DOC: 10.18372/2310-5461.63.18952
UDC 519.81.07

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COMPUTER DIAGNOSTICS OF THE CONDITION OF SHIP ROLLING BEARINGS DURING THEIR OPERATION

Introduction

The primary purpose of shipboard vehicle diagnostics is to promptly detect deviations of monitored parameters from the standard values, identify and localise detected defects, develop operating modes and strategies, and forecast resources.

The practical focus of such work is to change the overhaul cycle for diagnostics by switching from working according to the schedule to working according to the actual condition of the equipment. This optimisation of the monitoring process helps improve the equipment's reliability and uptime. This provides an additional economic effect, as in addition to reducing the labour intensity of diagnostic work, it eliminates the need to shut down equipment. Intelligent support for monitoring the technical operation of shipboard equipment is based on assessing the transformation of material structure deformation into a fixed signal of various origins. A combination of statistical, dynamic, deterministic and stochastic models with discrete and continuous time is used to increase monitoring efficiency. This makes it possible to replace analytical representations with digitalisation with fixed loads exceeding the normative ones.

The functional purpose of rolling bearings is to ensure shaft rotation with a minimum friction coefficient. Technical diagnostics by regulatory documents is the determination of the technical condition of an object. This is a higher assessment of the remaining service life than non-destructive testing and flaw detection methods. Technical diagnostics refers to the range of values used to determine the technical condition of an object. Non-destructive testing methods and the analysis and establishment of pattern changes in performance characteristics regulate it. Its tasks include finding the places and causes of faults and predicting the current state. Monitoring involves observing and checking the quality of equipment with mandatory notification. Residual life is the total operating time of an object from the moment of monitoring its technical condition to the limit state. In this case, the limit state of the equipment is understood as a condition in which further operation of the equipment is impractical. Assessment of the residual life in the absence of peak information and extreme loads on the equipment during overhaul cycles is subject to several limitations and inaccuracies caused by dynamic environmental changes, i.e., a risk situation.

Problem statement

Regular operation of ship power plants depends on the proper functioning of their main components: cylinder-piston group, fuel equipment, gas turbine chargers, bearings, etc. Among the failures of ship power plant components, the most common are rolling bearing failures. Ship rolling bearings are located in the propeller shaft support bearing, the main engine frame bearings, and the thrusters. Damage to ship rolling bearings is detected by measuring vibrations. Wear causes changes in the centre of mass displacement trajectory and the appearance of shock impulses. The spectrum of vibration signals contains the necessary information about the occurrence and development of bearing defects during their operation. The variety of statistical characteristics of vibration signals and the ambiguity of their trends complicate their practical use. The use of the principal component method is promising for this purpose.

Objective of the work is the search for and practical use of new information and diagnostic parameters for monitoring vibration signals in ship rolling bearings based on their computer mathematical processing. Based on this, an important issue in the operation and maintenance of vehicles is the creation of models, methods and diagnostic techniques.

Analysis of the latest research and publications

The information parameters for predicting the residual life can be significant damages manifested in the form of corrosion, wear, and deformation creep and parameters of related processes, such as vibration levels, leakage rates, the temperature of friction units, and product consumption relative to average values. The continued interest in the problem of the residual life of equipment is manifested in the availability of publications and reviews on various industry topics [1–3]. Based on the results of numerical methods of fracture mechanics, a method for predicting the residual life of bearings of rotating mechanisms is proposed in [4]. The method is based on noise reduction of wavelet packets and combining information in the form of complex characteristics of bearing life. The further development of methods for estimating the residual life based on the results of numerical methods of fracture mechanics was initiated in [5], where the problem of fatigue failure of hydraulic turbine parts after a long service life was considered. A failure intensity model was developed based on the stress-strength interaction. Paper [6] presents the results of developing methods for estimating strain fields, stresses, and residual life using experiments and numerical methods of fracture mechanics. In [7], it is shown that machinery and equipment failures are caused mainly by the intersection of critical states defined by the limit values of stresses and strains. The development of methods for non-destructive testing and technical diagnostics of the condition of equipment operating under pressure is described in [8]. In [9], an acoustic-emission method is proposed for predicting the degree of degradation of mechanical properties and residual life of metal structures under complex deformation stresses. A method for determining the residual life based on a polynomial approximation of the results of acoustic measurements and the construction of boundary curves separating the serviceability region from the fracture region is proposed. The experience of using non-destructive testing to assess the residual life of petrochemical transport equipment is described in [10]. Among the methods of non-destructive testing of the residual life and their practical applications, it is interesting to note [11], which formulates an approach to determining the kinetics of crack growth. Paper [12] shows that, based on the frequency of maintenance, an increase in the reliability of determining the residual life of the equipment is achieved by dynamically adjusting the time interval between diagnostic processes. Paper [13] analyses data on the operation of reactor equipment and their compliance with existing standards and regulatory frameworks. The authors established the need to develop uniform rules for selecting physical parameters that characterise the state of equipment, considering its degradation. To solve the problem of modelling the maintenance of complex electromechanical equipment, a model for predicting the residual life is proposed in [14]. The level of sensitivity of these methods does not allow us to detect the condition of objects and identify areas of future destruction. A reliable method of monitoring long-life equipment during its operation can be obtained by combining subjective expert and objective elements of technical diagnostics with methods of processing available information using mathematical modelling and probabilistic dynamics. The main diagnostics directions, including the information materials analysis, are shown.

Summary of the main material

The rules for the operation of ship power plants stipulate that after the bearings have been installed, they must be adjusted and lapped by running the engine. The condition of rolling bearings is monitored during maintenance or overhaul. As the objects of study, we used marine rolling bearings of the turbocharger VTR304P11/021 of the main engine MAN B&WL32/40 Fig. 1.

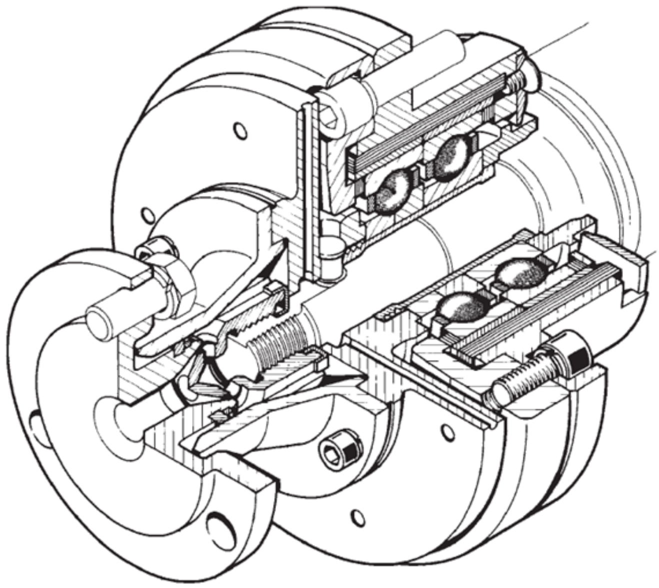

Fig. 1. Design features of the ship's turbocharger rolling bearing VTR304P11/021

Technological arrangement: 12 balls of 4 mm in two rows on the compressor side and 12 rollers of 14 mm in one row on the turbine side. The statistical characteristics of vibration signals during operation of these bearings were used as research materials. The principal component method was used as research methods, which consists in combining statistical features of different dimensions and obtaining new patterns.

The fundamental phenomena and concepts that can be used in the model of monitoring the state of rolling bearings can be represented either in a model with one degree of freedom, or in a model with several degrees of freedom, or in the model of an inelastic string. The fundamental phenomena of the concept of spectral statistical processing of vibration signals in their meaningful interpretation can be considered in the form of a propagating output signal, depending on both time and frequency, and their Fourier images

$$u(\omega) = \int u(t) e^{i\omega t} dt; \quad u(t) = \frac{1}{2\pi} \int u(\omega) e^{-i\omega} d\omega ,$$

where $u(t)$ time offset function; $u(\omega)$ – frequency offset function

The discrete structure of nanoscale objects is characterised by proximity [15,16]. The equation of motion of microparticles has the form

$$m\ddot{u}(n,t) + \sum_{n'} \Phi(n,n') u(n',t) = q(n,t),$$

where n, n' – numbers of interacting particles, $\Phi(n, n')$ – power constants, $u(n, t)$ – displacement.

At a high sampling rate in such a model, oscillatory signals can be filtered out and the most informative ones selected.

The invariance of energy with respect to translation makes it possible to replace the motions of atoms with the motion of the centre of mass in material objects of finite dimensions. The nodes of such a cell can contain domains, fullerenes, molecular clusters, etc. [17-19]. The kinematic variables of such a model are not only the longitudinal and transverse displacements of masses, but also the angle of rotation in the same plane. This state with these variables is close to rotational.

Having learnt through $q(n)$ and $\mu(n)$ generalised forces, we obtain the equation of motion of the whole cell

$$m\dot{u}(n) + \sum_{n'} \Phi^{00}(n-n') u(n') + \sum_{n'} \Phi^{01}(n-n') \eta(n') = q(n),$$

$$I\dot{n}(n) + \sum_{n'} \Phi^{10}(n-n') u(n') + \sum_{n'} \Phi^{11}(n-n') \eta(n') = \mu(n),$$

here $u(n)$ – centre of mass movement, $\eta(n)$ – displacement of particles in the middle of the cell.

$$\eta(n) = \frac{m_1 \xi_1 \omega(n,1) + m_2 \xi_2 \omega(n,2)}{I},$$

$$u(n) = \frac{1}{m} [m_1 \omega(n,1) + m_2 \omega(n,2)],$$

where I – moment of inertia of the cell, ξ_1 and ξ_2 – coordinates of particles relative to the centre of mass, $m = m_1 + m_2$, $I = m_1 \xi_1^2 + m_2 \xi_2^2$

Solving these equations allows us to find the equation of the energy spectrum of a continuous medium.

Another type of theories of diagnostic signals during the operation of rolling bearings belongs to the molecular theory of rolling, which is based on the energy interaction of contacting surfaces. Moving to larger scales of interacting bodies during rolling, it should be noted that the rolling friction force itself depends on the area of physical contact, being a function of pressure, sliding speed, temperature and other factors. Vibration diagnostics of rolling bearings in the process of dynamic and static loads occurring on operating equipment is carried out by direct spectrum analysis methods, envelope spectrum methods, peak-factor methods and shock pulse methods. Vibration diagnostics of rolling bearings of power plants is carried out by analyzing a large number of diagnostic parameters. A malfunction leads to a vibration of the turbocharger shaft torque with a characteristic frequency determined by the formula

$$f = 0.5 N_B \cdot f_r \left(1 - \frac{D_b \cos\theta}{D_C}\right),$$

where D_b – ball diameter, D_c – diameter of the circle drawn through the centres of the balls, θ – ball contact angle, f_r – bearing rotation speed, N_B – number of balls in the bearing.

The configuration of a ball bearing with a developing defect is shown in Fig. 2, and the bearing parameters are given in Table 1.

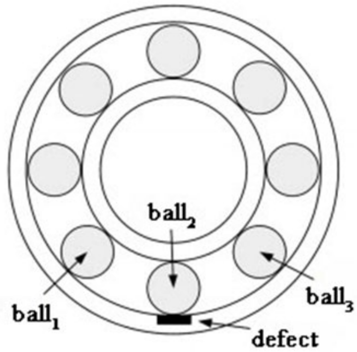

Fig. 2. Ball bearing with a defect in the outer ring

Table 1

Parameters of the VTR304P11/021 turbocharger rolling bearing and characteristic vibration frequency of the outer ring point defect

D_b, mm	D_c, mm	N_B	Θ, rad	f_r, Hz	f, Hz
14	90,9	12	0	485	2461,9

The diversity of causes and statistical features of vibration signals leads to the need for their complex integration and appropriate mathematical processing of experimental information. A promising method for solving this type of problem is the principal component method, which allows for the extraction of useful signals when their amplitude is lower than the noise level.

The principal component method is one of the main methods of reducing the dimensionality of data with the least loss of quantitative information. The calculation of the principal components is reduced to the calculation of the singular value decomposition of the data matrix or to the calculation of the eigenvectors of the covariance matrix. In the case of vibration diagnostics, the formalisation of the principal component method is the construction of an orthogonal transformation of the coordinates of a given multidimensional random variable, which makes the correlation between individual coordinates zero. Principal component analysis is the calculation of the principal components to change the structure of the input data using several basic iterations. In practice, the method begins with solving the problem of approximating a finite set of points by lines and planes.

Technologically for a set of vectors $x_1, x_2, \ldots, x_m \in R^n$ linear varieties take the following values $S_k \subset R^n$, in which the sum of squares of deviations x_i from S_k is maximal, i.e.

$$\sum_{i=1}^{m} dist^2(x_i, S_k) \to \min$$

where $k = 0, 1, 2, \ldots, n-1$ linear diversity in R^n, $dist(x_i, S_k)$ euclidean distance

The calculation of the principal components is reduced to a singular value decomposition of the eigenvectors of the covariance matrix of the original data. The formalisation of the principal components method is the construction of an orthogonal coordinate transformation, which will make the correlations between hotel coordinates turn to zero.

Technically, at each $2k$-1 step, the projections on the previous principal component are subtracted. The found vectors are orthonormalised as a result of solving the optimisation problem. The found vectors are orthonormalised as a result of solving the optimisation problem.

The mathematical content of the principal component method is reduced to the spectral decomposition of the covariance matrix. The implementation of the methodology is associated with continuous periodic registration of control parameters and comparison of the results with the reference values.

Linear varieties are defined by a set of principal components, vectors $\{a_1 \ldots a_{k-1}\}$ and the vector a_0, which is defined by minimising S_0:

$$a_0 = \underset{a_0 \in R^n}{\arg}\left(\sum_{i=1}^{m} dist^2(x_i, S_0)\right) = \underset{a_0 \in R^n}{\arg\min}\left(\sum_{i=1}^{m} \left|x_i - a_0\right|^2\right)$$

The variational definition of the mean as the point that minimises the sum of squares is

$$a_0 = \frac{1}{m}\sum_{i=1}^{m} x_i^2$$

The projection onto these axes retains the most information. The first principal component maximises the sample variance of the data projection. The task is to find an orthogonal transformation to a new coordinate system that maximises the sample variance of the data along the first coordinate.

The second principal component, provided that the first coordinate is orthogonal, maximises the sample variance of the data along the second coordinate.

K-th principal component under the condition of orthogonality k-1 coordinates maximises the sample variance of the data along the values k-1 coordinates. Solving the problem of the best approximation yields the same set of principal components as the search for orthogonal projections with the greatest scatter. The task of determining the principal components is reduced in its methodological plan to the task of diagonalising a sample of the covariance matrix.

The operations of the methodology of using the principal components method and finding specific components are

– centre the data by subtracting the average $x_i := x_i - \bar{X}_i$, where symbol := means equality by definition;

– calculating the first principal component by solving the problem

$$a_1 = \arg\min_{|a_1|=1}\left(\sum_{i=1}^{m}\left|x_i - a_1(a_1, x_i)\right|^2\right);$$

– subtracting the projection to the first principal component from the data

$$x_i := x_i - a_1(a_1 x_i);$$

– finding the second principal component as a solution to the problem

$$a_2 = \arg\min_{|a_2|=1}\left(\sum_{i=1}^{m}\left|x_i - a_2(a_2, x_i)\right|^2\right);$$

– subtracting the projection on the (k – 1) principal component

$$x_i := x_i - a_{k-1}(a_{k-1} x_i);$$

– finding the k-th principal component

$$a_k = \arg\min_{|a_k|=1}\left(\sum_{i=1}^{m}\left|x_i - a_k(a_k, x_i)\right|^2\right).$$

The resulting vectors are $\{a_1, \ldots, a_{k\text{-}1}\}$ orthonormalised. Thus, the methodology for finding the principal components is to subtract the projection to the previous principal component at each preparatory step ($2k - 1$).

Experiment

The measurements are carried out on the ship's bearing housing, namely in the lower part of the bearing assembly, because this is where the loads on the assembly are at their highest. The signals from the sensors can be digitised and recorded for trend analysis. An accelerometer is used to record vibration levels. A vibration signal of 6 s duration was received daily for 10 consecutive days. A bearing malfunction occurred, which led to its failure.

A visualisation of the vibration signals in the time domain is shown in Fig. 3. The colour indication is used to clearly distinguish the vibration signals obtained in each individual dimension. The vibration signals in the time domain show a tendency to increase the signal impulsivity.

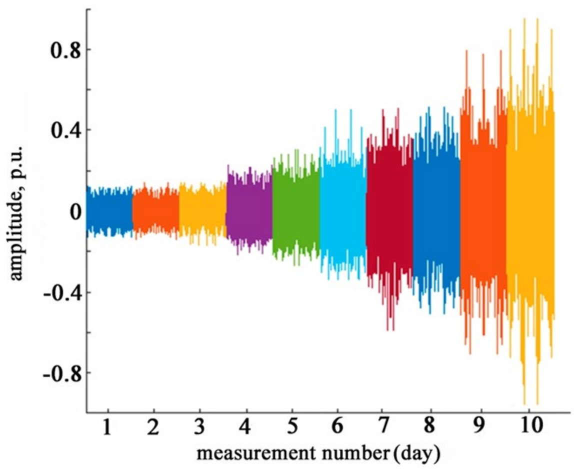

Fig. 3. Visualisation of vibration signals in the time domain for successive measurements on a bearing with a gradual increase in its misalignment

Results

Calculations of statistical characteristics of vibration signals in the time domain, such as standard deviation (Std), skewness (Skewness), kurtosis (Kurtosis), full range of oscillations (Peak2Peak), Root Mean Square (RMS), CrestFactor, ShapeFactor, ImpulseFactor, MarginFactor, Energy, showed an increase in their values during the accumulation of damage. This indicates that they can be potential indicators of bearing degradation (Fig. 4, Table 2).

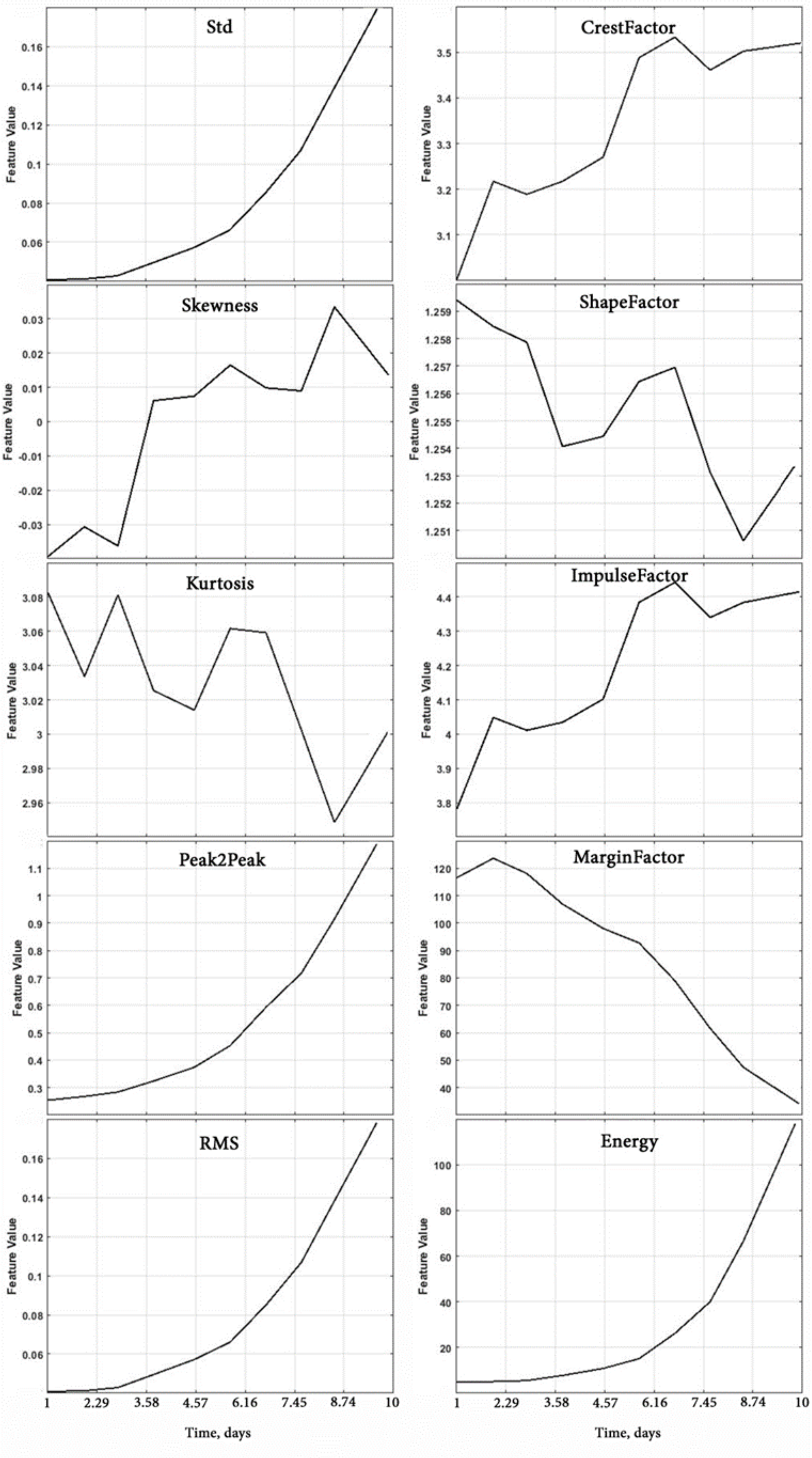

Fig. 4. Evolution of the dimensionless statistical characteristics of vibration signals during the operation of a sliding bearing

Table 2

Statistical characteristics of vibration signals of a ship bearing in the presence of a developing point defect in the outer ring

No. of measurement	Std	Skewness	Kurtosis	Peak2Peak	RMS	CrestFactor	ShapeFactor	ImpulseFactor	MarginFactor	Energy
1	0,0572	-0,0089	1,8192	0,1999	0,0572	1,7476	1,155	2,019	40,777	9,816
2	0,0578	0,0061	1,7982	0,2165	0,0578	1,8889	1,153	2,177	43,398	10,019
3	0,0603	0,0874	2,2855	0,3484	0,0603	3,2386	1,161	3,785	71,136	10,934
4	0,0690	0,1468	3,8063	0,6145	0,0689	4,5265	1,178	5,416	86,692	14,967
5	0,0801	0,2644	4,4138	0,7800	0,0801	5,1182	1,185	6,153	87,080	21,325
6	0,0930	0,2547	5,3490	1,0849	0,0930	5,7282	1,193	6,932	86,681	30,193
7	0,1198	0,4314	16,8085	2,1631	0,1198	7,991	1,251	10,430	106,292	52,310
8	0,1508	0,8135	29,2221	3,1804	0,1508	9,995	1,329	13,826	123,682	80,421
9	0,1958	0,7147	39,4535	4,3363	0,1958	10,885	1,456	16,309	123,719	134,515
10	0,2640	0,7340	47,5874	5,4602	0,2460	11,247	1,596	18,239	120,580	208,424

The variety of statistical characteristics of vibration signals creates the problem of selecting the most reliable and informative characteristic for bearing condition monitoring. Each individual characteristic may be more sensitive for some types of defects and less sensitive for others. Comprehensive monitoring of the condition of the mechanism in terms of the ability to detect various types of defects should be universal. Therefore, for reliable monitoring, the entire set of vibration signal characteristics available for analysis should be taken into account and analysed. This, in turn, makes it difficult to interpret the information obtained in this way. To solve this problem, it is proposed to combine all the analysed statistical characteristics into one generalised one, using the principal component method.

The Principal Component Analysis (PCA) method is used to reduce the dimensionality and combine the statistical characteristics of vibration signals in the time domain, which are given in Table 2. The calculations of the principal components of the vibration signals showed their acceptability for assessing the state of the turbocharger bearing, and the dependence of the change in the first principal component on the accumulation of damage was monotonically increasing, in contrast to other principal components, whose dependence is unstable oscillatory. Thus, the first principal component is a potential combined indicator of the state of the turbocharger bearing. The graph in Fig. 5 shows that the first principal component increases monotonically as the bearing approaches failure.

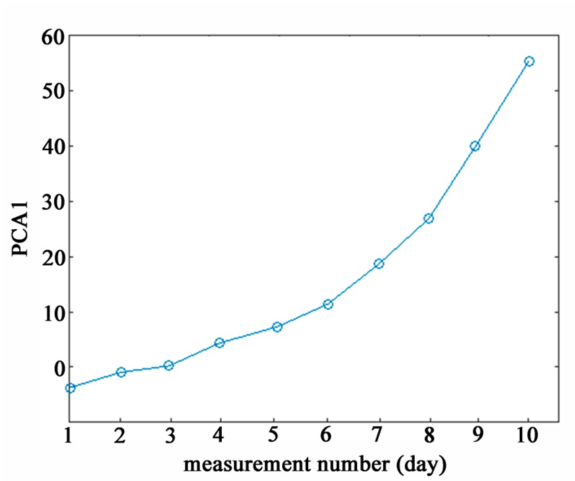

Fig. 5. First Principal Component as a condition indicator for turbocharger bearings

The spectral kurtosis is considered a powerful tool for predicting the condition of bearings in the frequency domain. The spectral kurtosis is a statistical value used in the frequency domain to determine the impulse response of a signal. It is a dimensionless quantity and compares the data distribution to a Gaussian distribution. To visualise the changes in spectral kurtosis over time, let's plot the spectral kurtosis value as a function of frequency and day (number) of measurement (Fig. 6).

The danger of the fault is indicated on the colour scale. It is a measurement number normalised on a scale from 0 to 1. At the beginning of the monitoring process, when the ship's bearing is in good condition, no peaks are observed.

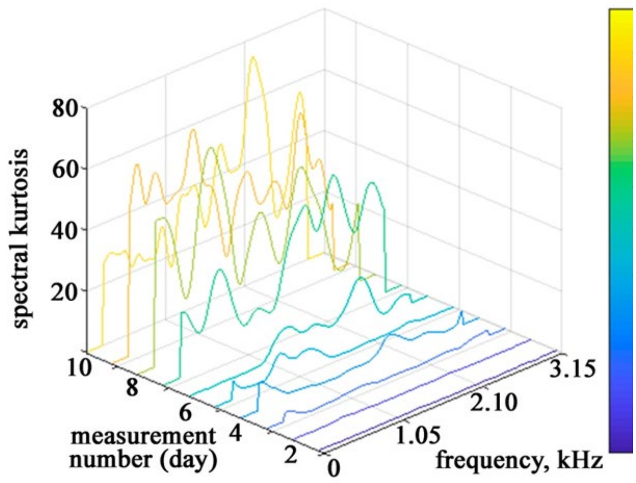

Fig. 6. Dependence of the spectral excess on the frequency and measurement number of vibration signals with a gradual increase in the unbalance of a ship's bearing

The appearance of a pinhole defect is manifested in the appearance of an oscillatory component of the spectral excess, the value of which increases with the approach of bearing failure. It can be clearly seen that the value of the spectral excess near the characteristic frequency of the defect of 2.46 kHz (Table 1) gradually increases as the bearing condition deteriorates.

The spectral excess becomes larger in the frequency band where the fault signal is dominant and is zero in the frequency band where the spectrum is dominated by normal vibration. Thus, the spectral excess makes it possible not only to judge the degree of damage to a ship's bearing, but also to observe the dynamics of the defect development and make a relative forecast of the bearing's service life.

Conclusions

The structure of the vibration spectrum is investigated on the basis of experimental data on vibration monitoring of the operational properties of ship rolling bearings of turbochargers and a large amount of digital information on the parameters of vibration signals preceding destruction. The principal component method was used to analyse the structure of the vibration spectrum.

A new information parameter for vibrodiagnostics of point defects based on the analysis of the magnitude of the change in the time of the first principal component as it approaches the state of fracture is revealed and experimentally confirmed.

An information parameter for predicting the state of ship bearings based on the analysis of frequency changes in the spectral excess of the vibration signal when approaching the state of failure is proposed. The visualisation of changes in the computer diagnostics of this parameter has confirmed the possibility of observing the dynamics of the development of point defects.

The paper considers a real practical situation of vibration monitoring of a point defect in the outer ring of a bearing. The study of the applicability of the principal component method to other types of defects performed in this paper has shown their prospects for vibration monitoring of defects located on the inner ring of a bearing and during ball dropout from the cage.

REFERENCE

[1] Abuelo A., Brester J. L., Starken K., Neuder L. M. (2020). Technical note Comparative evaluation of 3 methods for the quantification of non estenfied fatty acids in bovine plasma samples prepartum. *Journal of Dairy Science*. vol. 103(3), pp. 2711–2717.

[2] Surace C., Bovsunovsky A. (2020). The use of frequence ratios of diagnose structural damage in varying environmental conditions. Mechanical Systems and Signal Processing. Vol. 136, 106523.

[3] Kelin A., Larin O., Naryzhna R., Trubayev O., Vodka O., Shapovalova M. (2019) Estimation of residual life-time of pumping units of electric power stations International Scientific and Technical Conference on Computer Sciences and Information Technologies, 1, art. no. 8929748, pp. 153–159. Cited 7 times. DOI: 10.1109/STC-CSIT.2019.8929748

[4] Yang N., Ren G., Lin R., Li D., Zhang G. (2023) Research on Long Life Product Prognostics Technology Based on Deep Learning and Statistical Information Fusion. *Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*, 14094 LNCS, pp. 3–13. DOI: 10.1007/978-981-99-6222-8_1

[5] Xie L., Lin W., Zhang M., Yan S. (2012) Series system failure rate modeling and the mechanism to yield bathtub curve. Applied Mechanics and Materials, 121–126, pp. 4858–4862. Cited4 times. DOI: 10.4028/www.scientific.net/AMM.121-126.4858

[6] Trebuňa F., Pástor M., Šarga P. (2018) Assessment and increasing of lifetime and time of safe operation of machines and equipment by the experimental methods of mechanics. *Experimental Stress Analysis – 56th International Scientific Conference, EAN 2018 – Conference Proceeding*s, pp. 421–434

[7] Nikiforov A. S., Prikhodko E. V., Kinjibekova A. K., Karmanov A. E. (2022) Comprehensive Assessment of the Residual Life of Refractory Materials of High-Temperature Units. Refractories and Industrial Ceramics, 63 (1), pp. 105-109. DOI: 10.1007/ s11148-022-00688-8

[8] Louda P., Sharko A., Stepanchikov D. (2021) An acoustic emission method for assessing the degree of degradation of mechanical properties and residual life of metal structures under complex

dynamic deformation stresses. *Materials*, 14 (9), art. no. 2090 DOI: 10.3390/ma14092090

[9] Nakomcic B., Basic D., Ciupinski L., Manaj W., Kurzydlowski K. J. (2006) Non-destructive testing applied for risk reduction in petrochemical installations. *ECOS 2006 – Proceedings of the 19th International Conference on Efficiency, Cost, Optimization, Simulation and Environmental Impact of Energy Systems*, pp. 767–774

[10] Andreikiv O. E., Skal's'kyi V. R., Dolins'ka I. Y., Dzyubyk A. R. (2018) Influence of Corrosive Hydrogenating Media on the Residual Service Life of Structural Elements in the Maneuvering Mode of Operation. *Materials Science*, 54 (1), pp. 61–68 DOI: 10.1007/s11003-018-0158-3

[11] Dolins'ka I. Y. (2018) Evaluation of the Residual Service Life of a Disk of the Rotor of Steam Turbine with Regard for the Number of Shutdowns of the Equipment. Materials Science, 53 (5), pp. 637–644. DOI: 10.1007/s11003- 018-0118-y

[12] Silin N.V., Korovkin N.V., Hayakawa M. (2013) High-voltage equipment electromagnetic spectrum study for estimation of its technical state and prediction of the residual life. 2013 International Symposium on Electromagnetic Theory, EMTS 2013 - Proceedings, art. no. 6565792, pp. 522-524.

[13] Pakhalovich, N., Kucher, S., Levutzky, Y., Malyshko, S., Girya, M. (2016) Classification of regulatory support for extension of life of mechanical equipment of nuclear power plants. Eastern-European Journal of Enterprise Technologies, 1 (8), pp. 21–28. DOI: 10.15587/1729-4061.2016. 59441

[14] Liu W., Jiao S., Wen T., Zhu J. (2023) Remaining Life Prediction Method of Relay Protection Equipment Based on Digital Twin. 2023 4th International Conference on Computer Engineering and Application, ICCEA 2023, pp. 243–247. DOI: 10.1109/ICCEA58433.2023.10135436

[15] Marasanov V., Stepanchikov D., Sharko O., Sharko A. (2020) Technique of System Operator Determination Based on Acoustic Emission Method. Advances in Intelligent System and Computing 2020 12p.

[16] Marasanov V., Sharko A. (2017) Discrete models characteristics of the forerunners of origin of the acoustic emission signals. IEEE First Ukraine Conference on Electrical and Computer Engineering (UKRCON) Track 4: Nanoelectronics and Photonics, Electron Devices & Embedded Systems, pp. 680–684.

[17] Marasanov V., Sharko A., Sharko A., Stepanchikov D. (2019) Modeling of energy spectrum of acoustic-emission signals in dynamic deformation process of medium with microstructure. IEEE 39th International Conference on Electronics and nanotechnology (ELNANO) Kyiv, April 16–18, 2019, pp. 718–723.

[18] Marasanov V., Stepanchikov D., Sharko O., Sharko A. Operator of the Dynamic Process of the Appearance of Acoustic Emission Signals During Deforming the Structure of Materials. IEEE 40th International coference of Electronics and nanotechnology (ELNANO) Kyiv, 22–24 April 2020, pp. 646–650.

[19] Louda P., Sharko A., Stepanchikov D., Sharko A. (2022) Analysis and Processing of Acoustic Emission Signals Under Dynamic Loading of the Microstructure of Continuous Media," *2022 IEEE 41st International Conference on Electronics and Nanotechnology (ELNANO)*, pp. 566-570, doi: 10.1109/ELNANO54667.2022.9926763.

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КОМП'ЮТЕРНА ДІАГНОСТИКА СТАНУ СУДНОВИХ ПІДШИПНИКІВ КОЧЕННЯ ПРИ ЇХ ЕКСПЛУАТАЦІЇ

Запропоновано результати статистичної обробки вібраційних сигналів, отриманих під час діагностики суднових енергетичних установок протягом процесу експлуатації. Відмінною особливістю моніторингу технічного стану елементів суднових енергетичних установок є невизначеність у фіксації та тривалості екстремальних навантажень. Визначено особливість комп'ютерної вібродіагностику роторних механізмів, яка є у то тому що зокрема фізичних вимірювань вібраційних сигналів потребується їх використання у математичних моделях фізичного стану підшипнику. Виконано розрахунки статистичних характеристик вібраційних сигналів у часовій області, таких як стандартне відхилення (Std), асиметрія (Skewness), ексцес (Kurtosis), повний розмах коливань (Peak2Peak), середньоквадратичне значення (RMS), хрест-фактор (CrestFactor), форм-фактор (ShapeFactor), імпульсний фактор (ImpulseFactor), граничний фактор (MarginFactor), енергія (Energy). Різноманіття діагностичних сигналів наводить до необхідності злиття показників різної розмірності без втрати наявної інформації в єдиний узагальнюючий показник, для чого в роботі використано метод головних компонент. Описано методологію статистичного опрацювання та практичну реалізацію діагностики вібраційних сигналів при аналізі еволюції пошкоджень підшипників кочення турбонагнітачів суднових енергетичних установок. Виявлено й експериментально підтверджено новий комп'ютерний інформаційний параметр вібродіагностики, заснований на аналізі першого головного компонента у часової області та спектрального ексцесу в частотної області. Використання нових діагностичних параметрів надає змогу ні тільки судити про ступень пошкоджень підшипника кочення, а і спостерігати динаміку розвитку дефекту та робити відносній прогноз робочого ресурсу підшипника кочення. Розглянуто реальну практичну ситуацію – комп'ютерну діагностику вібраційних сигналів суднові підшипники кочення точкового дефекту зовнішнього дефекту кільця підшипника кочення. Визначення застосовності методу *головних компонент до інших видів дефекту показало їх перспективність для вібродіагностиці дефектів, розташованих на внутрішньому кільці підшипника і підчас випадання кульки з обойми.*

Ключові слова: комп'ютерна діагностика, вібраційні сигнали, суднові підшипники кочення, експлуатація, інтелектуальні системи, інформаційні параметри

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COMPUTER DIAGNOSTICS OF SHIP ROLLING BEARINGS CONDITION DURING THEIR OPERATION

The results of statistical processing of vibration signals obtained during diagnostics of ship power plants during the operation process are offered. A distinctive feature of monitoring the technical condition of elements of ship power plants is the uncertainty in the fixation and duration of extreme loads. The peculiarity of computer vibration diagnostics of rotary mechanisms is determined, which is that, in particular, physical measurements of vibration signals require their use in mathematical models of the physical state of the bearing. Calculations of statistical characteristics of vibration signals in the time domain, such as standard deviation (Std), asymmetry (Skewness), kurtosis (Kurtosis), full range of oscillations (Peak2Peak), root mean square value (RMS), cross factor (CrestFactor), form- factor (ShapeFactor), impulse factor (ImpulseFactor), marginal factor (MarginFactor), energy (Energy). The variety of diagnostic signals leads to the need to merge indicators of different dimensions without losing available information into a single generalizing indicator, for which the method of principal components is used in the work. The methodology of statistical processing and practical implementation of diagnostics of vibration signals during the analysis of damage evolution of rolling bearings of turbochargers of marine power plants are described. A new computer information parameter of vibration diagnostics based on the analysis of the first principal component in the time domain and spectral excess in the frequency domain has been identified and experimentally confirmed. The use of new diagnostic parameters makes it possible not only to judge the degree of damage to the rolling bearing, but also to observe the dynamics of the development of the defect and make a relative forecast of the working life of the rolling bearing. A real practical situation is considered – computer diagnostics of vibration signals of ship rolling bearings of a point defect of an external defect of a rolling bearing ring. Determining the applicability of the principal component method to other types of defects showed their potential for vibrodiagnosis of defects located on the inner ring of the bearing and when the ball falls out of the holder.

Keywords: computer diagnostics, vibration signals, ship rolling bearings, operation, intelligent systems, information parameters

Стаття надійшла до редакції 04.08.2024 р.
Прийнято до друку 11.09.2024 р.