Entropy approach in the analysis of vibration and partial discharge signals

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Abstract. The development of new methods of technical diagnostics is an important task aimed at improving the efficiency and safety of the operation of industrial equipment. Such methods are complexes of jointly used methods for obtaining diagnostic information, methods for extracting from it the actual data on the technical state of the diagnosed objects, and methods for organizing diagnostic processes. At the same time, the criteria of importance and value, as a rule, are different for the developers of these methods, developers of diagnostic systems, and direct operators of equipment, which requires the search for solutions that are a compromise for all interested parties and meet certain optimality requirements. One of the new approaches in the field of identifying and controlling new diagnostic information is the entropy method for evaluating data. Testing the applicability of this approach to the analysis of signals of vibration and partial discharges has shown the possibility of obtaining data on changes in the state of the diagnosed object. This information can be used to develop new diagnostic features designed for earlier detection of developing defects, as well as for checking and confirming technical diagnoses obtained by classical methods.

1. Introduction
Technical diagnostics, as a field of science and life, is developing all the time. New methods and approaches are emerging that serve to improve the efficiency and safety of industrial equipment operation. As a response to the request of technical progress, new diagnostic systems appear, based on various combinations of signal processing and conversion methods, with varying degrees of automation of condition assessment and diagnostics.

All of the above is also relevant for dynamic equipment, the diagnostic methods of which are the subject of this article. According to [1], such equipment includes equipment with moving parts, such as rotating machines, piston machines, air coolers, smoke exhausted, etc.

In the technical diagnostics of such machines, a combination of several factors is important, namely, methods of obtaining diagnostic information, methods of processing it to extract from it the actual knowledge about the technical state of the diagnosed object, and methods of organizing the diagnostic process.

It is obvious that the choice of the most optimal complex of all the listed methods is rather difficult because of the conflicting requirements for such a complex on the part of stakeholders [2, 3].

So, research scientists who directly develop diagnostic methods, due to the scientific and academic nature of their activities, often gravitate towards physically and mathematically complex methods that are well implemented in laboratory conditions, but face difficulties in practice. The primary criteria, in this case, are the novelty and science intensity of the development, and not its practical relevance and feasibility.

Developers of diagnostic systems, in turn, for various reasons, are often focused on one of the most developed and suitable for interpreting the results of the diagnostic method, which is put at the forefront. Accordingly, their criteria are the paramount importance of diagnostics and its subordination
to the interests of the very technological process of using the diagnosed equipment, as well as the maximum coverage of possible equipment diagnoses by this preferred method by providing a large amount of analytical data for processing by diagnosticians.

The personnel directly operating the diagnosed equipment, for obvious reasons, considers the diagnostics of the subordinate equipment as a secondarily auxiliary function among their job responsibilities. So the criteria, in this case, can be considered the maximum non-influence of diagnostics on technological processes and the possibility of diagnostics online, that is, without taking the equipment out of operation, with the maximum automation of the diagnostic process and the clarity of its results for non-specialists. Moreover, it is not necessary to immediately issue an accurate diagnosis, which is often simply impossible, but it is advisable to warn the operator about changes in the technical condition of the equipment as early as possible so that the person has time to assess the situation.

If we introduce into the reasoning the self-diagnosed dynamic equipment, as the fourth interested party, then one of the important typical features influencing approaches to diagnostics is its rather typical structure, determined by its purpose.

We can say that all industrial dynamic equipment is based on the conversion of energy, as a rule, mechanical energy into electrical energy and vice versa. A typical industrial unit consists of an electrical connection system, an electrical part, and a mechanical part. For example, a feed cell and cable line, an electric motor drive, a mechanical device that performs useful work and is usually based on a rotational or oscillatory motion (pump, fan, compressor, etc.). The same considerations are also true with a reverse flow of energy - a mechanical device that converts the energy of a source (wind machine, turbine, etc.), a generator (a machine similar to an electric motor), and, in turn, a cable line and a switching device for inclusion in the distribution network.

The above example shows that dynamic equipment, as a complex, consists of the main elements of mechanical and electrical types and therefore also requires the complex use of different diagnostic methods that are most suitable for these elements since it is obvious that the failure of any of the links in such a chain will lead to the shutdown of the entire complex, no matter how successfully the remaining links are diagnosed in this case [4, 5, 6, 7].

The point of view of the authors on the issue of diagnostics of dynamic equipment is that today, the most acceptable diagnostic methods for this are methods of vibration diagnostics for monitoring the technical state of mechanical systems [8, 9, 10, 11, 12, 13, 14] and methods control of parameters of partial discharges for monitoring electrical systems of dynamic equipment [15, 16, 17].

These methods are based, as a rule, on the registration of vibroacoustic and electrical signals, which have different sources, physical nature, causes of occurrence. Accordingly, typical methods of processing such signals have significant differences, which forces the use of several parallel mathematical mechanisms in diagnostic systems, which complicates these systems.

At the same time, these mathematical mechanisms often do not allow identifying deviations in the technical condition of machines that go beyond the previously described (formalized) ones, especially in the early stages of the occurrence of such deviations. That is, a diagnostic signal, the parameters of which do not exceed the set threshold values, but at the same time carrying information about such a deviation in the state of the diagnosed equipment, can be ignored.

Methods of entropy analysis, considered by many researchers from the first half of the 20th century [18, 19, 20, 21, 22, 23], can become an effective way to analyze such signals. At the same time, the currently growing number of publications devoted to the use of entropy in vibration diagnostics [24, 25, 26, 27] and diagnostics by the method of partial discharges [28, 29, 30, 31] indicates an increase in the interest of researchers in this method and its prospects.

2. Formulation of the problem

The purpose of this study is to select a method of entropy analysis unified for vibration and partial discharge signals and to test its applicability on real signals received from operating industrial equipment.

To achieve this goal, it is necessary to solve a number of tasks:
1. Choose a method of entropy analysis, suitable for both vibration signals and partial discharge signals;
2. Analyze the characteristic vibration signals by the selected method;
3. Analyze the characteristic signals of partial discharges using the selected method;
4. Compare the results obtained for both types of signals. As a result, an assessment should be obtained of the possibility of using a unified method of entropy analysis for working with both types of signals under study and the development of new diagnostic features suitable for determining changes in the technical state of the diagnosed equipment that were not previously formalized.

3. **Theory**

The text of your paper should be formatted as follows:

The entropy method under consideration was based on the method proposed in [21] for calculating the Shannon entropy $H$, expressed in bits:

$$
H = - \sum_{i=1}^{n} P_i \log_2(P_i) 
$$

where $H$ is the Shannon entropy for the signal under study; $P_i$ is the probability of occurrence of the $i$-th sample in the series of samples that make up the signal under study.

In this work, all the signals under study were considered as “black box” signals, that is, no distinction was made between signals of mechanical and electrical nature, just as the initial signals themselves were not normalized in any way based on considerations of the “unknown” of their true amplitude parameters.

Based on the foregoing, to detect changes in the state of the system, provided that neither the moments of such transitions nor the parameters of the system in these states are known, a special case of the above method was used, based on the calculation of the local entropy $h_i$. In this case, the empirical probability distribution is used, obtained directly from the sample, which is the original signal under study:

$$
h_i = - \log_2(P_i)
$$

where $h_i$ is the local entropy of the $i$-th sample of the signal under study; $P_i$ - the empirical probability of occurrence of the $i$-th sample in the series of samples that make up the signal under study.

To calculate the empirical probabilities of the appearance of samples in a signal ($P_i$ for each $i$-th sample), it is necessary to divide the entire series of samples into $m$ intervals to construct a probability distribution. In order to estimate the number of intervals $m$, the methods proposed in [32] were used to determine the optimal number of the grouping of experimental data. When evaluating the number of methods, the following conditions were taken into account:

- since the distribution law of the instantaneous entropy for the signals under study is unknown and its definition is beyond the scope of the problem under discussion, the number of intervals $m$ must satisfy the requirements of the main criteria for constructing such distributions, taking into account the possibility of using both intervals with equal length and intervals with equal probability;
- usually, the number of intervals is determined in such a way as to smooth out the outliers in the analyzed values, for which the number of intervals can be reduced. In the case under consideration, it is the outliers that have the highest entropy, therefore, they are of considerable interest. For this reason, to determine the number of intervals $m$, the methods that give the highest estimates were considered;
- in order to simplify the final signal analysis algorithm, a method was tested for dividing the samples of the studied signals into intervals by rounding them to include close samples in $m_{round}$ intervals of equal length.
To estimate the number of intervals $m$ for the number of samples $n$ in the case of intervals of equal length, the Heinhold-Gaede method was used:

$$m = n^{0.5} \quad (3)$$

To estimate the number of intervals $m_p$ in the case of intervals with equal probability, William's method was used:

$$m_p = 1.9 n^{0.4} \quad (4)$$

Also, to estimate the variation of the desired number of intervals, taking into account the unknown distribution law, we used the estimates $m_{\text{min}}$ for a uniform distribution and $m_{\text{max}}$ for the Laplace distribution, as for the boundary conditions:

$$m_{\text{min}} = 0.55 n^{0.4} \quad (5)$$

$$m_{\text{max}} = 1.25 n^{0.4} \quad (6)$$

Taking into account the foregoing about the estimation of the number of intervals and proceeding from considerations of practical registration of measuring signals, the number of samples $n = 8100$ were taken for all signals, while the numerical values of the samples are presented in dimensionless form.

The results of evaluating the number of intervals $m$ are given in table 1.

**Table 1. Results of estimating the number of intervals for calculating empirical probability distributions.**

| Signal | The number of samples $n$ | Maximum range, units | $m$, formula (3) | $m_p$, formula (4) | $m_{\text{min}}$, formula (5) | $m_{\text{max}}$, formula (6) | Rounding order | $m_{\text{round}}$ |
|--------|--------------------------|----------------------|------------------|-------------------|------------------|------------------|--------------|----------------|
| Signal 1 | 8100                     | 7800                 | 90               | 70                | 20               | 46               | Hundreds     | 78             |
| Signal 2 | 8100                     | 3000                 | 90               | 70                | 20               | 46               | Hundreds     | 30             |
| Signal 3 | 8100                     | 83                   | 90               | 70                | 20               | 46               | Units        | 83             |
| Signal 4 | 8100                     | 540                  | 90               | 70                | 20               | 46               | Tens         | 54             |

As you can see from the table 2, the values of the number of intervals $m_{\text{round}}$ obtained by the rounding method are quite close to the values obtained by formulas (3) - (6). Thus, before a more rigorous refinement of the parameters of the entropy distribution of signals, at this stage of research, this estimate was adopted to calculate the empirical probabilities of the occurrence of $P_i$ counts in the series of counts that make up the signal under study.

4. Experimental results

To assess the applicability of the proposed approach when processing vibration signals of mechanical assemblies and partial discharge signals in the isolation of dynamic equipment, the entropy approach was used to analyze the following set of signals of vibroacoustic and electrical nature:

– signal 1 – a vibroacoustic signal of a working electric motor (from the authors’ archive, figure 1);

– signal 2 – a vibroacoustic signal of an electric motor with a defective bearing (from the authors’ archive, figure 2);
– signal 3 – background noise signal of partial discharges (presented on the public resource [33], figure 3);
– signal 4 – a typical partial discharge signal (presented on the public resource [33], figure 4).

The proposed method of dividing the set of analyzed signal samples into intervals by arithmetic rounding of the sample values applied in the calculations made it possible to simplify and speed up the calculation procedure when processing these signals.

Studies have shown that the entropy approach allows extracting new information about the technical state of dynamic equipment from diagnostic signals, while the physical nature of the controlled processes does not affect the applicability of this method.

5. The discussion of the results
In figures 1 and 2 show the results of processing Signal 1 and Signal 2.

![Figure 1](image1.png)

**Figure 1.** An example of a vibroacoustic signal of a working electric motor (Signal 1) with entropy values for registered samples (lower graph).

![Figure 2](image2.png)

**Figure 2.** An example of a vibroacoustic signal from an electric motor with a bearing defect (Signal 2) with entropy values for registered samples (lower graph).

As can be seen from figure 1 and 2, the values and, accordingly, the graphs of the entropy of the vibration signals for different technical states of the electric motor have significant differences.

The results of processing the background noise signal and a typical signal of partial discharges of signals are shown in figure 3 and 4. These signals were selected to enable other researchers to use them in their work to compare and discuss the results.
As can be seen from figures 3 and 4, the values and, accordingly, the graphs of the entropy of the background noise signal and the typical partial discharge signal also have significant differences.

The results of filtering the initial signals of mechanical and electrical defects, presented in figures 5 and 6. Filtering was carried out by zeroing the samples, the entropy value of which was less than the threshold value. So, for the indicated vibration and partial discharge signals, the counts were zeroed, the entropy of which was less than 50% of the value of the maximum calculated entropy.

Figure 3. Example of a background noise signal of partial discharges (Signal 3) with entropy values for registered samples (lower graph).

Figure 4. Example of a typical partial discharge signal (Signal 4) with entropy values for registered samples (lower graph).

Figure 5. Result of entropy filtration vibroacoustic signal of an electric motor with a bearing defect (Signal 2).
As can be seen from figures 5 and 6, such entropy filtering makes it possible to exclude the noise component from the original signal by selecting the samples with the highest entropy, which, by definition, are related to more rare, unexpected events, that is, in fact, to the desired mechanical and electrical defects.

6. Conclusions
As a result of the experimental studies, the following conclusions can be drawn:
1. The unified method of entropy analysis proposed by the authors is suitable for both vibration signals and partial discharge signals;
2. The entropy parameters of vibration signals differ for the normal technical condition of the dynamic equipment and for its defective condition;
3. The entropy parameters of the partial discharge signals for the normal technical state of the dynamic equipment and for its defective state also differ;
4. The detected changes in the entropy parameters for dynamic equipment in different technical states can be used to develop new diagnostic features that allow tracking unformalized changes in the technical state of controlled objects.
5. The described entropy approach can be used to filter the noise component when processing measurement signals.

7. References
[1] ISO 13372:2012 Condition monitoring and diagnostics of machines – Vocabulary.
[2] Kostyukov V N, Naumenko A P 2012 Designing and operation experience of real-time monitoring systems 9th International Conference on Condition Monitoring and Machinery Failure Prevention Technologies (London United Kingdom 12-14 June 2012) Proceedings NY Curran Associates Inc. vol 1 pp 1053–60
[3] GOST 32106-2013 Condition monitoring and machine diagnostics. Monitoring the status of equipment in hazardous industries. Vibration of centrifugal pump and compressor units Moscow Standartinform
[4] Kostyukov V N, Naumenko A P 2012 The Piston Compressor: The Methodology of the Real-Time Condition Monitoring J. Phys.: Conf. Ser. 364 012130
[5] Kostyukov A V, Boichenko S N, Naumenko A P 2018 Some Problems of Vibration-Based Health Monitoring 15th International Conference on Condition Monitoring and Machinery Failure Prevention Technologies (Nottingham United Kingdom 10-12 September 2018) Proceedings NY Curran Associates Inc. pp 277–90
[6] Kostyukov V N, Kostyukov Al V, Boychenko S N, Schelkanov A V, Burda E A 2017 Complex Application of Vibration Diagnostics and Partial Discharges Methods at Various Stages of Dynamic Equipment Operation NDT World Moscow vol 20 3 pp 15-18
[7] Kostyukov A V, Boychenko S N, Schelkanov A V, Burda E A 2017 Multi-method automated diagnostics of rotating machines *AIP Conference Proceedings* *Oil and Gas Engineering* *OGE* 2017 p 020081

[8] Kostyukov V N and Naumenko A P 2013 Rationing of piston machines vibration 10th *International Conference on Condition Monitoring and Machinery Failure Prevention Technologies* (CM 2013 AND MFPT 2013) (British Institute of Non-Destructive Testing Printed by Curran Associates Inc. 2014) vol 1 of 2 pp 142-50

[9] Kostyukov V N, Naumenko A P 2015 Standardization in the sphere of vibrodiagnostic monitoring of piston compressors *Procedia Engineering* vol 113 pp 370-80

[10] Kostyukov V N and Naumenko A P 2012 Designing and operation experience of real-time monitoring systems 9th *International Conference on Condition Monitoring and Machinery Failure Prevention Technologies* (CM 2012 and MFPT 2012) (British Institute of Non-Destructive Testing Printed by Curran Associates Inc. 2012) vol 1 of 2, pp 1053-60

[11] Naumenko A P 2011 Modern methods and means of on-line monitoring of parameters and real-time health monitoring of piston machines 8th *International Conference on Condition Monitoring and Machinery Failure Prevention Technologies* (CM2011/MFPT2011) (British Institute of Non-Destructive Testing. Printed by Curran Associates Inc. 2011) vol 1 of 2. pp 809-21

[12] Kostyukov V N and Naumenko A P 2014 Technology of piston compressors real-time diagnostics and monitoring 11th *International Conference on Condition Monitoring and Machinery Failure Prevention Technologies* (CM2014/MFPT2014) (British Institute of Non-Destructive Testing. Printed by Curran Associates Inc. 2014) pp 580-90

[13] Kumenko A I, Kostyukov V N, Kuzminykh N Y, Timin A V 2016 Development of methodological support for turbine unit shaft defect and stress monitoring systems at thermal power stations and atomic power stations with application of shaft displacement sensors *Thirteenth International Conference on Condition Monitoring and Machinery Failure Prevention Technologies* (CM2016/MFPT2016) (Charenton-le-Pont France 10-12 October 2016) Northampton: British Institute of Non-Destructive Testing pp 182-95

[14] Kumenko A I, Medvedev S V, Bojchenko S N 2019 Problems of ensuring reliability in the design and development of high-power steam turbine units with nozzle steam distribution 16th *International Conference on Condition Monitoring and Machinery Failure Prevention Technologies* (CM 2019/MFPT 2019) pp 191-203

[15] Kudryavtseva I S, Naumenko A P, Odinets A I, Basakin V V 2020 Influence investigation of rolling bearing test conditions on the informativity assessment of their technical condition *Journal of Physics: Conference Series. IV International Scientific and Technical Conference "Mechanical Science and Technology Update"* MSTU-2020 p 012018

[16] Kostyukov A V, Boychenko S N, Burda E A 2018 Condition monitoring and diagnostics of drive isolation in rotating machinery of petrochemical facilities by partial discharge method *AIP Conference Proceedings, Oil and Gas Engineering, OGE* 2018 p 050009

[17] Kostyukov A V, Boychenko S N, Burda E A, Zhiltsov V V 2019 Method of diagnosing electrical insulation in process of remote computer monitoring of process equipment *Patent RU 2709604 C1*

[18] Khinchin A Ya 1953 The concept of entropy in probability theory *Uspekhi matematicheskikh nauk* vol 8 3(55) pp 3-20

[19] Prangishvili I V 2003 Entropy and other systemic patterns: Issues of management of complex systems *I V Prangishvili Institute of management problems of V A Trapeznikov Moscow Nauka* 428 p

[20] Chumak O V 2011 Entropy and fractals in data analysis *Research Center "Regular and Chaotic Dynamics", Institute of Computer Research* Moscow-Izhevsk 164 p

[21] Tsverkov O V 2015 Entropy data analysis in physics, biology and technology *Publishing house of ETU "LETI"* St. Petersburg 202 p
[22] Delgado-Bonal A, Marshak A 2019 Approximate Entropy and Sample Entropy: A Comprehensive Tutorial Entropy 21(6) p 541
[23] Bandt C 2019 Small Order Patterns in Big Time Series: A Practical Guide Entropy 21(6) p 613
[24] Rodriguez N, Barba L, Alvarez P, Cabrera-Guerrero G 2019 Stationary Wavelet-Fourier Entropy and Kernel Extreme Learning for Bearing Multi-Fault Diagnosis Entropy 2019 21(6) p 540
[25] Wan S, Peng B 2019 An Early Fault Diagnosis Method of Rolling Bearings on the Basis of Adaptive Frequency Window and Sparse Coding Shrinkage Entropy 21(6) p 584
[26] Tang G, Pang B, He Y, Tian T 2019 Gearbox Fault Diagnosis Based on Hierarchical Instantaneous Energy Density Dispersion Entropy and Dynamic Time Warping Entropy 21(6) p 593
[27] Dong Z, Zheng J, Huang S, Pan H, Liu Q 2019 Time-Shift Multi-scale Weighted Permutation Entropy and GWO-SVM Based Fault Diagnosis Approach for Rolling Bearing Entropy 21(6) p 621
[28] Chen J, Dou Y, Wang Z, Li G 2015 A Novel Method for PD Feature Extraction of Power Cable with Renyi Entropy Entropy 17(11) pp 7698-712
[29] Mitiche I, Morison G, Nesbitt A, Stewart B G, Boreham P 2018 Entropy-Based Feature Extraction for Electromagnetic Discharges Classification in High-Voltage Power Generation Entropy 20(8) p 549
[30] Shang H, Li Y, Xu J, Qi B, Yin J 2020 A Novel Hybrid Approach for Partial Discharge Signal Detection Based on Complete Ensemble Empirical Mode Decomposition with Adaptive Noise and Approximate Entropy Entropy 22(9) p 1039
[31] Li H, Huang J, Yang X, Luo J, Pang Y 2020 Fault Diagnosis for Rotating Machinery Using Multiscale Permutation Entropy and Convolutional Neural Networks Entropy 22(8) p 851
[32] Novitsky P V, Zograf I A 1985 Estimation of errors of measurement results Energoatomizdat Leningrad 248 p
[33] EA Technology 2021 Listen to the difference between background noise and Partial Discharge Partial Discharge Academy URL https://www.eatechnology.com/news/partial-discharge-academy

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