ISSN 1648-4142 / eISSN 1648-3480

TRANSPORT

2025
Volume 40
Issue 1
Pages 24–34
https://doi.org/10.3846/transport.2025.23229

Original Article

A CASE STUDY OF THE USE OF STATISTICAL PROCESSING OF THE ARMATURE ROTATION IRREGULARITIES FOR THE DIAGNOSTICS OF LOCOMOTIVE TRACTION ELECTRIC MOTORS

Boris BODNAR[1], Oleksandr OCHKASOV[1],
Tetiana HRYSHECHKINA[1], Viačeslav PETRENKO[2]✉

[1] *Dept of Locomotives, Faculty of Transport Engineering Faculty, Ukrainian State University of Science and Technologies, Dnipro, Ukraine*
[2] *Dept of Mobile Machinery and Railway Transport, Faculty of Transport Engineering Faculty, Vilnius Gediminas Technical University, Vilnius, Lithuania*

Highlights:

- a method for analysing armature rotation irregularity as a parameter for diagnosing traction motors of locomotives is presented;
- experiments were conducted using various traction motors to confirm the relationship between armature rotation irregularity and the technical condition of the traction motor;
- statistical indicators (skewness, kurtosis coefficient, and standard deviation) were utilized to assess the technical condition of the motors;
- a compact diagnostic system was developed, utilizing only a single sensor for data collection;
- the method's capability to identify mechanical defects in traction motors, including loose fastenings and increased bearing play, has been demonstrated.

Article History:

- submitted 9 October 2023;
- resubmitted 30 January 2024;
- accepted 15 April 2024.

Abstract. Locomotive Traction Electric Motors (TEMs) generate power to rotate the wheelsets of diesel or electric locomotives, electric or diesel multiple units. TEMs are the most critical parts of traction rolling stock on which exploitation costs, reliability and train traffic safety depend. The purpose of the article is to evaluate the possibility of diagnostics the technical condition of the TEM using the rotation irregularities of the armature shaft in the electric motor as a diagnostic parameter. The article analyses the main causes of TEM failures and methods for diagnosing electric motors in operation. The expediency of using the rotation irregularities of the armature shaft in the electric motor as a diagnostic parameter is substantiated. The structural flowchart of the device for measuring the rotation irregularities of the armature is presented. Diagnosing the mechanical part of an electric motor is chosen as an implementation example. The authors confirmed the connection between the technical condition of the electric motor and the statistical indicators calculated for the signal of the rotation irregularities of the armature shaft.

Keywords: locomotive, traction electric motor, defect, diagnostic, rotation irregularity, statistical metric, diagnostic signal.

✉Corresponding author. E-mail: *viaceslav.petrenko@vilniustech.lt*

1. Introduction

Traction Electric Motors (TEMs) are among the most loaded locomotive equipment from the viewpoint of the complex impact of thermal, electrical, mechanical, and climatic factors. Therefore, despite the constant implementation of structural and technological measures in the manufacture and repair of locomotives, the level of TEM damage, though declining in operation, remains quite high. Under operating conditions, it is very difficult to maintain the required level of reliability of electric machines. Analysing traction rolling stock malfunctions that occur during operation, one can be convinced that the TEMs are the most critical nodes of locomotives. TEM failures lead to train delays. The cost and time spent on eliminating the consequences of TEM failures are significant.

In world practice, technologies for the transition to maintenance and repair of equipment in accordance with its current technical condition are developing most rapidly. The basis of such technologies is equipment control and prediction of its technical condition using non-destructive testing methods and non-destructive diagnostics. The main direction of non-destructive diagnostics of power equipment is functional diagnostics in nominal operating modes. According to the ISO 17359:2018, functional diagnostics of the working equipment is recommended to be performed in line with working and indirect parameters, namely, vibration, temperature, electric motor current, compositional analysis of the lubricant. Diagnostic tools are being actively introduced into the process of repairing electrical machines. The task of diagnostic tools is to detect defects at an early stage of growth, to observe and predict defect growth. Based on the results of diagnostics, the residual life of the electric motor nodes is determined, and the scope of repairs and overhaul intervals are planned (Bodnar *et al.* 2013).

2. Review of the related researches

2.1. Methods of monitoring and diagnostic of locomotive TEMs

Conforming to data by Luk'janov *et al.* (2017), TEMs and auxiliary electrical machines of electric locomotives account for up to 40% of failures of the main equipment of electric locomotives. The experience in operating urban electric transport shows that TEM failures account for about 20% of electric transport failures (Pavlenko *et al.* 2017). Damage to Direct Current (DC) TEMs in operation accounts for about 20% of all failures and 30% of causes of unscheduled repairs of electric locomotives. Statistical data on the distribution of failure causes for locomotive are given in the research by Bodnar *et al.* (2013).

The main causes of DC TEM failures are:

- insulation breakdown and turn-to-turn short circuit of the armature winding – 16...25%;
- insulation breakdown and turn-to-turn short circuit of the main, additional poles and compensating winding – 12...16%;
- commutation failure (ring fire) – 8...16%;
- damage to anchor bearings – 14...16%;
- violation of disoldering of the armature winding connections in the commutator necks – 5...6%.

For Alternating Current (AC) TEMs, the distribution of failure causes is as follows:

- damage to stator elements – 38%;
- damage to rotor elements – 10%;
- damage to bearing – 40%;
- other damages – 12%.

A significant number of publications and scientific works are devoted to the issue of monitoring, diagnosing the technical condition, and testing electric machines. Among the diagnostic characteristics of electrical machines, temperature, vibration, and insulation resistance of the components of the electrical machine are distinguished.

Works by Kapitsa *et al.* (2018, 2019) describe problems of operational diagnostics of TEMs and methods of predicting the condition of insulation of electrical machines. Research by Kapitsa *et al.* (2018) analyses indicators by which the condition of insulation of TEMs can be determined. It is proposed to determine the condition of insulation by the value of the reverse voltage using absorption coefficients. The methodology for defining the limit values of predicted parameters and estimating the residual life is given in the research by Kapitsa *et al.* (2019). The authors suggest determining the limit parameters of the isolation condition and estimating the residual life with the help of methods of cluster and discriminant analysis. The evaluation of the insulation condition is performed on the basis of the recovery curve analysis of the reverse voltage.

A number of works are devoted to the monitoring of the technical condition of electric machines based on the analysis of the current consumption spectrum. The methods are based on the fact that any disturbances in the work of the electric or mechanical part of the electric motor and the mechanism associated with it lead to a change in the magnetic flux in the gap of the electric machine and, as a result, to the modulation of the current consumed by the electric motor.

The article by Serdjuk (2018) presents the results of the analysis of the spectrum and amplitudes of harmonics, which are typical for various types of induction motor failures. The application of the proposed monitoring system allows for detecting malfunctions at an early stage, minimizing the costs of damage elimination, and also later making a transition from scheduled preventive repair to repair according to the condition of the object. The method for determining defects in bearings of electric motors based on the spectral analysis of the current is given in research by Sakaidani & Kondo (2018). The authors use machine-learning methods to define bearing failure based on the analysis of current leakage. The proposed monitoring system automatically defines the technical condition of the bearings. The system envisages 2 technical conditions: (1) normal operation and (2) abnormal conditions. The impact of the irregularity in the distribution of the magnetic field in an induction motor on the occurrence of a malfunction is described in article by Asad *et al.* (2020). As a result of an irregularity in the distribution of the magnetic field, additional harmonics arise in the voltage and current of the electric motor stator. Using modern methods of modelling and analysis has made it possible to theoretically determine the relationship between the fault and the signal spectrum. The obtained modelling results were confirmed experimentally.

Using the digital twin technology for monitoring the condition of vehicle electric motors is discussed in the research by Venkatesan *et al.* (2019). On the basis of developed mathematical models, artificial intelligence technologies and fuzzy logic, the condition of the vehicle is monitored by the temperature parameters of the electric motor.

The methodology has been developed for vibration diagnostics of electrical machines at the initial stage of defect growth, rotor assemblies, and bearings. The use of vibration diagnostics is considered quite fully in works by Barkov & Barkova (2013) and Malla & Panigrahi (2019). As a rule, when diagnosing defects of a mechanical and electromechanical nature, vibration parameters are used as a diagnostic feature.

In the work by Barkov & Barkova (2013), it is noted that the parameters of the own housing vibration in the electric motor reflect the technical condition of almost all motor elements. The authors note that monitoring the current parameters of an electrical machine can detect approximately 16% of all defects, temperature monitoring – 20%, and vibration monitoring – 80%. That is, monitoring the level of vibration of an electrical machine allows you to notice 80% of violations in the operation of an electrical machine.

On the other hand, the causes of vibration are forces of mechanical, electromagnetic, and aerodynamic origin. The main cause of the increased vibration of electrical machines is imbalance. Its presence leads to accelerated wear of bearings, the armature shaft, and other components of the mechanism, an increased level of noise, a decrease in coefficient of efficiency, etc. The wide use of vibration diagnostics methods is due to both the sufficiently high level of scientific and technical developments and the simplicity of measurement implementation. The disadvantage of vibration diagnostics systems is that vibration control does not always allow one to divide the root causes of mechanical, electrical, and aerodynamic nature, which lead to the occurrence of vibration.

Vibration monitoring allows recording the fact of the deterioration of the technical condition in the electrical machine, at this, the causes of vibration can be both mechanical and other in nature. Most research is focused on identifying the causes of vibration of a mechanical nature.

The operating conditions of electrical machines, as a rule, do not allow monitoring the vibration of only the electrical machine itself, since the level and character of vibration are affected by the devices and mechanisms (gearboxes, pumps and other types of power transmissions) to which the electric motor is connected. As a result, the monitoring of vibration parameters allows for detecting anomalies in the work of the equipment while operating, the detection of the causes of the anomaly should be carried out in the conditions of bench tests and diagnostics.

In addition, the causes of vibration in the locomotive TEM may be the presence of malfunctions of the wheelsets and the traction gearbox. Research showing the relationship between the level of the TEM vibration and wheel flat lengths is given in research by Zhou *et al.* (2021). The authors show that by measuring the vibration of the traction motor in operation, it is possible to define the presence of a wheel flat on the wheelset. The presence of impact of malfunctions in wheelsets and traction gearbox on the vibration level of the TEM in operation requires additional test vibration diagnostics for the TEM to localize the cause of vibration during technical inspections and repairs.

Based on the above, it is possible to conclude about the relevance of improving the methods and means of vibration diagnostics of electrical machines.

2.2. Methods of processing measurement results

In addition to measuring physical quantities with the help of which the technical condition of the object under monitoring and diagnostics is determined, the method of processing and analysing the results of diagnostics is important. The task of methods for processing the results of diagnostics is to determine the fact of a malfunction and classify the type of malfunction. Model-based and data-driven approaches are defined as the main methods for analysing the results of diagnostics, the analysis of these approaches is in the work by Garramiola *et al.* (2018). The model-based approach is the development of an analytical simulation model of the monitoring object. The analysis of the technical condition of the object is performed by comparing the behaviour of the real system and the simulation model. The deviation value in the behaviour of the model and real systems is used to detect malfunctions and anomalous behaviour of the monitoring object. The disadvantage of the model-based approach is that in order to detect a specific malfunction, it is necessary to create an analytical model of the operation for the monitoring object for each type of failure. The creation of an adequate analytical model to detect the anomalous technical condition of the monitoring object and the identification of failures requires significant costs and cannot always be implemented due to the complexity of the mathematical description of the monitoring object.

The data-driven approach is based on the analysis of data obtained from the monitoring object using Industrial Internet of Things (IIoT) technology and other information measuring tools. As a result of the measurement, a set of data is obtained in the form of signals that characterize the technical condition of the monitoring object. Determining the technical condition and identifying the malfunction is performed based on the comparison of the behavioural templates of the system in the past. That is, for reliable identification of a malfunction, it is necessary to gather a sufficient number of statistics (templates) that allow to reliably divide the technical condition of the monitoring object. Accordingly, the work by Garramiola *et al.* (2018) singles out approaches based on signal analysis, statistical analysis, and the use of expert systems. The approach based on signal analysis involves the processing of sensor signals using mathematical processing methods such as wavelet analysis (Bodnar *et al.* 2018b), spectral analysis (Saleem *et al.* 2012), Fourier transform (Malla, Panigrahi 2019), and other signal processing methods. Each of the methods has its own advantages and sphere of application. As a rule, in modern systems, the results of signal processing are further analysed using artificial intelligence methods (Lis *et al.* 2021).

The data-driven approach also includes an approach based on the use of statistical methods of analysis. Statistical methods are used to quickly analyse signals without additional processing. In research by Malla & Panigrahi (2019), fundamental statistical parameters for evaluating signals are pointed out. The advantage of the static approach is the simplicity in the calculation, which makes it possible to use this approach to create monitoring systems and find anomalies in the operation of equipment. The disadvantage is that, as a rule, statistical methods allow to determine the fact of anomalous work, but do not allow classifying the cause of the anomaly. A significant number of statistical methods are based on evaluating the distribution law of the measured signal, comparing the correspondence of this signal to the Gaussian distribution, and calculating the measures of the mean (for example, 3·σ), determining the interquartile range, etc. Such a simplified approach is effective in the case when the condition of the monitoring object is described by one signal. If the condition of the monitoring object is described by a significant number of signals, it is not always possible to detect anomalies in the early stages using statistical analysis of the parameters set. In this case, it is advisable to use dimensionality reduction methods, such as Principal Component Analysis (PCA). The analysis of the set of signals from the received sensors installed on the monitoring object with the use of PCA allows for the formation of new diagnostic parameters that characterize the technical condition of the monitoring object from various technical aspects. The work by Bodnar & Ochkasov (2021) points out an example of the implementation of such an approach where the diagnostic parameters formed using PCA are proposed to be called latent parameters. The obtained latent parameters are used for further analysis, while the dimension of the parameter set that is under control is significantly reduced, simultaneously, the amount of information about the technical condition of the controlled object remains unchanged. An example of using latent parameters to calculate the technical condition index is presented in the article by Bodnar *et al.* (2021). Static methods may also include signal analysis methods based on the calculation of metrics that characterize the distance of each signal value from other observation data. Examples of such methods are the *k*-NN method (*k* is the Nearest Neighbours) (Lu *et al.* 2021), the Local Outlier Factor (LOF) method (Zhao *et al.* 2017), and others.

Knowledge-based methods of data analysis from the monitoring object belong to a separate group of methods. Knowledge-based methods can be considered an improvement of statistical methods. Such methods include autoregressive methods of Time series analysis (Munir *et al.* 2019; Li *et al.* 2019), methods of fuzzy logic (Udovenko *et al.* 2020; Dacun 2015), and the use of neural networks for data analysis has also become widespread (Al-Janabi, Saeed 2011; Kljushnyk 2017).

Modern methods of analysis use a combination of the considered methods, examples of which are given in articles by Udovenko *et al.* (2020) and Basaran & Fidan (2021). The approach focused on the step-by-step use of the considered approaches became widespread (Al-Janabi, Saeed 2011). At the initial stage, deviation detection is performed (fixation of the fact in the anomalous behaviour of the monitoring object). At subsequent stages, deviation classification is performed, that is, the technical condition of the object is assigned to one of the technical conditions known to the system. This distribution of functions in monitoring and diagnostic systems allows controlling the condition of the object with high velocity (in real-time mode) without using powerful computing resources. If an anomaly is detected in the operation of the monitoring object, the classification of the technical condition is performed using more powerful computing tools and analysis methods.

Thus, for the effective operation of monitoring systems, it is necessary to create simple and reliable methods for determining anomalies. Such methods can include static methods, due to their relative simplicity and availability of results interpretation.

3. Research methodology

The purpose of the article is to improve the monitoring and testing systems of traction motors due to the introduction of the latest methods and technology for diagnostics by the processing of rotational frequency of the armature shaft. This part of the research describes technical means of measuring equipment and methods of processing the results of measuring.

3.1. Methods of processing measurement results

One of the improvements in the systems for monitoring the technical condition of electric motors can be the introduction of means for determining the rotation irregularities of the armature shaft in the electric motor (Bodnar *et al.* 2013). The choice of the rotation irregularities of the armature shaft in the electric motor is explained by the fact that it is the rotation irregularities of the armature shaft are the primary factor that causes vibration of the TEM. The introduction of means of measuring the rotation irregularities of the armature shaft in the TEM will allow to more accurately determine the quality of the repair of the mechanical and electromechanical parts of the TEM.

Technical means for diagnosing the rotation irregularities of the motor shaft are much cheaper, and when using modern measuring systems, it is possible to obtain a sufficient amount of diagnostic information. In addition, only one sensor is installed on the electric motor in the diagnostics based on the rotation irregularities, while in the diagnostics by vibroacoustic methods, it is necessary to install a large number (up to several tens) of sensors, which increases the complexity of the process and reduces the reliability of the diagnostic equipment.

At the moment, there is a large number of various angular displacement sensors, for example, induction, optical, and others. However, based on their characteristics and requirements for the sensor, not all of them can be used to diagnose the TEM by the angular frequency of rotation of the armature shaft.

Based on the above requirements, the incremental optical sensor of the angular displacement (encoder) is more in line with them. The device for diagnosing rotation irregularities of the armature shaft is compact, and the signal from the optical incremental encoder is recorded on a portable computer. This ensures great mobility of the diagnostic complex.

The authors developed a diagnostic and measuring device for measuring the rotation irregularities of the armature shaft. The structural diagram is shown in Figure 1.

The sensor is installed on the technological cover of the bearing shield from the side of the collector. Using the adapter, the encoder shaft is rigidly connected to the armature shaft. The number of pulses (resolution) during measurements is 625 pulses per one complete revolution of the shaft.

By processing the signal from the incremental sensor, it is possible to obtain information about the current value of the rotational angle of the shaft relative to the reference index mark (by the method of chained addition), as well as about its angular velocity.

3.2. Methods of processing the results of measuring the rotation irregularities of the armature shaft of the TEM

When analysing the rotation irregularity signal, frequency analysis methods, filtering algorithms, calculation of signal parameters, spectral analysis, and several other methods are used. Given that the rotation irregularity of the armature shaft in the TEM is the cause of the vibration of the traction motor, methods of vibration signal analysis can also be used to analyse the irregularity signal. Analysis of the vibration signal is performed using the methods of spectral and statistical analysis, and autocorrelation methods. The authors propose to use the existing methods of statistical analysis for the vibration signal to analyse the signal of rotation irregularity of the armature shaft. Because, these methods allow you to determine the fact of abnormal technical state of the electric motor without the use of additional signal processing and the use of significant computing resources. When statistically analysing a signal, the distribution of the signal into components is not performed, but the shape of the density of the probability distribution of the signal is analysed. The originality of the proposed approach is the use of the existing processing method for the analysis of a new type of diagnostic signal in the locomotive TEM.

Statistical methods for the analysis of irregularities are used in those cases when it is impossible to accurately set the value of irregularities at any moment of time t or to establish an exact relationship between its values that differ by the time interval Δt, i.e., when the signal of irregularities is a stochastic, random process. In practical diagnostics, only some of the basic methods of one-dimensional statistical analysis of rotation irregularities or vibration are usually used.

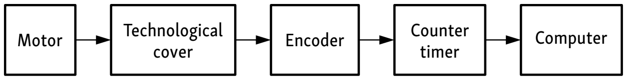

Figure 1. The structural diagram of the diagnostic and measuring device

Thus, 1st of such methods is the quantitative assessment (p-value) of the correspondence between the parameters of the real distribution of the probability density $p(x)$ for the measured signal and the parameters of the normal distribution law. A p-value greater than 0.05 indicates that the statistical data is distributed according to the normal law.

The 2nd method consists in determining the limit values for each of the selected parameters of irregularities, which divide the objects of control into classes with different properties by the results of periodic control of these parameters.

Accordingly, in articles by Malla & Panigrahi (2019) and Bodnar *et al.* (2018a) standard measures of the average, as well as the following parameters, are used as statistical parameters for vibration signal analysis.

The *peak* factor of the signal:

$$peak = \frac{1}{2} \cdot \left(\max\left(x_i\right) - \min\left(x_i\right) \right), \tag{1}$$

where: x_i – value; $\max(x_i)$ – the highest signal value during the measurement period; $\min(x_i)$ – the smallest value of the signal during the measurement period.

The peak factor is not a statistical value and is not always a reliable indicator of failure. Erroneous data caused by errors and uncertainty in measures can have a significant impact on the peak factor. As a result, it is more appropriate to use the value of the standard deviation of the signal for the rotation irregularities of the armature shaft when monitoring the motor condition. Peak factor and impulse factor are used as statistical indicators.

The crest factor CF is the peak amplitude of the signal divided by the root-mean-square value of the signal:

$$CF = \frac{\max\left|\left(x_i\right)\right|}{\sqrt{\frac{1}{n} \cdot \sum_{i=1}^{n} \left(x_i\right)^2}}, \tag{2}$$

where: n – results number.

The impulse factor IF is the peak amplitude divided by the average value of the signal:

$$IF = \frac{\max\left|\left(x_i\right)\right|}{\frac{1}{n} \cdot \sum_{i=1}^{n} x_i}. \tag{3}$$

Impulse factors characterize the ratio of peak of the signal to measures of the average value of the signal. The crest factor shows the ratio of the peak values to the effective value of the signal. This indicator reflects how extreme the peaks in the form of a signal are. A value of the crest factor, which is equal to one, indicates the absence of peaks. The value of the indicator will increase in the presence of pulses that have a larger amplitude than the background signal, and the values of the pulses are not large enough to significantly increase the root-mean-square level of the signal.

The main task of many statistical analyses is to characterize the location and variability of the data set. Analysis of the shape of the signal distribution law on the rotation irregularities of the armature shaft can also be used to evaluate the technical condition of the TEM. Most often, the probability density of a random variable is distributed by the normal law. In the presence of electrical machine defects, the probability density of random vibration $p(x_i)$ begins to differ from the normal distribution. To quantify this difference, the 3rd and 4th moments of the distribution, called the skewnesses are used.

Skewness is a measure of symmetry, or rather, lack of symmetry. A distribution or data set is symmetric if it looks equally to the left and right of the center point. A deviation from zero of the skewness may correspond to the appearance of shocks and the occurrence of rotation irregularities of the armature shaft.

$$SF = \frac{\frac{1}{n}\cdot\sum_{i=1}^{n}\left(x_i-\overline{x}\right)^3}{\left(\frac{1}{n}\cdot\sqrt{\sum_{i=1}^{n}\left(x_i-\overline{x}\right)^2}\right)^3}, \quad (4)$$

where: SF – skewness (asymmetry coefficient of the data distribution); $\overline{x}$ – average value.

In addition to the skewness, the kurtosis coefficient is used. Kurtosis coefficient characterizes the relative sharpness or smoothness of the distribution compared to the normal distribution. Data sets with high kurtosis coefficient tend to have heavy tails or outliers. Data sets with low kurtosis coefficient tend to have light tails or no outliers.

$$KF = \frac{\frac{1}{n}\cdot\sum_{i=1}^{n}\left(x_i-\overline{x}\right)^4}{\left(\frac{1}{n}\cdot\sqrt{\sum_{i=1}^{n}\left(x_i-\overline{x}\right)^2}\right)^4}, \quad (5)$$

where: KF – kurtosis coefficient.

Each considered statistical indicator has unique properties and allows obtaining a certain amount of information about the condition of the monitoring object. The use of statistical indicators to monitor the condition of electric motors based on the rotation irregularities of the armature shaft is relatively simple and cheap to implement. Analysis of changes in metrics over time will allow detecting the start in the failure development at the early stage (potential failure) and planning measures to prevent functional failure.

4. Experimental research

Experimental research was carried out using the diagnostic and measuring device for measuring the rotation irregularities of the armature shaft. The purpose of the research is to determine the relationship between the rotation irregularities of the armature in the TEM and damage to the TEM nodes. Experimental research was carried out during tests of the ČME3 diesel-electric locomotive (Czechia) synchronous TEM testing workbench (without load) in the conditions of a locomotive depot. Diagnosing the rotation irregularities of the armature carried out when the electric motor is running without load, the encoder was connected to the armature shaft using a technological cover.

4.1. Measurement results

4 different TEM were selected for the tests, and one of the TEM (motor *m*1) after the periodic repair, and the other 3 motors (*m*2, *m*3 and *m*4) without repair. During the disassembly of electric motors *m*2, *m*3 and *m*4, the following defects and malfunctions were found: loosening of the fixing and, as a result, loosening the front pressure washer on the shaft, microcracks in the welded connection of the front pressure washer with the armature shaft (motor *m*2), corrosion of the surface of the rolling elements of the anchor roller bearings, exceeding the permissible radial clearance of the anchor roller bearings (motor *m*3), a decrease in the insulation resistance of the armature winding, an increase in the radial clearance (motor *m*4), in the electric motor *m*4, the radial clearance of the bearings was equal to 0.13 mm and 0.17 mm at the limit value of 0.20 mm.

Experimental research was carried out in the running-out mode – reduction of the rotating velocity from the set value of the rotating velocity until the anchor stops.

To control the technical condition of the mechanical part in the electric motor, it is advisable to use the signal measurement results of the rotation irregularities of the armature shaft in running-out mode. The test in running-out mode is in the fact that the armature of the motor spins up to a set value of the rotating velocity, after which the power is turned off, the armature of the electric motor continues to rotate under the impact of inertial forces. A feature of the running-out mode is that the TEM armature shaft stops under the impact of frictional forces. Examples of the usage of the running-out mode for equipment diagnostics are given in works by Bodnar *et al.* (2018a, 2018b) and Evgrafov *et al.* (2019). The use of high-precision sensors allows you to record the rotation irregularities of the shaft, which are caused by the non-uniformity of the resistance forces. When testing the motor in running-out mode, the average rotating velocity is constantly changing, so the results of measurements for one revolution are used for statistical analysis. The measurement results for electric motors *m*1...*m*4 are shown in Figure 2.

As is seen from the graphs (Figure 2), the rotation frequency of the armature shaft in the electric motors

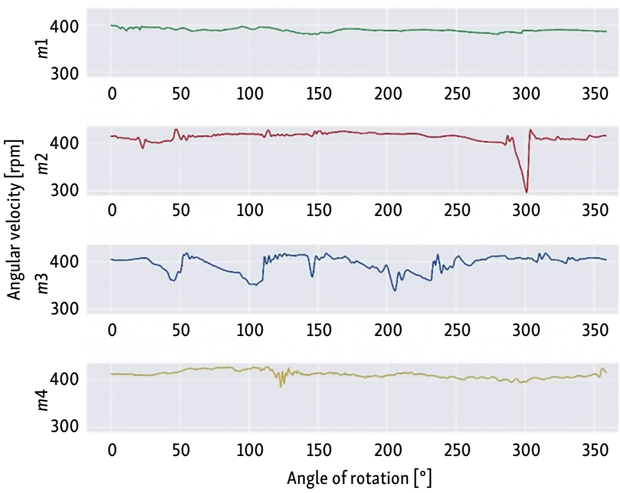

Figure 2. Instantaneous rotation velocity of the armature shaft in the TEM in the running-out mode (one revolution)

*m*2 and *m*3 has a pronounced irregularity. That is, during one revolution of the armature shaft, significant changes in the instantaneous rotation frequency occur, which in turn leads to an increase in the vibration of the traction motor. The presence of loosening the front pressure washer of the shaft in the electric motor *m*2 is manifested in the graph by a sharp decrease in the rotation frequency (approximately a rotation angle of 300°). Exceeding the permissible radial clearance of the armature bearings in the electric motor *m*3 is manifested by oscillations in the instantaneous rotation frequency of the armature shaft over the entire observation interval. As for electric motors *m*1 and *m*4, the graphs of instantaneous rotation frequency have a smoother shape, there are no significant changes in the oscillation frequency. The presence of increased radial clearance of the armature bearings in the electric motor *m*4 is manifested in the form of increased oscillations of the armature rotation frequency in the electric motor *m*4 compared to the electric motor *m*1.

Performing a visual analysis of the obtained graphs makes it possible to determine the technical state of the mechanical part in the traction motor while requiring the involvement of qualified specialists with significant experience. Analysis of the obtained results to define the technical state of the traction motor can be realized using information systems that perform statistical analysis of the signal for rotation irregularity of the armature shaft.

4.2. Processing of the results

For a visual display of the measurement results, diagrams of the range of values for the angular rotating velocity of the armature shaft are constructed. Figure 3 shows the distribution of angular velocity values with quartiles, interquartile range, median value, and anomalous numbers.

As can be seen from the Figure 3, the distributions for electric motors *m*2 and *m*3 have a significant number of outliers and are not symmetrical, which indicates the presence of mechanical damage in these electric motors. The statistical distributions of rotating velocity in electric motors *m*1 and *m*4 have a symmetrical distribution. The median values of the electric motors *m*1 and *m*4 distributions are close to the mean value. The distributions of electric motors *m*2 and *m*3 have a non-symmetrical distribution, the median value is shifted towards the maximum values, and there is also a significant number of outliers in the range of minimum values.

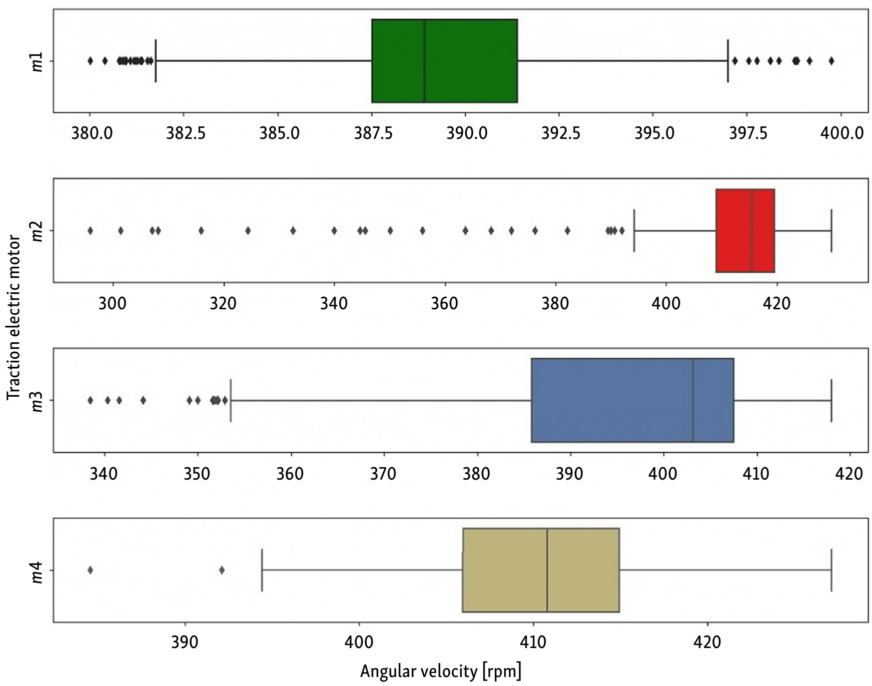

Figure 3. Diagrams of the statistical distribution of the angular rotating velocity of the armature shaft

One of the statistical criteria for the good technical condition of the equipment is compliance with the statistical law of distribution. Figure 4 shows the histograms of the angular velocity distribution of the motors.

For clarity, the histograms show the theoretical distribution that corresponds to the normal law, the average value and limits in ±3·σ range for values of the angular velocity of the armature shaft (where σ is the root-mean-square deviation). The electric motor *m*1 after repair has the greatest correspondence between the theoretical and empirical distributions of the angular rotation velocity of the armature shaft. Despite the fact that the radial clearance of the anchor bearings in electric motors *m*4 is 0.13...0.17 mm with a norm of 0.20 mm, the histogram of the frequency distribution shows the deviation of the empirical distribution of the angular frequency from the theoretical distribution. At the same time, the distribution for the electric motor *m*4 is symmetrical with a small number of abnormal values. The distributions of electric motors *m*2 and *m*3 reflect the presence of a significant number of outliers, the distributions are not symmetrical, the shape of the distribution does not correspond to the normal distribution law.

From Figures 3 and 4, the analysis of the graphical display of the values of the controlled values allows us to determine the presence of deviations that indicate the deterioration in the technical condition of the equipment. At the same time, it should be noted that the practical use of graphical analysis is appropriate in laboratory conditions or during test tests in cases where there is no need for quick interpretation of results and there is no automated analysis. It is also difficult to analyse the dynamics of process development using only graphic images. In production conditions, when monitoring is carried out, it is advisable to use information systems that operate much better with numerical values of characteristics. In this regard, calculating the statistical indicators of the values for the angular rotating velocity of the armature shaft in the electric motor was done. The calculation results are given in the Table.

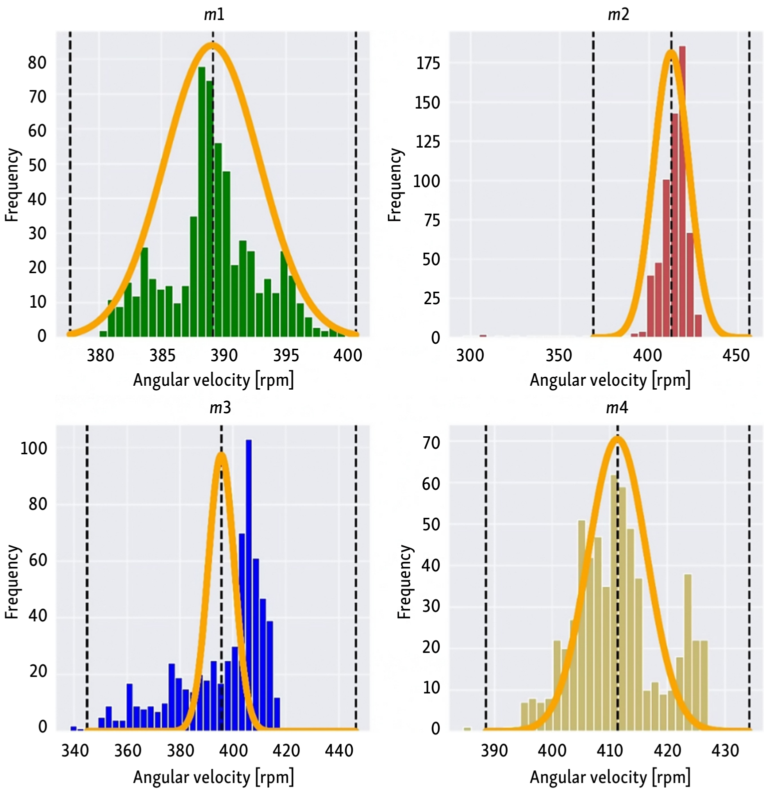

Figure 4. Histograms of the angular velocity distribution for the TEM

Table. Results of calculating the statistical indicators for running-out mode

Indicator	TEM			
	*m*1	*m*2	*m*3	*m*4
Distribution of the probability density *p*(*x*)	0.800	0.00	0.00	0.02
Peak factor *peak*	9.870	67.00	39.77	20.49
Standard deviation β(*x*)	3.820	14.55	16,60	7.34
Crest factor *CF*	2.590	4.60	2.35	2.79
Impulse factor *IF*	0.025	0.16	0.10	0.05
Kurtosis coefficient *KF*	–0.136	28.40	0.37	0.32
Skewness *SF*	0,023	–4.71	–1.11	0.21

5. Discussion of results

The result of the *p*-value calculation confirms that the statistical distribution of the angular rotating velocity of the armature in electric motor *m*1 corresponds to the normal distribution law. The value of *p*-value for electric motor *m*4 does not confirm the normal distribution of the angular rotating velocity. Thus, it can be asserted that compliance with the normal law of the angular rotating velocity of the armature in electric motor is a sign of the good technical condition of the TEM.

Rocking the front pressure washer on the shaft, microcracks in the welded connection of the front pressure washer with the armature shaft in the electric motor *m*2 led to a significant excess of such indicators as the peak factor, impulse factor, crest factor for this electric motor in comparison with other electric motors. Exceeding the values of electric motor *m*2 pulses indicates the presence of extreme peaks in the waveform. Since the electric motor *m*2 had significant malfunctions of a mechanical nature, it is possible to conclude that exceeding the peak factor and impulse factor values indicates an emergency condition of the electric motor.

Corrosion on the rolling elements surface of the anchor roller bearings, exceeding the permissible radial clearance of the anchor roller bearings in the electric motor *m*3 are manifested not so much due to the impulse factors as due to the root-mean-square deviation. That is, this type of malfunction is manifested to a greater extent due to fluctuations in the angular velocity in a wide range, without the presence of sharp changes in the form of pulses. Similarly to the electric motor *m*4, the approach of the radial gap of one of the bearings in the electric motor *m*4 to the limit value of 0.20 mm is also manifested by an increase in the root-mean-square deviation of the signal.

A value of the skewness close to zero (corresponding to the normal distribution law) is also a sign of the good technical condition of the electric motor. An increase in the skewness indicates the deterioration of the technical condition. A feature of using the skewness in running-out mode is that the absolute value of this indicator can be used as a measure of resistance forces. That is, the greater the absolute value of the skewness, the faster the angular velocity decreases, which is characteristic of electric motors *m*2 and *m*3. On the other hand, the presence of a pulse component in the signal also leads to an increase in skewness, electric motor *m*2 is an example. Therefore, it is more expedient to perform simultaneous analysis of several indicators.

The presence of a pulse component (outliers) in the signal corresponding to the electric motor *m*2 is emphasized by the high value of the kurtosis coefficient. For other motors, the kurtosis coefficient is significantly less than that in motor *m*2.

The analysis of the statistical indicators determined as a result of the calculation allows to identify the working and faulty condition of the electric motor. Such identification can be performed by evaluating the correspondence of the distribution law of the angular rotating velocity of the armature shaft to the normal distribution law. It should be noted that such an evaluation allows only to answer the question of a working/faulty technical condition. Deeper analysis can be performed by determining such indicators as root-mean-square deviation, peak factor, impulse factor, crest factor, kurtosis coefficient and skewness.

Taking into account the current trends in the development of machine-learning technologies, the introduction of *Industry 4.0* approaches, the transition to predictive maintenance in the process of managing the technical condition of equipment, the determination of the technical condition of equipment using artificial intelligence technologies is relevant. Despite the significant achievements in the development of algorithms and methods for finding anomalies, classifying conditions, predicting processes, etc., the basis of the successful operation of such systems is the quality of input data preparation, the preliminary calculation of features that describe the physical principles of the processes under research. In this regard, it is relevant to use the considered statistical indicators as input data for automated systems in monitoring the technical condition and preventing the occurrence of equipment failures in operation.

6. Conclusions

The rotation irregularity of the armature shaft in the TEM is one of the causes of vibration on the motor frame. The vibration is a consequence of the rotation irregularities of the armature. To detect failures of a mechanical nature in the electric motor, it is advisable to perform an analysis of the rotation irregularities of the armature shaft in the running-out mode.

The conducted analysis of the rotation irregularities of the armature shaft in electric motors confirmed the existence of a connection between the rotation irregularities and damage to the mechanical part in the electric motor.

During the existence of vibroacoustic diagnostics, a significant number of vibration analysis methods have been gathered, which can also be applied to the analysis of rotation irregularities. The same methods and indicators as for the vibration analysis can be used to analyse the rotation irregularities.

The use of statistical indicators in the analysis makes it possible to determine the fact of anomalous technical condition of the electric motor without the use of additional signal processing and the use of significant computing resources.

An assessment of statistical indicators obtained as a result of the calculations allows us to distinguish between a working and a faulty state of the TEM. Such an assessment can be made by evaluating the correspondence of the distribution law for the angular velocity of the armature shaft rotation to the distribution law, which is normal. It is important to note that this assessment can only answer the question about the working or faulty state of the TEM. A more in-depth analysis can be performed by determining parameters of the irregularity signal such as root-mean-square deviation, crest factor, impulse factor, kurtosis coefficient, and skewness.

Based on the analysis, a relationship was established between the increase in the root-mean-square deviation of the signal of the rotation irregularity of the armature shaft and the value of the radial clearance of the armature bearings. An increase in the pulse and crest factors of the rotation irregularity signal of the armature shaft indicates significant mechanical malfunctions in the TEM.

The proposed method of diagnosing the mechanical part of the TEM has limitations caused by the method of measuring the signal of the rotation irregularity of the armature shaft. The use of this method for measuring the signal of the irregularity can be used during bench tests of the traction motor without load. Such tests can be useful in assessing the technical state of the motor after major and current repairs.

Disclosure statement

The authors have no conflicts of interest to declare that are relevant to the content of this article.

References

Al-Janabi, S. T. F.; Saeed, H. A. 2011. A neural network based anomaly intrusion detection system, *2011 Developments in E-Systems Engineering* 12543636, 6–8 December 2011, Dubai, United Arab Emirates, 221–226. https://doi.org/10.1109/DeSE.2011.19

Asad, B.; Vaimann, T.; Belahcen, A.; Kallaste, A.; Rassõlkin, A.; Iqbal, M. N. 2020. The cluster computation-based hybrid fem–analytical model of induction motor for fault diagnostics, *Applied Sciences* 10(21): 7572. https://doi.org/10.3390/app10217572

Barkov, A. V.; Barkova, N. A. 2013. *Vibracionnaja diagnostika mashin i oborudovanija. Analiz vibracii*. Sankt-Peterburg: Sevzapuchcentr. 152 s. (in Russian).

Basaran, M.; Fidan, M. 2021. Induction motor fault classification via entropy and column correlation features of 2D represented vibration data, *Eksploatacja i Niezawodność – Maintenance and Reliability* 23(1): 132–142. https://doi.org/10.17531/ein.2021.1.14

Bodnar, B.; Ochkasov, O. 2021. Devising a procedure to form the diagnostic parameters for locomotives using a principal components analysis, *Eastern-European Journal of Enterprise Technologies* 2(1): 97–103. https://doi.org/10.15587/1729-4061.2021.230293

Bodnar, B.; Ochkasov, O.; Bobyr, D.; Korenyuk, R.; Bazaras, Ž. 2018a. Using the self-braking method when the post-overhaul diagnostics of diesel-hydraulic locomotives, in *Transport Means 2018*: *Proceedings of the 22nd International Scientific Conference*, 3–5 October 2018, Trakai, Lithuania, 2: 914–919.

Bodnar, B.; Ochkasov, O.; Chernyaev, D.; Skvireckas, R. 2018b. Use of the wavelet transform for the analysis of irregularity of crankshaft angular velocity, in *Transport Means 2018*: *Proceedings of the 22nd International Scientific Conference*, 3–5 October 2018, Trakai, Lithuania, 2: 962–967.

Bodnar, B. Je.; Ochkasov, O. B.; Chernjajev, D. V.; Shevchenko, Ja. I. 2013. Diagnostuvannja tjagovyh elektrodvyguniv za nerivnomirnistju obertannja jakorja, *Nauka ta progres transportu* 3(45): 13–21. https://doi.org/10.15802/stp2013/14793 (in Ukrainian).

Bodnar, B.; Ochkasov, O.; Ochkasov, M. 2021. Devising a procedure for calculating the technical condition index of locomotive nodes based on monitoring results, *Eastern-European Journal of Enterprise Technologies* 5(3): 37–45. https://doi.org/10.15587/1729-4061.2021.242478

Dacun, Ju. N. 2015. Vybor strategii tehnicheskogo obsluzhivanija i remonta lokomotivov na osnove metodov nechetkoj logiki, *Visnyk Shidnoukrai'ns'kogo nacional'nogo universytetu imeni Volodymyra Dalja* 1: 77–80. Available from Internet: http://nbuv.gov.ua/UJRN/VSUNU_2015_1_17 (in Russian).

Evgrafov, A. N.; Karazin, V. I.; Petrov, G. N. 2019. Analysis of the Self-braking Effect of Linkage Mechanisms, in A. N. Evgrafov (Ed.). *Advances in Mechanical Engineering*: *Selected Contributions from the Conference "Modern Engineering*: *Science and Education*", Saint Petersburg, Russia, May 2018, 119–127. https://doi.org/10.1007/978-3-030-11981-2_11

Garramiola, F.; Poza, J.; Madina, P.; Del Olmo, J.; Almandoz, G. 2018. A review in fault diagnosis and health assessment for railway traction drives, *Applied Sciences* 8(12): 2475. https://doi.org/10.3390/app8122475

ISO 17359:2018. *Condition Monitoring and Diagnostics of Machines*. *General Guidelines*.

Kapitsa, M.; Laguta, V.; Kozik, Y. 2019. Classification of quality conditions of a traction motor frame insulation of locomotives, *MATEC Web of Conferences* 294: 03002. https://doi.org/10.1051/matecconf/201929403002

Kapitsa, M.; Laguta, V.; Kozik, Y. 2018. Selecting the parameters of the diagnosis of frame insulation condition in electrical machines of locomotives, *International Journal of Engineering & Technology* 7(4.3): 110–114. https://doi.org/10.14419/ijet.v7i4.3.19718

Kljushnyk, I. A. 2017. Doslidzhennja mozhlyvosti vykorystannja nejronnyh merezh pry vyprobuvannjah gidravlichnyh peredach teplovoziv, *Informacijno-kerujuchi systemy na zaliznychnomu transporti* (5): 8–15. https://doi.org/10.18664/ikszt.v0i5.115370 (in Ukrainian).

Li, Y.; Lu, A.; Wu, X.; Yuan, S. 2019. Dynamic anomaly detection using vector autoregressive model, *Lecture Notes in Computer Science* 11439: 600–611. https://doi.org/10.1007/978-3-030-16148-4_46

Lis, A.; Dworakowski, Z.; Czubak, P. 2021. An anomaly detection method for rotating machinery monitoring based on the most representative data, *Journal of Vibroengineering* 23(4): 861–876. https://doi.org/10.21595/jve.2021.21622

Lu, J.; Qian, W.; Li, S.; Cui, R. 2021. Enhanced *k*-nearest neighbor for intelligent fault diagnosis of rotating machinery, *Applied Sciences* 11(3): 919. https://doi.org/10.3390/app11030919

Luk'janov, A. V.; Perelygina, A. Ju.; Chegaev, N. S. 2017. Obrabotka dannyh vibracionnogo kontrolja vspomogatel'nyh mashin jelektrovozov, *Sovremennye tehnologii*. *Sistemnyj analiz*. *Modelirovanie* 3(55): 119–125. (in Russian).

Malla, C.; Panigrahi, I. 2019. Review of condition monitoring of rolling element bearing using vibration analysis and other techniques, *Journal of Vibration Engineering & Technologies* 7: 407–414. https://doi.org/10.1007/s42417-019-00119-y

Munir, M.; Siddiqui, S. A.; Chattha, M. A.; Dengel, A.; Ahmed, S. 2019. FuseAD: unsupervised anomaly detection in streaming sensors data by fusing statistical and deep learning models, *Sensors* 19(11): 2451. https://doi.org/10.3390/s19112451

Pavlenko, T.; Shavkun, V.; Petrenko, A. 2017. Ways to improve operation reliability of traction electric motors of the rolling stock of electric transport, *Eastern-European Journal of Enterprise Technologies* 5(8): 22–30. https://doi.org/10.15587/1729-4061.2017.112109

Sakaidani, Y.; Kondo, M. 2018. Bearing fault detection for railway traction motors through leakage current, in *2018 XIII International Conference on Electrical Machines* (*ICEM*), 3–6 September 2018, Alexandroupoli, Greece, 1768–1774. https://doi.org/10.1109/ICELMACH.2018.8506796

Saleem, A.; Diwakar, G.; Satyanarayana, M. R. S. 2012. Detection of unbalance in rotating machines using shaft deflection measurement during its operation, *IOSR Journal of Mechanical and Civil Engineering* (*IOSR-JMCE*) 3(3): 8–20. https://doi.org/10.9790/1684-0330820

Serdjuk, T. M. 2018. Diagnostuvannja tryfaznyh asynhronnyh dvyguniv, *Elektromagnitna sumisnist' ta bezpeka na zaliznychnomu transporti* 16: 32–42. Available from Internet: http://ecsrt.diit.edu.ua/article/view/172537

Udovenko, S. G.; Kelembet, D. V.; Teslenko, O. V. 2020. Obrobka informacii'v skladnyh tehnichnyh systemah, *Systemy obrobky informacii'* 1(160): 7–17. https://doi.org/10.30748/soi.2020.160.01 (in Ukrainian).

Venkatesan, S.; Manickavasagam, K.; Tengenkai, N.; Vijayalakshmi, N. 2019. Health monitoring and prognosis of electric vehicle motor using intelligent-digital twin, *IET Electric Power Applications* 13(9): 1328–1335. https://doi.org/10.1049/iet-epa.2018.5732

Zhao, Y.; Liu, P.; Wang, Z.; Zhang, L.; Hong, J. 2017. Fault and defect diagnosis of battery for electric vehicles based on big data analysis methods, *Applied Energy* 207: 354–362. https://doi.org/10.1016/j.apenergy.2017.05.139

Zhou, Z.; Chen, Z.; Spiryagin, M.; Bernal Arango, E. J.; Wolfs, P.; Cole, C.; Zhai, W. 2021. Dynamic response feature of electromechanical coupled drive subsystem in a locomotive excited by wheel flat, *Engineering Failure Analysis* 122: 105248. https://doi.org/10.1016/j.engfailanal.2021.105248