# Identification of Developing Defects in Electromechanical Energy Converters by Statistical Analysis of Changes in their Operational Characteristics

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**ABSTRACT**

**The stable and efficient operation of Electromechanical Energy Converters (EECs) is largely determined by the early detection and prevention of developing defects. Early defect detection can be performed by monitoring changes in the behavior of the characteristic indicators/criteria of the EEC. Considering that EECs have a complex design and, in some cases, operate in non-standard modes and environments, a statistical analysis of changes in the most common indicators subject to monitoring is proposed. In this study, control charts of the dynamicity and asymmetry coefficients were generated using the Shewhart method to control the current state of the EEC. The necessary tests for selecting the values of the coefficients of dynamicity and asymmetry were performed on a physical model of the electromechanical system of a mill. The data were collected from electrical drive motors that were operated for 2 and 5 years. The charts generated by the average and range values of the dynamicity and asymmetric load coefficients showed that the change in the behavior of the characteristics was most significant when using an electric motor operated for five years. However, the evaluation of the results showed that the average values of the asymmetric load coefficient exceeded the limit value at more points than the dynamicity load coefficient. The findings of this study allow for the identification of EEC defects at an early stage of development and the implementation of appropriate measures to prevent them.**

***Keywords- monitoring; electric motor; control charts; dynamicity coefficient; asymmetry coefficient***

## I. INTRODUCTION

EECs are key links in energy and transport systems and technological processes for various purposes. During operation, the EEC may operate in various irregular modes and may fail. The damaged or the EEC operating in an irregular mode affects the stability of the system and may lead to a decrease in its performance, unnecessary energy costs, and sometimes to the occurrence of emergency situations in the system. Therefore, predicting malfunctions and ensuring safe operation are of special importance [1-3]. Of particular interest is the detection of defects in the EEC at the initial stage of its development and decision making regarding its further operation. This will prevent numerous malfunctions and undesirable consequences during EEC operation, and consequently, large material and time costs. Timely and accurate information on the state of the EEC's operability will help to avoid unscheduled repairs, preventive measures, and adjustments of its individual elements. Many studies have been devoted to the detection of faults in EECs [4-8]. The causes of faults are numerous, but they mainly manifest as damage to windings and wear of bearings [9-11]. Considering the above, the present paper analyzed the existing studies on the detection of damage to winding insulators and the wear of bearings. Authors in [12] developed a model for detecting, classifying and making fast and accurate decisions regarding the operation of the stator windings of an asynchronous generator based on an artificial neural network. The authors developed an approach that allows for making accurate decisions on the need to limit the operating time of a damaged generator in accordance with the requirements of the IEEE standards. It should be noted that the work described in [12] provides estimates of damage to winding insulators due to phase short circuits. Of particular interest is the online method for monitoring the state of insulation of the stator windings of an electric motor and generator [13]. In that work, a newly developed High-Sensitivity Current Transformer (HSCT) was used to accurately measure the insulation current of each phase winding from the motor distribution box. This approach can provide a low-cost solution for online assessment of the motor insulation condition. However, the feasibility of using HSCT has mainly been considered, while the insulation aging process during operation has not been clarified. These issues were also not addressed in [14], where an intelligent condition monitoring system for permanent magnet synchronous motor windings was proposed. The limitation of the developed system is that it can only detect faults that were included in the training set, i.e., the fault of the stator windings [14].

In [15], the effectiveness of vibration, stator current, acoustic emission, and shock pulse measurements were investigated to detect the presence of contaminants in the bearing lubricants. Authors in [16] comprehensively analyzed methods for detecting bearing faults in electric vehicles. The latest trends in diagnosing common bearing faults based on analytical data and new applications were discussed. Traditional monitoring methods do not allow analyzing current indicators of the EEC, identifying faults at early stages, or predicting the nature of fault development. These observations provided grounds to assert that monitoring the technical condition, considering the EEC features, is a pressing issue of scientific and technical interest.

Taking the above into account, in order to increase the reliability of identifying the most critical defects of the EEC and expand the possibilities of its application, it is necessary to conduct a statistical analysis of the change in its characteristics. The aim of this work is to propose a new approach to identifying emerging defects in EEC, which will allow the identification of developing faults through statistical analysis and charting of changes in the operational characteristics.

## II. METHODOLOGY

### A. *Statement of the Problem and Justification of the Methodology*

The extensive experience gained in the field of monitoring has shown that it is impossible to achieve the desired result of early fault detection if the collected data are presented only in flight logs, protocols, and other documents. Monitoring effectiveness is largely improved by the systematic and statistical analysis of data [17]. Statistical tools make it possible to assess the state of the controlled system and identify deviations of the relevant indicators from the established standards, as well as to prevent their development [18]. To monitor the current state of the EEC, it is proposed to conduct a statistical analysis of the behavior of the system characteristics by forming a control chart. The Shewhart method, which is a graphical environment for analyzing the behavior of indicators, is used for charting. This makes it possible to track the behavior of the occurrence and development of defects using charts compiled based on the average and range values of the EEC characteristic indicators [19-22]. Shewhart's control charts help in solving the following cases:

- To recognize and evaluate deviations of characteristic EEC indicators from the set values during operation.
- Tracking the occurrence of significant fluctuations.
- To consider the expected consequences of the proposed measures, as well as the need to improve and maintain the system.

The following algorithm is proposed for charting changes in the behavior of the characteristic indicators of the EEC:

1. The characteristic parameters necessary for controlling the motor's operating behavior are selected.

2. The order of collection of characteristic indicators is selected.

3. The arithmetic mean values $x_k$ are calculated for each k-th subgroup:

$$\overline{X_k} = \frac{1}{n}\sum_{n}^{i=1} X_i \tag{1}$$

4. The overall average values of $x$ are calculated for all available subgroups of data:

$$\overline{X} = \frac{1}{k}\sum \overline{X_k} \tag{2}$$

5. The range of $R_k$ in each subgroup is calculated:

$$R_k = X_{max} - X_{min} \quad (3)$$

6. The arithmetic mean values of the $R$ ranges are calculated for all subgroups of data:

$$\overline{R} = \frac{1}{k}\sum_{k=1}^{K} R_k \quad (4)$$

7. The control lines for the X-chart are calculated:

- Central Line: $CL = \overline{\overline{X}}$
- Upper Control Limit: $UCL_x = \overline{\overline{X}} + A_2\overline{R}$
- Lower Control Limit: $LCL_x = \overline{\overline{X}} - A_2\overline{R}$
- Upper and lower rejection limits:

$$\overline{V}_B = \left(T_B - 3\,\overline{R}/d_2\right) + A_2\overline{R} \quad (5)$$

$$\overline{V}_H = \left(T_H + 3\,\overline{R}/d_2\right) - A_2\overline{R} \quad (6)$$

where $T_B$ and $T_H$ and are the upper and lower tolerance limits, respectively.

8. The control lines for the R-chart are calculated:

- Central Line: CL = R
- Upper Control Limit: $UCL_R = D_4\overline{R}$.
- Lower Control Limit: $LCL_R = D_3\overline{R}$

9. Formation of a conclusion on EEC state.

10. Making decisions about maintenance.

### B. *The Object Under Investigation and the Observed Characteristics Indicators*

An electric motor of the electric drive providing the ore crushing process was selected as the object of the study. The latter converts electrical energy from the network into mechanical energy, which ensures the operation of the mill. This choice was selected because the electric motors used in the crushing process operate under difficult, dusty, and humid conditions and with randomly changing loads. Each of these factors makes its own contribution to the damage of the winding and units of the electric motor. Considering the specified dangers and based on the requirements for their timely detection and prevention, it became necessary to select the indicators to be monitored.

In this study, the dynamicity and asymmetric load coefficients of the motor phases were selected to construct the control chart required for monitoring. The quantitative and qualitative indicators of manufactured products depend largely on the conditions of the working bodies of the EEC. This is explained by the fact that these systems consist of flexible links that are subject to dynamic loads of an oscillatory nature. The dynamic load of the system can reach an unacceptable level owing to the increase in the speed and acceleration of the individual links and load torque. This unjustifiably increases the load on the transmission [23]. As a result, elastic links can deform, wear out, collapse over time, and eventually fail. The conducted studies showed a significant effect of changes in the load torque of the elastic link on the duration of the transient phenomena. The latter provides the basis for monitoring and evaluating the behavior of changes in the dynamicity load coefficient during system monitoring. The dynamic coefficient $k_D$ is the ratio of the current ($M_{12}$) and steady-state ($M_{12c}$) values of the load torque of the transmission link [24]:

$$k_D = \frac{M_{12}(t)}{M_{12c}} \quad (7)$$

The steady-state value of the load torque of the transmission link is determined by:

$$M_{12c} = M + J\varepsilon \quad (8)$$

where $M$ is the resistance torque of the mechanism, $J$ is the moment of inertia of the mechanism, $\varepsilon$ is the average acceleration of the drive.

During operation, negative sequence currents may arise in the EEC, which lead to unnecessary oscillations, losses, higher harmonics, and to distortion of the sinusoidality of currents and voltages. In the EEC, the current or voltage in the reverse sequence appears in cases of any asymmetry in the network (phase outage, unbalanced load connection, single-phase or two-phase short circuit) [24]. The detection of an unbalanced load in the motor phase was carried out by estimating the permissible value of the asymmetry coefficient. This is represented as the ratio of the currents or voltages of the reverse and forward sequences.

$$k_\varphi = \frac{I_2}{I_1} \quad (9)$$

The details of obtaining the asymmetry coefficient are presented in our previous work [28].

## III. RESULTS

To select the values of the dynamicity and asymmetric load coefficients, the necessary tests were carried out based on the physical model of the mill electric drive system shown in Figure 1, where an asynchronous motor with a power of 610 W was used. The data were collected for electric drive motors that had been in operation for 2 and 5 years.

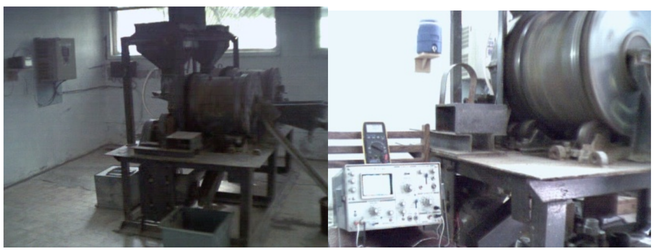


Fig. 1. Physical model of the electric drive system of an ore mill.

Table I displays the processed data of the system load dynamicity coefficient in the form of series of their $k_D$ averages and R-ranges. Table II depicts the processed data on the phase current asymmetry coefficient of the electric drive motor in the form of their $k_\varphi$ average values and R-ranges. The values of the selected $k_D$ dynamicity and $k_\varphi$ asymmetric load coefficients in Tables I and II are presented as *X*. Table III illustrates the control limits of the X and R charts.

TABLE I. DATA FOR CONSTRUCTING A DYNAMICITY COEFFICIENT CONTROL CHART OF AN ELECTRIC MOTOR OPERATING FOR 2 AND 5 YEARS

| **№ of Sample** | | **Duration of operation (years)** | **1** | **2** | **3** | **4** | **5** | **6** | **7** | **8** | **9** | **10** | **Σ** |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Sample values of the dynamicity coefficient | $X_1$ | 2 | 2.0 | 1.75 | 1,9 | 2.05 | 1,5 | 1.95 | 1.25 | 1.35 | 1,1 | 0.9 | |
| | | 5 | 2.2 | 1.9 | 2.0 | 2.3 | 1.9 | 2.1 | 1.6 | 1.9 | 2.0 | 0.9 | |
| | $X_2$ | 2 | 1.73 | 1.42 | 1.65 | 1.73 | 1.16 | 1.45 | 1.8 | 1.9 | 1.15 | 1.3 | |
| | | 5 | 1.93 | 1.9 | 1.95 | 2.0 | 2.1 | 2.0 | 2.1 | 1.9 | 1.95 | 1.63 | |
| | $X_3$ | 2 | 1,52 | 1,67 | 2.15 | 1.96 | 1.4 | 1.14 | 1.6 | 1.45 | 1.32 | 1.6 | |
| | | 5 | 1.82 | 1.97 | 2.2 | 2.1 | 1.9 | 1.8 | 1.9 | 1.9 | 1.5 | 1.9 | |
| | $X_4$ | 2 | 1.6 | 1.5 | 1.48 | 1,32 | 1.57 | 1.85 | 1.05 | 1.33 | 1.4 | 1.31 | |
| | | 5 | 1.9 | 1.7 | 2.0 | 1.8 | 2.0 | 2.1 | 1.8 | 2.0 | 1.9 | 1.8 | |
| | $X_5$ | 2 | 1,85 | 1.05 | 1.78 | 1.56 | 1.73 | 1.65 | 1.20 | 1.65 | 1,6 | 0.75 | |
| | | 5 | 1.85 | 1.75 | 1.9 | 1.8 | 2.2 | 1.9 | 1.7 | 2.3 | 2.2 | 1.3 | |
| $\sum X$ | | 2 | 8.7 | 7.39 | 8.96 | 8,62 | 7.36 | 8.04 | 6.9 | 7.67 | 6,57 | 5.86 | |
| | | 5 | 9.7 | 9.22 | 1 0.05 | 10.0 | 10.1 | 9.9 | 9.1 | 10.0 | 9.55 | 7.53 | |
| $\overline{X}$ | | 2 | 1.74 | 11.47 | 1.792 | 1.724 | 1.47 | 1.608 | 1.38 | 1.536 | 1.314 | 1.172 | 15.22 |
| | | 5 | 1.94 | 11.84 | 2.01 | 2.0 | 2.02 | 1.98 | 1.82 | 2.0 | 1.91 | 1.51 | 19.03 |
| $R$ | | 2 | 0.48 | 0.7 | 0,67 | 0,73 | 0,57 | 0.81 | 0.75 | 0.57 | 0.5 | 0.85 | 6.63 |
| | | 5 | 0.38 | 0.27 | 0.3 | 0.5 | 0.3 | 0.3 | 0.5 | 0.4 | 0.7 | 1.0 | 4.65 |
| Number of observations N=50 | | | Upper limit of tolerance of dynamicity coefficient $k_B$=2.0 | | | | | | Lower limit of tolerance of the dynamicity coefficient $k_H$=1 | | | | |

TABLE II. DATA FOR CONSTRUCTING AN ASYMMETRY LOAD COEFFICIENT CONTROL CHART OF AN ELECTRIC MOTOR OPERATING FOR 2 AND 5 YEARS

| **№ of Sample** | | **Duration of operation (years)** | **1** | **2** | **3** | **4** | **5** | **6** | **7** | **8** | **9** | **10** | **Σ** |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Sample values of the asymmetry coefficient | $X_1$ | 2 | 0.1 | 0.2 | 0.12 | 0.08 | 0.1 | 0.17 | 0.08 | 0.1 | 0.1 | 0.09 | |
| | | 5 | 0.12 | 0.3 | 0.12 | 0.13 | 0.13 | 0.19 | 0.1 | 0.1 | 0.15 | 0.2 | |
| | $X_2$ | 2 | 0.2 | 0.17 | 0.15 | 0.13 | 0.16 | 0.11 | 0.14 | 0.18 | 0.15 | 0.13 | |
| | | 5 | 0.21 | 0.2 | 0.19 | 0.16 | 0.2 | 0.15 | 0.19 | 0.21 | 0.18 | 0.19 | |
| | $X_3$ | 2 | 0.19 | 0.16 | 0.01 | 0.1 | 0.14 | 0.14 | 0.1 | 0.08 | 0.13 | 0.1 | |
| | | 5 | 0.3 | 0.19 | 0.1 | 0.13 | 0.17 | 0.17 | 0.12 | 0.1 | 0.15 | 0.12 | |
| | $X_4$ | 2 | 0.08 | 0,01 | 0.14 | 0.095 | 0.07 | 0,12 | 0.15 | 0.13 | 0.14 | 0.15 | |
| | | 5 | 0.11 | 0.13 | 0.18 | 0.1 | 0.1 | 0.15 | 0.2 | 0.15 | 0.17 | 0.3 | |
| | $X_5$ | 2 | 0.12 | 0.05 | 0.11 | 0.16 | 0.08 | 0.15 | 0.20 | 0.15 | 0.15 | 0.15 | |
| | | 5 | 0.13 | 0.1 | 0.13 | 0.1 | 0.13 | 0.2 | 0.25 | 0.12 | 0.2 | 0.2 | |
| X | | 2 | 0.67 | 0.59 | 0.53 | 0.565 | 0.55 | 0.69 | 0.67 | 0.64 | 0.67 | 0.62 | |
| | | 5 | 0.87 | 0.91 | 0.72 | 0.62 | 0.73 | 0.86 | 0.86 | 0.68 | 0.85 | 1.01 | |
| $\overline{X}$ | | 2 | 0.134 | 0.118 | 0.106 | 0.113 | 0.11 | 0.138 | 0.134 | 0.128 | 0.134 | 0.124 | 1.239 |
| | | 5 | 0.174 | 0.182 | 0.144 | 0.124 | 0.146 | 0.172 | 0.172 | 0.136 | 0.17 | 0.202 | 1.45 |
| $R$ | | 2 | 0.12 | 0.19 | 0.14 | 0.08 | 0.09 | 0.06 | 0.12 | 0.1 | 0.05 | 0.06 | 1.01 |
| | | 5 | 0.09 | 0.2 | 0.09 | 0.06 | 0.1 | 0.05 | 0.15 | 0.11 | 0.05 | 0.11 | 1.11 |
| Number of observations N=50 | | | Upper tolerance limit $k_{\varphi B}$= 0.14 | | | | | | Lower tolerance limit$k_{\varphi H}$<0.077 | | | | |

TABLE III. CONTROL LIMITS OF X-CHART AND R-CHART OF THE QUALITY INDICATOR OF THE DYNAMICITY COEFFICIENT AND THE ASYMMETRY COEFFICIENT OF AN ELECTRIC MOTOR OPERATING FOR 2 AND 5 YEARS

| **Statistics** | **Control boundaries** | **Duration of operation (years)** | **The quality indicator of the dynamicity coefficient** | **The quality indicator of the asymmetry coefficient** |
|---|---|---|---|---|
| R chart | CL | 2 | 0.663 | 0.101 |
| | | 5 | 0.38 | 0.11 |
| | UCL | 2 | 1.402 | 0.214 |
| | | 5 | 0.803 | 0.231 |
| | LCL | 2 | 0.0 | 0.0 |
| | | 5 | 0.0 | 0.0 |
| X chart | CL | 2 | 1.522 | 0.124 |
| | | 5 | 1.903 | 0.15 |
| | UCL | 2 | 1.907 | 0.1822 |
| | | 5 | 2.122 | 0.203 |
| | LCL | 2 | 1.137 | 0.0656 |
| | | 5 | 1.683 | 0.083 |
| | VB1 | 2 | 1.53 | 0.108 |
| | | 5 | 1.729 | 0.063 |
| | VH1 | 2 | 0.148 | 0.108 |
| | | 5 | 0.146 | 0.063 |

Based on the data presented in Tables I-III, the R- and X-charts for monitoring the change in the dynamicity load of the electromechanical system used in the ore crushing process were constructed, as shown in Figures 2-5. To determine the upper UCL and inner LCL control limits of the X and R charts, the coefficients $A_2$ = 0.577, $D_3$ = 0, $D_4$ = 2.114, $d_2$ = 2.326 were used, which were obtained for a sample size of n = 5, utilizing existing standards [25].

The R-charts portrayed in Figure 2 show that the fluctuations inside the system are uniform, and that there are no violations of control boundaries regardless of the service life of the motor. The X-chart illustrated in Figure 3 exhibits fluctuations in the average values of the dynamicity coefficient and their corresponding trends. By observing the data, it is clear that when testing the motor running for 2 years, in 3 cases the point $\overline{X}$ goes beyond the $\overline{V}_B$. When testing the motor that had been running for 5 years, in nine cases, the $\overline{X}$ went beyond the $\overline{V}_B$, but did not exceed the safe permissible limit. The maximum deviation of the defects caused by the dynamic coefficient from the confidence range did not exceed 11%. This implies that the system can both debug and develop undesirable situations, as displayed in Figure 3.

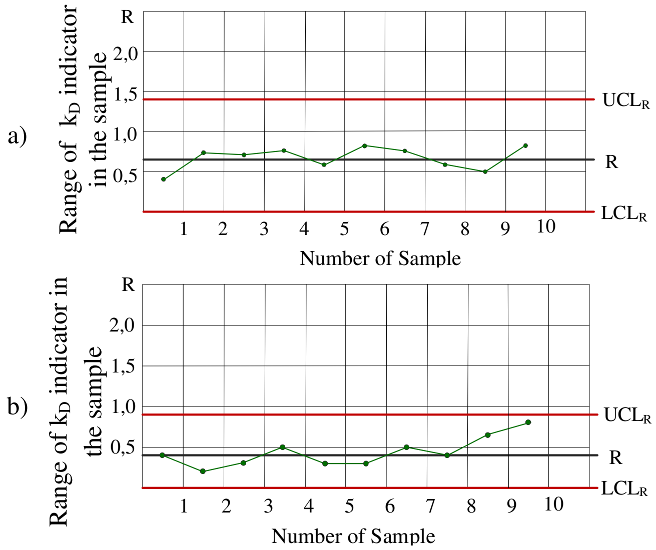



Fig. 2. R-chart of the $k_d$ dynamicity coefficient change control: a) the motor has been operated for 2 years, b) the motor has been operated for 5 years.

Figure 4 presents the R-chart of the asymmetry coefficient. The R-chart reveals no violations of the control boundaries for the motor running for 2 or 5 years.

A review of the chart of the selected midpoints indicates that when using the motor that has been in operation for 5 years, 6 midpoints exceed the upper permissible limit of the asymmetric load coefficient. The maximum deviation from the reliable range of the asymmetric load coefficient reached 15%, indicating the development of damage to the electric motor windings, as evidenced in Figure 5.

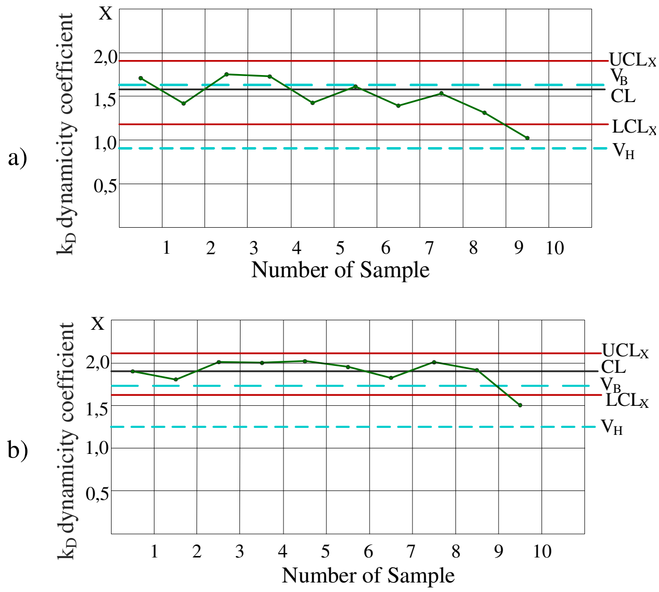



Fig. 3. X-chart of $k_D$ dynamicity coefficient change control: a) the motor has been operated for 2 years, b) the motor has been operated for 5 years.

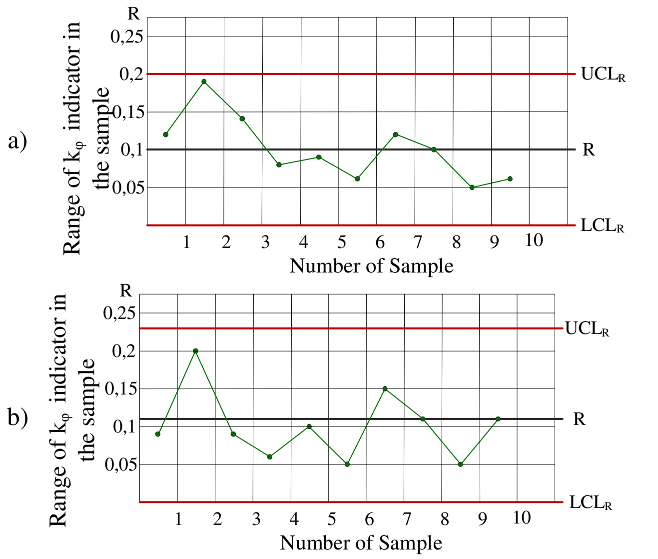
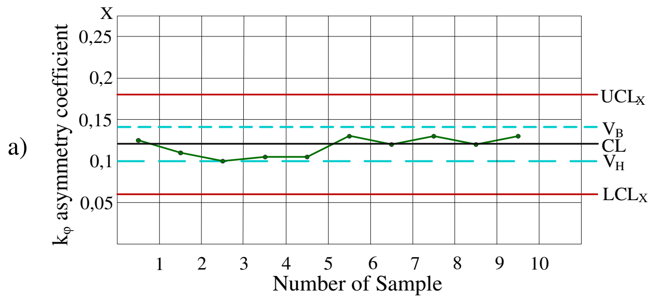



Fig. 4. R-chart for monitoring changes in the asymmetry coefficient: a) the motor has been running for 2 years, b) the motor has been running for 5 years.



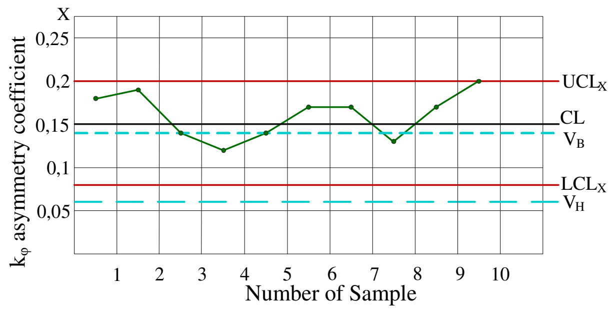
b) 


Fig. 5. X-chart for monitoring changes in the $k_\varphi$ asymmetry coefficient: a) the motor has been running for 2 years, b) the motor has been running for 5 years.

## IV. CONCLUSIONS

In this study, a statistical analysis of the changes in the indicators that have the greatest impact on the operating modes of Electromechanical Energy Converters (EECs) based on Shewhart control charts was developed and proposed for further application. Considering that the causes of EEC failures are mainly electrical or mechanical, the current work proposes a new approach. In particular, the coefficients of dynamicity and load asymmetry can be used to monitor the EEC, and changes in the EEC behavior allow the tracking of the occurrence and development of mechanical and electrical failures. The innovativeness of the proposed approach lies in the idea of introducing complex indicators for detecting defects, which allows identifying developing electrical and mechanical faults in the EEC without using a large number of measuring and control devices and human resources, thereby reducing production costs.

Statistical analysis of the dynamicity and asymmetry coefficients of the electric motor showed that, regardless of the duration of operation (2 years or 5 years), they were stable in terms of the range and unstable in terms of the sample average parameters (X-chart). The mechanical and electrical indicators of the motor that operated for 2 years met the established requirements and had sufficient capacity to operate effectively.

The change in the behavior of the motor's mechanical indicator over 5 years of operation indicates that it must operate under constant monitoring conditions, as some points on the X-chart are close to the permissible limit values. A change in the behavior of the electric indicator of the motor over 5 years of operation indicates that the points on the X-chart are outside the permissible upper limit value, which can lead to undesirable phenomena.

The findings allow us to draw the following conclusions:

- The Shewhart control chart can best be used for the timely detection and system analysis of critical operating situations of the EEC.
- The proposed approach can be successfully used to monitor the operating modes of industrial and energy systems operating under heavy conditions. This will enable the formation of an effective mechanism for preventing unforeseen situations, and as a result, improve the qualitative and quantitative indicators of the products.

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