DOI: 10.32703/2617-9059-2024-44-3

UDC 629.4.023

Denys Lakusta[1], Sergey Maliuk[2*]

[1]Postgraduate, Department of Electromechanics and rolling stock of railways, State University of Infrastructure and Technologies, 9, Kyrylivska str., Kyiv, 04071, Ukraine. ORCID: https://orcid.org/0009-0000-6563-757X.

[2]Senior Lecturer, Department of Electromechanics and Rolling Stock of Railways, State University of Infrastructure and Technologies, 9, Kyrylivska str., Kyiv, 04071, Ukraine. ORCID: https://orcid.org/0000-0003-1777-2384.

***Corresponding author:** Corresponding author: maliuk_sv@gsuite.duit.edu.ua.

Development of a functional system for diagnosing the presence of rotor damage in induction traction motors

The aim of this work is to develop a system for functional diagnostics of rotor bar breakage in induction traction motors of railway rolling stock. In order to achieve this aim, the following tasks have been solved: developed an algorithm for diagnosing the condition of rotor bars based on the statistics of fractional moments; developed a block diagram of the unit for diagnosing the condition of rotor bars of the induction motor based on the statistics of fractional moments; developed a block diagram of the system for functional diagnosis of rotor bars condition as part of the traction motor with direct torque control. The most important result consists in obtaining a mathematical model of fractional moment statistics with less volume of calculations and improved sensitivity of the method. This result was achieved by determining the information-frequency range, which made it possible to analyze not all the spectral components of the analyzed signal, but only that part of it where there may be spectral components typical for the breakage of rotor bars of the induction motor. This approach to diagnosing the condition of rotor bars can also be applied in traction motors of rolling stock with vector control system of induction motors.

Keywords: *induction motor, fractional moment statistics, rotor bars, direct torque control*

Introduction. The railway is one of the critical infrastructure facilities, an element of which is rolling stock. Therefore, improving the reliability of rolling stock operation has always been an urgent task [1, 2]. The most effective way to improve the reliability of rolling stock is the use of the systems for diagnosing its condition during operation (operational diagnostic systems) [3]. Traction motors are the elements of rolling stock that most often suffer damage. [4].

Induction motors (IM) are increasingly used as traction motors in railway rolling stock. This fact is explained by the simplicity of their design, low production cost and ease of maintenance [5]. The reliable operation of IM directly affects the operational stability of traction motors used in the rolling stock. In case of damage to traction motor, economic losses can be significant. One of the most common defects in IM is the breakage of rotor bars. This defect accounts for approximately 10% of all IM failures [6]. This defect is characterized by its invisibility and gradualness, which makes it difficult to detect it in the early stages. Untimely detection of a defect leads to an increase in the degree of its malfunction during the IM further operation. In connection with this fact, detecting a defect at an early stage is an important task.

The use of functional diagnostics diagrams will allow for effective detection of rotor bars damage at an early stage of the occurrence of this defect during the rolling stock operation. To build such diagnostic diagrams, it is necessary to develop algorithms for diagnosing and determining the degree of the specified defect at an early stage, taking into account the railway rolling stock operational factors [7].

Analysis of existing technical solutions. The following signals can be used to diagnose damage to rotor bars in IM:

- signals of phase currents of the ID stator [8];
- vibration signals [9];
- acoustic signals [10];
- signals of instantaneous power [11];
- signals of flux linkages [12].

The analysis of the specified diagnostic methods conducted in the work [12] showed that due to their availability and non-invasiveness, the method of analyzing IM stator current signatures was the most widely used in diagnosing damage to rotor bars. It should be noted that despite its advantages, this method has one drawback: it does not work correctly in the conditions of IM idle operation or at low loads [14]. This is explained by the fact that the sideband frequency, which is a diagnostic sign of the defect presence, coincides (at IM idle operation) or is located too close (when operating with low loads) to the frequency of the IM supply voltage. Therefore, to detect a defect, you should have algorithms with a high spectral resolution.

To solve this problem, the following methods were proposed to effectively eliminate the fundamental frequency harmonic of the stator phase currents:

- rejection filter [15];
- extended Kalman filter [16];
- matched filter [17];
- sparse Bayes filter [18].

These methods, in addition to eliminating the harmonics of the fundamental frequency of the stator phase currents and noise, weaken the characteristic harmonics of the defect, which can lead to a false diagnosis of IM rotor bar defect at early stages.

In a number of studies, high-frequency resolution methods were used in order to distinguish the sideband frequency accurately, which indicates the presence of a defect, from the frequency of the supply voltage. These methods are based on the decomposition of current signal values into signal and noise subspaces. The resolution can be improved by applying special ratios between subspaces. Thus, in the work [19] we used the classification of multiple signals to detect rotor defect under different conditions of load and speed. In the work [20], we used the estimation of signal parameters based on the method of rotational invariance instead of the fast Fourier transform (FFT) to diagnose rotor bar breaks. This algorithm, unlike the IM stator current signature analysis method, is capable to increase effectively the resolution of the spectrum estimation and improve the sideband detection with limited data. The disadvantage of these two methods is that they require a significant amount of computation and their speedwork depends on the selected parameters of the model.

Another approach to eliminating harmonics of the supply voltage frequency is the use of modulation methods. In these methods, the harmonic of the frequency of the supply voltage is converted into a direct current component. In the work [21], we used the Park's vector method to diagnose the rotor bar breakage. To diagnose the said defect, in the work [22] we used the sum of adjacent productions. To use these two approaches, it is necessary to have data on two- or three-phase IM stator currents.

In this study [23] we proposed to use Teager-Kaiser energy operator for the diagnosis of IM rotor damage. To demodulate IM stator phase current signals based on the approach proposed in [23], it is necessary to have only three consecutive sampling points. This allows for excellent speedwork. However, such calculations represent causal processing and can lead to signal distortion and non-ideal filter characteristics. In [24], we proposed to use the method of normalized energy operator in the frequency domain to diagnose the breakage of IM rotor bars. Instead of using causal processing, in this method we use Hilbert transform to calculate the energy operator. But at the same time, the volumes of calculations increase. In contrast to the above considered approaches, in this work [25] we proposed a technique based on the spectral analysis of rectified current signals. This technique can be implemented either in hardware (using a simple rectifier) or in software (by saving current signal counts). All demodulation algorithms considered above are based on FFT, which provides complete information about the spectra of the analyzed signals. In the works considered during the analysis, it was noted that the frequency that determines the presence of breaks of the rotor bars is located in the low frequency range. Therefore, when developing diagnostic algorithms to determine this frequency, it is enough to focus on the analysis of spectrum within the low frequency range. In addition, for the implementation of the algorithms given in the works [23-25], it is required to have information about the angular speed of motor shaft rotation, for the determination of which, it is required to use angular speed sensors.

A new statistical approach, called Statistics of Fractional Moments (SFM), is given in [26] for distinguishing signals with a low signal-to-noise ratio [26]. The 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 signals under study. This makes it possible to imagine and describe any random sequence of data in the space of fractional moments [27]. The function of the generalized average (FGA) is approximated by a linear combination of exponential functions, thanks to which random sequences are presented as a small number of parameters (much less than the number of data). This representation is convenient for comparing different sequences that have different numbers of points in the studied samples. It should be noted that it is impossible to compare samples with different numbers of points in ordinary statistics. FGA and other functions obtained within the SFM framework are widely used to solve classification tasks. This approach has great potential for application in IM diagnostics, since classification tasks in diagnostics are one of the main ones. SFM approaches have not been previously used in IM diagnostics, but they have great potential as they can be implemented in continuous monitoring systems of IM technical condition due to their efficiency and high sensitivity.

The purpose of this work is to develop a system for functional diagnostics of the presence of breaks of rotor bars in induction traction motors of the railway rolling stock.

The research contributions of this work are as follows:

- developed an algorithm for diagnosing the condition of rotor bars based on fractional moments statistics;
- developed a block diagram of the unit for diagnosing the condition of rotor bars of the IM based on the statistics of fractional moments;
- developed a block diagram of the system for functional diagnosis of rotor bars condition as part of the traction motor with direct torque control.

Development of an algorithm for monitoring and diagnosing the condition of induction motor rotor based on the method of fractional order moments. The proposed method of fractional order moments for solving the tasks of monitoring and diagnosing technical condition of motors includes of the following basic steps:

1. Measurement of one or more IM stator phase currents signals.
2. Application of the Fourier transform to the measured signal to display the signal in frequency domain.
3. Calculation of the function of the generalized average (FGA) for the spectrum obtained at the previous step according to the expressions (1) and (2).

The FGA for a moment of order p is calculated according to the following expression

$$\Delta_{(mom_p)} = \left(\frac{1}{L} \cdot \sum_{i=1}^{L} y_i^{mom_p} \right)^{\frac{1}{mom_p}}, \tag{1}$$

where y_i – input sequence;
L – number of points;
p=1, 2, ..., P - positive integer;
mom_p - moment of order p.

Moment of order p is calculated according to the expression:

$$mom_p = exp\left\{min + \frac{p}{P} \cdot \left(max - min\right)\right\}, \tag{2}$$

min, *max* and P – are FGA parameters. *min* and *max* parameters determine the range of moments in a logarithmic scale;
P - is the coefficient that determines the permission of moment orders.

4. Comparison of the obtained FGA with the FGA obtained for IM in different technical conditions. If the FGA obtained for the IM in good condition is "close" to the FGA obtained for the motor under test, then a decision is made that the motor is in good condition. Otherwise, a decision is made that there are anomalies and possible malfunctions. The method of comparing FGA and the "closeness" criterion is determined in the specific implementation of the proposed method. For example, in the works [27] the tangent of the angle of inclination between the FGA obtained for the tested motor and the FGA obtained for a fault free motor are calculated to compare FGA. In order to solve the tasks of diagnosing defects, it is necessary to obtain FGA of the motors with malfunctions and to compare with the FGA of the motor under test not only with the FGA of a fault free motor, but also with the FGA obtained for motors with defects. The proposed method does not depend on the specificity of the measured signal and is free from model assumptions about the signal.

Signal processing algorithm contains the stage of signals pre-processing, which includes: α-β transformation, decimation, FFT and selection of informative frequency ranges (IFR), as well as the stage of main processing, which includes: calculation of the function of the generalized average (FGA) and calculation of the slope of the current FGA with respect to the FGA obtained for a fault free IM, comparing the slopes with tabulated values and deciding on the IM technical condition.

Block diagram of the algorithm is shown in Fig. 1.

The algorithm includes the following steps:

1. α-β transformation

The three-phase IM stator currents are represented as a rotating space vector in the frame of reference, which is attached to the stator phase plane. The real axis α is connected to the axis of one of the stator windings, and the imaginary axis β is shifted in phase by 90 degrees. The transformation of coordinates from the measured currents of phases i_a, i_b, i_c to coordinates i_α and i_β is determined by the operation

$$\begin{bmatrix} i_\alpha \\ i_\beta \end{bmatrix} = \frac{2}{3} \cdot \begin{bmatrix} 1 & -\frac{1}{2} & -\frac{1}{2} \\ 0 & \frac{\sqrt{3}}{2} & -\frac{\sqrt{3}}{2} \end{bmatrix} \cdot \begin{bmatrix} i_a \\ i_b \\ i_c \end{bmatrix}. \tag{3}$$

2. Decimation

Modern measuring equipment provides an opportunity to increase the sampling frequency significantly. Moreover, modern sensor technologies allow measuring signals at high frequencies without increasing the noise. High-frequency information may contain diagnostic information. However, a high sampling rate increases the memory capacity. Therefore, the proposed method uses the procedure of decimation by averaging. Thus, only the average value of several measurements is used for further analysis. The input sample of the output signal $\mathbf{x}$ is represented as an observation vector $\mathbf{x}^T$ using the expression

$$\mathbf{x}^T = \left[x_1 \quad x_2 \quad \cdots \quad x_M\right], \tag{4}$$

$$M = T \cdot F_s, \tag{5}$$

where M - is the total number of measurements;

T - time interval of data collection;
F_s - initial sampling frequency.

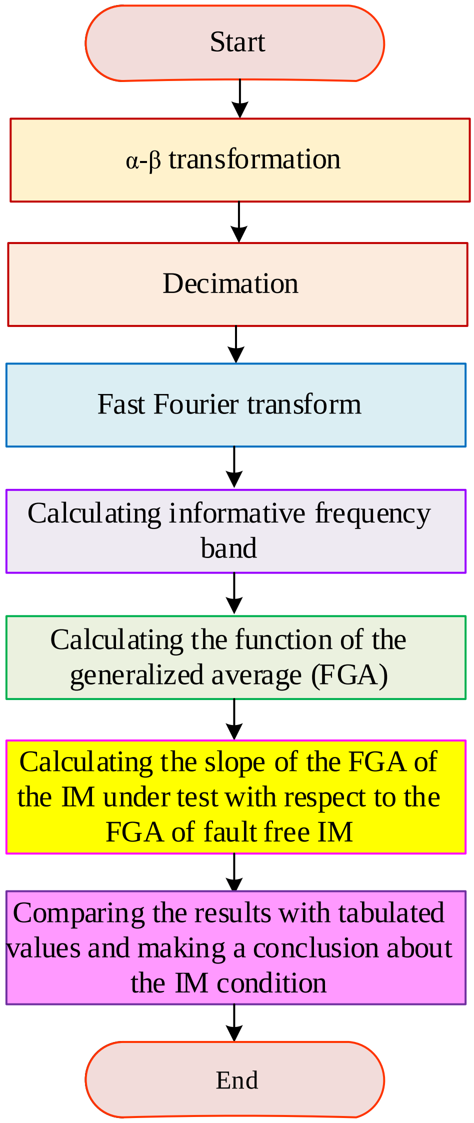

Fig. 1. **Block diagram of the algorithm for processing current signals to solve the tasks of monitoring and diagnosing the IM technical condition**

Decimation by an averaging process yields a signal **y** that can be represented as an observation vector $\mathbf{y}^T$

$$\mathbf{y}^T = \left[\frac{1}{K_d} \cdot \sum_{n=1}^{K_d} x_n \quad \frac{1}{K_d} \cdot \sum_{n=K_d}^{2K_d} x_n \quad \cdots \quad \frac{1}{K_d} \cdot \sum_{n=M-K_d}^{M} x_n \right], \tag{6}$$

$$K_d = \frac{F_s}{F_{dec}}, \tag{7}$$

where K_d - decimation coefficient;
F_{dec} – frequency obtained after decimation.

Size N of vector $\mathbf{y}^T$ after decimation is equal to:

$$N = \frac{M}{K_d}. \tag{8}$$

For further processing, it is enough to store only the signal $\mathbf{y}$, represented by a data buffer of size N, which is K_d times smaller than the initial vector $\mathbf{x}^T$.

3. Fast Fourier Transform (FFT)

Calculation of the full spectrum of the signal is performed using the FFT according to the expression

$$fftFull_k = \left| \frac{1}{\sqrt{N}} \cdot \sum_{n=1}^{N} y(n) \cdot e^{\frac{-(2\cdot\pi\cdot j)\cdot(n-1)\cdot(k-1)}{N}} \right|, \tag{9}$$

$$fFull_k = k \cdot \frac{F_{dec}}{N}, \tag{10}$$

where y – the signal after decimation;
N – the number of points after decimation;
$fftFull_k$ – amplitude module of the full Fourier spectrum;
$fFull_k$ – frequency of the full Fourier spectrum, k=1, 2, ..., N.

In order not to consider the real and imaginary parts, a separate module is used.

4. Selection of informative frequency range

Informative frequency range (IFR) is a segment of the Fourier spectrum limited to a certain frequency range. The frequency range itself is selected depending on the type of analyzed defect. This allows to reduce the required number of calculations by increasing the sensitivity of the method, since non-informative harmonics will be absent in FGA calculations. Each defect affects the spectrum of IM signals differently. In order to analyze only the informative segment of the spectrum, the procedure of IFR selection was introduced. IFR depends on:

(a) supply voltage frequency;
(b) type of analyzed fault;
(c) resulting frequency after decimation.

Selection of IFR is carried out in accordance with the following expression

$$IFR_l = fftFull_p, \tag{11}$$

$$l = 1, 2, ..., p_{max} - p_{min}, \tag{12}$$

$$p = p_{min}, ..., p_{max}; \quad p_{min} = floor\left(f_{min} \cdot \frac{N}{F_{dec}} \right); \quad p_{max} = floor\left(f_{max} \cdot \frac{N}{F_{dec}} \right), \tag{13}$$

where IFR – a segment of the Fourier spectrum included in IFR;
f_{min} - lower IFR limit;
f_{max} - upper IFR limit;
$floor(.)$ - rounding to a whole number.

5. Calculating the function of the generalized average (FGA)

FGA is calculated for the segments of the Fourier spectrum that are part of IFR according to the expression

$$\Delta_{(mom_p)} = \left(\frac{1}{L} \cdot \sum_{i=1}^{L} IFR_i^{\,mom_p} \right)^{\frac{1}{mom_p}}, \tag{14}$$

where L - the number of harmonics that are part of the segment of the IFR spectrum under consideration; mom_p - the moment order, which can be calculated according to the expression (2)

6. Calculation of the tangent of the inclination angle of the obtained FGA with respect to the reference FGA

The FGA calculated in the previous step is compared with the reference FGA. To compare the FGA with each other, it is required to calculate the tangent of the angle of inclination of the FGA obtained for the motor under test with respect to the reference FGA. The FGA for a fault free IM without load is proposed as the reference FGA. The tangent of the slope angle is calculated using the well-known linear least squares method. In case of complete coincidence of the studied FGA and reference FGA, the tangent of the slope angle will be equal to 1.

7. Comparison of slopes and a conclusion about technical condition

In this step, the calculated slopes are compared with predetermined values obtained for IM in different conditions. Initially, the obtained inclinations are checked for going beyond a certain confidence interval, which is selected empirically. If the inclinations go beyond this interval, a conclusion is made that the machine is not in a normal technical condition. This is the way the control of IM technical condition is implemented. Next, the value that exceeded the confidence interval of the inclination is compared with the values of the inclinations of previously obtained for various defects. If the obtained inclination value is close to the values of defect inclinations, then the corresponding fault is present in the IM under test. This is the way the diagnosis of the technical condition is implemented. The conclusion about technical condition of the motor under test is made based on this comparison.

Development of a structural diagram of the functional diagnostic system for monitoring the condition of induction traction motor rotor. The railways of Ukraine operate the rolling stock with induction traction motors with the use of field-oriented control system (FOC). In the literature, it is sometimes called a vector control system [28]. The latest trends in the design of rolling stock traction motors consider the use of a direct torque control (DTC) system [29]. Compared to FOC this system is more energy efficient, especially on rolling stock operating with frequent stops and starts, such as electric trains, shunting diesel locomotives, etc. Block diagram of the traction motor with DTC is shown in Fig. 2 [30].

Implementation of the proposed algorithm for diagnosing the rotor bars breaks of the IM rotor during the operation of the rolling stock (Fig. 1) requires the following signals: stator phase currents expressed in α-β I_α, I_β coordinates and supply voltage frequency f_s. As can be seen from Fig. 2, in the direct torque control system, the indicated currents are already determined. In the “Observer of torque and flux”, in contrast to the systems with FOC [31], only the flux linkage is determined. Frequency of the supply voltage in traction motors changes in accordance with the change of the value of ω_{rset} signal. That is, during the operation of the rolling stock, the frequency of the supply voltage constantly changes.

Angular frequency of the supply voltage is defined as [31]

$$\omega_s = p \cdot \omega_r + s, \tag{15}$$

where ω_r – mechanical angular frequency of the motor shaft rotation;
s – rotor slip;
p – number of pole pairs

Rotor slip is determined from the equation [31]

$$s = \frac{I_{sy} \cdot k_r \cdot R_r}{\Psi_r}, \tag{16}$$

where I_{sy} - the value of stator current according to y coordinate;
k_r - coefficient of the rotor circuit;

R_r - resistance of the rotor circuit;
ψ_r - flux linkage of the rotor according to x coordinate.

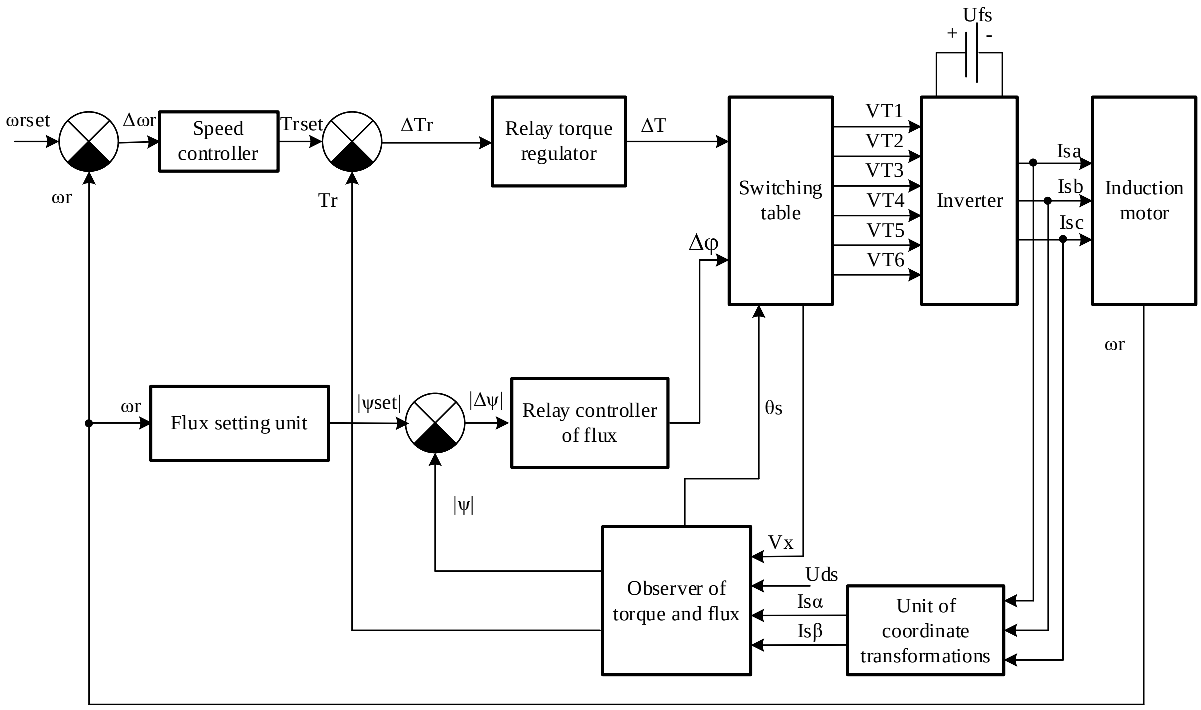

Fig. 2. **Block diagram of the system for direct torque control in the induction traction motor**

The rotor circuit coefficient is defined as

$$k_r = \frac{L_\mu}{L_{\sigma r} + L_\mu}, \tag{17}$$

where L_μ – inductance of the IM magnetizing circuit;
$L_{\sigma r}$ – inductance of the rotor circuit dissipation.

To determine such values as I_{sy} and ψ_r, it is required to determine the values of the currents according to x and y. For this purpose, the Park transformation should be performed, which is defined in accordance with the expression [31]

$$\begin{cases} i_{sx} = i_{s\alpha} \cdot cos\theta + i_{s\beta} \cdot sin\theta; \\ i_y = -i_{s\alpha} \cdot sin\theta + i_{s\beta} \cdot cos\theta. \end{cases} \tag{18}$$

Magnetization circuit of the induction motor can be described by the equation [31]

$$\psi_r = \frac{k_r \cdot R_r \cdot T_r}{1 + T_r \cdot s} \cdot I_{sx}, \tag{19}$$

where I_{sx} - stator current value by x coordinate;
T_r - rotor circuit time constant.

$$T_r = \frac{L_{\sigma r} + L_{\mu}}{L_r}. \tag{20}$$

The angle of rotation of the coordinate system θ is defined using the equation [31]

$$\theta = \int \omega_s dt, \tag{21}$$

The supply voltage frequency f_s is defined as

$$f_s = \frac{\omega_s}{2 \cdot \pi}. \tag{22}$$

Then the block diagram of the traction motor with IM direct torque control and with the unit for diagnosing rotor condition looks like it is shown in Fig. 3.

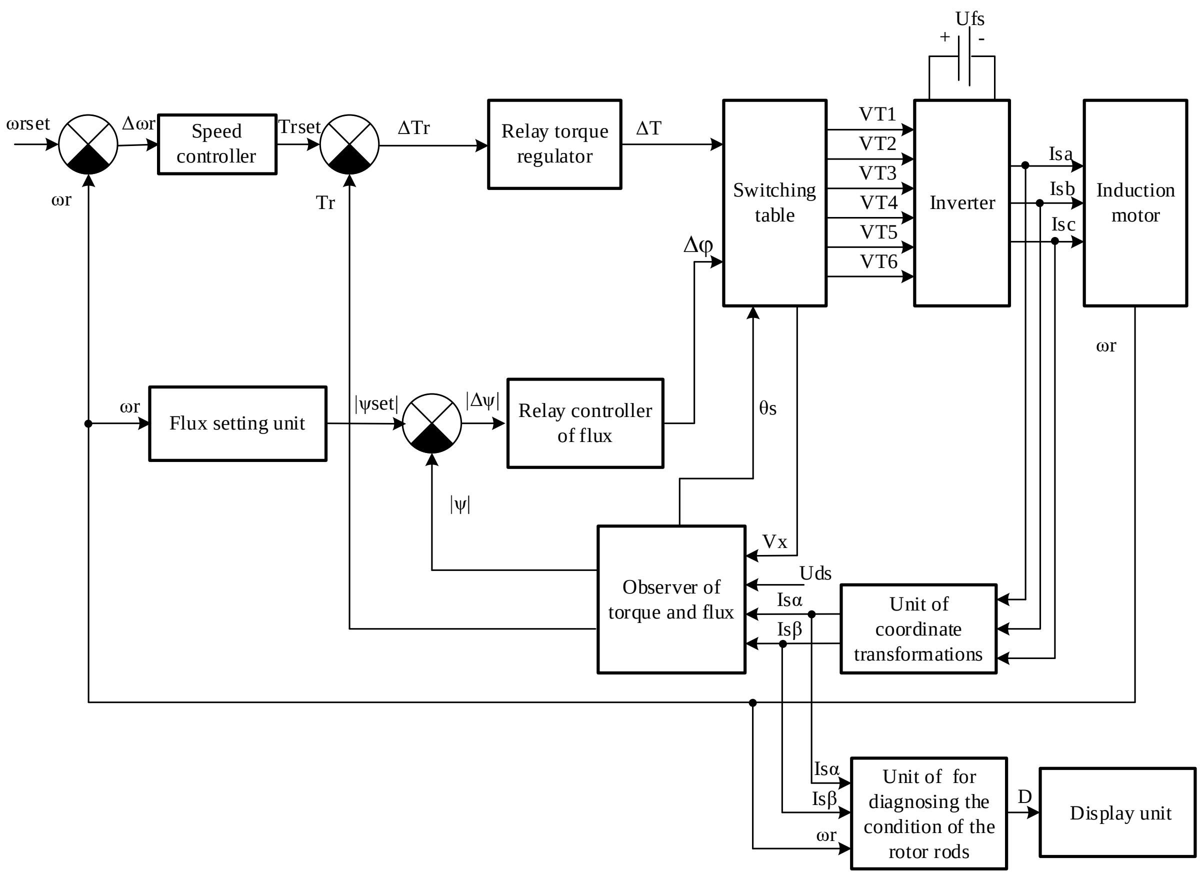

Fig. 3. **Block diagram of traction motor with IM direct torque control and with the unit for diagnosing the rotor condition**

Block diagram of the unit for diagnosing the presence of presence of rotor bar breaks is shown in Fig. 4. Calculating the frequency of the supply voltage f_s is performed in the "Unit for calculating the frequency of the supply voltage". Equations (15)-(22) are implemented in this unit. Decimation of the input signal **x** is performed based on the implementation of equations (4)-(8) in the "Decimation unit". Decimation using the averaging process produces signal **y**. The fast Fourier transform algorithm is implemented in "FFT", where the spectral components of signal **y** are calculated using equations (9) and (10).

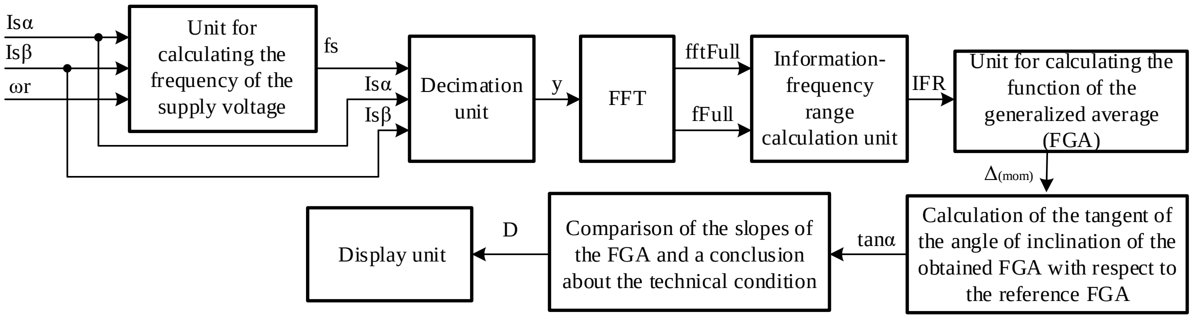

Fig. 4. **Block diagram of the unit for diagnosing the presence of rotor bar breaks**

In order to reduce the number of calculations and increase the sensitivity of the method, we applied the "Information-frequency range calculation unit". It is used to calculate the informative frequency range (IFR) based on equations (11)-(13). For the calculated IFR in the "Unit for calculating the function of the generalized average (FGA)" based on equations (1) and (14), the function of the generalized average (FGA) is calculated. The calculation result is entered in the "Calculation of the tangent of the angle of inclination of the obtained FGA with respect to the reference FGA", where FGA, calculated at the previous stage, is compared with the reference FGA. To compare FGAs with each other, the tangent of FGA angle of inclination obtained for the motor under test is calculated relative to the reference FGA. It is proposed to use the FGA for a fault free IM without load as the reference FGA. The tangent of angle of inclination is calculated using the well-known linear least squares method. In case of complete coincidence of the tested and reference FGA, the tangent of angle of inclination (*tanα*) will be equal to 1.

The values of the calculated tangent of the angle (*tanα*), i.e. the slopes of FGA, are entered the "Comparison of the slopes of the FGA and a conclusion about the technical condition". In this unit, they are compared with the predetermined values obtained for IM in different conditions. Initially, the obtained slopes are checked for going beyond a certain confidence interval, which is selected empirically. If the slopes exceed this interval, it is concluded that the machine is not in normal technical condition. This is the way technical condition of the IM is fulfilled. Next, the value that exceeded the confidence interval of the slope is compared with the values of the slopes previously obtained for various defects. If the obtained slope value is close to the slope values of the defects, then the corresponding malfunction is present in the IM under test. In this case, the diagnostic signal *D* takes on a value equal to 1. In the opposite case, *D*=0. The value of the diagnostic signal is displayed on the information display device "Display unit". Based on the value of the diagnostic signal, the driver makes a decision to shut down the traction motor with damaged rotor bars.

Conclusions. The work proposes a system for diagnosing the presence of rotor bar breakages in induction traction motor. The results of the work are as follows:

- performed analysis of technical solutions for diagnosing breakages of the rotor bars in induction traction motors, as a result of which it was established that the most effective method for diagnosing rotor bar breakages in the IM rotor is fractional moments statistics;
- developed an algorithm for diagnosing the condition of rotor bars based on the fractional moments statistics, which will allow its application in building a functional diagnostic system taking into account the operating condition of the traction motor;
- developed a block diagram of the unit for diagnosing the condition of IM rotor bars based on the fractional moment's statistics;
- developed a block diagram of the system for functional diagnostics of the condition of rotor bars as part of traction motor with direct torque control.

REFERENCES

1. del Castillo, A. C., Marcos, J. A., & Parlikad, A. K. (2023). Dynamic fleet maintenance management model applied to rolling stock. *Reliability Engineering & System Safety*, *240*, 109607. https://doi.org/10.1016/j.ress.2023.109607.
2. Gubarevych, O., Duer, S., Melkonova, I., Woźniak, M., Paś, J., Stawowy, M., ... & Bernatowicz, D. (2023). Research on and Assessment of the Reliability of Railway Transport Systems with Motors. *Energies*, *16*(19), 6888. https://doi.org/10.3390/en16196888.
3. Licow, R., & Tomaszewski, F. (2024). Application of vibration signals in railway track diagnostics using a mobile railway platform. *Archives of Transport*, *71*(3), 127-145. https://doi.org/10.61089/aot2024.gk7vs246.
4. Jarillo, J. M., Moreno, J., Alfi, S., Barcet, S., Bouvet, P., Bruni, S., ... & Licciardello, R. (2021). Novel technology concepts and architecture for on-board condition-based monitoring of railway running gear: The RUN2Rail vision. *Proceedings of the Institution of Mechanical Engineers, Part F: Journal of Rail and Rapid Transit*, *35*(5), 616-630. https://doi.org/10.1177/0954409720951409.
5. Gangsar, P., & Tiwari, R. (2020). Signal based condition monitoring techniques for fault detection and diagnosis of motors: A state-of-the-art review. *Mechanical systems and signal processing*, *144*, 106908. https://doi.org/10.1016/j.ymssp.2020.106908.
6. Dias, C. G., da Silva, L. C., & Alves, W. A. L. (2020). A histogram of oriented gradients approach for detecting broken bars in squirrel-cage motors. *IEEE Transactions on Instrumentation and Measurement*, *69*(9), 6968-6981. https://doi.org/10.1109/TIM.2020.2975388.
7. Goolak, S., Gorobchenko, O., Holub, H., & Dudnyk, Y. (2024). Increasing the efficiency of railway rolling stock operation with traction motors due to implementation of the operational system for diagnostic condition of rotor. *Diagnostyka*, *25*(4), 1-11. https://doi.org/10.29354/diag/193809.
8. Halder, S., Bhat, S., Zychma, D., & Sowa, P. (2022). Broken rotor bar fault diagnosis techniques based on motor current signature analysis for motor - A review. *Energies*, *15*(22), 8569. https://doi.org/10.3390/en15228569.
9. Rezazadeh, N., De Luca, A., Lamanna, G., & Caputo, F. (2022). Diagnosing and balancing approaches of bowed rotating systems: a review. *Applied Sciences*, *12*(18), 9157. https://doi.org/10.3390/app12189157.
10. Jaros, R., Byrtus, R., Dohnal, J., Danys, L., Baros, J., Koziorek, J., ... & Martinek, R. (2023). Advanced signal processing methods for condition monitoring. *Archives of Computational Methods in Engineering*, *30*(3), 1553-1577. https://doi.org/10.1007/s11831-022-09834-4.
11. Puka, M., Bardhi, A., Pjetri, A., & Mucka, A. (2024). Diagnostics of Damage to the Rotor of an Machine Using the Method of Instantaneous Power Analysis. *Qubahan Academic Journal*, *4*(1), 150-166. https://doi.org/10.48161/qaj.v4n1a263.
12. Mazaheri-Tehrani, E., & Faiz, J. (2022). Airgap and stray magnetic flux monitoring techniques for fault diagnosis of electrical machines: An overview. *IET Electric Power Applications*, *16*(3), 277-299. https://doi.org/10.1049/elp2.12157.
13. Choi, S., Haque, M. S., Arafat, A. K. M., & Toliyat, H. A. (2017). Detection and estimation of extremely small fault signature by utilizing multiple current sensor signals in electric machines. *IEEE Transactions on Industry Applications*, *53*(3), 2805-2816. https://doi.org/10.1109/TIA.2017.2660463.
14. de Deus, D. B. B., Sobrinho, C. A. N., Belo, F. A., Brito, A. V., de Souza Ramos, J. G. G., & Lima-Filho, A. C. (2020). Density of maxima approach for broken bar fault diagnosis in low slip and variable load conditions of motors. *IEEE Transactions on Instrumentation and Measurement*, *69*(12), 9797-9804. https://doi.org/10.1109/TIM.2020.3003107.
15. Shifat, T. A., & Hur, J. W. (2020). An effective stator fault diagnosis framework of BLDC motor based on vibration and current signals. *IEEE Access*, *8*, 106968-106981. https://doi.org/10.1109/ACCESS.2020.3000856.
16. Garcia-Calva, T., Morinigo-Sotelo, D., Garcia-Perez, A., & Uribe-Murcia, K. (2024). Rotor speed estimation for half-broken bar detection in motors using Kalman filtering. *Measurement Science and Technology*, *35*(7), 076115. https://doi.org/10.1088/1361-6501/ad3496.
17. Niu, G., Dong, X., & Chen, Y. (2023). Motor fault diagnostics based on current signatures: a review. *IEEE Transactions on Instrumentation and Measurement*, *72*, 1-19. https://doi.org/10.1109/TIM.2023.3285999.
18. Lu, Y., Yao, Z., Gao, Q., Zhu, D., Zhao, D., & Huang, D. (2024). A novel fault diagnosis method for bearing based on maximum average kurtosis morphological deconvolution. *Measurement Science and Technology*, *35*(11), 116137. https://doi.org/10.1088/1361-6501/ad6e10.

19. Gundewar, S. K., & Kane, P. V. (2021). Condition monitoring and fault diagnosis of motor. *Journal of Vibration Engineering & Technologies*, *9*, 643-674. https://doi.org/10.1007/s42417-020-00253-y.

20. Orlowska-Kowalska, T., Wolkiewicz, M., Pietrzak, P., Skowron, M., Ewert, P., Tarchala, G., ... & Kowalski, C. T. (2022). Fault diagnosis and fault-tolerant control of PMSM drives–state of the art and future challenges. *IEEE Access*, *10*, 59979-60024. https://doi.org/10.1109/ACCESS.2022.3180153.

21. Messaoudi, M., Flah, A., Alotaibi, A. A., Althobaiti, A., Sbita, L., & Ziad El-Bayeh, C. (2022). Diagnosis and fault detection of rotor bars in squirrel cage motors using combined Park's vector and extended Park's vector approaches. *Electronics*, *11*(3), 380. https://doi.org/10.3390/electronics11030380.

22. Garcia-Calva, T. A., Morinigo-Sotelo, D., Garcia-Perez, A., Camarena-Martinez, D., & de Jesus Romero-Troncoso, R. (2019). Demodulation technique for broken rotor bar detection in inverter-fed motor under non-stationary conditions. *IEEE Transactions on Energy Conversion*, *34*(3), 1496-1503. https://doi.org/10.1109/TEC.2019.2917405.

23. Blaut, J., & Breńkacz, Ł. (2020). Application of the Teager-Kaiser energy operator in diagnostics of a hydrodynamic bearing. *Eksploatacja i Niezawodność*, *22*(4), 757-765. https://doi.org/10.17531/ein.2020.4.20.

24. Li, H., Feng, G., Zhen, D., Gu, F., & Ball, A. D. (2020). A normalized frequency-domain energy operator for broken rotor bar fault diagnosis. *IEEE Transactions on Instrumentation and Measurement*, *70*, 1-10. https://doi.org/10.1109/TIM.2020.3009011.

25. Puche-Panadero, R., Martinez-Roman, J., Sapena-Bano, A., & Burriel-Valencia, J. (2019). Diagnosis of rotor asymmetries faults in machines using the rectified stator current. *IEEE Transactions on Energy Conversion*, *35*(1), 213-221. https://doi.org/10.1109/TEC.2019.2951008.

26. Niu, H., & Chen, Y. (2023). 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* (pp. 15-53). Cham: Springer Nature Switzerland. https://doi.org/10.1007/978-3-031-52645-9_2.

27. Deng, J. (2022). Probabilistic characterization of soil properties based on the maximum entropy method from fractional moments: Model development, case study, and application. *Reliability Engineering & System Safety*, *219*, 108218. https://doi.org/10.1016/j.ress.2021.108218.

28. Goolak, S., Liubarskyi, B., Riabov, I., Lukoševičius, V., Keršys, A., & Kilikevičius, S. (2023). Analysis of the Efficiency of Traction Drive Control Systems of Electric Locomotives with Asynchronous Traction Motors. *Energies*, *16*(9), 3689. https://doi.org/10.3390/en16093689.

29. Ronanki, D. (2022). Overview of rolling stock. *Transportation Electrification: Breakthroughs in Electrified Vehicles, Aircraft, Rolling Stock, and Watercraft*, 249-281. https://doi.org/10.1002/9781119812357.ch11.

30. Goolak, S., Liubarskyi, B., Riabov, I., Chepurna, N., & Pohosov, O. (2023). Simulation of a direct torque control system in the presence of winding asymmetry in motor. *Engineering Research Express*, *5*, 025070-025086. http://doi.org/10.1088/2631-8695/acde46.

31. Goolak, S., & Liubarskyi, B. (2024). Vector Control System Taking into Account the Saturation of a Motor. *Tehnički vjesnik*, *31*(4), 1170-1178. https://doi.org/10.17559/TV-20221015124239.

Денис Лакуста[1], Сергій Малюк[2*]

[1]Аспірант, Кафедра «Електромеханіка та рухомий склад залізниць», Державний університет інфраструктури та технологій, вул. Кирилівська, 9, м. Київ, 04071, Україна. ORCIDhttps://orcid.org/0009-0000-6563-757X.

[2]Старший викладач, Кафедра «Електромеханіка та рухомий склад залізниць», Державний університет інфраструктури та технологій, вул. Кирилівська, 9, м. Київ, 04071, Україна. ORCID: https://orcid.org/0000-0003-1777-2384.

Розробка функціональної системи діагностики наявності ушкодження ротора в тягових асинхронних двигунах

Метою даної роботи є розробка системи функціональної діагностики наявності обривів стрижнів ротора в тягових асинхронних двигунах рухомого складу залізниць. Для досягнення мети були вирішені такі задачі: розроблено алгоритм діагностування стану стрижнів ротора на основі статистики дробових моментів; розроблено структурну схему блоку діагностики стану стрижнів ротора асинхронного двигуна на основі статистика дробових моментів; розроблено структурну схему системи функціональної діагностики стану стрижнів ротора в складі тягового приводу з прямим керуванням моментом. Найбільш важливими результатами є отримання математичної моделі статистики дробових моментів, зі зменшеним об'ємом обчислень та зі покращеною чутливістю методу. Ці результати були досягнені шляхом визначення інформаційно-частотного діапазону, що дозволило аналізувати не усі спектральні складові аналізованого сигналу, а тільки ту його частину, де можуть бути спектральні складові, характерні для обриву стрижнів ротора асинхронного двигуна. Даний підхід до діагностування стану стрижнів ротора може бути застосований також в тягових приводах рухомого складу з векторною системою керування асинхронними двигунами.

Ключові слова: *асинхронний двигун, статистика дробових моментів, стрижні ротора, пряме керування моментом.*