Article citation info:
Goolak S, Gubarevych O, Yurchenko V, Kyrychenko M. A review of diagnostic information processing methods in the construction of systems for operating diagnostics of rotor eccentricity of induction motors. Diagnostyka. 2025;26(1):2025104. https://doi.org/10.29354/diag/202757.

DIAGNOSTYKA, 2025, Vol. 26, No. 1

e-ISSN 2449-5220
DOI: 10.29354/diag/202757

A REVIEW OF DIAGNOSTIC INFORMATION PROCESSING METHODS IN THE CONSTRUCTION OF SYSTEMS FOR OPERATING DIAGNOSTICS OF ROTOR ECCENTRICITY OF INDUCTION MOTORS

Sergey GOOLAK [1], Oleg GUBAREVYCH [1,*], Victor YURCHENKO [1], Mykhailo KYRYCHENKO [2]

[1] Department of Electromechanics and Rolling Stock of Railways, State University of Infrastructure and Technologies. Kyiv, Ukraine
[2] Department of Heat Motorering, Kyiv National University of Construction and Architecture (03307), Ukraine
*Corresponding author, e-mail: oleg.gbr@ukr.net

Abstract

Induction motors are widely used in traction drives of rolling stock of railways. For timely detection of faults that may occur in an induction motor during operation, a functional diagnostics system is used. Thanks to such a system, it is possible to detect and prevent further development of a fault at the initial stage of its occurrence in real time. When developing a functional diagnostics system, it is important to select the most relevant method for processing diagnostic information for a specific type of damage. One of the most difficult to detect defects is rotor eccentricity. Rotor eccentricity is a consequence of a wide range of motor damages that must be monitored during operation. The paper offers an analysis of modern methods for processing diagnostic information that can be used to build a functional diagnostics system for the presence of rotor eccentricity in an induction traction motor and also provides recommendations for choosing a more effective method.

Keywords: diagnostic information, induction motor, rotor eccentricity, operational diagnostics

1. INTRODUCTION

The reliable and trouble-free operation of even individual industries depends on ensuring the reliable operation of the most widely used type of electric machines, induction motors. This is especially relevant in the transport sector, where induction motors with a short-circuited rotor are gaining significant momentum. Sudden failure of electric drive mechanisms during the operation of transport equipment leads to disruption of logistics and related economic losses. In addition, the violation of established logistics tasks leads to a decrease in the competitiveness of even certain types of transport.

In such conditions, research on the establishment and development of methods for controlling the development of manifestations and deviations from normal operation in the design elements of electric motors of transport systems acquire special relevance. During the operation of induction motors in the drives of vehicles, in addition to the occurrence of overheating and overloading phenomena, a number of external influences on the modes of operation and factors of natural aging also act [1-3]. Under the influence of a whole range of such factors, various defects develop in electric motors, which, in the absence of monitoring systems or with later detection, can develop to an emergency stop with an increase in restoration costs [4].

Fig. 1 shows the averaged statistical data of the main types of damage to induction motors (IM), which have the most impact on further operation and can develop to the complete failure of the motor in the emergency mode [5-7].

The largest part of failures is caused by damage to the stator, where up to 70% [3, 8] is due to inter-turn short circuits in the phase of the stator winding, and the remaining part to the breakdown of the insulating materials of the stator package design and the violation of inter-circuit connections. When inter-turn short circuits occur in the stator winding, an asymmetric rotating field occurs, which is accompanied by the occurrence of vibration of the unit.

Received 2024-10-07; Accepted 2025-03-08; Available online 2025-03-09

© 2025 by the Authors. Licensee Polish Society of Technical Diagnostics (Warsaw. Poland). This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license (http://creativecommons.org/licenses/by/4.0/).

Bearing damage for induction motors can account for 12-20% of failures, and for some types of traction motors it can reach up to 40%. The main manifestation of bearing damage is an increase in the radial gap, which causes vibration [7].

The unevenness of the air gap is caused by abrasive wear of the bearings, deformation of the end shields of the machine, errors in assembly and installation after repair, etc. This leads to one-sided magnetic attraction and, as a result, the occurrence of electromechanical vibration [5].

When operating motors with a damaged short-circuited winding structure, pulsation of currents occurs in the stator with a slip frequency, which creates vibration and affects the torque of the motor. At the same time, the frequency of rotation of the rotor fluctuates even with changes in small loads.

The rest shown in Fig. 1, damage to the motor, including those discussed above, have a structural origin and, in the event of occurrence, leads to the appearance of mechanical vibration of the motor elements.

Thus, all considered types of motor damage during its operation are accompanied by the appearance of vibration, which can be used for diagnostic monitoring [9].

A number of damages shown in Fig. 1 cause the appearance of eccentricity of the rotor, the detection of the nature of which is the most difficult and currently relevant issue when conducting diagnostics of electric motors. Rotor eccentricity is the most common mechanical failure of an induction motor. The presence of eccentricity leads to one-sided magnetic attraction and increased bearing wear. The engagement of the rotor with the stator can lead to a violation of the packages of the structure of the rotor and stator or overheating, which can lead to a breakdown of the disturbed layer of insulation in the friction zone. According to various sources, eccentricity accounts for 20 to 40% of IM failures [5, 7].

The nature of eccentricity is different, but it leads to similar negative consequences. Eccentricity of the rotor can appear due to low-quality manufacturing or repair of motors, as a result of operational factors with a violation of the geometry of the motor design, as a result of bearing wear, shaft deflections, etc. Common for the occurrence of this type of damage is the possibility of continued operation of the motor without its immediate failure. However, eccentricity leads to a decrease in the reliability and durability of the induction motor, which progress over time and affect the reduction of technical and economic and operational parameters.

When operating such a motor, a one-sided magnetic attraction is created, which affects, of course, a decrease in efficiency and, accordingly, an increase in heating and contributes to a decrease in starting torque. Additional higher harmonics that arise affect a number of electromagnetic parameters of the motor [10, 11]. For these reasons, it is important to detect this malfunction at the earliest possible stage of its appearance and development. In the practice of research, two types of eccentricity are considered: static and dynamic. Static eccentricity is caused by the shift of the motor rotation axis relative to the stator package boring axis, that is, the eccentric position of the rotor in the stator boring. The most common causes of static eccentricity are load imbalance, vibrations, misalignment of shafts, sharply changing loads and overloads, malfunction of bearings, etc.

Dynamic eccentricity is caused by the displacement of the axis of the outer surface of the rotor relative to the axis of its rotation and is accompanied by the beating of the rotor, which occurs due to the forces of one-sided magnetic attraction as a result of poor repair or manufacturing defects.

The dynamic eccentricity is usually much smaller than the static eccentricity and for determination during motor operation for the purpose of current diagnosis of the motor condition is not of decisive importance.

Therefore, to diagnose the most common damages that cause eccentricity in an electric motor, it is advisable to conduct a study of static eccentricity indicators, which carry more diagnostic information.

The relative eccentricity can be determined by the formula (%):

$$\alpha = \frac{a}{\delta} \cdot 100\%, \tag{1}$$

where a – the displacement of the rotor axis from the stator axis;
δ – the size of the air gap between the rotor and the stator at a symmetrical position of the rotor.

The general practice of monitoring the eccentricity of the motor is the relative eccentricity parameter itself (1).

The main methods for diagnosing rotor eccentricity include the following methods:

- vibration measurements;
- direct measurement of the air gap;
- current.

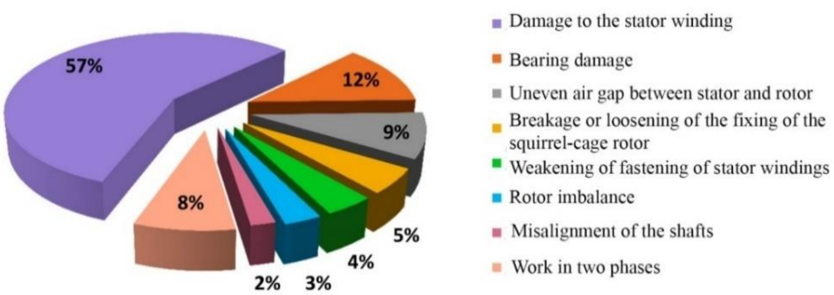

Fig. 1. Distribution of types of induction motor damage

Vibrodiagnostic methods have become widely used to determine a number of damages to motor elements, however, they have not been used to determine the causes of eccentricity of transport motors.

One of the reasons is the need to use a certain number of sensors, the lack of reference values of vibration manifestations of a number of damages and low accuracy during the operation of the mechanism with additional vibration sources. In addition, vibration methods do not always provide the necessary diagnostic information [12].

The method of direct measurement of the air gap at several points is used in the repair and maintenance of motors and requires partial disassembly of the electric motor. At the same time, the electric motor must be stopped for a long time and conditions of access to the end zone of the magnet wire, which excludes the use of the method during operation.

Current methods can provide the most effective diagnosis of the occurrences and causes of eccentricity. Current methods are based on the analysis of the main electrical and magnetic parameters of the motor, namely phase currents, phase voltage, power consumption, flux linkage and induction of the magnetic field in the air gap during the operation of the equipment [13, 14]. However, for the full use of current methods, a number of separate studies are needed to establish the diagnostic parameters for assessing the type and degree of the motor defect.

Timely detection of eccentricity of the rotor and recognition of the cause of its occurrence during motor operation without stopping the equipment is an urgent diagnostic problem. which contributes to increasing the reliability and durability of the use of induction motors in vehicles. In addition, ongoing monitoring and determination of the causes of rotor eccentricity ensure the safety and economy of transportation [15].

In this work, an analysis of the methods of processing diagnostic signals for detecting the eccentricity of the rotor of induction motors is carried out in order to determine the diagnostic strategy for establishing the reasons for their appearance during the period of operation of the equipment for predicting the resource of trouble-free operation.

The purpose of this article is to analyze existing methods of processing diagnostic information that can be used in the construction of a functional diagnostics system for monitoring eccentricity in induction traction motors of rolling stock.

The research contributions of the article are as follows:

- for the construction of a system of functional diagnostics for monitoring the presence of eccentricity in induction traction motors of rolling stock, the choice of a diagnostic method was substantiated;
- as a result of the analysis of the spectral components of phase currents of an induction motor in the presence of different degrees of defect, the choice of diagnostic features for monitoring eccentricity in induction traction motors was substantiated;
- Based on the conducted analysis of operational factors, the features of obtaining selected diagnostic features for monitoring eccentricity in induction traction motors were established;
- Based on the peculiarity of obtaining the selected diagnostic features for monitoring eccentricity, an analysis of the methods for processing diagnostic information was performed, which can be used to build a system for functional diagnostics for monitoring the presence of eccentricity in induction traction motors of rolling stock.

2. ANALYSIS OF DIAGNOSTIC SYMPTOMS USING CURRENT METHODS OF CONTROLLING THE PRESENCE OF ECCENTRICITY IN AN INDUCTION MOTOR

In works [16, 17] it is shown that current methods are the most effective for diagnosing damage to an induction motor as part of the drive. To build a system of operational diagnostics (as part of the drive), diagnostic symptoms should be determined, which will be used to control the presence of eccentricity in IM.

Eccentricity is characterized by several diagnostic symptoms that are manifested in changes in the amplitudes of characteristic harmonics in the magnetic flux, current signals, and vibrations [18, 19]. These characteristic harmonics are:

- rotor slot harmonics (RSH);
- side harmonics of the rotor around the supply frequency;
- doubled supply frequency and side harmonics around it.

In the current signal [20-22], in the presence of increased eccentricity, the amplitudes of RSH harmonics change, which are determined by the following equation [23]:

$$f_{RSN} = f_s \cdot \left(\left(l \cdot N_B \pm n_d \right) \cdot \frac{1-s}{p} \pm \eta_{ws} \right) = \\ = f_s \cdot \left(l \cdot N_B \cdot \frac{1-s}{p} \pm \eta_{ws} \right) \pm f_s \cdot n_d \cdot \frac{1-s}{p}, \tag{2}$$

where f_s – stator supply voltage frequency;
l=1,2,3,...– any positive integer;
n_d=0 – with static eccentricity;
n_d=1,2,3,... – with dynamic eccentricity (n_d is the order of eccentricity);
p – the number of pairs of poles;
s – slip of electric motors;
N_B – total number of rotor bars;
η_{ws} – the sequence of time harmonics of the stator, which are present in the power source that drives the

motor. η_{ws} takes odd values for current signals and axial magnetic flux [24-26].

Expression (2) consists of two terms. The left term is the frequency of passage of the rotor grooves f_{rS}, which is determined by the formula:

$$f_{rS} = f_s \cdot \left(l \cdot N_B \cdot \frac{1-s}{p} \pm \eta_{ws} \right). \tag{3}$$

The right term defines the frequencies of the side harmonics f_r from the rotor channel passage frequency, which are the frequency components of the subsynchronous type of rotor speed [27]. The frequencies of these harmonics are determined by the expression [28]:

$$f_r = f_s \cdot \frac{1-s}{p}, \tag{4}$$

Lateral harmonics of the rotor around the supply frequency are a sign of dynamic eccentricity [28]. These harmonics are inherent in current signals and magnetic flux. The frequencies of these harmonics are determined according to the following expression:

$$f_{sbr} = f_s \pm k \cdot f_s, \tag{5}$$

where k =1,2,3,... – any positive integer.

Works [29-31] give an analytical expression for the current signal at eccentricity, in which side harmonics of the rotor appear around the fundamental harmonic:

$$\begin{aligned} I_{ecc}(k) &= I_m \cdot \left(1+\alpha \cdot cos\left(2\cdot\pi\cdot f_r \cdot \Delta t \cdot k + \varphi_0\right)\right) \cdot \\ &\cdot cos\left(2\cdot\pi\cdot f_s \cdot \Delta t \cdot k\right) + \eta(k), \end{aligned} \tag{6}$$

where $I_{ecc}(k)$ – value of the phase current of the stator of the IM with eccentricity;
I_m – amplitude of phase current of IM stator without eccentricity;
$\eta(k)$ – harmonics of the power supply of the stator of IM;
k=1,2,…,N – serial number of the count;
N – total number of measurements;
Δt – discretization step;
α – the eccentricity modulation coefficient, which is directly proportional to the eccentricity degree.

For further analysis of methods of processing diagnostic signals, simulations of IM current signals were performed in the following states: (a) in good condition, (b) with eccentricity.

The motor parameters presented in Table 1 [32, 33] were used in the simulation. Based on the specified IM parameters, the following was calculated: synchronous frequency of rotation, slip, as well as the frequency of fault signatures. The obtained data are shown in Table 2. In the MATLab/Simulink software environment, the phase current signals of the IM stator were modeled for the following cases: in the absence of eccentricity (α=0); with eccentricity equal to 5% (α=0.05); with eccentricity equal to 10% (α=0.1); with eccentricity equal to 15% (α=0.15); with eccentricity equal to 20% (α=0.24); with eccentricity equal to 25% (α=0.25). Such defect levels were chosen for the purpose of investigating the possibility of detecting rotor eccentricity at an early stage. In order to take into account, the thermal processes occurring in IM, the simulation used the superimposition of "white" Gaussian noise. This is due to the fact that thermal noise is "white" Gaussian noise [34, 35]. When modeling the signal-to-noise ratio, SNR=30 dB was selected. SNR determines the maximum amplitude of the noise, according to the expression

$$\begin{aligned} &SNR = 20 \cdot log_{10}\left(\frac{I_m}{I_n}\right) \Rightarrow \\ &\Rightarrow I_n = \frac{I_m}{10^{\frac{SNR}{20}}} = \frac{I_m}{10^{\frac{30}{20}}} = 17.8, A \end{aligned} \tag{7}$$

The time history plots of the simulated signals are shown in Fig. 2.

From the analysis of the plots (Fig. 2), it follows that the stator phase current signal is an amplitude-modulated signal with a carrier frequency equal to f_s, a modulation frequency equal to f_r, and a modulation depth equal to α.

Table 1. Parameters of an induction motor

Parameter	Designation	Unit	Value
Capacity	P_{nom}	kW	1200
Power frequency	f_{snom}	Hz	55.8
Rated stator phase voltage	U_{smon}	V	1080
Rated stator phase current	I_{snom}	A	450
Nominal rotation frequency	n_r	rpm	1110
The number of pairs of poles	p	r. u.	3
The initial phase of the signal	φ_0	rad	0

Table 2. Parameters of the simulated system

Parameter	Expression	Unit	Value
Synchronous frequency of IM rotation	$n_s=f_s\cdot 60/p$	rpm	1116
IM slip	$s=(n_s-n_r)/n_s$	-	0.005376
Rotor speed	$f_r=n_r/60$	Hz	18.5
The frequency of the left-side harmonic of the rotor from the power supply frequency, which characterizes the presence of eccentricity, at k=1	$f_{ess1}=f_s-k\cdot f_r$	Hz	37.3
The frequency of the right-side harmonic of the rotor from the power supply frequency, which characterizes the presence of eccentricity, at k=1	$f_{ess1}=f_s+k\cdot f_r$	Hz	74.3

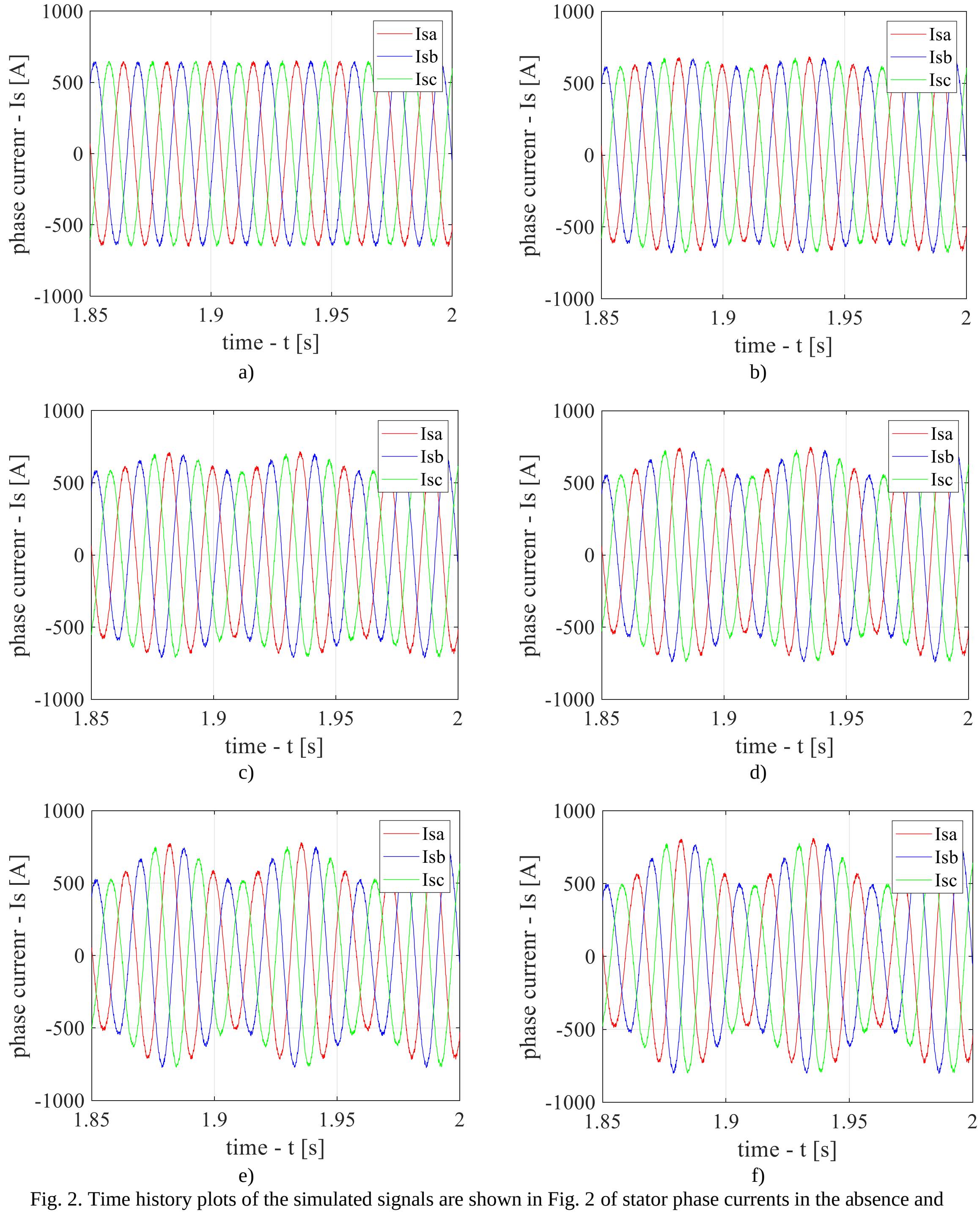

Fig. 2. Time history plots of the simulated signals are shown in Fig. 2 of stator phase currents in the absence and presence of eccentricity:
a) α=0; b) α=0.05; c) α=0.1; d) α=0.15; e) α=0.2; f) α=0.25

For the stator current signal of phase A, the amplitude-frequency spectra of the stator current of phase A were calculated and plotted in the absence and presence of eccentricity (Fig. 3).

As follows from the analysis of the amplitude-frequency spectra shown in Fig. 2, using the obtained characteristics to establish the eccentricity degree of the rotor is a difficult task. Fig. 3 determines levels of subharmonics at different eccentricity degrees of the rotor. The results are summarized in Table 3.

The analysis of the results presented in Table 3 shows that the level of subharmonics can be used as a diagnostic parameter when monitoring the presence of rotor eccentricity even at an early stage of the development of a defect. As can be seen from the results presented in Table 3, thermal noise affects the value of subharmonics. This influence is manifested in the fact that the subharmonics are not symmetrical with respect to the frequency of the stator supply voltage.

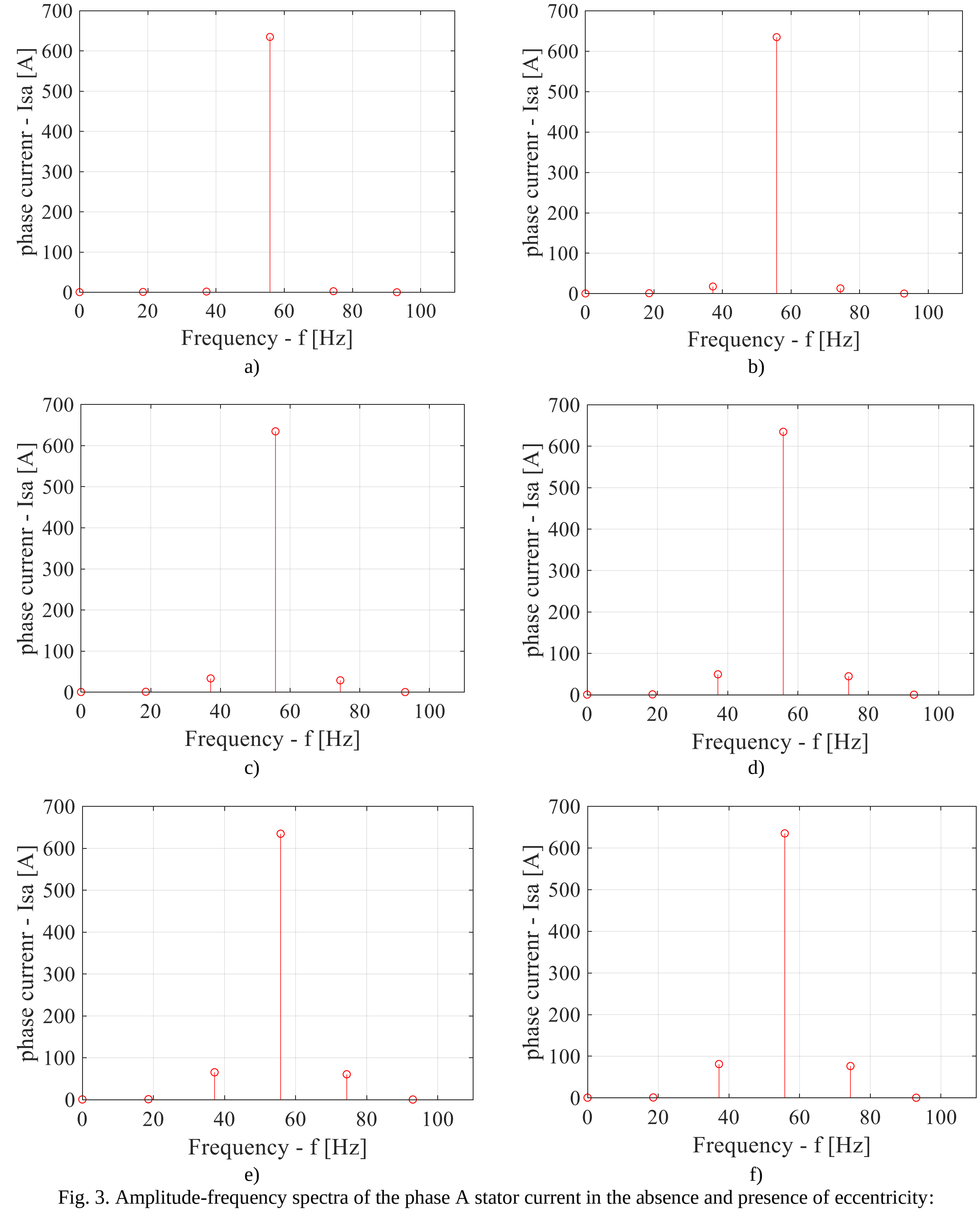

Fig. 3. Amplitude-frequency spectra of the phase A stator current in the absence and presence of eccentricity:
a) α=0; b) α=0.05; c) α=0.1; d) α=0.15; e) α=0.20; f) α=0.25

Table 3. Values of subharmonics at different eccentricity degrees of the rotor

Eccentricity degrees α [%]	Amplitude of sub-synchronous type components I_{sa} [A]	
	left	right
0	0	0
5.0	12.53	17.14
10.0	28.94	33.62
15.0	44.79	49.5
20.0	60.64	65.39
25.0	76.49	81.27

3. METHODS OF CURRENT DIAGNOSTICS OF INDUCTION MOTORS

3.1 General information about methods of current diagnostics

Diagnostic methods based on the analysis of the current flowing in the stator winding are based not only on the consumed power and electrical impedance of the winding, but also on the dependence on the electromotive force (EMF) induced by the magnetic field from the rotating rotor [36]. In other words, the stator winding is an element sensitive to rotor defects. The task of the analysis is to separate the stator current required for the rotation of the rotor from the additional current induced by the rotor itself in the event of its failure.

One of the advantages of current diagnostic methods is the possibility of measuring the current remotely from the laboratory, as in some cases direct access to the machine is difficult. Also, in many systems, electric currents and voltages are measured in protection systems, which allows reduction of the costs of introducing current diagnostic methods into existing installations.

The main disadvantage of current diagnostics is the complexity of existing signal processing methods. This difficulty is caused by the presence of a dominant harmonic component associated with the frequency of the power network, which is much larger than the harmonics caused by faults.

3.2 Method of analysis of motor current signatures

One of the most common current signal processing techniques is motor current signal signature analysis (MCSA) [36-38]. This method is based on the analysis of the spectrum of the phase currents of the stator, namely, the amplitudes of harmonics associated with malfunctions (signatures of malfunctions) are checked for exceeding the specified values. The transformation to the frequency domain is carried out using the fast Fourier transform (FFT). The FFT has a fairly low computational complexity [39, 40], which makes it suitable for implementation in control and diagnostic devices.

Disadvantages of MCSA are related to the need for a long measurement sample and dependence on the motor slip value. The need for a long sample arises from the FFT property: the frequency resolution is directly proportional to the length of the sample. The required frequency resolution depends on IM slip, which can vary depending on IM power and load. In [41], it is noted that the required frequency resolution for recognizing the signatures of defects in the rotor rods is 0.01 Hz. This corresponds to a sample length of 100 s. Using a sample of this duration presents the following challenges for continuous monitoring devices: high memory requirements and the need for stable operation during IM measurements. For example, traction motors of railway rolling stock are in unstable conditions for a long period of their operation. This leads to the appearance of quasi-asymmetric modes in the system of phase currents of the stator [42], which affects the reliability of the MCSA analysis results.

As the IM load increases, the slip increases [43], on which the frequencies of fault signatures depend. For MCSA to work correctly, motor slip information should also be obtained to calculate fault signature frequencies. For this, an additional IM rotation speed sensor is required [41], based on the readings of which slip is calculated, or special algorithms for calculating the IM speed should be used [44, 45]. Both options increase the complexity of the system.

Also, the MCSA disadvantages should include the effect of spectral leakage and picket fence effect, which is associated with the fact that when performing FFT, the received frequencies may not coincide with the frequencies of faults. In this case, the fault amplitudes decrease and it is difficult to use them as a diagnostic feature.

To improve the FFT properties, a multi-frequency signal processing (MSP) technique was proposed in [46]. This technique is based on the use of decimation and interpolation and allows to get rid of the spectral leakage effect that MCSA has. The computational complexity of this technique is higher than that of FFT, as this technique requires performing FFT as many times as there are fault signatures to be investigated. The disadvantages of this technique, in addition to the absence of spectral leakage, coincide with the disadvantages of MCSA, since both approaches use FFT.

3.3 Method of harmonic order tracking

Harmonic Order Tracking Analysis (HOTA) methods [41, 47, 48], based on the tracking of order harmonics, make it possible to reduce the number of harmonics required for analysis, due to the construction of the spectrum not from the signal frequency, but from the ordinal number of fault signatures. FFT is used to calculate the spectrum. Different algorithms are used to convert the stator phase current into the rotor coordinate system in different HOTA modifications. In order to perform the specified conversion, in [41], it is proposed to use a rotation angle sensor, which is synchronized with current measurements, to measure the angular velocity. The yaw angle sensor is also used to calculate slip.

The HOTA disadvantages are:

- the need for an additional angular position sensor;
- low slip requires a long sample because. an FFT is used;
- the method may give incorrect results in the presence of a constant load change.

3.4 Parametric methods

The MUSIC (Multiple Signal Classification) and ESPRIT (Estimation of the Signal Parameters) methods given in [49-51] are adapted for solving problems of diagnostics and detection of malfunctions of electric machines. These methods are based on the division of the measured signals into the subspace of the model component and the noise subspace [52, 53] and allow detecting stator faults, defects in rotor rods and rings, eccentricity, bearing defects, and others. With the help of these methods, it is possible to transform the time signal into the frequency domain and, with a low signal-to-noise ratio, detect the frequency components associated with malfunctions.

The advantage of these methods is that a smaller number of readings is needed to ensure a high frequency resolution of the spectrum, for example in [54] it is stated that 256 readings are enough to detect defects in the rotor core. The disadvantages of these methods include high computational complexity [55, 56].

3.5 Methods based on Park vectors

One of the most effective and least computationally expensive algorithms for detecting IM faults is the method based on Park vectors (PVA) [57-59]. When using this diagnostic method, signals are analyzed in the time domain, not in the spectral domain. This method is used to detect the following malfunctions of three-phase IM's:

• asymmetry of the supply voltage [59, 60];
• eccentricity of the air gap [61, 62];
• interturn defects in the stator winding [51, 63];
• inconsistency of mechanical connections [64, 65];
• break in the phase rotor winding [66, 67];
• defects of short-circuited rotor rods and rings [51].

This method is used for motors powered directly from the network or through an inverter to detect both individual faults and their combinations. PVA allows detecting the presence of a malfunction, but does not allow identifying the type of malfunction [68]. To solve this problem, PVA modifications have been developed:

- an extended approach based on Park vectors, in the English-language literature – Extended Park Vector Approach (EPVA) [69, 70];
- an approach based on a set of Park's vectors [68];
- an approach based on basic transformations [49].

These approaches are combinations of PVA and FFT. EPVA is based on the fact that for the components of the Park's vector, spectra are calculated using FFT, which are used to analyze fault signatures. This approach is similar to MCSA, but differs in that the components of the Park's vector are calculated based on all components of the stator phase currents. This makes EPVA more comprehensive than MCSA. In addition, in MCSA it is often difficult to remove the fundamental supply frequency component from the current signal without distorting the fault signatures. EPVA does not have this problem, since the fundamental frequency component of the supply is automatically removed during the Park's conversion. MPVA involves in first calculating the FFT spectra of the stator currents of IM phases, then signals are generated based on the amplitudes of fault signatures, which are separately analyzed using classical PVA. This approach allows to separately analyze the presence of certain malfunctions, present in a certain random combination, and the level of development of defects. The method of base transformations bases on the fact that if there is an angle of inclination of the ellipse, the hodograph of the Park's vector is transformed from an orthogonal-elliptic basis to an orthogonal-circular one. After that, the angle of ellipticity is analyzed. The defect is identified on the basis of the obtained values of the angles of inclination of the ellipse and ellipticity. EPVA, MPVA and the method of basis transformations include FFT, so they inherit all the main FFT advantages and disadvantages.

3.6 Prony method

Methods of diagnosing IM malfunctions based on the modified Prony method are proposed in works [71-73]. They are based on the Prony model, the fitting of which makes it possible to estimate the amplitudes of the characteristic frequencies associated with fault signatures. This approach allows the use of short samples of signals with a low sampling rate, since the sample length is determined by the order of the model, and the sampling rate is determined by the maximum frequency of the analyzed to be signal. Thus, in [71], the order of the model was chosen equal to 7, the corresponding sample length was 3 milliseconds. The advantages of this method are the absence of spectral leakage, as well as the possibility of tracking changes in the amplitudes of fault signatures, which allows these methods to be used both in stable and unstable IM operation modes. Solving the problem of optimal fitting, which is complicated by the presence of noise and other random components present in the original measured signal, is a necessary condition for using this method. These problems are the main ones that prevent the use of this approach in reliable systems for monitoring the IM technical condition. Separate solutions to these problems are proposed in works [71-73]. Sophisticated preprocessing of the output signals using high-order band-pass filters to virtually completely remove all signal components except those stored for research is used in these solutions. In these works, the optimization task is solved using the method of least squares. The method of least squares has a high computational complexity, but due to the small number of calculations, this disadvantage is eliminated. Despite the fact that this group of methods is new and promising, the problems of choosing and justifying optimal fitting criteria and choosing the order of the model are open and unresolved. In works [74-76], the physical content of the Prony method was found and it was shown that it can be applied to highly correlated or so-called almost periodic data. If the influence of uncontrolled parameters becomes significant, the data is distorted, the memory between successive measurements weakens, and they become almost reproducible. In this case, the fitting function changes and it is necessary to use another function obtained in [75]. However, these approaches have not previously been sufficiently investigated in the tasks of monitoring and diagnosing the technical condition of motors.

3.7 Methods of artificial intelligence

Methods based on artificial intelligence (AI) are becoming more and more widespread. The following

main AI approaches are used for diagnosis and detection of IM malfunctions [77]:
- neural networks;
- fuzzy logic;
- expert systems;
- machine learning.

These approaches do not depend on the system model and have a high level of generalization. Due to their independence, these methods can be used inside each other and/or use several methods combined in a combination. The requirement of a mandatory preliminary stage – training is a characteristic feature of these AI-based methods. For security purposes, a large volume of data is required for each condition to be detected and/or evaluated. AI methods are used in the process of decision-making and cluster analysis, while diagnostic features are pre-set. Usually, classical methods based on proven models are used to assign diagnostic symptoms.

3.7.1 Neural networks

Neural networks (NNs) are one of the AI approaches. NN is a structure of neurons, each of which performs simple arithmetic operations. NNs imitate the behavior of the human brain. The method of monitoring the technical condition of rolling bearings of an induction traction electric motor of locomotives is proposed in [78]. In this work, the task of classification was solved with the help of artificial NN’s. In [79], a method for detecting defects of the following defects is proposed: jamming of the electromechanical drive motor shaft, broken gear teeth, excessive clearance of the ball screw, and two internal leakage faults. The proposed method [79] uses multiple-scale analysis to construct basic wavelets and fast wavelet transformation to obtain diagnostic features. To make a decision, NN trained by the method of backpropagation of the error is used [79].

3.7.2 Fuzzy logic

Fuzzy logic (FL) [80, 81] is one of the approaches included in the arsenal of AI methods. FL is a more powerful variation of traditional logic. Not only binary values such as true and false are used, but a much larger number of possible values. Thanks to this, the presentation of information becomes closer to human thinking. FL systems are able to process fuzzy input parameters using fuzzy "if" rules based on a priori knowledge. In the study [82], the FL is used to detect defects in the rotor, with the help of supplying the residual current of the stator to the FL input. In work [83], the diagnosis of rotor rod breakage in a wind turbine based on an induction generator with a short-circuited rotor is investigated using a fuzzy logic system to analyze the power range of the stator currents.

3.7.3 Expert systems

Expert systems (ES) are systems that are able to fully or partially replace an expert specialist. ESs consist of a knowledge base, mechanisms of logical conclusions, and a subsystem of explanations [84]. The knowledge bases used to solve the tasks of IM control and diagnosis include:
- information about IM nodes;
- sensors;
- software;
- hardware resources, including the data collection environment and diagnostic algorithms.

Development and training of ES is a complex, long and expensive process. In work [85], a knowledge base for ES was developed, intended for diagnosing the rotor of the IM state in continuous mode based on the instantaneous values of the stator current. The proposed knowledge base is organized as a two-level system. The first level is intended for initial diagnostics using MCSA, it is simpler and requires only a few parameters of the machine under test. The second level is activated when a defect is detected in the rotor by the first level. The second level allows to more accurately localize the defect and estimate the number of damaged rotor rods. The second level requires a detailed specification of the machine under test. In work [86], expert systems are used to diagnose the traction induction electric motor of a locomotive.

3.7.4 Machine learning

Machine learning (ML) is one of the AI approaches. In it, the solution to the problem is not achieved by a direct solution, but by learning through the application of solutions to many similar problems. ML was formed as a result of dividing the science of neural networks into methods of learning networks and types of topologies of their architecture. Support-Vector Machine (SVM) is one of the most widely used ML approaches for IM control and diagnosis tasks. In [87], a method for detecting rotor rod breakage using a combination of SVM and MCSA is proposed. In [88], a predictive model for predicting the technical condition of IM bearings was built based on the wavelet decomposition of the stator current, obtained using SVM learning.

3.7.5 Conclusion of artificial intelligence methods

AI-based methods allow solving decision-making tasks. Due to their versatility and separation, these approaches are used not only individually, but also in combinations to increase efficiency and accuracy. At the same time, signal processing and criteria calculation takes place outside of AI methods, but beforehand. Classical methods of monitoring and diagnosing the technical condition of IM are usually used for such preliminary processing. Thus, it is impossible to generalize the parameters of AI-based diagnostic methods, such as the required duration of data sampling and computational complexity, since each implementation has its own specific refinement using classical methods and its own AI methods. However, it is obvious that the required duration of data sampling and computational complexity will be no less than classical methods, since these approaches use classical methods together with AI methods. Another important feature of AI methods is the need for preliminary training activities, which are time-consuming and expensive. Training requires large data sets of motors in various states and conditions to be detected and diagnosed.

3.7.6 Statistics of fractional moments

Recently, a new statistical approach called Fractional Moment Statistics (FMS) was developed to distinguish signals with a low signal-to-noise ratio [89]. Signals are transformed in the space of fractional moments, where they can be distinguished and grouped according to the level of their correlation with each other. SFM is extremely sensitive to very small differences between the investigated signals. This allows to imagine and describe any random sequence of data in the space of fractional moments [90, 91]. The generalized mean function (GMF) is approximated by a linear combination of exponential functions. Due to this, random sequences are presented as a small number of parameters (much less than the number of data). This image is convenient for comparing different sequences that have different numbers of points in the studied samples. It should be noted that in ordinary statistics it is not possible to compare samples with different numbers of points.

GMF and other functions obtained within the framework of FMS are widely used to solve classification problems. In [91], this approach is used for automatic classification of video streams. In work [92], calibration curves for two-phase electrical mixtures were obtained using GMF. This approach has a greater application potential in the IM diagnosis, since the tasks of classification in diagnosis are one of the main ones. The GMF computational complexity is of great importance. FMS approaches were not previously used in the IM diagnosis, however, they have great potential, as they can be implemented in systems for monitoring the IM technical condition in a continuous mode, due to their efficiency and high sensitivity, which has already been tested in other tasks [91, 93].

3.8 Comparison of methods of current diagnosis of rotor eccentricity

A comparison of the considered methods of current diagnosis of rotor eccentricity and a view of the advantages and disadvantages of implementation in devices for monitoring the IM technical condition is presented in Table 4.

The summary of Table 4 can be useful for choosing a method of processing diagnostic information when building a system for diagnosing the eccentricity of the IM rotor as part of the drive.

When choosing a method of processing diagnostic information, the following factors should be taken into account. Traction drive systems use either a vector system or a direct IM torque control system [94-96]. In such traction drive systems, the frequency of the traction motor supply voltage is proportional to the rotation frequency of the induction motor shaft. From the analysis of equation (4), it follows that when the value of the frequency of the supply voltage of the induction motor changes, the values of the frequencies of the subharmonics will also change. In addition, a change in the profile of the railway track will lead to a

Table 4. Comparison of methods of current diagnosis of rotor eccentricity

Method name	Advantages	Disadvantages
The method of electric motor current signature analysis (MCSA)	Low computational complexity	A long selection of measurements; dependence on blood pressure sliding; spectral leakage; dominant harmonic with the supply voltage frequency
Harmonic tracking methods (HOTA)	Low computational complexity; slip is calculated automatically; a shortened spectrum is used for fault analysis	A long selection of measurements; spectral leakage; susceptibility to noise, during load oscillations; an additional rotor speed sensor is required; dominant power frequency
Parametric methods (MUSIC, ESPRIT)	Short signal sampling; absence of the effect of spectral leakage	High computational complexity
Methods based on Park vectors	High sensitivity; low computational complexity; lack of a dominant power frequency	A long selection of measurements; dependence on IM sliding; spectral leakage
Prony method	Short signal sampling; absence of the effect of spectral leakage; low sampling rate	Complex signal processing is required; there are no criteria for choosing the order of the model and the fitting method
AI methods	High sensitivity; high level of automation of the entire system	The problem of learning; the difficulty of choosing diagnostic symptoms
Statistics of Fractional Moments	High sensitivity; the possibility of comparing samples with different numbers of points; possibility of application in classification tasks	High computational complexity

change in the load on the motor shaft. This circumstance will lead to a change in slip [43], which, in turn, will affect the sub-synchronous type components frequencies before their values change. In addition, from the analysis of the results given in Table 2, it follows that the sub-synchronous type components frequencies are not multiples of the frequency of the supply voltage. As the load increases, the magnitude of the IM slip will increase [16]. According to expression (4), this will lead to a decrease in the magnitude of the sub-synchronous type component frequencies. Therefore, the sub-synchronous type components will be located closer to the supply voltage frequencies.

Thus, the chosen method of processing diagnostic information should have a high spectral resolution.

Also, when choosing a method of processing diagnostic information, the influence of thermal processes should be taken into account. Thermal processes lead to the appearance of thermal noises, which, in turn, generate EMF noise. An increase in the temperature of the IM windings leads to an increase in the thermal noise EMF. This leads to a decrease in the signal-to-noise ratio (SNR). A decrease in SNR means an increase in the influence of thermal processes on the value of the IM stator phase currents and, as a consequence, on their spectral components [97]. In addition, the heating time constant of an induction motor is several orders of magnitude higher than the largest time constant (rotor time constant) of the induction motor itself. In other words, thermal noise parameters will change all the time. That is, the chosen method of processing diagnostic information must work correctly under conditions of constant changes in thermal noise parameters.

5. CONCLUSION

The work is devoted to the analysis of existing methods of processing diagnostic information that can be used in the construction of a system of functional diagnostics for monitoring eccentricity in induction traction motors of rolling stock.

Based on the analysis conducted, it was established that the diagnostic method using current is the most effective for constructing a system of functional diagnostics for monitoring the presence of eccentricity in induction traction motors of rolling stock.

When constructing functional diagnostics systems, the advantages of the current method are: simpler implementation of the functional diagnostics scheme, its lower cost, greater ease of identifying diagnostic features in conditions of interference caused by operational factors of rolling stock.

As a result of simulation modeling in the MATLab software environment, time diagrams of phase currents of the stator of an induction motor were obtained in the absence and presence of eccentricity. In the presence of eccentricity, modeling was performed for cases with different degrees of defect. Based on the obtained time diagrams of phase currents of the stator of an induction motor, their amplitude-frequency spectra were calculated and constructed. Analysis of the amplitude-frequency spectra of phase currents with different degrees of defects showed that harmonic components of the sub-synchronous type can be used as a diagnostic feature for monitoring the presence of eccentricity.

Based on the analysis of operational factors, it was found that the harmonic components of the sub-synchronous type are affected by the load of the induction motor, namely, a change in load leads to a change in the frequencies of the harmonic components of the sub-synchronous type. In addition, the value of these components is affected by thermal processes in the elements of the traction drive. These factors make it difficult to determine the parameters of the harmonic components of the sub-synchronous type and, as a result, make it difficult to monitor the eccentricity.

The analysis of diagnostic information processing methods for eccentricity monitoring was conducted. When analyzing diagnostic information processing methods in traction drives, such operational factors as the ability to operate under conditions of constant change in supply voltage frequency, the ability to operate with constant load change, the ability to operate with constant changes in thermal noise parameters, low computational complexity, and high spectral resolution were taken into account.

The next work of the authors will be aimed at researching the use of one of the considered methods in the construction of a diagnostic system for operational detection of defects in induction motors as part of the drive of transport equipment based on rotor eccentricity parameters.

***Source of funding**: This research received no external funding.*

***Author contributions:** research concept and design, S.G., O.G.; Collection and/or assembly of data, O.G., M.K., V. Vu.; Data analysis and interpretation, S.G., O.G., V.Yu., M.K.; Writing the article, S.G., O.G., V.Yu., M.K.; Critical revision of the article, O.G., S.G.; Final approval of the article, S.G., O.G.*

***Declaration of competing interest:** The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.*

REFERENCES

1. Gorobchenko O, Fomin O, Gritsuk I, Saravas V, Grytsuk Y, Bulgakov M, Volodarets M, Zinchenko D. Intelligent locomotive decision support system structure development and operation quality assessment. In: IEEE 3rd International conference on intelligent energy and power systems (IEPS). Kharkiv. 2018: 239-243. https://doi.org/10.1109/IEPS.2018.8559487.
2. Sheikh MA, Bakhsh ST, Irfan M, Nowakowski G. A review to diagnose faults related to three-phase industrial induction motors. Journal of Failure Analysis and Prevention. 2022;22:1546–1557. https://doi.org/10.1007/s11668-022-01445-2.
3. Li Y, Dong Y, Guo H. Copula-based multivariate renewal model for life-cycle analysis of civil infrastructure

considering multiple dependent deterioration processes. Reliability Engineering & System Safety. 2023;231: 108992. https://doi.org/10.1016/j.ress.2022.108992.
4. de Araújo ÁS, Rocha OP, Santos AÁB. Computational model for electrical motors condition analysis and monitoring. VI Simpósio Internacional de Inovação e Tecnologia, Blucher Engineering Proceedings. 2020; 7(2): 543-550. https://doi.org/10.34178/jbth.v5i2.206
5. Rauf A, Usman M, Butt A, Ping Z. Health monitoring of induction motor using electrical signature analysis. Journal of Donghua University. 2022;39(177(03)):265-271. https://doi.org/10.19884/j.1672-5220.202104001.
6. Gubarevych O, Goolak S, Golubieva S. Systematization and selection of diagnosing methods for the stator windings insulation of induction motors. Rev. Roum. Sci. Techn.–Électrotechn. et Énerg. 2022;67(4):445-450.
7. Bazan GH, Goedtel A, Duque-Perez O, Morinigo-Sotelo D. Multi-fault diagnosis in three-phase induction motors using data optimization and machine learning techniques. Electronics. 2021;10:1462. https://doi.org/10.3390/electronics10121462
8. Wei S, Zhang X, Xu Y, Fu Y, Ren Z, Li F. Extended Park's vector method in early inter-turn short circuit fault detection for the stator windings of offshore wind doubly-fed induction generators. IET Gener. Transm. Distrib. 2020;14:3905-3912. https://doi.org/10.1049/iet-gtd.2020.0127.
9. Arhun S, Migal V, Hnatov A, Ponikarovska S, Hnatova A, Novichonok S. Determining the quality of electric motors by vibro-diagnostic characteristics. EAI Endorsed Transactions on Energy Web. 2020:7(29):e6-e6. https://doi.org/10.4108/eai.13-7-2018.164101.
10. Balakrishna P, Khan U. An autonomous electrical signature analysis-based method for faults monitoring in industrial motors. IEEE Transactions on Instrumentation and Measurement. 2021;70:1-8. https://goi.org/10.1109/TIM.2021.3059466.
11. Yatsugi K, Pandarakone SE, Mizuno Y, Nakamura H. Common diagnosis approach to three-class induction motor faults using stator current feature and support vector machine. In: IEEE Access. 2023;11:24945-24952. https://goi.org/10.1109/ACCESS.2023.3254914.
12. Gubarevych O, Gerlici J, Gorobchenko O, Kravchenko K, Zaika D. Analysis of the features of application of vibration diagnostic methods of induction motors of transportation infrastructure using mathematical modeling. Diagnostyka. 2023;24(1):2023111. https://doi.org/10.29354/diag/161308.
13. Benbouzid MEH. A review of induction motors signature analysis as a medium for faults detection. IEEE transactions on industrial electronics. 2000;47(5):984-993. https://doi.org/10.1109/41.873206.
14. Sabir H, Ouassaid M, Ngote N, Benbouzid M. A novel experimental method to detect early rotor faults in induction machines. International Journal on Energy Conversn (IRECON). 2021;9(5);191-202. https://doi.org/10.15866/irecon.v9i5.21214.
15. Fomin O, Sulym A, Kulbovskiy I, Khozia P, Ishchenko V. Determining rational parameters of the capacitive energy storage system for the underground railway rolling stock. Eastern-European Journal of Enterprise Technologies. 2018;2(1(92)):63-71. https://doi.org/10.15587/1729-4061.2018.126080.
16. Goolak S, Gerlici J, Gubarevych O, Lack T, Pustovetov M. Imitation modeling of an inter-turn short circuit of an induction motor stator winding for diagnostics of auxiliary electric drives of transport infrastructure. Communications-Scientific letters of the University of Zilina. 2021;23(2):C65-C74. https://doi.org/10.26552/com.C.2021.2.C65-C74.
17. Gubarevych O, Goolak S, Daki O, Tryshyn V. Investigation of turn-to-turn closures of stator windings to improve the diagnostics system for induction motors. Problemele Energeticii Regionale. 2021;2(50):10-24. https://doi.org/10.52254/1857-0070.2021.2-50.02.
18. Pal RSC, Mohanty AR. A simplified dynamical model of mixed eccentricity fault in a three-phase induction motor. IEEE Transactions on Industrial Electronics. 2020; 68(5): 4341-4350. https://doi.org/10.1109/TIE.2020.2987274.
19. Khalique U, Xu G, Xining Z, Fei L, Ahmad S, Xun Z, Jin Z. A novel detection method for diagnosis of rotor eccentricity in three-phase induction motor. Measurement Science and Technology. 2021;32(11): 114002. https://doi.org/0.1088/1361-6501/ac06fe.
20. Petryna J, Duda A, Sułowicz M. Eccentricity in induction machines - A useful tool for assessing its level. Energies. 2021;14(7):1976. https://doi.org/10.3390/en14071976.
21. Viswanath S, Praveen Kumar N, Isha TB. Static eccentricity fault in induction motor drive using finite element method. In Advances in Electrical and Computer Technologies: Select Proceedings of ICAECT 2019. 2020:1291-1302. https://doi.org/10.1007/978-981-15-5558-9_108.
22. Liu Z, Zhang P, He S, Huang J. A review of modeling and diagnostic techniques for eccentricity fault in electric machines. Energies. 2021;14(14):4296. https://doi.org/10.3390/en14144296.
23. Li H, Zou Z. Sun X, Gu F, Ball AD. A numerical study of rotor eccentricity and dynamic load in induction machines for motor current analysis based diagnostics. Maintenance, Reliability and Condition Monitoring. 2021;1(2):71-86. https://doi.org/10.21595/mrcm.2021.22145.
24. Deekshit KK, Rao MVG, Rao RS. Fault indexing parameter based fault detection in induction motor via MCSA with wiener filtering. Electric Power Components and Systems. 2021;48(19-20):2048-2062. https://doi.org/10.1080/15325008.2021.1910376.
25. Zhou L, Wang B, Lin C, Inoue H, Miyoshi M. Static eccentricity fault detection for psh-type induction motors considering high-order air gap permeance harmonics. In 2021 IEEE International Electric Machines & Drives Conference (IEMDC). 2021:1-7. https://doi.org/10.1109/IEMDC47953.2021.9449496.
26. Garcia-Calva T, Morinigo-Sotelo D, Fernandez-Cavero V, Romero-Troncoso R. Early detection of faults in induction motors - A review. Energies. 2022;15(21): 7855. https://doi.org/10.3390/en15217855.
27. Tennakoon S, Perer S, Robinson D. Flicker attenuation—Part I: Response of three-phase induction motors to regular voltage fluctuations. IEEE Transactions on Power Delivery. 2008;23(2):1207-1214. https://doi.org/10.1109/TPWRD.2007.908788.
28. Gnaciński P, Hallmann D, Muc A, Klimczak P, Pepliński M. Induction motor supplied with voltage containing symmetrical subharmonics and interharmonics. Energies. 2022;15(20):7712. https://doi.org/10.3390/en15207712.
29. Alimardani R, Rahideh A, Kia SH. Mixed eccentricity fault detection for induction motors based on time synchronous averaging of vibration signals. IEEE Transactions on Industrial Electronics. 2023;71(3):3173-3181. https://doi.org/10.1109/TIE.2023.3266589.
30. Yepes AG, Fonseca DS, Antunes HR, López O, Cardoso AJM, Doval-Gandoy J. Discrimination between eccentricity and interturn faults using current or voltage-reference signature analysis in symmetrical six-phase induction machines. IEEE Transactions on Power

Electronics. 2022;38(2):2421-2434. https://doi.org/10.1109/TPEL.2022.3206141.
31. Duda A, Drozdowski P. Induction motor fault diagnosis based on zero-sequence current analysis. Energies. 2020; 13(24):6;528. https://doi.org/10.3390/en13246528.
32. Goolak, S, Liubarskyi B, Sapronova S, Tkachenko V, Riabov Ie. Refined model of induction traction electric motor of electric locomotive. Transport Means - Proceedings of the International Conference. 2021:455–460.
33. Goolak S, Riabov I, Gorobchenko O, Yurchenko V, Nezlina O. Improvement of the model of an induction traction motor of an electric locomotive by taking into account power losses. Przeglad Elektrotechniczny. 2022; 98(5):1–10. https://doi.org/10.15199/48.2022.05.01.
34. Madhavan S, Gundabattini E, Mystkowski A. Thermal analysis and heat management strategies for an induction motor, a review. Energies. 2022;15(21):8127. https://doi.org/10.3390/en15218127.
35. Al-Musawi AK, Anayi F, Packianather M. Three-phase induction motor fault detection based on thermal image segmentation. Infrared Physics & Technology. 2020; 104:103140. https://doi.org/10.1016/j.infrared.2019.103140.
36. Widagdo RS, Hermawati FA, Hariadi B. Unbalanced voltage detection with measurement current signature analysis (MCSA) in 3-phase induction motor using fast fourier transform (FFT). Jurnal Teknologi Elektro. 2024; 15(02); 95-101. https://doi.org/10.22441/jte.2024.v15i2.003.
37. Deeb M, Kotelenets NF. Fault diagnosis of 3-phase induction machine using harmonic content of stator current spectrum. In 2020 International Youth Conference on Radio Electronics, Electrical and Power Engineering (REEPE). 2020;1-6. https://doi.org/10.1109/REEPE49198.2020.9059213.
38. Krishnasarma A, Mostafavi Yazdi SJ, Taylor A, Ludwigsen D, Baqersad J. Acoustic signature analysis and sound source localization for a three-phase AC induction motor. Energies. 2021;14(21):7182. https://doi.org/10.3390/en14217182.
39. Eleftheriadis C, Karakonstantis G. Energy-efficient fast Fourier transform for real-valued applications. IEEE Transactions on Circuits and Systems II: Express Briefs. 2022;69(5):2458-2462. https://doi.org/10.1109/TCSII.2022.3163280.
40. Yu D, Zhan X, Yang LJ, Jia Y. Theoretical description of logical stochastic resonance and its enhancement: Fast Fourier transform filtering method. Physical Review E. 2023;108(1):014205. https://doi.org/10.1103/PhysRevE.108.014205.
41. Sapena-Bano A, Pineda-Sanchez M, Puche-Panadero R, Martinez-Roman J, Kanović Ž. Low-cost diagnosis of rotor asymmetries in induction machines working at a very low slip using the reduced envelope of the stator current. IEEE Transactions on Energy Conversion. 2015; 30(4):1409-1419. https://doi.org/10.1109/TEC.2015.2445216.
42. Goolak S, Liubarskyi B, Lukoševičius V, Keršys R, Keršys A. Operational diagnostics system for asymmetric emergency modes in traction drives with direct torque control. Applied Sciences. 2023;13(9):5457. https://doi.org/10.3390/app13095457.
43. Gubarevych O, Goolak S, Daki O, Yakusevych Yu. Determining an additional diagnostic parameter for improving the accuracy of assessment of the condition of stator windings in an induction motor. Eastern-European Journal of Enterprise Technologies. 2021;5(5(113):21–29. http://doi.org/10.15587/1729-4061.2021.239509.
44. Niu G, Dong X, Chen Y. Motor fault diagnostics based on current signatures: A review. IEEE Transactions on Instrumentation and Measurement. 2023;72:1-19. https://doi.org/10.1109/TIM.2023.3285999.
45. Lee SB, Shin J, Park Y, Kim H, Kim J. Reliable flux-based detection of induction motor rotor faults from the fifth rotor rotational frequency sideband. IEEE Transactions on Industrial Electronics. 2020;68(9): 7874-7883. https://doi.org/10.1109/TIE.2020.3016241.
46. de Jesus Romero-Troncoso R. Multirate signal processing to improve FFT-based analysis for detecting faults in induction motors. IEEE Transactions on Industrial Informatics. 2016;13(3):1291-1300. https://doi.org/10.1109/TII.2016.2603968.
47. Allal A, Khechekhouche A. Diagnosis of induction motor faults using the motor current normalized residual harmonic analysis method. International Journal of Electrical Power & Energy Systems. 2022;141:108219. https://doi.org/10.1016/j.ijepes.2022.108219.
48. Chen X, Feng Z. Order spectrum analysis enhanced by surrogate test and Vold-Kalman filtering for rotating machinery fault diagnosis under time-varying speed conditions. Mechanical Systems and Signal Processing. 2021;154:107585. https://doi.org/10.1016/j.ymssp.2020.107585.
49. Chehaidia SE, Cherif H, Alraddadi M, Mosaad MI, Bouchelaghem AM. Experimental diagnosis of broken rotor bar faults in induction motors at low slip via hilbert envelope and optimized subtractive clustering adaptive neuro-fuzzy inference system. Energies. 2022;15(18): 6746. https://doi.org/10.3390/en15186746.
50. Guezam A, Bessedik SA, Djekidel R. Fault diagnosis of induction motors rotor using current signature with different signal processing techniques. Diagnostyka. 2022;23(2):1-9. https://doi.org/10.29354/diag/147462.
51. Gangsar P, Tiwari R. Signal based condition monitoring techniques for fault detection and diagnosis of induction motors: A state-of-the-art review. Mechanical Systems and Signal Processing. 2020; 144: 106908. https://doi.org/10.1016/j.ymssp.2020.106908.
52. Dehina W, Boumehraz M, Kratz F. Detectability of rotor failure for induction motors through stator current based on advanced signal processing approaches. International Journal of Dynamics and Control. 2021;9(4):1381-1395. https://doi.org/10.1007/s40435-021-00765-9.
53. Tran TH, Liang H, Li W, Pham MT. Comparison of machine learning algorithms for induction motor rotor single fault diagnosis using stator current signal. International Journal of Advanced Trends in Computer Science and Engineering. 2021;10(3):1509-1514. http://dx.doi.org/10.30534/ijatcse/2021/031032021.
54. Ferrucho-Alvarez ER, Martinez-Herrera AL, Cabal-Yepez E, Rodriguez-Donate C, Lopez-Ramirez M, Mata-Chavez RI. Broken rotor bar detection in induction motors through contrast estimation. Sensors. 2021; 21(22):7446. https://doi.org/10.3390/s21227446.
55. Halder S, Bhat S, Zychma D, Sowa P. Broken rotor bar fault diagnosis techniques based on motor current signature analysis for induction motor - A review. Energies. 2022;15(22):8569. https://doi.org/10.3390/en15228569.
56. Amanuel T, Ghirmay A, Ghebremeskel H, Ghebrehiwet R, Bahlibi W. Comparative analysis of signal processing techniques for fault detection in three phase induction motor. Journal of Electronics. 2021;3(01):61-76. https://doi.org/10.36548/jei.2021.1.006.

57. Gerlici J, Goolak S, Gubarevych O, Kravchenko K, Kamchatna-Stepanova K, Toropov A. Method for determining the degree of damage to the stator windings of an induction electric motor with an asymmetric power system. Symmetry. 2022;14(7):1305. https://doi.org/10.3390/sym14071305.
58. Gubarevych O, Goolak S, Melkonova I, Yurchenko M. Structural diagram of the built-in diagnostic system for electric drives of vehicles. Diagnostyka. 2022;23(4):1-13. https://doi.org/10.29354/diag/156382.
59. Gubarevych O, Gerlici J, Kravchenko O, Melkonova I, Melnyk O. Use of Park's vector method for monitoring the rotor condition of an induction motor as a part of the built-in diagnostic system of electric drives of transport. Energies. 2023;16(13):5109. https://doi.org/10.3390/en16135109.
60. Laadjal K, Antunes HR, Sahraoui M, Bento F, Cardoso AJM. Online diagnosis and discrimination of stator faults in six-phase induction motors based on voltage symmetrical components. IEEE Transactions on Transportation Electrification. 2022;9(2):3115-3126. https://doi.org/10.1109/TTE.2022.3219722.
61. Frosini L. Novel diagnostic techniques for rotating electrical machines - A review. Energies. 2020;13(19): 5066. https://doi.org/10.3390/en13195066.
62. Abdellah C, Mama C, Meflah Abderrahmane MR, Mohammed B. Current Park's vector pattern technique for diagnosis of broken rotor bars fault in saturated induction motor. Journal of Electrical Engineering & Technology. 2023;18(4):2749-2758. https://doi.org/10.1007/s42835-022-01342-6.
63. Jiang Y, Ji B, Zhang J, Yan J, Li W. An overview of diagnosis methods of stator winding inter-turn short faults in permanent-magnet synchronous motors for electric vehicles. World Electric Vehicle Journal. 2024; 15(4): 165. https://doi.org/10.3390/wevj15040165.
64. Kahraman E, Ulusoy AE, Şerifoğlu MO, Kara. B. Park Vector approach based misalignment detection strategy for IMs. In 2023 14th International Conference on Electrical and Electronics Engineering (ELECO). 2023:1-5. https://doi.org/10.1109/ELECO60389.2023.10416077.
65. Messaoudi M, Flah A, Alotaibi AA, Althobaiti A, Sbita L, Ziad El-Bayeh C. Diagnosis and fault detection of rotor bars in squirrel cage induction motors using combined Park's vector and extended Park's vector approaches. Electronics. 2022;11(3):380. https://doi.org/10.3390/electronics11030380.
66. Wei L, Rong X, Wang H, Yu S, Zhang Y. Method for identifying stator and rotor faults of induction motors based on machine vision. Mathematical Problems in Engineering. 2021;1:6658648. https://doi.org/10.1155/2021/6658648.
67. Chen P, Xie Y, Hu S. Electromagnetic performance and diagnosis of induction motors with stator interturn fault. IEEE Transactions on Industry Applications. 2020; 57(2): 1354-1364. https://doi.org/10.1109/TIA.2020.3043214.
68. Lang W, Hu Y, Gong C, Zhang X, Xu H, Deng J. Artificial intelligence-based technique for fault detection and diagnosis of EV motors: A review. IEEE Transactions on Transportation Electrification. 2021; 8(1): 384-406. https://doi.org/10.1109/TTE.2021.3110318.
69. Ouerghemmi N, Salem SB, Salah M, Bacha K, Chaari A. V-belt fault detection using extended Park vector approach (EPVA) in centrifugal fan driven by an induction motor. Mechanical Systems and Signal Processing. 2023;200:110566. https://doi.org/10.1016/j.ymssp.2023.110566.
70. Gyftakis KN, Cardoso AJM. Reliable detection of stator interturn faults of very low severity level in induction motors. IEEE Transactions on Industrial Electronics. 2020;68(4):3475-3484. https://doi.org/10.1109/TIE.2020.2978710.
71. Laadjal K, Sahraoui M, Alloui A, Cardoso AJM. Three-phase induction motors online protection against unbalanced supply voltages. Machines. 2021;9(9):203. https://doi.org/10.3390/machines9090203.
72. Chen X, Feng Z. Tacholess speed estimation for rotating machinery fault diagnosis of induction motor drivetrain. IEEE Transactions on Power Electronics. 2024;39(4): 4704-4713. https://doi.otg/10.1109/TPEL.2023.3349138.
73. Laadjal K, Cardoso AJM, Sahraoui M, Alloui A. A novel stator faults indicator in three-phase induction motors, based on voltage and impedance symmetrical components. In IECON 2022–48th Annual Conference of the IEEE Industrial Electronics Society. 2022;1-6. https://doi.org/10.1109/IECON49645.2022.9968349.
74. Sørensen RB, Nielsen JJ, Popovski P. Machine learning methods for monitoring of quasiperiodic traffic in massive IoT networks. IEEE Internet of Things Journal. 2020;7(8):7368-7376. https://doi.org/10.1109/JIOT.2020.2983217
75. Rundle JB, Stein S, Donnellan A, Turcotte DL, Klein W, Saylor C. The complex dynamics of earthquake fault systems: New approaches to forecasting and nowcasting of earthquakes. Reports on progress in physics. 2021; 84(7):076801. https://doi.org/10.1088/1361-6633/abf893.
76. Bonizzi P, Zeemering S, Karel J, Lankveld T, Schotten U, Crijns H, Meste O. Body-surface atrial vector similarity as a new way to investigate atrial fibrillation propagation dynamics. Computing in Cardiology (CinC). 2021;48:1-4. https://doi.org/10.23919/CinC53138.2021.9662731.
77. AlShorman O, Alkahatni F, Masadeh M, Irfan M, Glowacz A, Althobiani F, Glowacz W. Sounds and acoustic emission-based early fault diagnosis of induction motor: A review study. Advances in Mechanical Engineering. 2021;13(2):1687814021996915. https://doi.org/10.1177/1687814021996915.
78. Li Y. Exploring real-time fault detection of high-speed train traction motor based on machine learning and wavelet analysis. Neural Computing and Applications. 2022;34(12):9301-9314. https://doi.org/10.1007/s00521-021-06284-0.
79. Lee CY, Huang KY, Jen LY, Zhuo GL. Diagnosis of defective rotor bars in induction motors. Symmetry. 2020;12(11):1753. https://doi.org/10.3390/sym12111753.
80. Butko T, Babanin A, Gorobchenko A. Rationale for the type of the membership function of fuzzy parameters of locomotive intelligent control systems. Eastern-European Journal of Enterprise Technologies. 2015;1(73):4-8. https://doi.org/10.15587/1729-4061.2015.35996.
81. Gorobchenko O, Nevedrov O. Development of the structure of an intelligent locomotive DSS and assessment of its effectiveness. Archives of Transport. 2020;56(4):47-58. https://doi.org/10.5604/01.3001.0014.5517.
82. Mohamed M, Mohamed E, Mohamed AA, Abdel-Nasser M, Hassan MM. Detection of inter turn short circuit faults in induction motor using artificial neural network. In 2020 26th Conference of Open Innovations Association (FRUCT). 2020:297-304. https://doi.org/10.23919/FRUCT48808.2020.9087535.
83. Amrolia H, Badgujar K. An overview of techniques for detecting mechanical anomalies in induction motors.

Transactions of the Indian National Academy of Engineering. 2024;9(1):71-86. https://doi.org/10.1007/s41403-023-00446-3.
84. AlShorman O, Irfan M, Saad N, Zhen D, Haider N, Glowacz A, AlShorman A. A review of artificial intelligence methods for condition monitoring and fault diagnosis of rolling element bearings for induction motor. Shock and Vibration. 2020;1:8843759. https://doi.org/10.1155/2020/8843759.
85. Kumar RR, Andriollo M, Cirrincione G, Cirrincione M, Tortella A. A comprehensive review of conventional and intelligence-based approaches for the fault diagnosis and condition monitoring of induction motors. Energies. 2022; 15(23): 8938. https://doi.org/10.3390/en15238938.
86. Li L, Wang J, Xiao S. Research and design of an expert diagnosis system for rail vehicle driven by data mechanism models. Railway Sciences. 2024;3(4):480-502. https://doi.org/10.1108/RS-05-2024-0016.
87. Yatsugi K, Pandarakone SE, Mizuno Y, Nakamura H. Common diagnosis approach to three-class induction motor faults using stator current feature and support vector machine. IEEE Access. 2023;11:24945-24952. https://doi.org/10.1109/ACCESS.2023.3254914.
88. Kim MC, Lee JH, Wang DH, Lee IS. Induction motor fault diagnosis using support vector machine, neural networks, and boosting methods. Sensors. 2023;23(5): 2585. https://doi.org/10.3390/s23052585.
89. Niu H, Chen Y. Why do big data and machine learning entail the fractional dynamics? In smart big data in digital agriculture applications: acquisition, advanced analytics, and plant physiology-informed artificial intelligence, 2023:15-53. Cham: Springer Nature Switzerland. https://doi.org/10.1007/978-3-031-52645-9_2.
90. Nigmatullin RR, Sabatier J. How to detect and fit “fractal” curves, containing power-law exponents? Part 2. In 2023 International Conference on Fractional Differentiation and Its Applications (ICFDA). 2023:1-5. https://doi.org/10.1109/ICFDA58234.2023.10153375
91. Nigmatullin RR, Lino P, Maione G. The statistics of fractional moments and its application for quantitative reading of real data. New Digital Signal Processing Methods: Applications to Measurement and Diagnostics. 2020: 87-139. https://doi.org/10.1007/978-3-030-45359-6_3.
92. Nigmatullin RR, Lino P, Maione G. “Fuzzy” calculus: The link between quantum mechanics and discrete fractional operators. Fractional Calculus and Applied Analysis. 2020;23(3):764-786. https://doi.org/10.1515/fca-2020-0038.
93. Zhang X, Low YM, Koh CG. Maximum entropy distribution with fractional moments for reliability analysis. Structural Safety. 2020;83:101904. https://doi.org/10.1016/j.strusafe.2019.101904.
94. Goolak S, Liubarskyi B, Riabov I, Lukoševičius V, Keršys A, Kilikevičius S. Analysis of the efficiency of traction drive control systems of electric locomotives with induction traction motors. Energies. 2023;16(9): 3689. https://doi.org/10.3390/en16093689.
95. Goolak S, Liubarskyi B, Riabov I, Chepurna N, Pohosov O. Simulation of a direct torque control system in the presence of winding asymmetry in induction motor. Engineering Research Express. 2023;5:025070-025086. http://doi.org/10.1088/2631-8695/acde46.
96. Goolak S, Liubarskyi B. Vector control system taking into account the saturation of an induction motor. Tehnički Vjesnik. 2024 31(4):1170-1178. https://doi.org/10.17559/TV-20221015124239.
97. Issa R, Clerc G, Hologne-Carpentier M, Michaud R, Lorca E, Magnette C, Messadi A. Review of fault diagnosis methods for induction machines in railway traction applications. Energies. 2024;17(11):2728. https://doi.org/10.3390/en17112728.

Sergey GOOLAK
candidate of technical sciences, Associate Professor
Department of Electromechanics and Rolling Stock of Railways of State University of Infrastructure and Technologies, Kyiv, Ukraine. Scientific interests – technical diagnostics of drives of transport systems.
E-mail: sgoolak@gmail.com

Oleg GUBAREVYCH
candidate of technical sciences, Associate Professor Corresponding Member of the Academy of Applied Sciences, Department of Electromechanics and Rolling Stock of Railways of State University of Infrastructure and Technologies, Kyiv, Ukraine.
The main research is aimed at improving reliability and developing diagnostic methods for electrical equipment.
E-mail: oleg.gbr@ukr.net

Victor YURCHENKO
postgraduate Department of Electromechanics and Rolling Stock of Railways of State University of Infrastructure and Technologies, Kyiv, Ukraine. Scientific interests – methods of diagnosing induction motors.
E-mail: holub.hm@gmail.com

Mykhailo KYRYCHENKO
candidate of technical sciences, Kyiv National University of Construction and Architecture. Field of scientific interests – mathematical modeling of thermodynamic processes.
E-mail: kirichenkom@ukr.net