Cross-Spectrum of Signals of Vibrations and their Application for Determination of the Technical Condition of Dynamic Equipment

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Abstract: The aim of the paper is to develop ranking techniques for dynamic equipment based on its technical conditions, the estimation of recovered resource value and the determination of critical points of time after which equipment operation has to be terminated. Accelerometer data, cross-spectrum for wave analysis and a TOPSIS-based method have been used to achieve the goal. The most significant result of the work is a method of estimating the technical condition of the equipment, which allows: 1) to perform the transition to condition-based equipment maintenance by predicting non-normative work time; 2) to plan preventive repairs; 3) to select performers for repairs and maintenance of equipment based on objective estimates of work quality. The importance of the results is as follows: 1) the application of multi-criteria ranking method allowed to make ranking according to the technical condition of the equipment units for which condition monitoring groups of sensors are used; 2) it is shown that equipment condition changing is non-linear and there are areas of accelerated degradation; when the latter ones are reached, an accelerated condition deterioration is encountered; 3) the application of the technique on the data simultaneously taken from four sensors has shown its ability to conduct a comprehensive estimation without reference to a specific type of failure in conditions when the data from individual accelerometers give different information about the failure due to the different distance from the problem area. The verification of the proposed theoretical results is carried out on the basis of operating time data before a bearing failure, as well as monitoring data on the operation of wind turbine gearboxes.

1 INTRODUCTION

The transition to predictive equipment maintenance and repair is one of the ways to improve the efficiency of production systems due to the fact that it makes it possible to plan equipment maintenance based on the upcoming load (deferred maintenance at high load and conducting predictive maintenance and repair at low load of the production system), as well as reduce the ecological load [1]. There are situations when monitoring and predicting the condition of equipment is a prerequisite for the production systems to function. For example, in China, for oil distillation stations located in the Gobi Desert [2], each maintenance event is very expensive, and because of the remoteness of the object, it is difficult to carry out timely repairs in case of an unexpected accident. The widespread use of wind turbines and their construction on the shelves of the seas and other remote locations from service centers make the task of reducing maintenance costs due to logistical features more acute than before [3].

To predict equipment failures and make an optimal maintenance schedule, statistical approaches were initially considered [4]. However, the use of statistics on equipment failures yields low accuracy, as shown by research in which we proposed to identify the equipment operating condition based on the analysis of the amplitude characteristics of the vibration signal using machine learning methods.

Furthermore, to process statistical data, methods of regression and data mining, machine learning, and neural networks are used, which do not give equally good results on all data and all types of equipment [5]. It is assumed that improving the accuracy is possible if one knows the distribution function of the occurrence of accidents [6] and the cause of failures, which requires large amounts of statistical information or data on the operating time of the investigated dynamic equipment units [7]. In practice, the use of excessive amounts of data leads to the phenomenon of overfitting [8] and erroneous prediction of abnormal equipment operation. In addition, the collected datasets will be unbalanced due to the rarity of some phenomena, which makes the use of machine learning methods inefficient [9]. Currently, regression methods are used to predict the values of critical parameters (equipment characteristics) and machine learning methods to solve the classification problem (determining the current condition of the research object) [10]. In such cases, the parameters to be monitored are, as a rule, technological parameters secondary to the state of the equipment (current consumption values, resistance, friction, etc.).

A large group of methods that have received wide applications are wave methods, the implementation of which is possible after refining the equipment with vibration sensors, installed on the device body, the most important blocks or axes of rotating parts. The basis of all methods using such data is the suggestion that certain changes and/or configurations of recorded signals (wave characteristics) will tell about a particular condition or the process of approaching some desired or not condition [11]. Successful applications of wave process analysis can be found in various fields of science:

- To effectively predict strong earthquakes, seismic wave parameters are analyzed using methods such as spectral analysis based on Fast Fourier Transform and continuous wavelet transform. In seismic exploration, the elastic vibration field data are processed and further analyzed using amplitude control, migration, deconvolution, velocity analysis, and various types of filtering.
- Another example of wave-based diagnostics is the analysis of human sleep, particularly the detection of snoring activity, where sound pressure level and MFCC (Mel-frequency cepstral coefficients) are used to analyze the sound signal, based on which the classification models [12] are trained using the support vector method (SVM), deep learning and multi-core learning [13], also to detect apnea and asthma diagnosis, for which the spectrum analysis of breath noises is used.
- There are widely known cases of application of wave analysis generated by aircraft equipment for noise analysis, technical conditions, analysis of operating modes, and search for solutions to reduce acoustic cluttering of the space [14].
- Wave quality control of static products and monitoring of their condition during operation by wave reflections (it allows to find cracks, material irregularities, cavities) and analysis of vibrations of dynamic equipment are carried out.

Methods of this group can be divided into methods that evaluate changes in indirect parameters (e.g., the frequency parameters of the alternating current device), methods that use information from specially installed sensors (e.g., accelerometers) and methods that require action on the object to evaluate its condition (e.g., hammering and evaluation of wave propagation parameters) [15].

Two types of tasks are considered [16]: 1) predicting the equipment lifetime, 2) classification of the condition, and identification of faults.

The use of the wave description allows us to formulate a mathematical apparatus that will not impose requirements on the mechanisms and technical methods of obtaining a wave, i.e., to use any sensors capable of obtaining the necessary representation of the signal: sound, vibration, electromagnetic radiation, current, light, special characteristics of control systems.

In practice, the presence of a single sensor, as a rule, turns out to be insufficient, which leads to the statement of problems of multicriteria choice, among which only methods of ranking of decisions are applicable for the decision of the received problems as allow to receive stable decisions [17] and, do not apply convolution of criteria [18] (such approach brings certain assumptions in behavior and importance of estimations which lead to errors in decisions) and expert estimations [19] (the system should work in real-time).

Currently, a comprehensive equipment condition analysis taking into account a group of sensors is not carried out. As a result, only a certain type of fault is determined on complex devices [20] or the results obtained are not reproducible in conditions different from the initial conditions [21]. Thus, the purpose of this research is to develop a methodology for ranking equipment by its technical condition (based on information collected from a group of sensors), which will allow prioritizing the order of maintenance, making predictions about the operating time to failure, and estimating the value of restored resource after repairs and maintenance.

2 METHODOLOGY FOR INVESTIGATING THE CONDITION OF DYNAMIC EQUIPMENT

To analyze the vibration signal, it is necessary to identify the features that characterize the degradation of the investigated equipment. For this purpose, the spectral analysis of time series was considered.

Each wave signal can be described by the corresponding power spectral density (PSD) of initial signals, characterizing the energy, which is carried by the considered frequency.

In general case PSD is defined as the Fourier transform of the covariance function[22]:

$$\varphi(\omega) = \sum_{k=-\infty}^{\infty} r(k) e^{-i\omega t},$$

where the covariance function $r(k) = E\{y(t)y^*(t-k)\}$, $y(t)$ – time series.

The most common assessment of PSD is the periodogram:

$$\varphi_p(\omega) = \frac{1}{N} \left| \sum_{t=1}^{N} y(t) e^{-i\omega t} \right|^2.$$

In practice, the frequency variable ω must be discretized and is usually considered $\omega = \frac{2\pi}{N}k,\ k = 0, \dots, N-1$

The use of periodograms has the disadvantage of large fluctuations relative to the true PSD. To solve this problem, smoothing is used using various window functions.

However, the use of window functions can have negative consequences [22]:

- there is the phenomenon of smearing in smoothing. This arises due to the fact that if two peaks of the function $\varphi(\omega)$ are located at a frequency of less than $1/N$, they will appear as one broader peak. Because of this, periodogram-based methods cannot distinguish details in the investigated spectrum that are separated by less than $1/N$ in cycles per sampling interval. Thus, $1/N$ is the limit of spectral resolution for the periodogram method;
- there is the effect of leakage, which is caused by the transfer of power from frequency bands with a large power concentration to bands with less or no power. This leads to a false estimation of the PSD, where the power will be contained at frequencies where it is absent.

Thus, for the most accurate PSD estimation, it is necessary to:

- Select the window length based on a compromise relationship between spectral resolution and statistical variance.
- Select the window type based on a compromise relationship between smearing and leakage effects.

It is possible to solve the above–described problem of selecting smoothing parameters only experimentally for the specifies investigated signal, which requires additional research and is beyond the scope of this work.

Therefore, the Daniell window was used in this work to obtain the PSD estimation because of the simplicity of the software implementation, since this method is based on the idea of reducing the variance by averaging the periodogram over small intervals.

Then the periodogram is calculated as follows [23]:

$$\varphi_D = \frac{2}{f_\Delta N^2} \sum_{m=0}^{M-1} \left| \sum_{n=0}^{N-1} y(t) \cdot e^{-2\pi \frac{n}{N}\left(\frac{f}{f_\Delta / M} + m - \frac{M-1}{2}\right)} \right|^2,$$

where N – number of time series elements; M – averaging factor; f_Δ - frequency resolution equal to M/T ; T – time series length.

As a result, the PSD for frequencies in the range from 0 Hz to Nyquist frequency is calculated for the investigated time series. Nyquist frequency is the cutoff frequency equal to half of the sampling frequency, i.e., $\frac{f_\Delta N}{M}/2$.

Obtaining periodograms for the initial vibration signals allows identifying the significant frequencies that will characterize the condition of the equipment, as can be noticed the spectral density during normative operation and emergency operation is distributed differently (Figure 1), whereas the periodograms of two signals taken during normative operation are similar (Figure 2).

As can be seen from the above figures, it can be assumed that the degree of equipment deterioration may be identified by comparing the PSD distribution of the recorded signal with the benchmark.

Definition. *The characteristic taken at the first run of the new equipment can be used as a benchmark.*

Thus, the condition of each equipment unit will be estimated from the similarity degree of vibration signal PSD estimation with the benchmark one, thereby allowing to track the deterioration dynamics of a particular equipment unit, as well as to compare the deterioration degrees of several equipment units among themselves. This assumption allows us to refuse from singling out the frequencies contributed by each component of the investigated equipment unit [24] and tracking the changes by the set of these frequencies. Such an approach, on the one hand, makes it unnecessary to decompose the signal into separate components contributed by each element of the dynamic system but excludes the possibility of precise identification of the failure cause, which will require stopping and carrying out maintenance of the equipment.

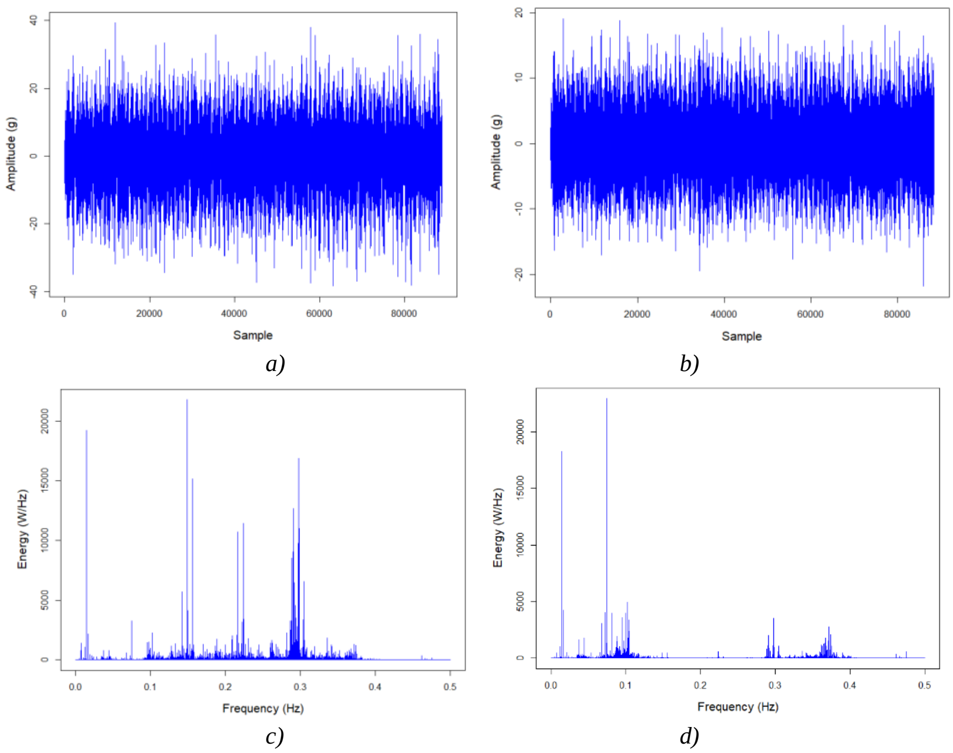

Figure 1: a) Initial vibration signal during normative wind turbine gearbox operation; b) initial vibration signal during emergency wind turbine gearbox operation; c) periodogram of the signal a); d) periodogram of the signal b).

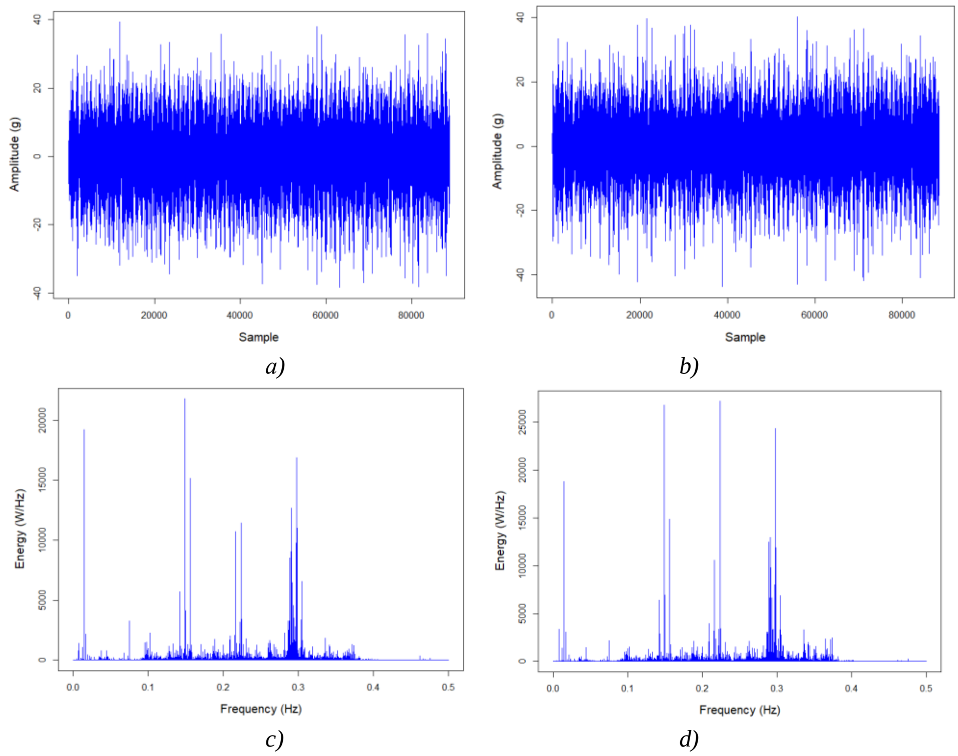

Figure 2: Periodograms c), d) of vibration signals a) and b) respectively, taken during normative operation of wind turbine gearboxes.

To estimate the similarity of PSD of two time series a cross-spectrum is used [25]:

$$\varphi_{xy}(\omega) = \frac{1}{\pi} \sum_{k=-\infty}^{\infty} r_{xy}(k) e^{-i\omega k},$$
$$\text{where } 0 < \omega < \pi,$$

where cross-covariance function $r_{xy}(k) = E\{x(t)y^*(t-k)\}$.

In contrast to the PSD estimation of a single time series by periodogram $\varphi_p(\omega)$, the function $\varphi_{xy}(\omega)$ is complex:

$$\varphi_{xy}(\omega) = c(\omega) - iq(\omega),$$

where the function $c(\omega) = \frac{1}{\pi}\sum_{k=-\infty}^{\infty} r_{xy}(k)\cos(\omega k)$ – co-spectrum, and the function $q(\omega) = \frac{1}{\pi}\sum_{k=-\infty}^{\infty} r_{xy}(k)\sin(\omega k)$ – quadrature spectrum.

As a result of cross-spectrum calculation for each frequency of the investigated vibration signal, the similarity with the benchmark signal is evaluated.

Since the power spectral density is usually measured in decibels, it is necessary to convert $f_{xy}(\omega)$ to $\lg\left(f_{xy}(\omega)\right)$ before performing any operation on the obtained cross-spectrum.

As mentioned earlier, the cross-spectrum allows estimating the similarity at each frequency between two time series, while the criterion for ranking should be one number, which would uniquely characterize the state of the investigated equipment. Since the closer, the current state to the benchmark condition, the greater the cross-spectrum values, and respectively the average value across all frequencies at normative operation will be greater than at faulty operation, and as the equipment wears, the average value of the cross-spectrum will decrease. Accordingly, the average value of the cross-spectrum will be used as a criterion.

Due to the fact that $\varphi_{xy}(\omega)$ is a complex function, the criterion is also a complex value, but, as seen in Figure 3, information about the magnitude of the imaginary and real parts of the criterion (averaged co-spectrum and averaged quadrature spectrum) is not so important for the condition evaluation, but the criterion closeness to the coordinate origin on the complex plane is important, so the complex value of the criterion can be replaced by its modulus.

The dynamic equipment is a complex device consisting of many elements, so the signal is taken not from one vibration sensor, but from several, located on different parts of the equipment. This leads to the task of estimating each piece of equipment condition, based on multiple signals.

The task of evaluating dynamic equipment conditions is reduced to comparing the current states of different pieces of equipment with each other or tracking the deterioration dynamics, in other words, comparing the current state with the previous measurements taken at certain intervals. Then for the task of condition estimation according to the data from several sensors, one of the solutions is the use of outranking methods for multi-criteria ranking of the equipment condition.

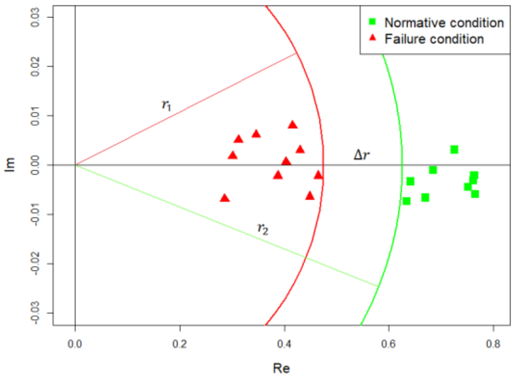

Figure 3: Divergence of wind turbine gearbox condition estimations by the vibration signal in the complex plane.

Among outranking methods, the TOPSIS [26] method is based on the identification of positive ideal (PIS) and negative ideal (NIS) solutions which, in the presence of data on the operating time of failure, will correspond to the conditions of new equipment and out of service (shutdown). Thus, all units of equipment or characteristics of one device removed during the operation will be systematized in relation to these states if we assume that values of criteria monotonically increase or decrease (the technical condition cannot spontaneously improve during operation).

The work of the method can be described in seven steps.

Step 1: Create a scoring matrix consisting of m measurements for n sensors, with scoring values in intersections P_{ij}; $i = 1, \dots, m$; $j = 1, \dots, n$.

Step 2: Normalize the matrix of P_{ij} values and obtain a matrix R consisting of elements r_{ij} calculated by the formula: $r_{ij} = \frac{P_{ij}}{\sqrt{\sum_{k=1}^{m} x_{kj}^2}}, \forall i, j$.

Step 3: Calculate the weighted normalized decision matrix $t_{ij} = r_{ij} \cdot w_j$, $\forall i, j$, where $w_j = W_j \big/ \sum_{k=1}^{n} W_k$, $\forall j$, where W_j – is the initial weight assigned to the j- th criterion (indicator). Obtain the values of the weights satisfying the following equality $\sum_{i=1}^{n} w_i = 1$.

Step 4: Determine the worst (A^-) and the best (A^+) alternatives:
$A^- = \{(\max(t_{ij}) \,|j \in J^-), (\min(t_{ij}) \,|j \in J^+)\} \equiv t_j^+,$
$A^+ = \{(\min(t_{ij}) \,|j \in J^-), (\max(t_{ij}) \,|j \in J^+)\} \equiv t_j^-,$
$\forall j,$
where J^- is the set of indicators an increase in the value of which brings a negative result, J^+ is a set of indicators, an increase in the value of which has a positive result.

Step 5: Calculate the Euclidean distance for the *i*-the alternative with the worst solution:

$$A^- \, (d_i^- = \sqrt{\sum_{j=1}^n (t_{ij} - t_j^-)^2}, \forall i)$$

and with the best solution:

$$A^+ \, (d_i^+ = \sqrt{\sum_{j=1}^n (t_{ij} - t_j^+)^2}, \forall i),$$

where d_i^- and d_i^+ are the Euclidean distances to the worst and best solutions.

Step 6: Calculate the closeness to the best or worst state: $s_i^- = {d_i^-}/{(d_i^- + d_i^+)}$ или ${d_i^+}/{(d_i^- + d_i^+)}$.

Step 7: Ranking the alternatives by the values of s_i^- or s_i^+, $\forall i$.

For successful application of such approach, it is necessary: to choose criteria for ranking; to choose the most appropriate ranking method; to determine the internal parameters of the chosen ranking method (criterion weights, maximization/minimization of each specific criterion, etc.). The general scheme of the algorithm for a set of sensors can be represented in Figure 4.

3 EXPERIMENTAL RESEARCH ON THE APPLICABILITY OF THE PROPOSED METHODOLOGY

Due to the presence of moving elements in the dynamic equipment design, constant state degradation of such elements is unavoidable. One of the most common elements in dynamic equipment is bearings, which ensure the rotation or rolling of the connected structural elements with the least resistance, so bearing wear will noticeably affect the operation of the equipment as a whole.

To verify the proposed approach, we will use the data on the failure time of the bearings, which can be downloaded from the link[1]. The availability of the data on the operating time between failures allows estimating the distance to the breakdown condition

The vibration signal is received from two sensors; therefore, the ranking will be performed according to two criteria. In this case, the task is to track how far the technical condition of the equipment is from the emergency condition, so we will take the emergency condition as an ideal-positive solution, respectively, when reducing the criteria, the condition will approach the emergency condition, that is, the criteria must be minimized.

So, at the dynamic condition change, it is impossible to evaluate which of the sensors most clearly shows degradation, the weights will be equal.

According to the obtained results (Figure 6), it can be concluded that the condition is gradually moving from normative to emergency and the rating score is also increasing, as expected.

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[1]https://drive.google.com/drive/folders/1_ycmG46PARiykt82ShfnFfyQsaXv3_VK

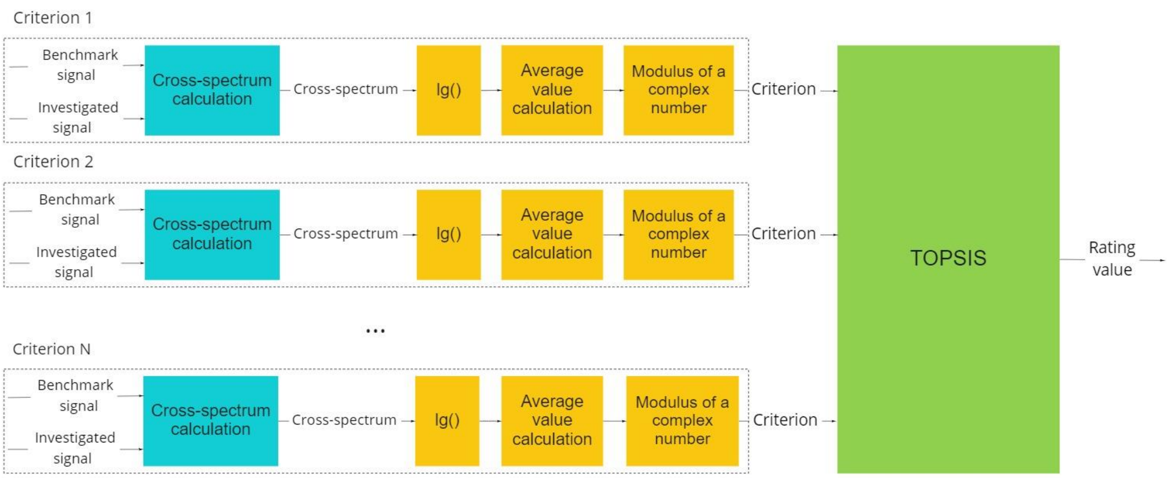
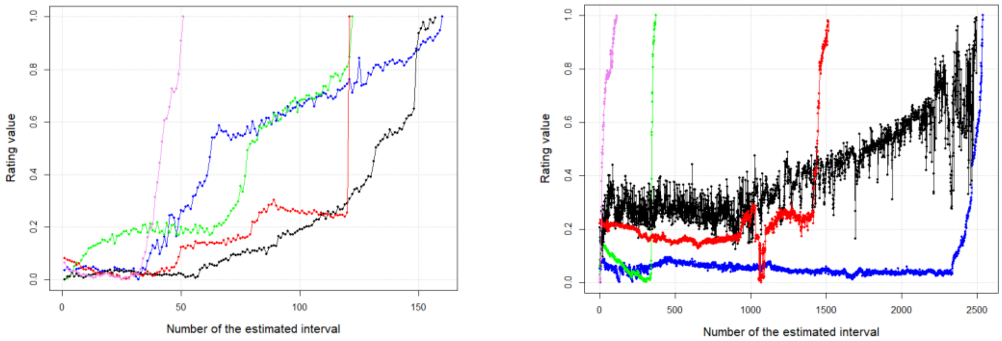


Figure. 4: Algorithm for estimating the condition of the equipment with multiple sensors installed.

The problem. There is no monotony of change and there are fluctuations in the process of tracking the deterioration, and as the bearing rotational speed increases, the fluctuations increase

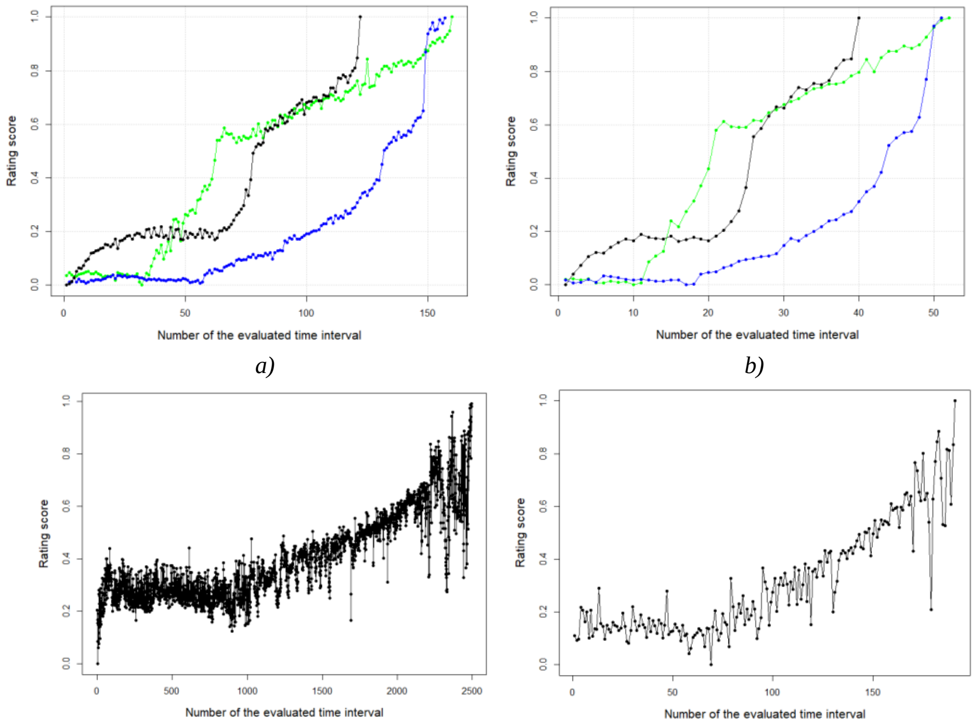
This problem can be caused by the fact, that the experiments were carried out in conditions of accelerated degradation far from the normative ones, assuming sharp random bursts of vibration signal fluctuations, which worsen the method performance. as well as when solving the problem of tracking wear dynamics, an important factor is the choice of the estimation time interval size, the method of smoothing, and the size of the smoothing window.

By increasing the size of the evaluation interval, we can notice a decrease in fluctuations in the dynamics of change in the condition of the investigated equipment (Figure 7), but another problem arises, related to the fact that with too large an interval the probability of untimely detection of critical equipment wear increases.



a) *b)*

Figure 6: Result of 5 bearing deterioration dynamics ranking a) first experiment at 35 Hz rotation speed and 12 kN load, b) third experiment at 40 Hz rotation speed and 10 kN load.



a) *b)*

c) *d)*

Figure 7: Influence of the evaluation time interval on the quality of the ranking. With an initial interval of 1 minute for experiments a), there were small fluctuations, which were noticeably smoothed out in experiment b) when the interval size was changed from 1 minute to 3 minutes. In experiment c) the evaluation was made with an interval of 1 minute and in this case very strong fluctuations and sharp jumps can be observed, when the interval is changed to 13 minutes in experiment d) it is possible to notice a decrease in the number of fluctuations and emissions, but they are still present.

Experiments show that depending on the period of the data taken for analysis, there is an increase or decrease in the magnitude of fluctuations in the analysis data, which indicates the need to choose for each equipment unit the value of time for data acquisition, as well as the periodicity of these operations.

A more complex example is the gearbox in a wind turbine structure. As soon as a failure occurs in the wind turbine gearbox, the efficiency of power generation inevitably decreases, and eventually, unplanned downtime happens [27]. Thus, monitoring the condition of dynamic equipment is necessary not only to prevent emergency breakdown and resulting downtime but also to avoid losses in operational efficiency.

There is open-source data on the performance of generators and gearboxes of wind turbines (data available on the portal of the U.S. National Renewable Energy Laboratory[2], but the results obtained in the currently known studies carried out on them show their effectiveness only on this data [28], which confirms the relevance of the goal.

Since there are four vibration sensors on the investigated equipment, the TOPSIS ranking will be estimated according to four criteria.

As mentioned earlier, and as can be seen from previous calculation results, the criteria decrease as the equipment deteriorates. Since the ranking on this dataset involves comparing several wind turbine gearboxes relative to each other, the larger the criterion, the larger the score should be since it is closer to the benchmark condition, therefore each criterion within the TOPSIS method should be maximized.

Not all sensors can track the wear of equipment, so it is necessary to calculate the matrix of weights W_j so that the criteria from the sensors that show the most obvious wear of equipment have a greater impact on the condition evaluation.

- Calculate the average values for each criterion for each state (normative/emergency):

$$P_j^+ = \frac{\sum_{i \in S^+} P_{ij}}{N^+}, \forall j,$$

where P_j^+ – the average value of j-th criterion during normative operation, S^+ – set of gearboxes operating in normal mode, N^+ – the number of gearboxes operating in normal mode;

$$P_j^- = \frac{\sum_{i \in S^-} P_{ij}}{N^-}, \forall j,$$

where P_j^- – the average value of j-th criterion during emergency operation, S^- – set of gearboxes operating in emergency mode, N^- – the number of gearboxes operating in emergency mode;

- calculate the weights $W_j = \frac{|P_j^+ - P_j^-|}{max\{|P_j^+ - P_j^-|\}_{\forall j}}$.

Thus, the criterion that has on average a large difference between the values at different modes of operation will have a greater weight.

Based on the results of the ranking (Figure 8) it can be seen that the equipment units, the state of which was classified as normative are at the top of the rating with some gap, which confirms the hypothesis about the divergence of equipment estimates, which are in normal and emergency modes.

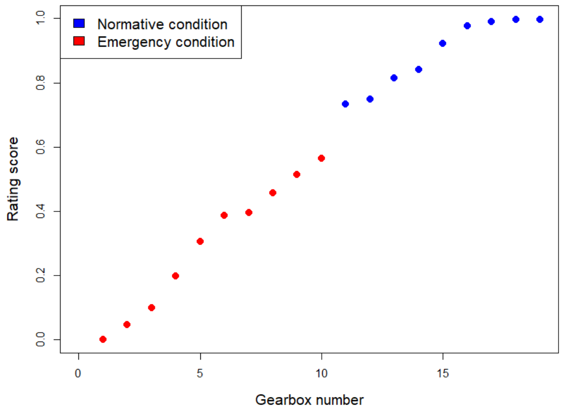


Figure 8: Ranking of wind turbine gearboxes by deterioration using TOPSIS method.

4 DISCUSSION

Thus, we obtain several options for using the approach described in the article, related to the ranking of the same type of equipment by its technical condition to determine the maintenance priorities.

Another way to use the results obtained can be to estimate the change in the condition of the equipment after maintenance or repair. In this way, it is possible to estimate the value of restored lifetime and on the basis of such statistics to solve the problem of selecting a service provider.

The performance quality of the algorithm depends on the accuracy of the ranking, which in its turn depends on such parameters of the algorithm as the time period of equipment vibration measurement, the number of used signals/sensors, the type of the time window function used to build cross-spectrum.

[2]https://openei.org/datasets/dataset/gearbox-fault-diagnosis-data/resource/affa53da-cae6-42f2-b898-ad018ff91641

The proposed algorithm provides the necessity of selecting the internal parameters such as the type of smoothing window, the size of the smoothing window, the size of the estimation time interval, which allows for each case to choose the solutions best suited by the morphological synthesis method (Table 1) and [29].

In the literature, tasks related to failure time prediction are most often considered. The application of the described approach made it possible to reduce the amount of information that contains information about the equipment condition. Thus, the dimensionality of the problem is reduced to one degree of freedom (DOF), which simplifies the task of selecting the estimation/descriptive data function or selecting the ML method for predicting failures [24], and also makes it possible to estimate the condition by an expert method.

Experiments show that when using S-curve regression methods and machine learning methods, the algorithms, correctly, predict trends [30]. In the case of S-curves [31], the inflection point shows the transition from normative operation to non-normative operation (Figure 9), and when using ML algorithms, we predict the time of complete failure and shutdown of equipment unit (Table 2) [32].

Table 1: Example of a morphological table.

	Alternatives				
Parameter	1	2	3	4	…
A) Smoothing window type for cross-spectrum calculation	Daniell's Window	Blackman-Harris Window	Hann and Hamming windows	Kaiser-Bessel Window	…
B) Smoothing window size when calculating the cross-spectrum	2	4	6	8	…
C) Size of the time interval for the evaluation of the equipment condition	1 min	2 min	3 min	4 min	…

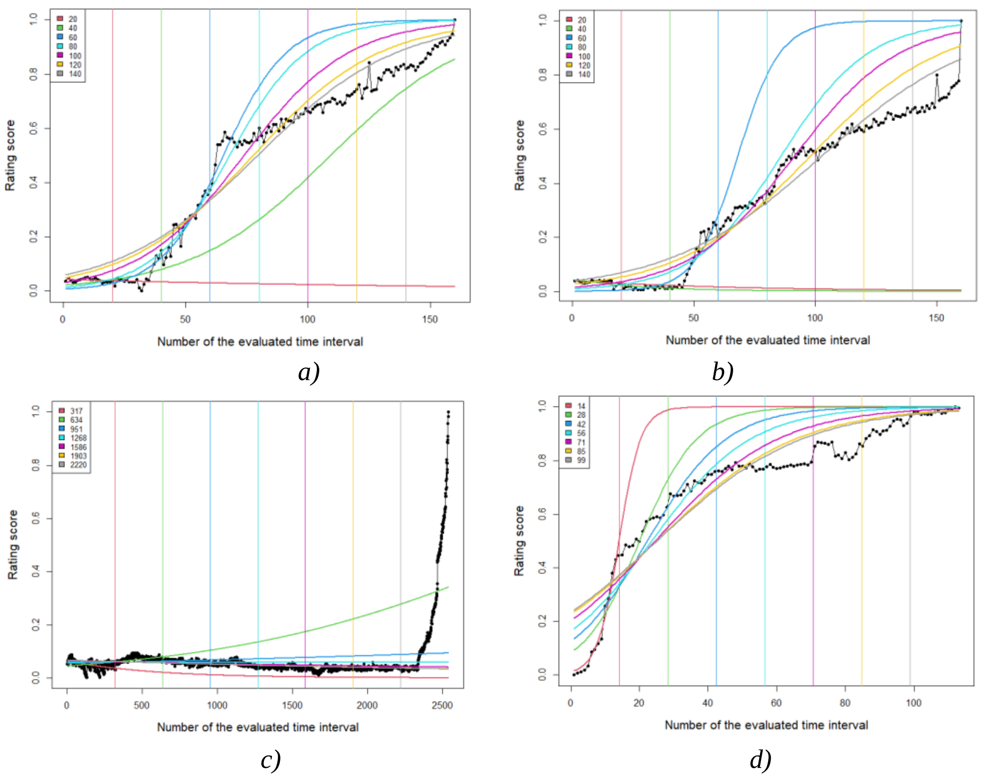


Figure 9: Results of S-curves for a) experiment 1_2, b) experiment 2_2, c) experiment 3_1, d) experiment 3_5.

Table 2: Comparison of real time to failure in estimation intervals with predicted one using models trained by ElasticNet, Ridge, and Lasso methods for experiment 2_2.

Real number of evaluation intervals to failure	Predicted value		
	ElasticNet	Ridge	Lasso
140	90.278476	89.387534	88.718160
130	91.299122	90.818057	90.454385
120	91.353579	90.635841	90.125312
110	84.615569	86.434416	83.321456
100	73.156105	73.173403	72.412751
90	68.560701	68.295393	67.208324
80	67.148999	65.342441	66.392584
70	51.773237	53.533065	53.360640
60	53.740850	50.701370	51.854554
50	47.007266	47.528948	50.048620
40	43.904362	42.878614	45.834927
30	39.439278	40.118334	42.781805
20	36.810094	37.415678	41.023638
10	34.584381	35.482358	39.560329

Even though the conducted experiments show that it is possible to refuse from using all the data collected from the sensors, the accuracy of the algorithms is not high, which indicates the need for additional adjustment associated with the choice of algorithm parameters (see Table 1) and additional research associated with the choice of data description method and/or machine learning method that gives the best results in each specific case [5].

5 CONCLUSIONS

The article presented the research related to the identification of the equipment condition based on vibration signals through vibration diagnostics signal analysis, namely: 1) developed a model of equipment condition identification, distinguished by the use of periodograms of signals coming from vibration sensors; 2) developed a method of equipment condition estimation, distinguished by the use of multi-parameter ranking of equipment condition.

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