], i.e. it is possible to determine the regularities of vibration phenomena in the engine itself, and therefore it exceeds the harmonic analysis of the currents feeding the motor in terms of information.

Schemes for diagnosing the engine when measured on the motor supply cable, i.e. characteristics of the motor feeding the network, is possible taking into consideration two conditional directions:
- the first direction is the low-frequency range representing the "mechanical defects": the informative characteristic of which are supply current spikes in the "power supply wires or motor leads", these defects can be detected by the harmonic analysis of the supply current (MCSA) during the galvanic analysis from the supply wire or input into the motor (e.g. see Figure 3, a).

- the second direction is for the circuit in the high-frequency range or "defects of the electric type": the informative characteristic of which is the voltage surges on the "motor power wires". These defects are fixed by the measurements of pulsations (voltage surges) on the motor power cables during galvanic analysis of capacitive currents from the motor to ground (CTG) (e.g. see Figure 3, b).

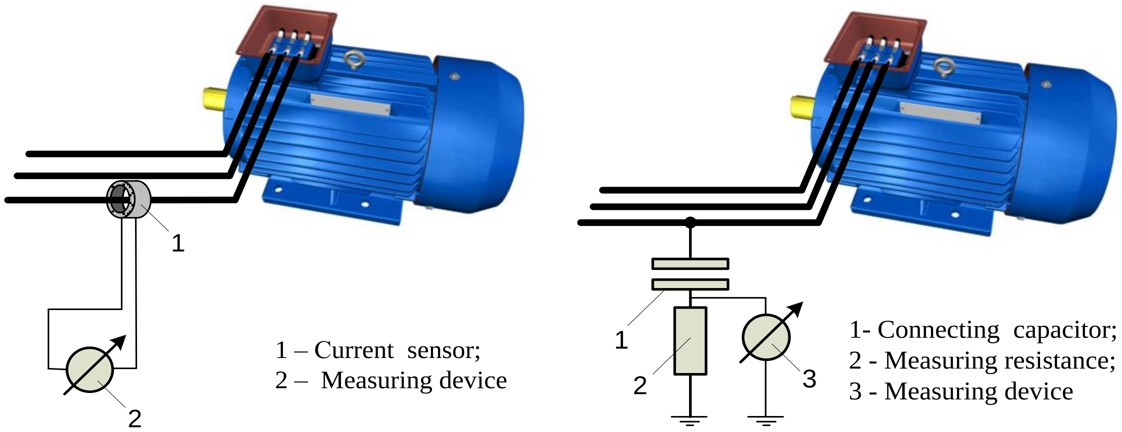

Figure 3. General scheme of galvanic connection for measurements and harmonic analysis of the current feeding the motor a) for the control of "mechanical defects" (MCSA-Technology), b) for the control of defects of "electric nature" (CTG-Technology).

4 Technical condition diagnosis method

At the present time the most popular method for current signals analyzing is Fourier transform, which has a number of disadvantages [11]. This method leads to the loss of valuable diagnostic information. In general, it is not suitable for use in the composition of the cyber-physical system.

An analogue of the Fourier expansion is the wavelet transformation is considered. It treats the signal as a two-dimensional sweep in time and frequency. The wavelet functions of the basis allow us to identify local signal features that cannot be detected using the traditional Fourier and Laplace transformations. The wavelet transformation of a signal is represented in the form of a generalized series or as Fourier integral over a system of basic functions [12]

$$\psi_{ab}(t) = 1/\sqrt{a}\,\psi((t-b)/a), \qquad (1)$$

constructed from the parent (original), the wavelet $\psi(t)$ possesses certain properties, due to the time shift operations b and the time scale change a. The factor $1/\sqrt{a}$ ensures that the norm of these functions is independent of the scaling number a. Small values of a correspond to small scales $\psi_{ab}(t)$, or high frequencies ($\omega \sim 1/a$), large parameters of a - to large scale $\psi_{ab}(t)$. The wavelet scale, as a unit of the time-frequency representation of the signals, is inversely proportional to the frequency (e.g. see Figure 4).

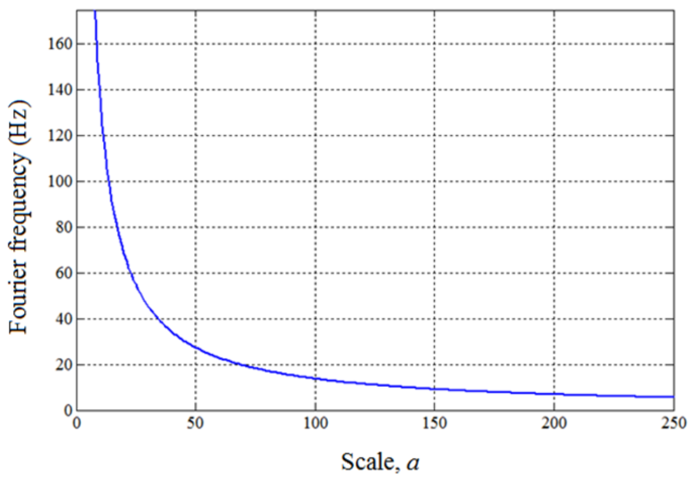

Figure 4. Correspondence of the Fourier frequency and the scale of the wavelet

To troubleshoot using wavelet transforms, it is necessary to recalculate the Fourier frequencies of the spectrum into the scale of the wavelet, according to the relationship in Fig. 5. The analysis of the signal at the received characteristic frequencies allows finding the object malfunctions. A large number of experiments conducted on DC and AC engines under various loading conditions made it possible to reveal the regularity illustrated in Figure 5.

The wavelet coefficients at the characteristic scales of the healthy and faulty motors significantly differ from each other. With a serviceable unloaded engine, they have minor oscillations at start-up, then the process is practically linearized. When a load occurs, the oscillatory process at the start of the engine is more pronounced, but then decreases with repetition at certain periodicity. While the process is stable, there is no significant increment in the amplitude of the oscillations with time (Fig. 5, a). The coefficients of the wavelet transformation of the faulty motor are much lower than the serviceable ones and have constant oscillations. This phenomena increases when the load appears (e.g. see Figure 5, b).

The plot of wavelet coefficients on an uncharacteristic scale for a faulty and faulty motor is identical (e.g. see Figure 5, c). The signal has a high density and small values of wavelet coefficients, while the signal is regular and completely repeated at a specified repetition rate. This regularity is valid for the current, voltage, and vibration for AC and DC drives.

The received five characteristic signals can be used to design the identification of the state of electric drives in the structure of the cyber-physical diagnostic systems based on an artificial intelligence approach.

To apply the obtained experimental information in cyber-physical diagnostic systems, it is necessary to develop a method for automatic signal analysis without the involvement of an expert. One of the methods for solving this problem is the development of a neural signal classification network [13]. As the initial data, the values of the wavelet coefficients are used on a characteristic scale uncharacteristic for the failure (e.g. see Figure 5). As an input, a matrix containing five lines of characteristic signals is given. The output of the network is the class of diagnosis: "1" - normal or "2" - defective.

To classify the technical state of an object, a neural network of direct signal transmission having the structure shown in Figure 6 is modeled.

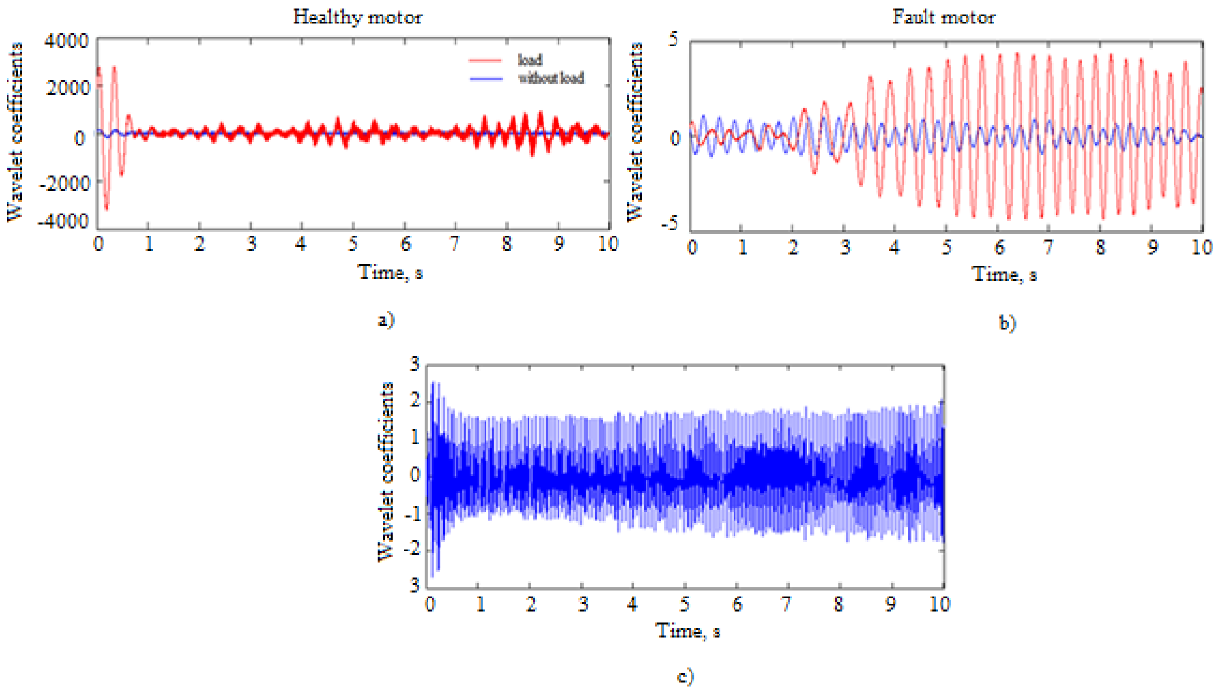

Figure 5. The wavelet current signal: (a) the characteristic scale of the serviceable engine, (b) the characteristic scale of the faulty engine, (c) the uncharacteristic scale of the faulty and faulty engines

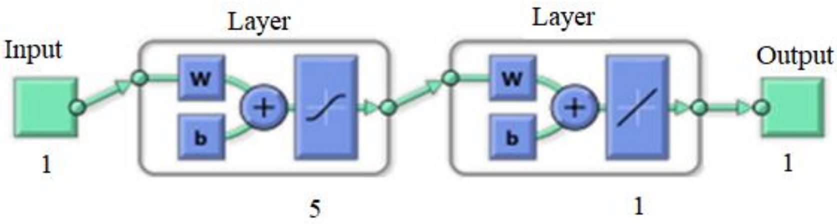

Figure 6. Structure of the neural network classification of the technical state of the electric drive

The network contains three layers: input, hidden and output layers. The hidden layer has five neurons with a tangential activation function while the output layer is a linear neuron. To train the neural network, the Levenberg-Marquardt algorithm [14] which is designed to optimize the parameters of nonlinear regression models is used. The network training and validation results are shown in Figure 7. The output of the neural network is a vector string containing the given technical state number "1" - normal, "2" defective. The size of the output vector is equal to the number of wavelet coefficients. Therefore, for the convenience of analysis, it is necessary to find the mean value and round it according to the rules of mathematics. As a result, you can evaluate the status of the diagnostic object.

To test the trained network, samples of the training set were randomly assigned to the input, and the network unmistakably assigned them to a given class. The status of the technical condition was checked during the diagnosis of the induction motor (e.g. see Figure 8). The analysis was performed on a faultless and faulty engine at various rotational speeds. To simulate a malfunction, an additional resistance was introduced into one of the phases of the stator winding, which is equivalent to closing the turns of the stator winding. This fault can be determined on the first three harmonics of the reverse frequency.

The wavelet coefficients of the supply current at these frequencies were fed into the trained neural network, which unmistakably classified the serviceable engine to class "1", and the faulty engine to class "2". An analysis of the other scales of both engines has shown that the state of the engine belongs to class "1". The received neural network therefore allows the determination of the technical state and the cause of the failure.

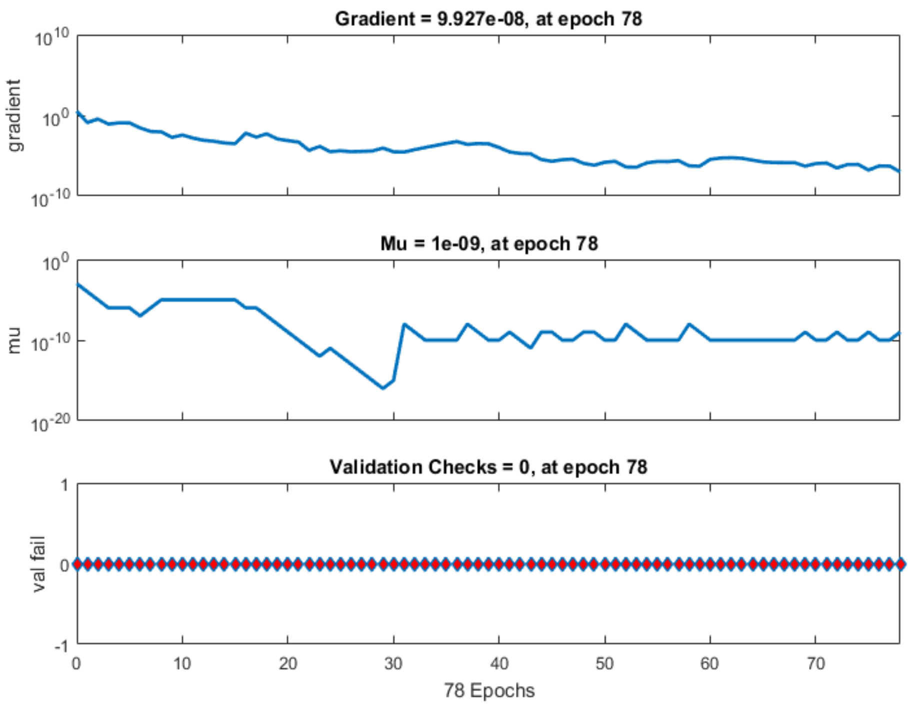

Figure 7. Learning outcomes of signal classification neural network

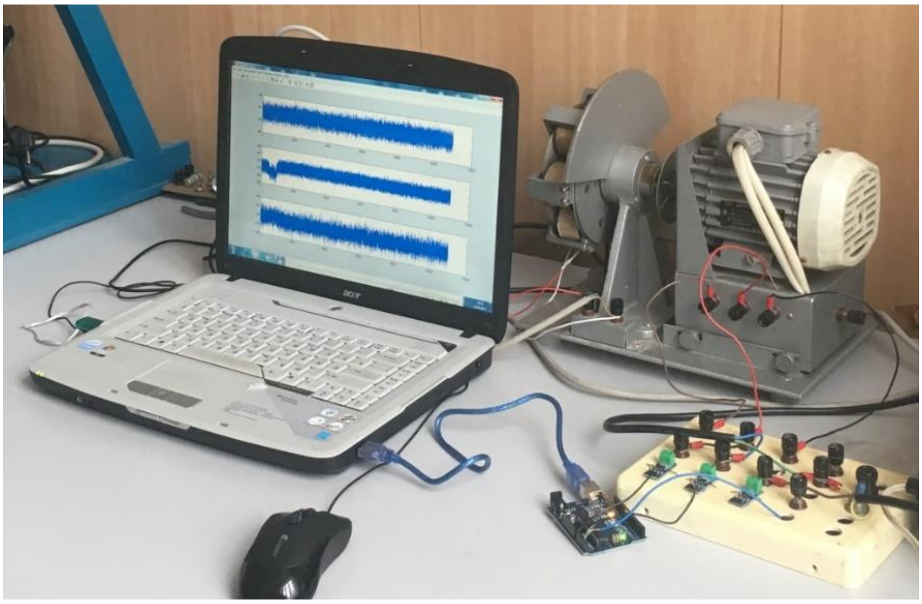

Figure 8. Experimental researches

A method for diagnosing electric drives of building robots has been obtained, which makes it possible, without using expensive measuring instruments, to determine their current state of failure, a malfunction from changing the operating mode. This will increase the efficiency of such robots and the quality of construction operations.

The performed efficiency analysis shows that the introduction of the proposed methods makes it possible to increase the productivity of the facility by 17-18%, the technical utilization factor by 14% and obtain an economic effect if the modernization costs do not exceed 20% of the cost of the facility.

5 Conclusion

In this paper, the design of a cyber-physical system for diagnosing and predicting the technical condition of electric drives of construction robots is presented. Furthermore, the structure of the cyber-physical system consisting of five levels is defined and the work of each system level is also described. The statistics of defectiveness of asynchronic drives were shown and their existing diagnostic methods considered.

The optimal set of diagnostic parameters for drives used in building robots was selected taking into account operating conditions. The existing methods for measuring and analyzing selected parameters have been described and a method for analyzing diagnostic parameters proposed. This method allowed the determination of the technical state of the robot drives under different load conditions of the drive. To implement this method, wavelet transformation and neural networks for the classification of signals were proposed. It was further established that any maternal wavelet may be used. Finally, the validity of the theoretical calculations and the adequacy of the model were confirmed by the large volume of experimental studies.

REFERENCES:

[1] H. Giese, B. Rumpe, B. Schätz, and J. Sztipano vits, “Science and Engineering of Cyber-Physical Systems *(Dagstuhl Seminar 11441)”*, *Dagstuhl Reports:* 1(11) 1–22, 2012.

[2] Horvath and B. Gerritsen, Cyber-physical systems: Concepts, technologies and implementation principles in Tools and Methods of Competitive Engineering Symposium *(TMCE)* 19–36, 2012

[3] T.W. Körner.Fourier Analysis. - *Cambridge University Press*, 1988.

[4] I. Daubechies. The wavelet transform time-frequency localization and signal analysis. *IEEE Trans. Inform. Theory,* 961–1004, 1992.

[5] T.N. Kruglova. Intelligent Diagnosis of the Electrical Equipment Technical Condition *Procedia Engineering*:129, 219–224, 2015

[6] W. T. Thomson and M. Fenger Current signature analysis to detect induction motor faults *IEEE Industry Applications Magazine*: 7, 26-34, 2001.

[7] B. Liu, S.F. Ling.On the selection of informative wavelets for machinery diagnosis. *Mechanical*

Systems and Signal Processing 13 (1) 145–162.), 1999

[8] Subhasis Nandi, Hamid A. Toliyat, and Xiaodong Li.Condition Monitoring and Fault Diagnosis of Electrical Motors – A Review, *IEEE Conference Transactions on energy conversion, Vancouver, Canada. Journals & Magazines* 20 (4), 719-729. 2005

[9] Yoon-Seok Lee, Kyung-Tae Kim, JinHur. Finite-Element Analysis of the Demagnetization of IPM-Type BLDC Motor With Stator Turn Fault *IEEE transactions on magnetics*, 50 (2), 7022004-7022004, 2015

[10] M. Shakouhi, M. Mohamadian, E. Afjei Fault Tolerant Control of Brushless DC Motors Under Static Rotor Eccentricity *IEEE transactions on industrial electronics*, 62 (3), 1400 - 1409. 2015

[11] Kruglova T. Wavelet analysis for fault diagnosis of electrical machines using current signals . *2nd International Conference on Industrial Engineering, Applications and Manufacturing (ICIEAM)*, 1-5, 2016

[12] Tatiana Kruglova, Danil Shaykhutdinov, Dmitriy Shurygin, Sergey Yanvarev, Roman Leukhin, Dmitriy Litvin, Stas Tarkovalin and Aleksey Zinin Intelligent Sensorless Fault Diagnosis of Mechatronics Module Wavelet Transformation *Asian Journal of Information Technology*. 15(22). 4694-4697. 2016

[13] Tatyana Kruglova, Alexey Bulgakov, Alexander Vlasov, and Ivan Shmelev Artificial Intelligence Method for Electric Drives Mode Operating and Technical Condition Determination *MATEC Web Conf. XIII International Scientific-Technical Conference "Dynamic of Technical Systems" (DTS-2017)* 132, 04017, 2017

[14] Kruglova, T., Glebov, N., Shoshiashvili, M. Smart sensorless prediction diagnosis of electric drives *IOP Conference Series: Earth and Environmental Science* 87, 2017