Monitoring State of Marine Plain Bearings Based on Exponential Degradation Model

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Abstract

Some aspects of mathematical, algorithmic, and software apparatuses for modelling ship power equipment condition monitoring are considered. A predictive model of technical state change by parameters of generated vibration is developed. The principal components method is used to reduce the dimensionality of input information. The results of digitalisation and spectral analysis of vibroacoustic characteristics generated during the operation of dynamic equipment of ship sliding bearings are presented. The sharp increase of the first principal component compared with the rest and its monotonous increase at degradation of material properties are established. It is shown that developing predictive models of technical state change by vibration parameters is a major step in the transition to qualitatively new forms of maintenance and repair necessary for equipment safety.

Keywords

monitoring, exponential model, degradation, prediction, residual life, principal component method.

1. Introduction

Ship sliding bearings with antifriction layers made of tin and lead-based alloys are used on ship low- and medium-speed diesel engines, turbines, and shafts. By their design and direct purpose, they support rotating parts and are the most important units of power equipment. Nowadays, methods of vibration signal processing in frequency and frequency-time domains are used to estimate the technical condition of plain bearings. The most widespread are spectral methods of vibration diagnostics on the basis of the Fourier transform, where each defect of the equipment corresponds to a set of discrete frequencies. Because defects of plain bearings generate both low-frequency and high-frequency vibration, their diagnostics are carried out by joint analysis of the spectrum of low-frequency vibration and envelope spectrum of the vibration signal. Monitoring of technical conditions and diagnostics of arising defects is the basis for ensuring the high reliability of equipment elements. According to the totality of defective frequencies detected in the spectrum a conclusion is made about the defect and the degree of its development. The disadvantage of spectral methods is the low efficiency of non-stationary signal processing due to the blurring of spectra. The causes of defects are the variability of the shaft rotation speed when changing the operating mode, different degrees of wear of elements, etc.

Physical processes occurring in sliding bearings depend on the design's peculiarities and the correlation of many external and internal factors determining bearing operating conditions. The operation of plain bearings is based on the principles of sliding friction, the realisation of which requires constant lubrication control. The inner ring is made of an antifriction material to ensure a low coefficient of friction, and the outer ring is made of high-strength material. The advantages of plain bearings are their resistance to radial loads and vibrations, their

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separability, which simplifies installation and maintenance, and their lower operating noise. The disadvantage is the high wear of contacting surfaces. The main reason for the occurrence of defects in plain bearings is abrasive wear of mating surfaces of shaft journal and liners, as a result of getting on the contact surface of various particles, being in lubricants and load differences, leading to semi-dry friction at starting and stopping of the bearing. Defects in the bearing shells indicate a malfunction of the diesel engine. If the bearing shell has been in service for a long time, various defects will appear on its surfaces. Under the weight of the rotor and other static loads in the plain bearing, oscillating forces of kinematic and impulse character can occur caused by the action of friction forces. Besides, these forces in plain bearings can be observed as vibrations with a rotation frequency of 0,42...0,48, excited by auto-oscillations of the rotor on the oil wedge. The short-term appearance of cavitation zones causes shocks of hydrodynamic origin.

The time interval until the first signs of material fatigue appear depends on the bearing speed and load. The actual durability of plain bearings is lower than the calculated durability due to high loads, insufficient lubrication, incorrect choice of lubricant, and installation errors.

The relevance of the work is to investigate the possibility and develop a methodology to observe the development of defects in a plain bearing in real-time.

The exponential model of material degradation is chosen as the hypothesis used in the analysis of monitoring of vibration signals received during the operation of sliding bearings.

The experience of creating models of degradation of the technical state of dynamic equipment based on the analysis of mechanical vibrations is described in [1]. In [2], the results of vibration characteristics are considered in detail, and the classification of defects is given, based on which specific vibration analysis methods are justified.

In [3], the statistical analysis of failures and the causes of their occurrence is described. Peculiarities of monitoring transport technology elements are devoted to [4-6]. It is shown that the timely detection of the origin and development of defects in bearings, compressors, and turbines of high-speed technological equipment is the basis for the safety of transport devices. Frequency-time analysis of the steady-state helpful life of bearings is presented in [7]. An improved strength degradation model for fatigue life prediction considering material characteristics is presented in [8]. The model has high prediction accuracy, but its implementation needs to be improved to account for the influence of associated factors. The prediction of the remaining service life of a self-lubricating liner of a high-frequency plain bearing is presented in [9]. However, it should be noted that the problem of anomaly evaluation in trends still needs to be addressed. Life prediction of self-lubricating spherical plain bearings based on a failure physics model and accelerated degradation tests is presented in [10]. The accuracy of the forecast is determined by the number of diagnostic measurements, which restrains the broad application of the method.

The information support system for monitoring the development of equipment degradation state is presented in [11-13]. It is shown that the organisation of monitoring observation of the state of the operating equipment is a means of increasing its reliability and failure-free operation. Some scientific interest in solving the problem of identifying the state of shipboard equipment is represented by [14-16]; intellectual support of forecasts of approaching the state of destruction and estimation of residual life is presented in [17-19].

The given review of literature sources shows that, despite the variety of scientific directions to improve the efficiency of equipment monitoring in the process of its operation, the interest in publications in this area is particularly noticeable. The purpose of the present work is to monitoring the condition of ship sliding bearings on the basis of the exponential degradation model.

2. Materials and Methods

Methods of analysing vibrodiagnostic signals with an exponential degradation model were applied to monitoring state of marine plain bearings.

The exponential degradation model forecasts residual life based on prior information about equipment operation conditions and the latest diagnostic measurements. The model allows for observing the degradation trend in real time and updating its priori parameters, when new information is received using data collection, post-processing, ranking, and merging essential functions with a selection of forecasting curves. This realises the principle of observing the continuous wear of the equipment material during its lifetime.

Materials for analysing vibrodiagnostic signals ship sliding bearings of mark TPL-88 were used. Their parameters are given in Table 1.

Table 1
Parameters of bearing TPL-88

Maximum shaft speed, rpm	Bearing inner diameter, mm	Bearing outer diameter, mm	Weight, kg	Anti-friction coating
12000	114.073	164.672	7.7	CuPb15Sn

The arrangement of the plain bearings on the motor is shown in Fig. 1.

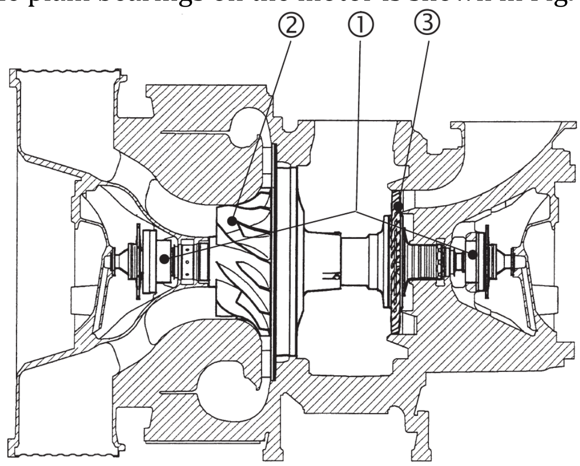

Figure 1: Placing of plain bearings on the engine: 1 - plain bearing, 2 - compressor, 3 – turbine

Measurements are carried out on the bearing unit housing, namely in its lower part, because here the loads on the unit are maximum [20]. The signals from the sensors can be digitised and recorded for trend analysis. An accelerometer is used to record the vibration levels. A vibration signal of 6 s duration was obtained daily for 50 consecutive days. A bearing failure occurred and caused the bearing to fail.

3. Methodology

The exponential degradation model at its inception assumes that the failure rate function failures $\lambda(t)$ is constant during the entire life of the bearing.

$$\lambda(t) = const > 0 \quad (1)$$

Probability of its failure-free operation

$$P(t,\lambda) = \exp(-\lambda t) \quad (2)$$

Accordingly, the probability failures of bearing failures

$$Q(t,\lambda) = 1 - P(t,\lambda) = 1 - \exp(-\lambda t) \quad (3)$$

In the framework of such a model, aging and wear processes are absent. This model is used to approximate the unknown failure rate at the stage of normal operation under the assumption that the failure rate remains constant.

The failure rate during damage accumulation is described by a Weibull distribution

$$\lambda(t,\alpha) = \alpha(\lambda,t)^{\alpha-1}, t > 0, \alpha > 0, \lambda > 0 \quad (4)$$

where α - intensity index.

The probability of failure-free operation for time t is equal to

$$Q(t) = 1 - \exp\left(-(\lambda t)^{\alpha}\right) \tag{5}$$

If $\alpha>1$ the failure rate function increases monotonically, which describes the processes of wear and ageing of equipment.

Maintenance based on interactive condition monitoring, fault detection and resource forecasting of power equipment requires a whole set of information characteristics: amplitude, time, frequency, etc. The method of principal components allows to reduce their dimensionality without significant loss of input information. Based on linear algebra and mathematical statistics, the method of principal components, which works with continuous data streams, allows us to avoid multidimensionality and select only the main characteristics of objects. It is designed to divide the matrix of initial data into two parts: meaningful and noise. The principal component method approximates an n-dimensional cloud of observations to an n-dimensional ellipsoid, the semi-axes of which will be the principal components. The exponential model allows real-time prediction of residual life based on statistical processing of data and their integration. In this paper, the method of principal components is applied to the data written in the form of a matrix of numbers of dimensionality $n\times m$. In preparing the data, the sample is centred so that the mean of the features is zero by replacing the finite set of points with lines and planes. For a finite set of vector sets $x_1,x_2,.., x_n \in \mathrm{R}^n$ where R^n – linear manifolds, we need to find such values of the set of linear combinations of $S_k \subset R^n$, so that the sum of squares of deviations x_i from S_k would be minimal.

$$\sum_{i=1}^{m} dist^2(x_i, S_k) \to \min \tag{6}$$

where dist (xi, Sk) is the Euclidean distance from a point to a line, k = 0,1,2…n-1.

Linear varieties are represented by a set of principal components. When describing a random variable, the mathematical expectation representing the centre of gravity of this variable and dispersion representing its dimensions in the form of spread are used. To describe a multidimensional special quantity at occurrence of vibration signals, in addition to the mathematical expectation $E(x)$ and dispersion of its projections on the axis, we used the concept of covariance matrix, the elements of which are correlations of the features x_i and x_j.

$$\operatorname{cov}(x_i, x_j) = E\left[\left(x_i - E|x_i|\right)\cdot\left(x_j - E|x_j|\right)\right] \tag{7}$$

In the covariance matrix, the eigenvalues are used to estimate the contribution of the principal components to the overall variability of the process.

Before proceeding to the calculation of principal components, it is necessary to standardise the data to zero mean and unit variance. The algorithm of the principal component method is an orthogonal linear transformation that maps the data from the original feature space into a new space of linear dimension. By projecting the principal components of the axis, a new basis is formed, dimensionality is reduced, and the greatest amount of information is retained. This method is incorporated into analytical platforms and used based on data preprocessing. Having centred the input data sample, we shift it linearly so that the mean values of the features are zero. To describe the shape of the random vector, we need a covariance matrix that has i,j elements are a correlation of attributes x_i and x_j. The covariance matrix is a generalisation of the variance of a multivariate random variable.

The calculation of principal components is reduced to the calculation of eigenvectors and eigenvalues of the covariance matrix. In the matrix on the diagonal will be the variance of the features, and in the remaining cells - the covariance of pairs of these features.

Modelling of the exponential probability distribution of the diagnostic parameters is conveniently performed using the logarithmic subharmonic function to preserve the scale. A random variable obeys the logarithmic normal distribution θ, if its logarithm has a normal distribution.

The formula for the density of the log-normal distribution of a random variable has the following form

$$P(x) = \frac{1}{\sigma\sqrt{2\pi}}\frac{1}{x} + \exp\left[-\frac{1}{2}\left(\frac{\ln x - m}{\sigma}\right)^2\right] \quad (8)$$

σ, m – distribution parameters.

The logarithmic normal distribution of a random variable is asymmetric when compared to the Gaussian normal distribution of a random variable β.

The exponential degradation model is defined as

$$h(t) = \phi + \theta \exp\left(\beta t + \varepsilon - \frac{\sigma^2}{2}\right) \quad (9)$$

where $h(t)$ – bearing state indicator as a function of time; ϕ – tipping constant; θ and β are random parameters that determine the slope of the model, where θ is a logarithmic normal distribution, and β is Gaussian distributed. At each time step t distribution θ and β is updated to a posteriori based on the latest observation of $h(t)$. Parameter ε is a Gaussian white noise, σ^2 – variance.

Member $-\frac{\sigma^2}{2}$ exponentially should force the expectation $h(t)$ fulfil the condition

$$E[h(t)|\theta, \beta] = \phi + \theta \exp(\beta t) \quad (10)$$

In information theory, Gaussian white noise is an abstract mathematical model of a stationary random process with constant spectral density at all frequencies, which is a mixture of sounds reproduced simultaneously at all frequencies. Gaussian white noise is completely uncorrelated, i.e. any instantaneous noise value is uncorrelated with the previous one.

Degradation models extrapolate past behaviour to predict future behaviour. This type of calculation is suitable when determining the steady-state useful life of complex equipment. The degradation profile of the test component is then used to statistically calculate the remaining time until the diagnostic indicator reaches some level of degradation consistent with regulatory guidelines.

4. Experiment, results and discussion

Fig.2 shows in one scale the whole set of received vibration signals in the order of their occurrence and fixation in the course of 50-day operation life of the plain bearing, which gives a visual representation of the change of peak amplitudes.

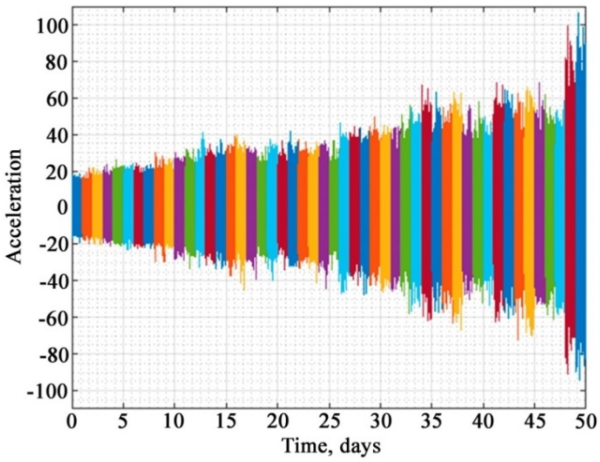

Figure 2: Sequence of received vibration signals in the order of their occurrence and fixation during the operation of the plain bearing

As can be seen from the consideration of Fig.2, the vibration signals in the time domain show a tendency to increase the impulsiveness of the signal.

Statistical characteristics of vibration signals in time and frequency domains were determined during post-processing. In the time domain, 11 statistical characteristics were determined: Mean, Std, Skewness, Kurtosis, Peak2Peak, RMS, CrestFactor, ShapeFactor, ImpulseFactor, MarginFactor, Energy. In the frequency domain 4 statistical characteristics were determined: spectral mean (SKMean), spectral standard deviation (SKStd), spectral asymmetry (SKSkewness) and spectral excess (SKKurtosis). All the above statistical characteristics of vibration signals can serve as potential indicators of bearing condition degradation (Fig.2).

The extracted statistical characteristics of vibration signals are related to noise. Noise is detrimental for residual life prediction. In addition, one of the most important properties of the function, its monotonicity, is unstable to noise. Therefore, a filtering and smoothing procedure is applied to the extracted statistical features. The comparison of the original and filtered characteristics of vibration signals is presented in Fig.3.

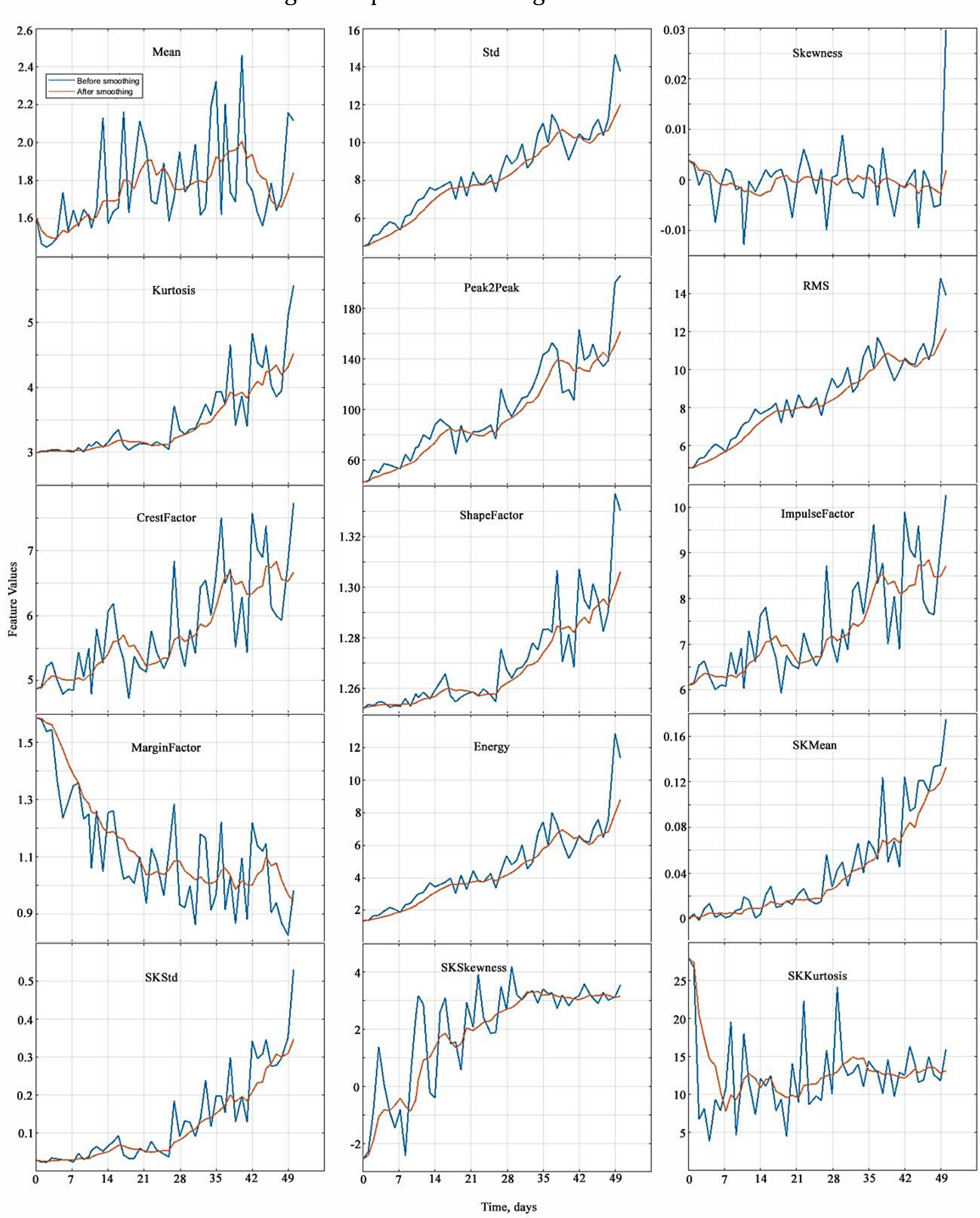

Figure 3: Evolution of dimensionless statistical characteristics of vibration signals in the process of sliding bearing operation (blue line - initial values, red - smoothed values)

The main criterion of belonging of the extracted statistical characteristics of vibration signals in the frequency and time domain to their further analysis is the numerical value of monotonicity. For quantitative estimation of the belonging of statistical characteristics to their further analysis it is proposed to use the formula

$$\text{Monotonicity}(x_i) = \frac{1}{m}\sum_{j=1}^{m}\frac{|\text{number of positive diff}(x_i^j) - \text{number of negative diff}(x_i^j)|}{n-1} \qquad (11)$$

where n – number of measurement points, in our case n = 50. m – number of controlled samples, in our case m = 1, x^i_j – i-th characteristic measured on the j-th sample, diff(x^j_i) = $x^j_i(t)$ – $x^j_i(t-1)$. The results of calculation of monotonicity of statistical characteristics of vibration signals in frequency and time domain by formula (11) are presented in Fig.4.

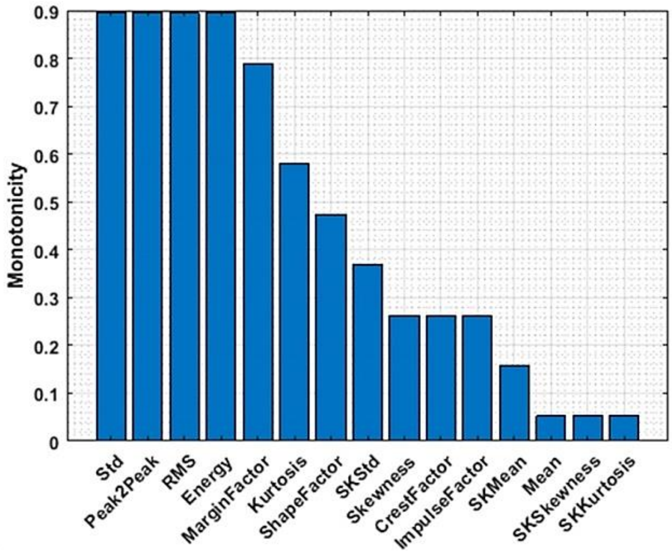

Figure 4: Monotonicity of statistical characteristics of vibration signals arising in the process of operation of the sliding bearing

Characteristics with a monotonicity score greater than 0.3 are selected to combine them in the subsequent analysis using the principal component method. As the monotonicity calculations have shown, the following values greater than 0.3 were obtained: standard deviation (Std), full range of oscillations (Peak2Peak), RMS value (RMS), energy (Energy), marginal factor (MarginFactor), excess (Kurtosis), shape factor (ShapeFactor), standard spectral deviation (SKStd).

In order to reduce the dimensionality of the analysed quantities and to combine the features of vibration signals, the PCA principal component analysis method was applied. Using the computer mathematics system Matlab 2018b, the first PCA principal component1 was calculated when processing the statistical characteristics of vibration signals with monotonicity greater than 0.3. Its distribution depending on the measurement day, which correlates with the successive approach of the plain bearing state to failure, is shown in Fig. 5.

The graph in Fig.5 shows that the first principal component increases as the bearing approaches failure. Thus, the first principal component is a promising combined indicator of the condition of a plain bearing.

In practice, the data of the whole life cycle of a plain bearing is not enough to develop a prognostic algorithm, but it can be considered as data for training a system for monitoring the condition of marine plain bearings during their operation. Therefore, the data collected in the first 20 days (40% of the life cycle) are considered as training data. In the subsequent operations of ranking and combining the importance of features, only the training data are used.

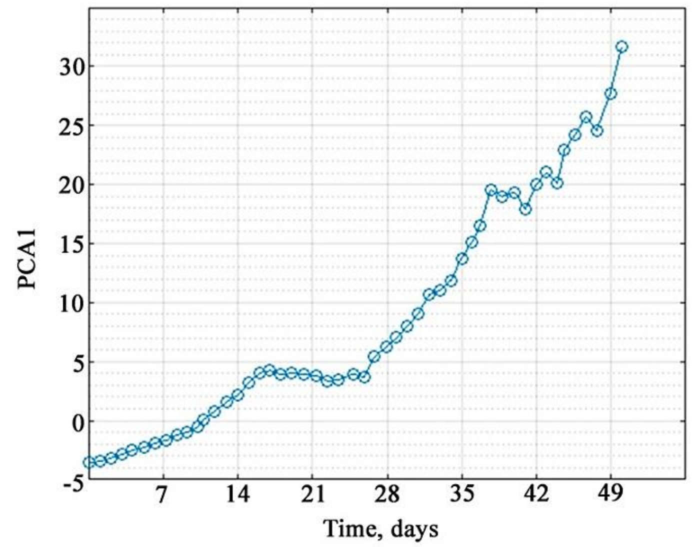

Figure 5: The first principal component for successively recorded vibration signals during the operation of a plain bearing and its approaching to the failure state

In this paper, the Echronic Degradation Model algorithm implemented in the Matlab 2018b computer mathematics system is used to model the exponential degradation process and estimate the Remaining Useful Life (RUL) of a bearing. The degradation models estimate RUL by predicting when the monitored signal crosses a predetermined threshold value.

The selection of the condition indicator threshold value may be based on chronological records of bearing condition or some subject matter knowledge. Since there is no chronological data in the study set, the last value of the health indicator is selected as the threshold value $h(t)$. The threshold value is selected on the basis of smoothed chronological data.

As follows from the graphs Fig.2,5 the study of statistical characteristics of vibration signals reveals predominantly ascending trend with increasing operation time of the sliding bearing. A priori of slope parameters varies within the limits ($E(\theta) = 1$, $\mathrm{Var}(\theta) = 10^6$, $\mathrm{E}(\beta) = 1$, $\mathrm{Var}(\beta) = 10^6$), where 10^6 – scale factor of the distribution. The model relies mainly on observed data. Based on the relationship $E[h(0)] = \phi + E(\theta)$, intersection ϕ is set to -1 so that the model also starts with a 0.

The relationship between the change in state index and the change in noise can be obtained as follows:

$$\Delta h(t) \approx (h(t) - \phi)\Delta\epsilon(t) \quad (12)$$

Here it is assumed that the standard deviation of noise causes a 10% deviation in the performance indicator when it approaches a threshold value.

The exponential degradation model also provides functionality to assess the significance of the slope. Once a significant slope of the performance indicator is detected, the model will forget previous observations and restart the estimation based on the original a priori values.

Fig.6 shows the operation of the exponential model of the sliding bearing state degradation on the example of the vibration signals considered above. It is clearly seen how the prediction changes depending on the slope of the state indicator curve. The threshold value of the state indicator is chosen equal to *h(t)* = 36 on the 20th day of monitoring, as the first twenty days were used to train the model.

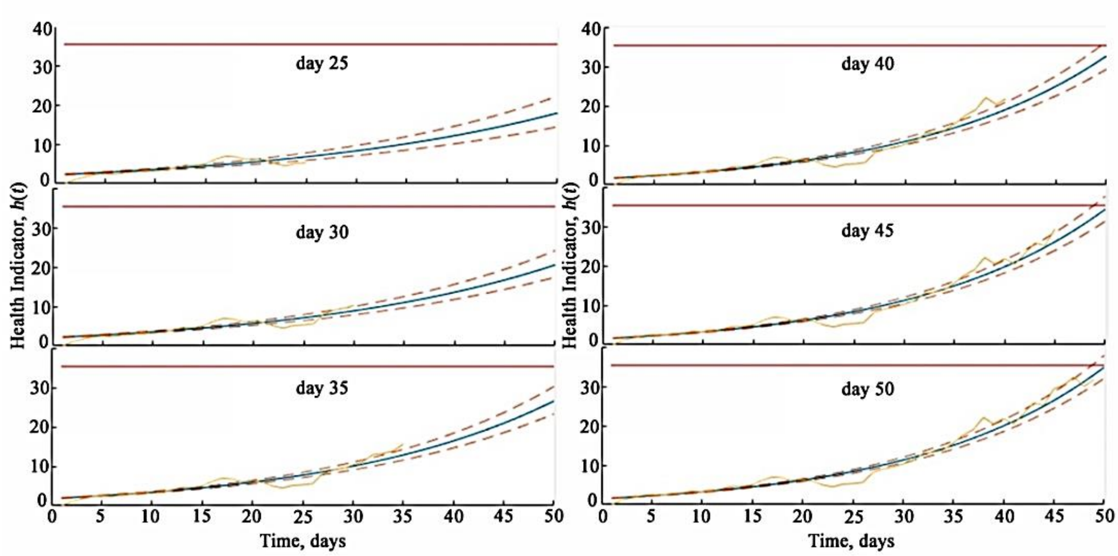

Figure 6: Estimation of the residual life of a plain bearing based on the exponential model of state degradation (red line - threshold value of the state indicator, blue line - exponential degradation model, yellow line - current value of the state indicator, dotted line - confidence interval limits)

As can be seen from Fig.6, if the data for the first twenty days of operation of the plain bearing are used for training of the exponential model, the exponential model gives exceeding of the threshold value on the fiftieth day. However, it should be noted that the boundary of the confidence interval, shown by the dotted line in Fig.6, crosses the threshold already on the fortieth day of the bearing operation. Therefore, it can be stated that after forty days of operation, further operation of the bearing is unsafe.

The chronological data on the technical state of the object may include structural and functional schemes of subsystems interaction, control algorithms, data on modes, characteristics of control and diagnostics systems, methods of operation and technical support. The disadvantage of such an assessment is the lack of uncertainty accounting, which is characterised by the actual results of the diagnostics device operation, as well as the assessment of the influence of external influences.

For predictive performance analysis the following is used α-λ graph shown in Fig. 7, where the threshold is set to α=20%. The probability that the estimated RUL is between the boundary of the true RUL is calculated as a measure of model performance:

$$\Pr(r^*(t) - \alpha r^*(t) < r(t) < r^*(t) + \alpha r^*(t) | \Theta(t)) \quad (13)$$

where $r(t)$ - estimated RUL during t, $r^*(t)$ - true RUL during t, $\Theta(t)$ - are the estimated parameters of the model during t.

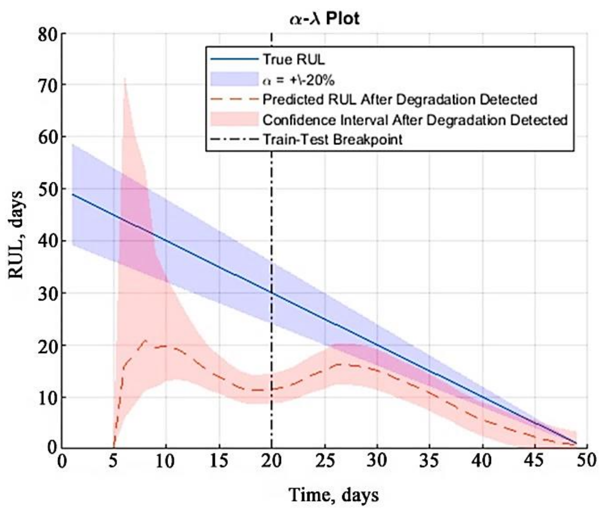

Figure 7: α-λ graph used for prognostic analysis of the performance of a plain bearing

Since the preset a priori values do not reflect the true a priori value, the model usually needs several time steps to adjust to the correct parameter distribution. Emergence, recognition, and evolution are statistical characteristics of prediction that require a large amount of input information. In these states, the initial position is uncertain and therefore the statistical characteristics cannot be accurately calculated. Improving the accuracy of prediction requires a constant replenishment of current information at each RUL prediction step, estimated by the corresponding probabilities. The prediction becomes more accurate as more data points become available.

Conclusions

1. A framework for conducting turbine plain bearing condition monitoring based on vibration signal measurements is proposed. A set of statistical characteristics of vibration signals in time and frequency domains has been identified, and their statistical processing and analysis has been performed.
2. On the basis of the performed calculations of the sliding bearings state monitoring using the method of principal components a new information diagnostic parameter in the form of the first principal component is established, which allows to combine a set of statistical characteristics of vibration signals at reduction of the noise component.
3. The exponential degradation model used in the paper, taking into account probabilistic uncertainty estimates and confidence estimation of predictions, has shown that for cases in which a normal distribution is used it is sufficient to use a confidence interval in the form of a propagating band around the predicted point and to estimate the RUL based on a predetermined failure threshold.
4. It is found that forecasts made at an early stage have access to less information on damage dynamics and require forecasting to more distant horizons.

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