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Visualization and Analysis Method of Defect Manifestation in Electromechanical Equipment

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Abstract

This study focuses on the problem of diagnosing electromechanical equipment and aims to prevent its failures by timely detecting hidden signs of defects in diagnostic signals. This paper considers the possibility of improving systems whose equipment monitoring relies on measuring and analyzing the diagnostic signal of vibration or motor current. Fourier series decomposition for processing complex signals is not always effective because the contribution of harmonics reflecting the specific effect of the defect is less than that of non-specific harmonics and is comparable to the influence of noise. It has been proposed to apply the singular spectral analysis method for visualizing and analyzing the regularities of defect manifestations. It is reasonable to supplement the classical algorithm of this method by comparing the analyzed eigenvalue spectrum corresponding to the operating condition. Detection of hidden defects for the first time involves analyzing initial data projections in the directions of the singular basis that reflect deviations under the defect influence. Numerical and field experiments confirm the possibility of analyzing comparatively weak generations essential for equipment condition identification. The experiments demonstrate the opportunity for timely defect detection due to preprocessing when the probability of defect detection using the frequency method is close to zero. Thus, the approach to timely detection of equipment defects and making adequate decisions to manage its condition is justified.

Keywords:

Diagnostic Signal;
Eigenvalue Spectrum;
Electromechanical Equipment;
Singular Spectral Analysis (SSA);
Visualization of Defect Manifestation.

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1- Introduction

Detection of defects in electromechanical equipment ensures the efficiency and safety of industrial production [1]. The quality and cost of production depend on the failure-free operation of the pumps, fans, and control valves. Equipment monitoring usually relies on measuring the diagnostic signals of vibration or motor current during the operation of objects [2]. The problem of equipment diagnostics using portable systems is that full diagnostics is possible only during scheduled repair. The results of periodic diagnostics establish the possibility of failure-free equipment operation during the period between repairs. Modern diagnostic systems do not consider the experience of previous diagnostics at the system level. However, the results obtained over a long period are stored in the database and can serve to improve the quality of diagnostics [3]. Visualization of diagnostic results is of great importance. The reliability of the technical condition assessment of objects depends on the informativeness of the diagnostic information. However, noise distortions of diagnostic information drastically reduce the probability of defect detection [4]. Increasing the sensitivity and visualization of diagnostic methods to incipient defects is an urgent task due to the economic need to increase the inter-repair period and reduce repair time. Timely detection of defects in electromechanical equipment is especially essential in critical industries, such as nuclear power plants, where unprevented equipment failures can affect the

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environmental and energy safety of the region [3, 5]. Electromechanical equipment is challenging to diagnose because the applied analysis methods do not consider the nature of vibration or motor current signals, which can be nondeterministic and chaotic [5].

2- Literature Review

The interpretation of diagnostic information usually uses statistical parameters and frequency methods. The statistical approach typically involves calculating the signal root-mean-square (RMS) value and its comparison with a threshold value (ISO 10816. Mechanical vibration. Evaluation of machine vibration by measuring non-rotating parts). The diagnostic technique for motor-operated valves uses a statistical approach [5]. Its application makes it possible to estimate the risks of diagnostic errors (defect skipping, fault signaling) [6]. However, this approach does not localize the defect in a particular functioning node. Frequency methods [7] theoretically provide localization of the defect down to the individual part by visual or automatic comparison of the operating frequency of this part with the frequency distribution of the diagnostic signal amplitudes. Many modern systems of amplitude-frequency distribution apply Fourier transforms, which are not always effective because the contribution of harmonics reflecting the specific influence of the defect may be less than that of non-specific harmonics and is comparable to the influence of noise [8]. Spectral analysis, including its advanced interpretations, such as Fourier fuzzy analysis [9, 10], can be much more effective and illustrative because of the selection of relatively weak but essential equipment condition generations in the initial diagnostic information. The applied analysis methods do not consider the mathematical nature of signals [11, 12], which can be nondeterministic and chaotic. This disadvantage can be compensated by approximating the most valuable diagnostic information using a reference basis [13] by methods invariant to nondeterminism and the chaotic nature of processed time series [3].

3- Research Methods

3-1- Description of the Diagnostic Signals

According to the literature devoted to the description of vibration signals of electromechanical equipment [14] and directly from the analysis of diagnostic information, a typical signal of serviceable equipment can be modeled as follows:

$$X_n(t) = \left(\sum_{i=1}^{K} A_{n_i} \sin 2\pi \cdot f_i t\right) + \delta_n(t) \tag{1}$$

where i – counting index, f_i – fundamental, supreme frequencies, and sub-frequencies of mains harmonic and harmonics of rotor rotation, A_{n_i} – amplitudes of the corresponding harmonics, K – number of harmonics, $\delta_n(t)$ – chaotic component distributed near 0.

In the presence of abnormalities in the operation of equipment parts, the signal corresponds to the following description:

$$X(t) = \left(\sum_{i=1}^{P} \mathrm{A}_i \sin 2\pi \cdot f_i t\right) + \left(\sum_{j=P+1}^{Q} \mathrm{A}_{s_j} \sin 2\pi \cdot f_{s_j} t\right) + \delta(t) \tag{2}$$

where j – counting index, f_i – fundamental, supreme frequencies, and sub-frequencies of mains harmonic and harmonics of rotor rotation, A_i – amplitudes of these harmonics (the number of harmonics and amplitude values differ from those observed in the operating condition), f_s – frequencies corresponding to the harmonics of the rotation of defective parts, A_s – their amplitudes (which may be less than A_i), P,Q – number of corresponding harmonics, $\delta(t)$ – chaotic component (whose contribution increases in the presence of a defect).

Equations 1 and 2 may include a slowly changing component (e.g., one of the frequencies $f_i = 0.1$). It is assumed that signal generation occurs at a sampling rate of 0.001 s (as in many actual systems).

Thus, in expression 2, the first component describes deterministic but invaluable defect localization information. The second component with certain reservations is a deterministic (quasi-periodic) component important for defect localization. The third component, on the one hand, is noise interference, and, on the other hand, its contribution can be an unambiguous sign of the defect. Because the contribution of harmonics reflecting the specific influence of the defect is less than that of non-specific harmonics and comparable to the noise influence, there are difficulties in identifying the defect by frequency methods, especially in the initial stage of development.

Singular spectral analysis (SSA) is used to solve noise reduction problems in the field of communication [15], identifying weak and strong trends for forecasting in the fields of economy [16] and energy consumption.

3-2- SSA Application to Diagnostic Signals: Theory

SSA is a method where matrix $[A]$ of rang L can be decomposed into the product of three matrices $[U]$ (orthogonal matrix), $[S]$ (diagonal matrix) and $[V]^T$ (transpose of orthogonal matrix [V]). In other words, the matrix can take the following view:

$$[A]_{m\times n} = [U]_{m\times n}[S]_{m\times n}[V]^T_{m\times n} \tag{3}$$

where m, n – number of rows and columns of the matrix, $\mathrm{U^TU} = 1$ and $\mathrm{V^TV} = 1$; S is diagonal matrix, containing square roots from eigenvalues $\mathrm{A^TA}$, which can be expressed as $S = diag(\sigma_1, \sigma_2, \dots \sigma_L)$, where data $\sigma_i(i = 1, 2, L)$ are singular values of matrix [A], $L = min(m, n)$.

The diagnostic signals $X_n(t)$ and $X(t)$ described by Equations 1 and 2 are time series rather than matrices. Therefore, the discrete diagnostic signal x_i (i=1, 2, ..., N) is transformed into a Hankel matrix. The Hankel matrix is obtained by moving a window of length *m* along the time series and can take the following form:

$$[A] = \begin{pmatrix} x_1 & \cdots & x_n \\ \vdots & \ddots & \vdots \\ x_m & \cdots & x_N \end{pmatrix} \tag{4}$$

where $m + n - 1 = N$. Matrix $[A]$, also as signals $X_n(t)$ and $X(t)$, contains deterministic and chaotic components.

The SSA method states that the matrix $[\bar{A}]_{m\times n}$ of rank $L < l$, which minimizes the sum of squares of the error between the elements of matrix $[A]$ and the corresponding elements of matrix $[\bar{A}]$, can be generated as

$$[\bar{A}] = [U_l][S_l][V_l]^T \tag{5}$$

where $[\bar{A}]$ is a reconstructed matrix using only the number *l* of singular values.

$$\sigma_i > \varepsilon_1, i = 1, \dots l \tag{6}$$

where ε_1 is a threshold value that separates deterministic components from chaotic ones. The remaining singular values are replaced by zero. Thus, the matrix $[\bar{A}]$ concentrates the deterministic components contained in the initial signal.

Remember that according to Equation 2, the deterministic component of the failed equipment signal includes both harmonics directly indicating the defect and harmonics inherent to the signals of the operating and failed equipment. Thus, the application of SSA involves the problem of choosing singular numbers $i = p, \dots l$, by which the most valuable information can be recovered to identify the condition of the unit under test. A successful solution to this problem provides matrix reconstruction:

$$[\hat{A}] = [U_{l-p+1}][S_{l-p+1}][V_{l-p+1}]^T \tag{7}$$

where $[\hat{A}]$ is a reconstructed matrix using $l - p$ of singular values.

$\varepsilon_1 < \sigma_i \leq \varepsilon_2, i = l - p, \dots l,$

where ε_2 is a threshold value component directly indicating a defect.

Matrix $[\check{A}]$ characterizing the components that make the statistically most significant contribution to the original signal formation can also be reconstructed, if necessary:

$$[\check{A}] = [U_{p-1}][S_{p-1}][V_{p-1}]^T \tag{8}$$

where $[\check{A}]$ is a reconstructed matrix using $l - p$ of singular values.

$\sigma_i > \varepsilon_2, i = 1, \dots p - 1$

Solving some research problems [17] may require the reconstruction of a matrix $[\Delta]$ containing non-deterministic, chaotic components:

$$[\Delta] = [U_{L-l-1}][S_{L-l-1}][V_{L-l+1}]^T \tag{9}$$

After obtaining matrix $[\hat{A}]$ related to $l - p$ singular values, it must be transformed into a time series reflecting the specific defect influence. The reconstruction involves arithmetic averaging over the antidiagonals of the matrix $[\hat{A}]$, which is the diagonal averaging method [18] that can take the following form:

$$\hat{x}_i = \frac{1}{\beta-\alpha+1}\sum_{j=\alpha}^{\beta}\hat{A}_{i-j+1,j} \tag{10}$$

where $\alpha = \max(1, i-m+1)$ and $\beta = \min(n, i)$. Similarly, it is possible to reconstruct exceptionally deterministic and chaotic signals by matrices $[\check{A}]$ and $[\varDelta]$.

The successful application of SSA is related to the choice of l and p numbers depending on the threshold values of ε_1 and ε_2. Guns & Rousseau [19] justifies the choice of numbers l and p by the shape of the value graph commonly referred to as the eigenvalue spectrum (ES). The ES is a decreasing graph representing the dispersion contribution of each component along each component of the decomposition. The ES obtained by singular value decomposition provides a visualization of defect manifestations: as the defect progresses, the spectrum plot becomes gentler, showing the contribution of harmonics associated with the defect influence and increased randomness. Value σ_i, at which the decrease of eigenvalues maximally slows down [20], can be taken as the threshold ε_1, above which the decomposition components of the matrices described by expression 4 reflect the influence of the chaotic components of the initial data.

Since this work, in addition to the separation of the chaotic and deterministic components in the signal, sets the task of selecting the component, reflecting the influence of the equipment condition on the signal formation, it is proposed to choose ε_2 based on the comparison of ES signals of operating and failed equipment. Numerical and field experiments justify the choice approach.

In previous studies by González et al. [4], for visualizing and analyzing defect manifestations in electromechanical equipment, the SSA method was used together with high-pass filters, which reduced the performance of diagnostic systems. In this study, the SSA method provides signal denoising and does not require additional processing. The SSA method identifies defect features in the reconstructed signal that are not detected by frequency domain analysis in the original complex signal. Thus, the SSA method applies in conjunction with Fourier series decomposition and other classical analysis methods

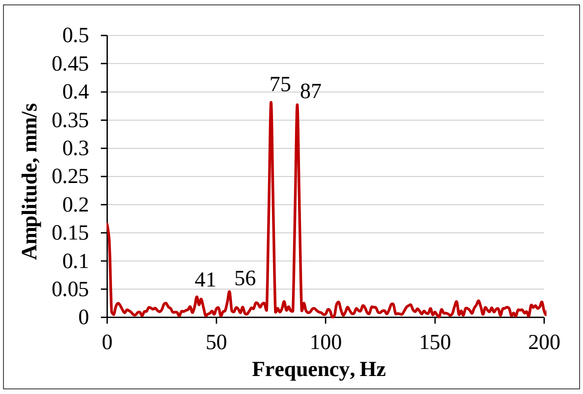
4- Testing the SSA on the Results of Computational Experiments

To test the ES method as applied to diagnostic signals, a time series similar to the vibration signal of failed equipment was generated, corresponding to the following equation:

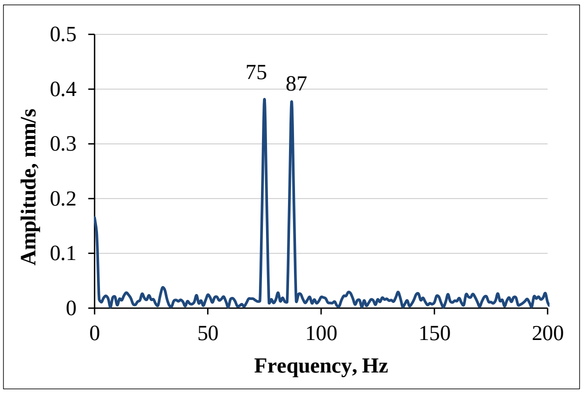
$$X(t) = \left(\sum_{i=1}^{5} A_i \sin 2\pi \cdot f_i t\right) + \delta(t) \tag{11}$$

where $f_1 = 75$, $f_2 = 87$, $f_3 = 41$, f_4 =56, f_5 =0.1 Hz, A_1=A_2=0.4, A_3=A_4=0.05, A_5=0.1, $\delta(t)$ is a random component distributed according to the normal law with a standard deviation of 0.1.

The spectrum of the initially generated signal correlates with Equation 11. It reflects the presence of a trend (frequency 0.1 Hz), "strong" harmonics (with frequencies 75 and 87 Hz), "weak" (with frequencies 41 and 56 Hz), and random components. As Figure 1 shows, the "weak" but informative harmonics are complicated to identify. For comparison, the spectrum of the signal was generated, which differs from the first one by the absence of harmonics at the frequencies of 41 and 56 Hz (Figure 1-b).



(a)



(b)

Figure 1. Frequency spectra of the initially generated vibration speed signals: a) with harmonics at frequencies of 41, 56, 75, and 87 Hz and noise, b) without harmonics at frequencies of 41 and 56

Transformations 3 and 4 were applied to the signal generated according to Equation 11 and to the second signal (without harmonics at 41 and 56 Hz), obtaining orthogonal matrices and ESs. Figure 2 shows that these ESs are almost identical. However, the decrease in eigenvalues maximally slows down in the ES of the signal without additional harmonics starting from No. 5 and in the ES with additional harmonics starting from No. 9

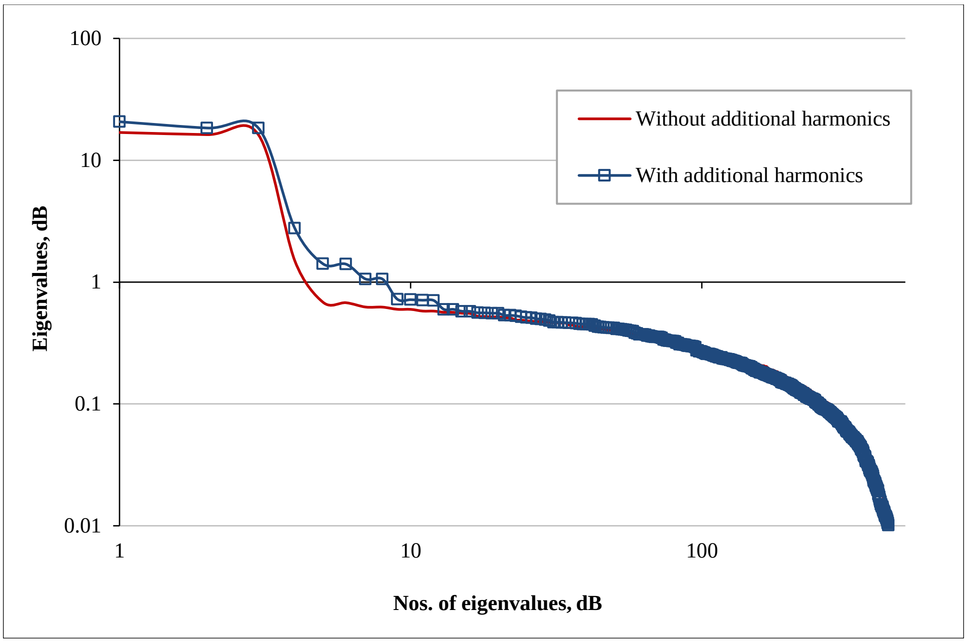
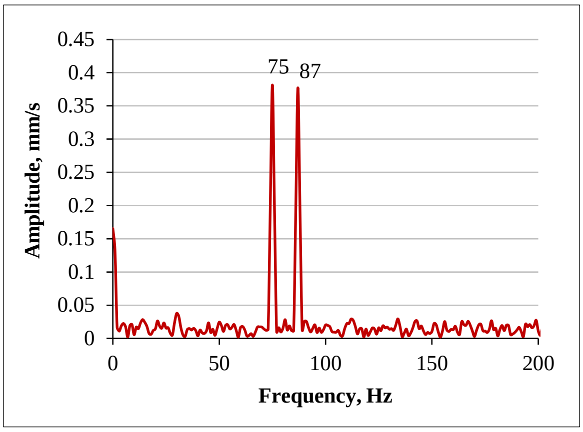


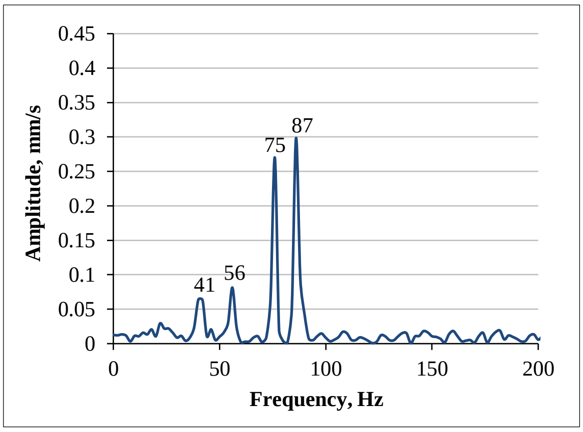
Figure 2. Eigenvalue spectrum of the generated signals

There is a difference in the values of nos. 5-8, a sign that mismatched harmonics (with frequencies of 75 and 87 Hz) manifest themselves in the projections of the singular basis to the directions with these numbers. It is reasonable to accept the threshold values $l = 8$ and $p = 5$ for data recovery according to Equation 7. A gentler shape of the graph visualizes the manifestation of the defect in components nos. 5-8.

Indeed, the frequency spectrum of the series reconstructed by projections with nos. 5-8 (Figure 3-a), according to (10), demonstrates the presence of harmonics with frequencies of 41 and 56 Hz more clearly than the spectrum of the initial signal (Figure 1-a). The spectrum of the signal without additional harmonics, reconstructed by projections with numbers nos. 5-8 (Figure 3-b), demonstrates only the presence of harmonics at frequencies of 75 and 87 Hz.



(a)



(b)

Figure 3. Frequency spectra of the reconstructed generated vibration speed signals: a) with harmonics at frequencies of 41, 56, 75, and 87 Hz and noise, b) without harmonics at frequencies of 41 and 56

Projections on different directions of the singular basis, being in a sense the result of filtering, make it possible to distinguish deterministic and chaotic components in the signal. Figure 4 shows components with nos. 1, 4, and 450 (columns with the corresponding numbers of matrix V obtained from decomposition (3)). The first component corresponds to the "strongest" periodic component, the fourth component (whose contribution is "weaker") corresponds to the trend, and the highest component shows chaotic behavior. The form of the chaotic component changes at different realizations of $\delta(t)$, while the other two components remain almost unchanged.

Thus, the SSA method can be used to visualize the regularities of defect manifestations. The processing of time series simulating the generation of diagnostic signals demonstrates the possibility of analyzing relatively weak generations in the diagnostic signal and revealing hidden defects.

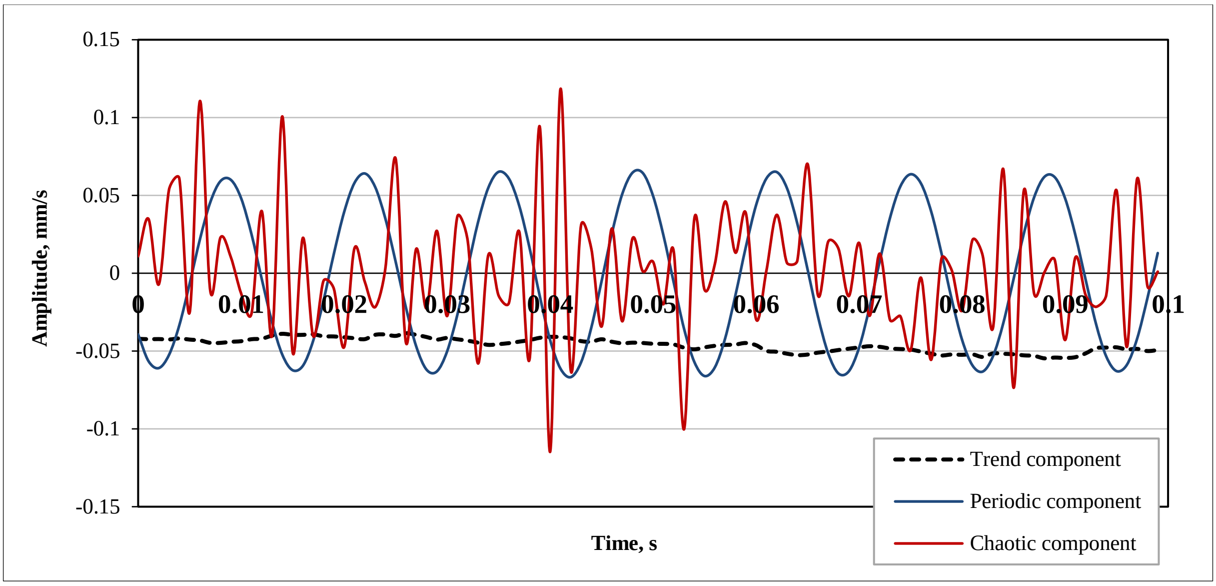


Figure 4. Components of signal singular value decomposition

Figure 5 shows the sequence of transformations required to implement the author's methodology.

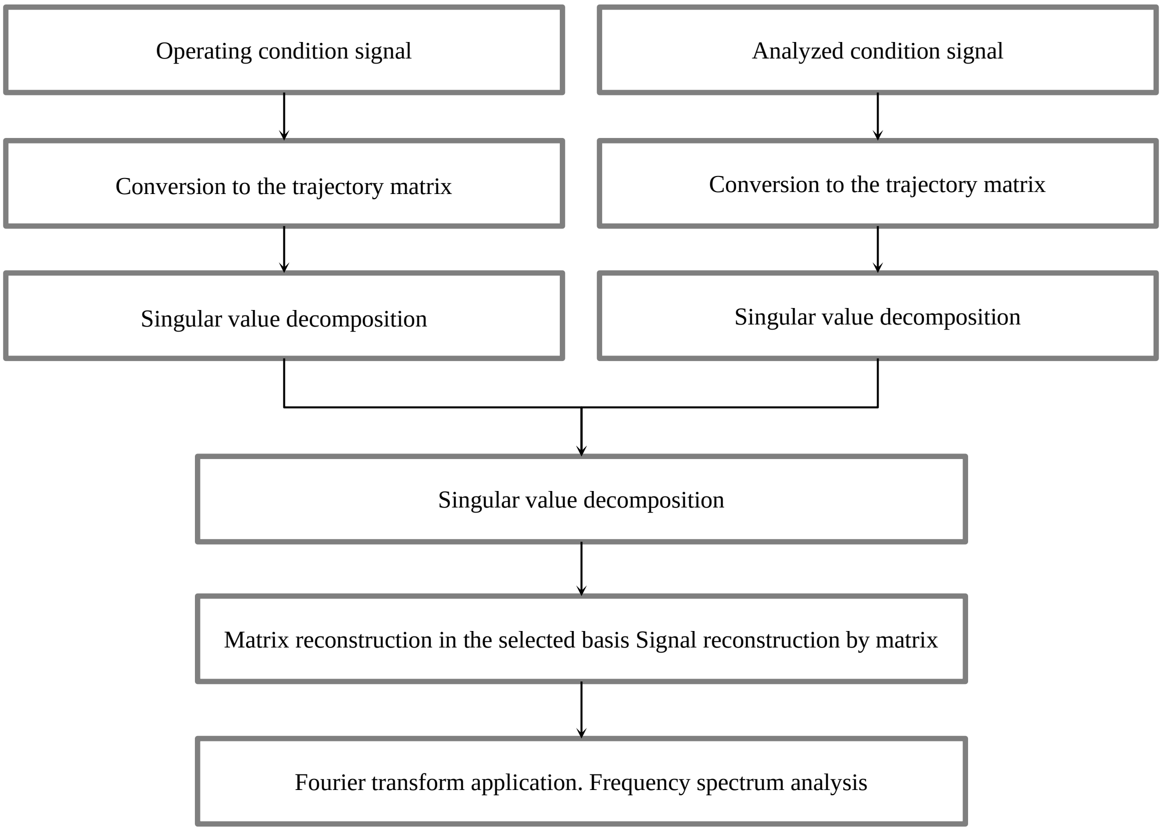


Figure 5. Processing of diagnostic signals

Note that not only frequency but also statistical methods can be applied to the data after recovery, and their efficiency increases because of pre-processing [21].

5- Results and Discussion

5-1- Application of SSA to the Results of Field Experiments

The experiment involved accelerated abrasive wear of ball bearings using a test setup (Figure 6) to verify the proposed method of analyzing the regularities of manifestations, nucleation, and development of defects in electromechanical equipment.

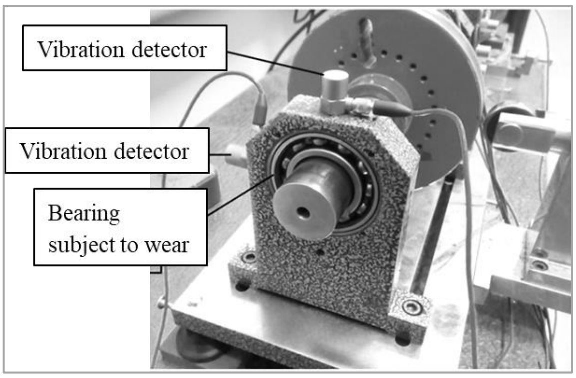


Figure 6. Test setup. Bearing support, view along the shaft axis

The vibration speed level was measured before the failure, at the start of the failure, and 80 min after the failure. RMS values were calculated using the measured signals (similar to industrial diagnostic systems) and presented as probability distribution density functions [6], as shown in Figure 7.

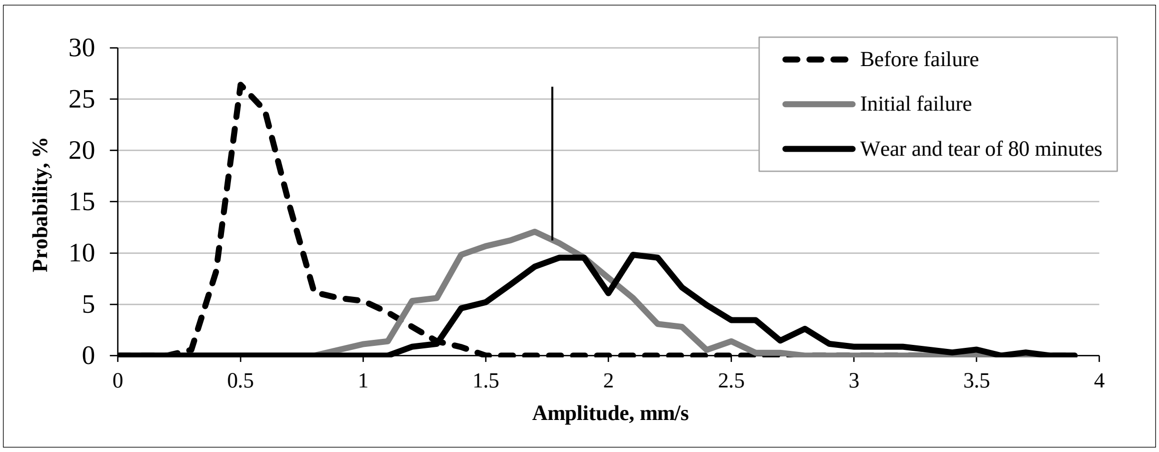


Figure 7. Density functions of the RMS probability distribution of the vibration speed experimental signals

A comparison with the threshold values given in normative documents classifies failed conditions in industrial diagnostic systems. According to GOST10816-1, considering the low motor power of the test setup, the threshold of 1.8 mm/s (border of zones B/C) should be the threshold above which long-term operation of this equipment is inexpedient. Given that approximately half of the values corresponding to failure (first 10 minutes from the start of wear) and wear (80 minutes) are below the threshold, the probability of defect absence is approximately 50 %.

Signal spectra in Figure 8 demonstrate the presence of higher and subharmonic components of the supply current harmonic ($\frac{k \cdot 50}{2^n} \approx 25, 37,52, 75, 87, 112, 125, 137\ Hz$ k=1,2,3,4 at n=0,1,2), which are not specific signs of the defect [17]. After the initial failure (Figure 8-b), the subharmonic components slightly increase, and the noise component increases. As wear progresses, the manifestation of deterministic components decreases and that of chaotic components increases (Figure 8-c).

Particular signs of the bearing defect are the excitation of harmonics at the frequencies of the separator rotation, rolling elements, and their rolling around the outer and inner rings [22]. Assuming that the specified harmonics are "weak" and "sink" in the noise, it is possible to identify them using the proposed algorithm based on the SSA method.

5-2- Discussion of the Results of the Field Experiments

Transformations 3 and 4 were applied to the experimental signals. As Figure 9 shows, the operating condition corresponds to the most significant difference in the contribution of the first and higher components: nos. 1-6 contribute more than 10 dB; subsequent components insignificantly contribute and demonstrate a "slowing down" starting from No. 8. Initial failure is accompanied by a sharp increase in the first component, a relative increase in components nos. 8-700, and a "slowing down" starting from No. 15. Subsequent wear has the gentlest ES and the most significant contribution of components nos. 2-700. The projections on components nos. 8-15 can be the most informative because their contribution is more than 10 dB and differs from the contribution of the signal components before the failure.

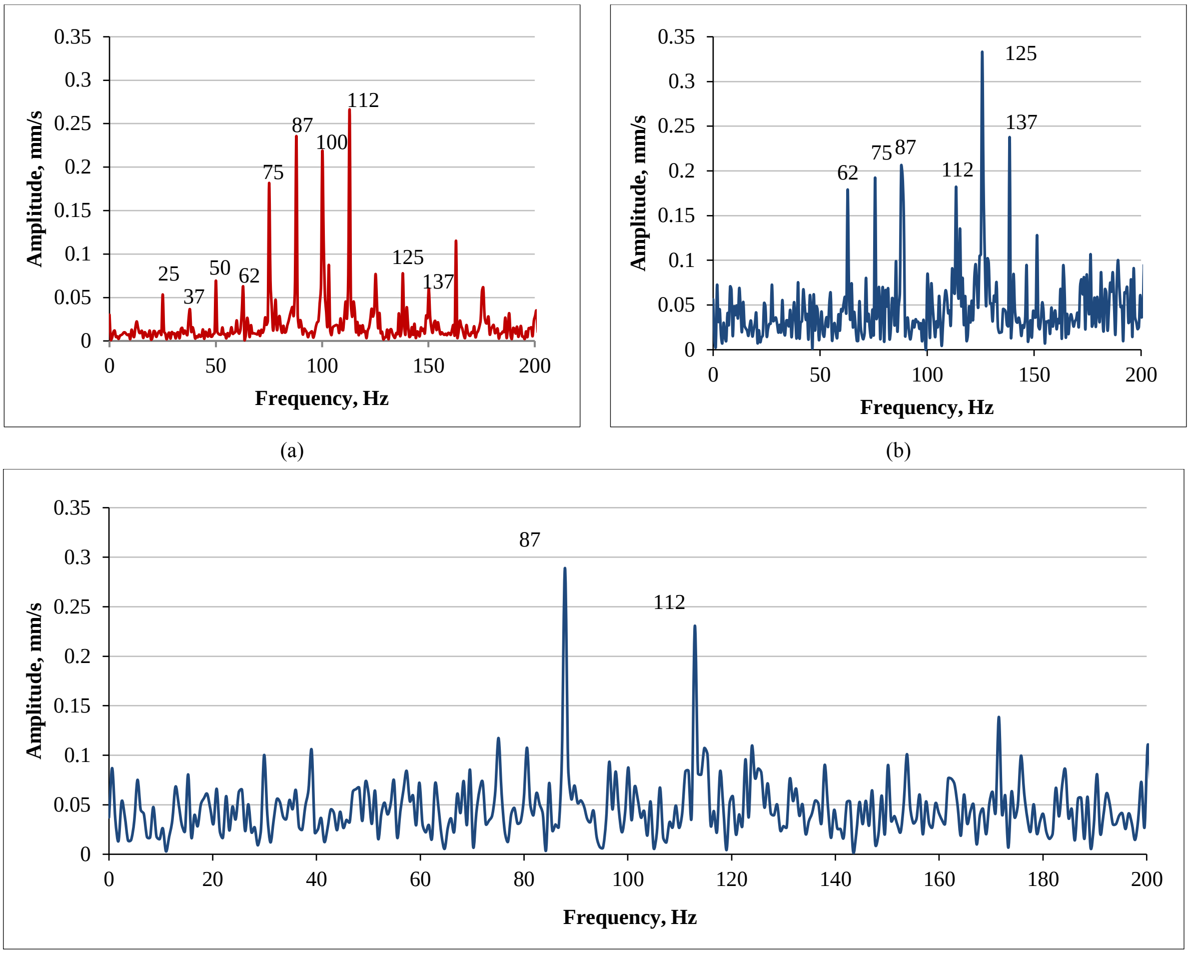


Figure 8. Frequency spectra of the initial experimental signals of vibration speed: (a) before failure, (b) initial failure, and (c) wear and tear after 80 min

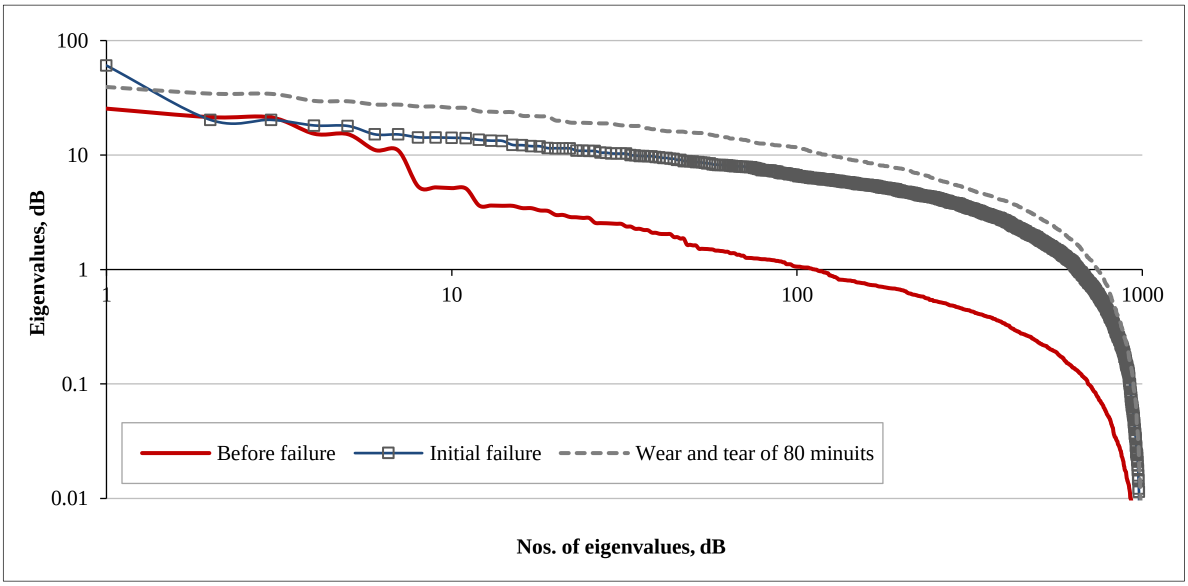


Figure 9. Eigenvalue spectrum of the experimental signals

The decomposed experimental signals were reconstructed using nos. 1-7, 8-15, 600-700. As expected, components Nos. 1-7 in Figure 10-a characterize the contribution of "strong" deterministic (but low-informative) components. The higher component nos. 600-700 in Figure 10-b characterize the contribution of chaotic components (whose very presence indicates the defect development). The reconstruction using components Nos. 8-15 (Figure 10-c) is of the most interest because the time series contains harmonics that can be associated with the rotation of the separator (9 Hz) and rolling elements (41 Hz).

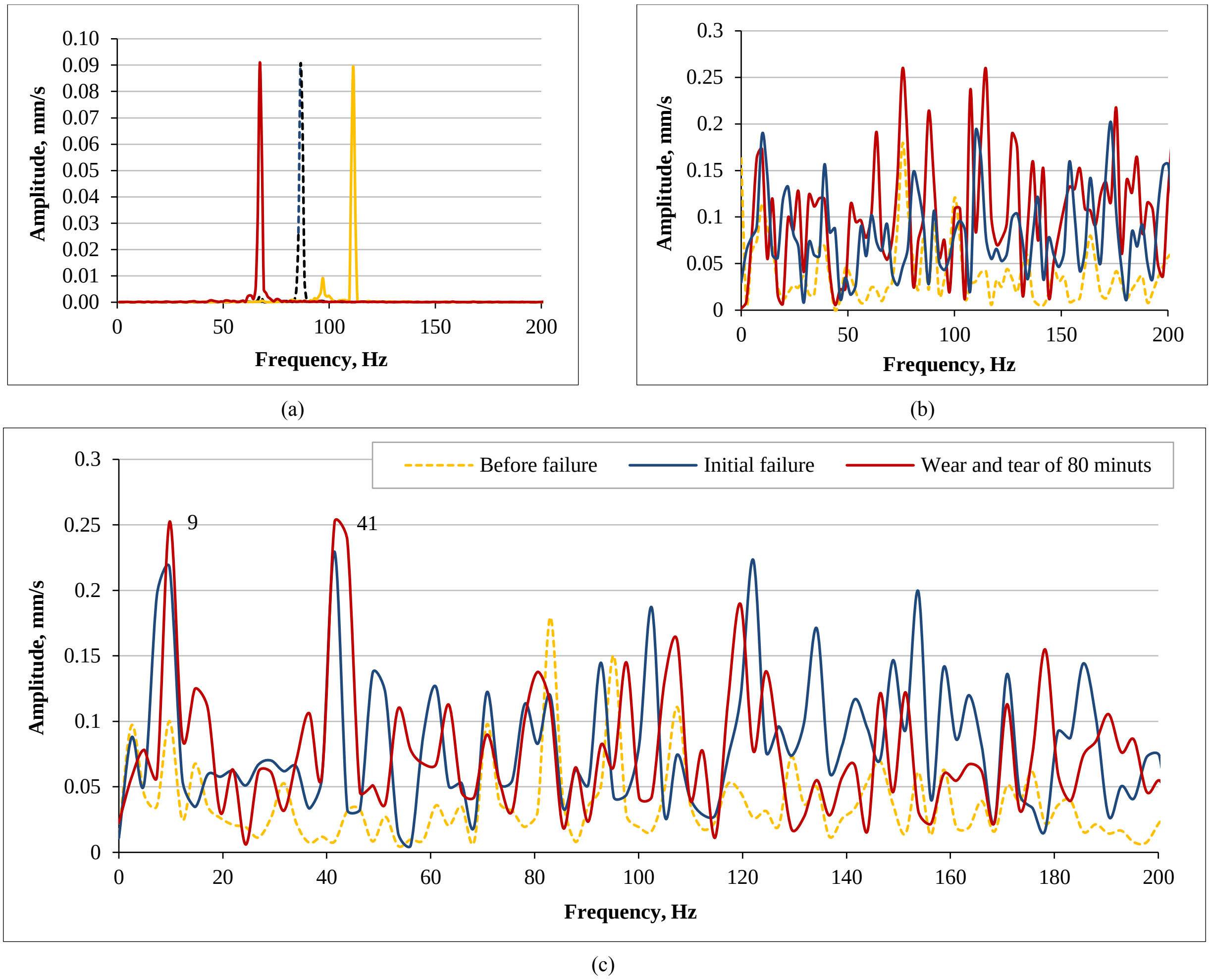


Figure 10. Frequency spectra of the reconstructed vibration speed signals: a) nos. 1-7, b) nos. 600-700, c) nos. 8-15

It is possible to recover the most valuable information for identifying the object condition by ES and comparing the analyzed spectrum with that corresponding to the operating condition. The last figure demonstrates that applying the SSA method to the initial diagnostic information increases the efficiency of frequency analysis methods. The proposed method incorporates the experience of previous diagnostics and thus contributes to the development of diagnostic systems. In contrast to conventional systems that only archive data, the previous results improve the quality of diagnostics at the system level.

Note that the SSA method eliminates the limitations of existing methods that do not consider the non-deterministic and chaotic nature of the processed signals. Detection of hidden defects in noise-distorted diagnostic signals is achieved by approximating the most valuable diagnostic information using a reference basis. Note that not only frequency-based methods but also other methods apply to the data after recovery; their efficiency increases because of preprocessing. The more efficiency, the longer the length of the signal implementation. However, the existing computational power limits the amount of processed information.

The results of numerical and field experiments show that the spectrum of eigenvalues obtained as a result of the singular decomposition of diagnostic signals provides visualization of defect manifestations when other methods are ineffective. As the defect develops, the spectrum graph becomes gentler, demonstrating the contribution of harmonics associated with the influence of the defect and increasing randomness.

6- Conclusion

This paper considers the problem of detecting the signs of defects in electromechanical equipment using a diagnostic signal containing informative components and noise. The insufficient efficiency of known methods is because the contribution of harmonics reflecting the specific influence of the defect is less than that of non-specific harmonics and is comparable to the influence of noise. This study solves the applied scientific problem of searching for weak but informative generations in the diagnostic signal using the SSA method adapted for solving this problem. A valuable observation is that if a defect develops, the spectrum graph becomes gentler, demonstrating the contribution of harmonics associated with the influence of the defect and increasing randomness. As shown, ES singular value decomposition provides visualization of defect manifestations when other methods are ineffective.

The proposed method differs from the known SSA implementation aimed at noise filtering by selecting the metric with the best (in terms of information about the object condition) computation of data approximation. For the first time, the choice of metric is to compare the ESs corresponding to the signals of the working and failed equipment. Using ES, it is possible to select areas where eigenvalues for the failed condition characterize a significant contribution, whereas for the operating condition, the contribution along the directions with these numbers is insignificant. Thus, the directions of the singular basis that reflect the deviations under the defect influence are selected.

The possibility of analyzing relatively weak generations but essential ones for identifying the equipment condition, confirmed by numerical and field experiments, is of great practical significance. The study results are suitable for improving the performance of technical diagnostics systems for equipment of potentially hazardous industries, contributing to the prevention of failures due to the timely detection of hidden defect signs in the diagnostic signal.

For further research, it is promising to adapt the method for its consistent application to dynamically updated equipment diagnostic data and make timely decisions on its condition management.

The sensitivity of the diagnostic method to incipient equipment defects may be in demand at critical production facilities, such as nuclear power plants. In addition to electromechanical equipment, the improved SSA method is applicable to the diagnostics of stepping electromagnetic drives, for example, drives of control and protection systems of the SHEM-3 reactor plant.

7- Declarations

7-1- Data Availability Statement

The data presented in this study are available in the present article.

7-2- Funding

The author received no financial support for the research, authorship, and/or publication of this article.

7-3- Institutional Review Board Statement

Not applicable.

7-4- Informed Consent Statement

Not applicable.

7-5- Conflicts of Interest

The author declares that there is no conflict of interest regarding the publication of this manuscript. In addition, the ethical issues, including plagiarism, informed consent, misconduct, data fabrication and/or falsification, double publication and/or submission, and redundancies have been completely observed by the author.

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