

Synthesis of the AC and DC Drives Fault Diagnosis Method for the Cyber-physical Systems of Building Robots

Alexey Bulgakov^{1*}, Tatiana Kruglova² and Thomas Bock³

¹Southwest State University, Department for Construction Management, 305040, Kursk, Russia

²South-Russia State Polytechnic University, Institute for Mechatronic, 346428 Novocheerkassk, Russia

³Technical University of Munich, Department for Building Realisation and Robotics, 80333 Munich, Germany

Abstract. This article studies the development of a prediction diagnosis cyber-physical system for DC and AC electric drives of construction robots. 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. As a result of numerous experiments has been revealed the dependence of measurement of wavelet transformation coefficients on the characteristic scales of a serviceable and faulty engine under different loading regimes. Based on the received information has been developed a neural classification network which makes it possible to reveal the current state of the object.

1 Introduction

The modern construction site is a large number of robots working in direct interaction with each other. The efficiency of the production line is determined by the function reliability of its elements. The main elements determining the reliability of building robots are electric motors. Failure of one engine can lead to a violation of the quality of work or long downtime of the entire production line. Therefore, it is necessary to ensure the reliability of each electric drive that is part of the production line. This can be achieved by constant monitoring of the technical condition of all actuators. This can be achieved by constantly monitoring the technical condition of all drives and recording the diagnostic results in a common database for further optimization of the construction equipment operation mode depending on the condition of its electric motors. Such a diagnostic system must be built into the robot's end-effector, 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

* Corresponding author: a.bulgakov@gmx.de

functioning efficiency of the equipment assumes the integration of computing resources into physical processes, i.e. application of cyber-physical systems [1].

2 Methodologies

A cyber-physical diagnostic system includes sensors, mechanical equipment and information system are connected during all stages of the life cycle and interact with each other using standard Internet protocols to adapt to changes in operating conditions and technical condition of the equipment. The structural diagram of the cyber physical predictive system for diagnosing a construction robot is shown in fig. 1.

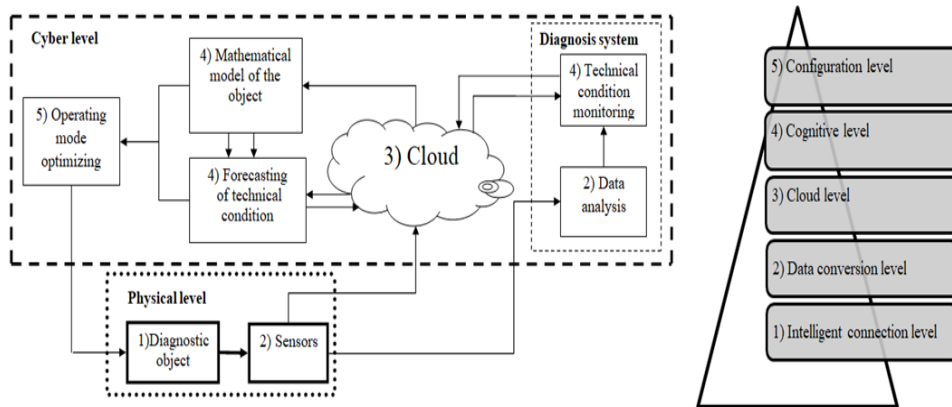


Fig. 1. Cyber-physical system of the technical condition prediction diagnosis for electrical equipment

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.

To implement the cyber-physical system for construction robot, it is necessary to have a diagnostic method that meets the following requirements:

- the possibility of assessing the technical state in real time;
- 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;
- possibility to use on a moving object with high humidity and dustiness;
- applicable for DC and AC motors;
- the ability to automatically analyze the measured parameters;
- the ability to distinguish a malfunction from a change in operating mode.
- the ability to record and store diagnostic results in a cloud server and to provide the user with an Internet protocol.

The most applicable motors types for construction robots are medium-power asynchronous motors (AC) and direct current (DC) motors, which operate in a short-time mode and must have a high overload capacity and dust and waterproof design criteria known as IP standard. The available statistics (e.g. see Table 1) [3,4] shows that all engine failures of the aforementioned types are of mechanical or electrical origin.

Table 1. Constriction robots motors typical defects

AC motor	
Discharge and 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
DC motor	
Commutation defects	15
Rotor defects	48
Voltage ripple	12
Stator defects	25

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 connection 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: 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.

The most common diagnostic parameters for electric drives are 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) [7], harmonic

analysis of capacitive currents to ground (CTG technology) [8] 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.

The analysis of current supply harmonics (MCSA-Technology) consists in the decomposition of the signal using Fourier transform and amplitude analysis at characteristic frequencies (table 2). Each fault has its own characteristic frequencies, including sub-harmonics, harmonics and intera-harmonics between the spectral lines of the reverse frequency - f_{rot} .

Table 2. Characteristic frequencies of the current signal

Motors faults	Current signal frequency
DC - motor	
Commutation defects	$2 \cdot k \cdot p \cdot f_{rot}$
Rotor defects	$2 \cdot p \cdot f_{rot}, (k \pm 2 \cdot p) \cdot f_{rot}$
Voltage ripple	$k \cdot f_s$
Stator defects	$k \cdot f_{rot}$
AC-motor	
Stator defects	$k \cdot f_{rot}$
Bearing defects	$\frac{1}{4} \cdot f_{rot}, \frac{1}{2} \cdot f_{rot}, f_{rot}, 1.5 \cdot f_{rot}$
Misalignment or no parallelism of the motor shafts and the mechanism	$f_{rot}, 3 \cdot f_{rot}, 5 \cdot f_{rot}$

At this table f_s - frequency of the network supplying the rectifier, (Hz); f_{rot} - motor rotor speed, (Hz); $k = 1, 2, 3$ - number of current harmonic ; p - the number of poles.

At the present time the most popular method for current signals analyzing is Fourier transform, which has a number of disadvantages [9-11]. 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]

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

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 domain.

At the present time has been accumulated a considerable amount of knowledge to trouble-shoot of electrical equipment using Fourier transforms, and have been calculated the characteristic frequencies for all major faults. The recalculation of the Fourier frequencies of the spectrum into the scale of the wavelet, according to the dependence in

fig. 1, will allow the analysis of signals into wavelet space [6] and find new signal characteristics that can not be detected using Fourier analysis.

It is assumed that the use of the wavelet transformation will allow a more accurate identification of the state of the electric drive, distinguishing the faulty state from a change in load, and to reveal all its faults. For this, it is necessary to carry out a series of experimental studies, based on the results of the analysis of which it is planned to develop a model for diagnosing the technical condition, which makes it possible to distinguish a faulty state of an object from a change in its operating mode.

3 Factors exploration

To synthesize the diagnostic method, a number of experimental scientific researches were performed at the stand shown at fig. 2.

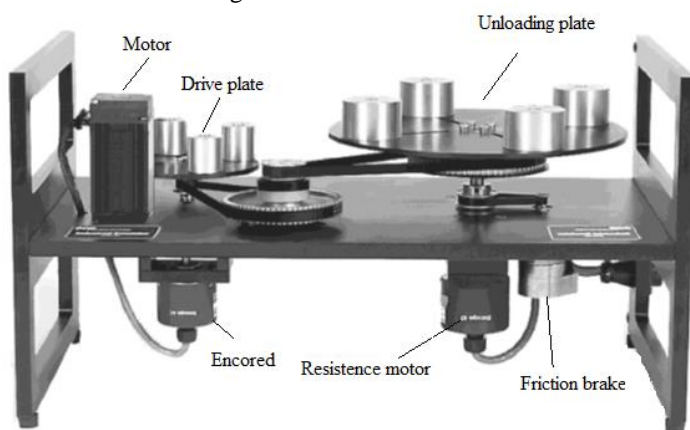


Fig. 2. Laboratory stand which DC motors

The system includes two identical brushless DC motors PITTMAN 5413 (voltage 38.2 V), connected to each other by a system of toothed belts. One engine is the master motor, the second - load motor. To create a resistance to the rotation of the master motor turns on the load motor, which rotates in the opposite direction. The encoder is used to determine the position of the motor shaft.

To analyze a current signal using the wavelet transformer, it is necessary to recalculate the characteristic frequencies of the Fourier analysis (Table 2) in the wavelet scale. As a parent function, anyone can be selected that meets the requirements for a wavelet. Table 3 shows the result of converting to the Morlet wavelet scale.

Table 3. The ratio of the characteristic frequencies of the Fourier transform and the scale of the wavelet

Servo drive faults	Frequencies of the Fourier spectrum	Scale of the Morlet wavelet
Commutation defects	24	48
	48	24
	72	16
Rotor defects	24	48
	27	43
	30	39
	33	35
Voltage ripple	50	23
	100	12
	150	8

Stator defects	3	386
	6	193
	9	129

It can be seen from the table that the range of the characteristic wavelet scales is in the range up to 400, therefore it is expedient to carry out all calculations in the range of scales from 1 to 400. The experimental studies were carried out according to the program presented in Table 4

Table 4. The experimental researchers program

Operating mode of the driving motor	Operating mode of the load motor
Healthy, rotation speed of 3 Hz	Switched off
Healthy, rotation speed of 3 Hz	Rotation speed of 1 Hz
Faulty, rotation speed of 3 Hz	Switched off
Faulty, rotation speed of 3 Hz	Rotation speed of 1 Hz

Experimental studies were carried out on an engine rotating at a frequency of 3 Hz. The load motor is switched off in the first and third experiments. In the second and fourth experiments, the resistance motor rotates in the opposite direction relative to the main motor at a frequency of 1 Hz, creating phases of the motor, which simulates the short circuit of the stator winding. The obtained time signals (Table 3) of the current and voltage of the two phases of the motor were decomposed using a Morlet wavelet in the selected range of scales and has been obtained a comparative analysis of the results.

The purpose of the diagnosis is to identify the cause of the failure of the object. To solve this problem will allow analysis of wavelet coefficients on characteristic scales (Table 3). On the fig. 3 is showed the time dependence of the wavelet coefficients of the current signal on the scale that typical for stator malfunction.

The coefficients of the wavelet transform of the faulty motor are much lower than those of the serviceable one and have constant oscillations, which increase when the load appears. The time dependence of the wavelet coefficients on the characteristic scale for the serviceable phase "B" from which it can be seen that the dependence is similar.

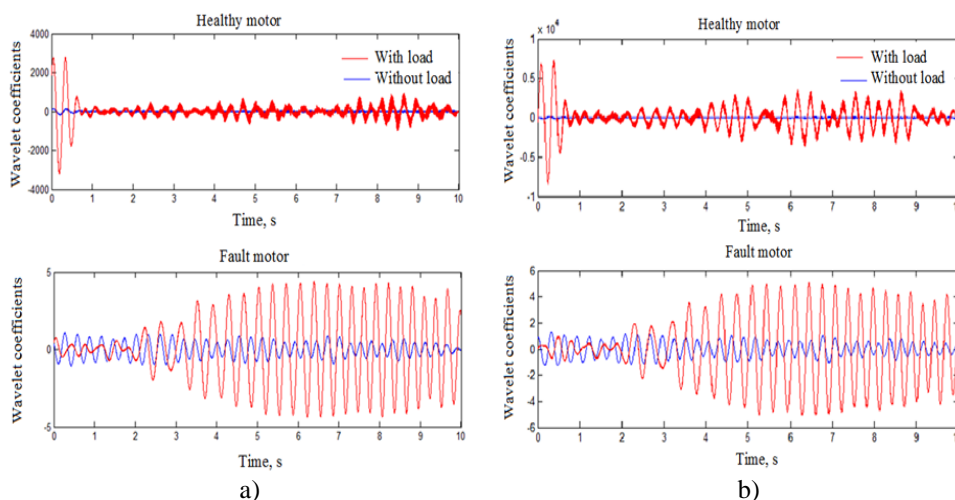


Fig. 3. Wavelet stator current factors at characteristically scale: (a) phase A (b) phase B

The carried-out analysis shows what wavelet values coefficients of current and tension at the scales corresponding to malfunction has an identical characteristic appearance that

can be used for intellectual diagnosing of engines. Wavelet values coefficients at the scales not characteristic of the entered malfunction has the appearance given on fig. 4.

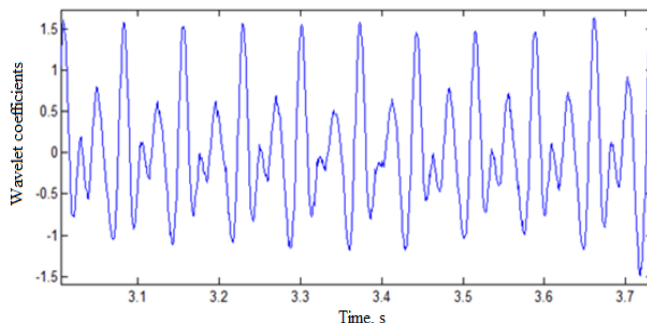


Fig. 4. The wavelet coefficients of the feeding tension of the serviceable and faulty engine at a non-characteristic scale

From this diagram it is visible, the signal has high density and wavelet small values coefficients, at the same time the signal is regular and completely repeats with the given frequency of following. This type of a signal is characteristic to all frequencies not characteristic the selected failure in independence of technical condition of the motor [13].

Thus, on analysis results we receive five characteristic signals for diagnosing. Signals of characteristic frequencies for the operational off-load and loaded engines (fig. 4), and also an unrepresentative signal (Fig. 5), it is expedient to carry to a class "is serviceable" while faulty loaded and off-load to a class "is faulty". This information can be used for simulation of a neural network of classification of technical condition of the engine.

4 Applying the diagnosis method

For automatic detection of technical condition of the electric drive without involvement of the specialist expert expediently develop a neural network of classification. As basic data values are used wavelet coefficients at a scale (fig. 3), characteristic of malfunction, and an uncharacteristic signal (fig. 4). The structure of neural network is introduced (fig. 5)

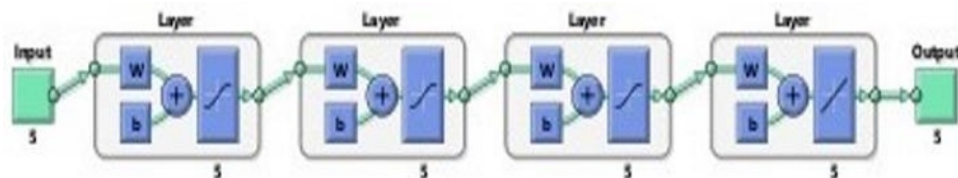


Fig. 5. Neural network for electric drive technical condition and mode operation classification

The neural network consists of five inputs, four hidden layers with five neurons in each and five outputs. The goal of the neural network training is to distribute the five input signals to four classes: «11» - functional unload, «12» --functional loaded, «21» - faulty unload, «22» - faulty loaded. For neural network training the Levenberg-Markvardt algorithm was used.

For testing of the trained network were given on an input the samples of learning selection in turn and the network carried unmistakably them to the given class. Further, on an input of a neuro network values were given wavelet coefficients at all characteristic scales (Tab. 2). Then similarly on an input of a network values for the serviceable loaded drive (rotating speed of the motor of resistance, of 1 Hz) moved and the network carried it to the "12" class.

6 Conclusion

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 which allowed to determinate 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.

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