Показано, що при зародженні дефектів настає період переходу морських платформ в аварійний стан. При цьому з'являються перешкоди, що корелюють з корисним сигналом. Пропонуються алгоритми обчислення робастних оцінок спектральних характеристик вібраційних сигналів і технології формування множин інформативних ознак з спектральних оцінок перешкоди

Ключові слова: діагностика, перешкода, морські платформи, моніторинг, спектральний аналіз, спектральні характеристики, вібраційні сигнали

Показано, что при зарождении дефектов наступает период перехода морских платформ в аварийное состояние. При этом появляются помехи, коррелирующие с полезным сигналом. Предлагаются алгоритмы вычисления робастных оценок спектральных характеристик вибрационных сигналов и технологии формирования множеств информативных признаков из спектральных оценок помехи

Ключевые слова: диагностика, помеха, морские платформы, мониторинг, спектральный анализ, спектральные характеристики, вибрационные сигналы

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DEVELOPMENT OF THE TECHNOLOGY FOR THE SPECTRAL NOISE CONTROL OF THE VIBRATION CONDITIONS OF OFFSHORE PLATFORMS

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1. Introduction

Because of the shortcomings in both control and diagnostic systems, the accident rate for offshore oil and gas extracting facilities remains unreasonably high [1, 2]. Accidents are often caused by the errors resulting from the application of traditional analytical technologies to noisy signals received from corresponding sensors. Our research shows that these technologies generally provide the informative attributes required to perform defect diagnostics only after the defect has already become strongly pronounced [3–6]. For this reason, the results of monitoring of the beginning of transition of the platforms into an emergency state is sometimes delayed. And this possibly leads to catastrophic consequences [7].

By analysing the causes of the transitions of offshore platforms into emergency states, we find that they usually consist of the onsets of physical defects, such as cracks, wear and tear, and corrosion. As a rule, the process of crack development starts with the formation of micro-cracks, "coarsening" of the surface, grain boundary cracking, and cracking around solid inclusions, and is accompanied by further infiltration deep into the material of the structure. Sometimes, a micro-crack becomes a macro-crack and spreads quickly through the metal. The rate of crack growth depends on both the cyclic stress and the operating conditions. For instance, cracks result from the continuous oscillations of platforms that are caused by ocean waves.

Wear between contacting surfaces that are in motion relative to one another is another major cause of offshore platform equipment service life reduction. Therefore, wear is also one of the most common defects found in offshore platforms. In addition to these causes, many offshore platform accidents are caused by defects resulting from either corrosion or fatigue deformation, both of which are unavoidable under continuous operation in marine conditions.

In consideration of the above, it is obvious that the creation of algorithms and other technologies to monitor the early onset and the development of cracks, wear and tear, corrosion, and other defects in offshore platforms is of enormous importance. Timely, preventive maintenance performed on these platforms can make it possible to avoid catastrophic accidents.

2. Literature review and problem statement

First, it should be noted that the technical conditions, both of the individual structural elements of an offshore platform as well as of other oil and gas production facilities, each taken as a whole, usually remain within normal ranges over long periods of operation, each referred to as

T_0 [1, 8–10]. Subsequently, due to the formation of cracks, corrosion, or wear and tear, each facility moves into a latent form of an emergency state, corresponding to the period T_1, inevitably followed by a period T_2, when the facility moves into a critical emergency state. Finally, the period T_3 begins when an accident occurs and the facility ceases to operate [1, 11–13].

Therefore, to eliminate the causes of accidents in a timely manner, it is necessary to develop technologies that ensure reliable monitoring of the onset of time T_1, the latent period of changes in the technical conditions of offshore platforms [1, 14]. Assume that during the time T_0 that a platform is operating in a normal state, the known classical conditions are fulfilled for the centred noisy signals $g(i\Delta t) = X(i\Delta t) + \varepsilon(i\Delta t)$ that are received at the outputs of the corresponding sensors, meaning that the following equalities hold:

$$\omega_{T_0}\left[g(i\Delta t)\right] = \frac{1}{\sqrt{2\pi D_g}} e^{\frac{-(g(i\Delta t))^2}{2D_g}},$$

$$D_\varepsilon \approx 0, \quad D_g \approx D_X,$$

$$R(\mu) \approx R_{XX}(\mu);$$

$$m_g \approx m_X \approx m_\varepsilon \approx 0;$$

$$r_{X\varepsilon} \approx 0, \qquad (1)$$

where $\omega_{T_0} g(i\Delta t)$ is the distribution law of the signal $g(i\Delta t)$, D_ε, D_X and D_g are the variances of the noise $\varepsilon(i\Delta t)$, the useful signal $X(i\Delta t)$, and the sum signal $g(i\Delta t)$, respectively, $R_{XX}(\mu)$ and $R(\mu)$ are the correlation functions of the useful signal $X(i\Delta t)$ and the sum signal $g(i\Delta t)$, m_ε, m_X and m_g are the mathematical expectations of the noise $\varepsilon(i\Delta t)$, the useful signal, and the sum signal, respectively, and $R_{X\varepsilon}(\mu = 0)$ and $r_{X\varepsilon}$ are the cross-correlation function and the coefficient of correlation $X(i\Delta t)$ of the noise $\varepsilon(i\Delta t)$, respectively.

In this case, we have the obvious equality

$$R(\mu) = M\left[g(t)g(t)\right] = M\left[\left(X(t)+\varepsilon_1(t)\right)\left(X(t)+\varepsilon_1(t)\right)\right] =$$
$$= M\left[X(t)X(t) + \varepsilon_1(t)X(t) + X(t)\varepsilon_1(t) + \varepsilon_1(t)\varepsilon_1(t)\right].$$

Due to the lack of correlation between the useful signal $X(i\Delta t)$ and the noise $\varepsilon(i\Delta t) = \varepsilon_1(i\Delta t)$, the following conditions hold:

$$M\left[X(t)X(t)\right] \neq 0, M\left[\varepsilon_1(t)X(t)\right] = 0,$$

$$M\left[X(t)\varepsilon_1(t)\right] = 0, M\left[\varepsilon_1(t)\varepsilon_1(t)\right] = 0,$$

$$R(\mu) = M\left[X(t)X(t) + \varepsilon_1(t)\varepsilon_1(t)\right]. \qquad (2)$$

Therefore, when $\mu = 0$, we have

$$R(0) = M\left[X(t)X(t) + \varepsilon_1(t)\varepsilon_1(t)\right] = R_{XX}(0) + D_\varepsilon,$$

where

$$D_\varepsilon = M\left[\varepsilon_1(t)\varepsilon_1(t)\right] = M\left[\varepsilon(t)\varepsilon(t)\right]. \qquad (3)$$

When these defects arise in control objects, the noise $\varepsilon_2(t)$, correlated with the useful signal $X(i\Delta t)$, appears in the signals $g(i\Delta t)$ received from the corresponding sensors. Once this occurs, the period T_0 of the normal state of facility operations ends, the period T_1 of the latent change in the technical conditions begins, and condition (1) and equalities (2) and (3) are violated.

Due to the presence of a correlation between the useful signal $X(t)$ and the noise $\varepsilon(t) = \varepsilon_1(t) + \varepsilon_2(t)$, when $\mu = 0$, the following conditions hold:

$$M\left[X(t)X(t)\right] \neq 0,$$

$$M\left[\varepsilon_2(t)X(t)\right] \neq 0,$$

$$M\left[X(t)\varepsilon_2(t)\right] \neq 0,$$

$$M\left[\varepsilon_1(t)\varepsilon_1(t)\right] \neq 0. \qquad (4)$$

Therefore, we have

$$R(0) = M\begin{bmatrix} X(t)X(t) + \varepsilon_2(t)X(t) + \\ + X(t)\varepsilon_2(t) + \varepsilon_1(t)\varepsilon_1(t) \end{bmatrix} =$$
$$= R_{XX}(0) + 2R_{X\varepsilon_2} + D_{\varepsilon_1\varepsilon_1}, \qquad (5)$$

where

$$D_\varepsilon = 2R_{X\varepsilon_2}(0) + D_{\varepsilon_1\varepsilon_1} =$$
$$= M\left[\varepsilon_2(t)X(t) + X(t)\varepsilon_2(t) + \varepsilon_1(t)\varepsilon_1(t)\right] = 2R_{X\varepsilon} + D_{\varepsilon\varepsilon}. \quad (6)$$

As a result, the statistical estimates of the signal $g(i\Delta t)$ contain certain errors when calculated using traditional technologies. For this reason, timely detection of the initial stage of the T_1 processes described above is difficult. After the period T_1 ends, period the T_2, in which the defects become strongly pronounced, begins, and the acquisition of monitoring results indicating the platform's transition into an emergency state is delayed.

In consideration of the above, both noise technologies and systems that register changes in the technical conditions of offshore platforms at the beginning of the time period T_1 are proposed in [1]. Our experimental research has shown that the defects that cause the transitions of facilities into emergency states are mainly generated by the continuous oscillations of platforms caused by ocean waves [1, 11]. Moreover, various weather conditions, helicopters landing on platforms, the operations of drilling rigs, compressor stations, and pumping stations, and the mooring of tankers and other watercraft to platforms cause vibrations in all of the structural elements. It should be noted both that the vibration parameters of platforms are significantly different in calm seas, with moderate wind, and in stormy weather, and that the influences of these external factors both on individual structural elements and on each platform as a whole also affect vibration signals. Thus, the vibration signal noise received from the vibration sensors contains valuable information about the onset of changes in the technical conditions of a platform. Therefore, this paper attempts to create both algorithms and technologies for spectral analyses of the vibration signal noise to monitor the onsets of the latent periods of changes in the vibration conditions of offshore platforms and other oil production facilities for cases that conform to equalities (4)–(6).

3. The aim and objectives of the study

The main aim purpose of the article is the creation of algorithms and technologies that provide monitoring of the onset of the origin and development of cracks, wear, corrosion and other defects on offshore platforms at the early stages.

To achieve this goal, the following tasks were set:

1. To develop the algorithms for calculating robust estimates of spectral characteristics of noisy vibration signals by means of calculating the estimates of equivalent variance of the vibration signal.

2. To propose technologies for calculating estimates of spectral characteristics of vibration signal noise.

3. To offer the spectral noise subsystem for monitoring the onset of changes in the vibration conditions of offshore platforms.

4. Algorithms for calculating robust estimates of spectral characteristics of noisy vibration signals

The vibrational signal $X(t)$, received from the vibration sensors, can be represented as a sum of harmonic functions, cosine waves, and sine waves [15]:

$$X(t)=\frac{a_0}{2}+\sum_{i=1}^{\infty}(a_n\cos n\omega t+b_n\sin n\omega dt), \tag{7}$$

where $X(t)$ is the centered continuous vibration signal with a mathematical expectation of zero, $a_0/2$ is the mean value of the vibration signal $X(t)$ in the period T, a_n and b_n are the amplitudes of the cosine and the sine waves, respectively, with frequencies nω.

The coefficients a_n and b_n of the vibration signal $X(t)$ are calculated from the formulas

$$a_n=\frac{2}{T}\int_0^T X(t)\cos n\omega t\mathrm{d}tw,\ \text{when}\ n=1,2,...$$

$$b_n=\frac{2}{T}\int_0^T X(t)\sin n\omega t\mathrm{d}tw,\ \text{when}\ n=1,2,... \tag{8}$$

Theoretically, if signal $X(t)$ both does not contain noise $\varepsilon(t)$ and has a limited spectrum, then the estimates of a_n and b_n can be calculated with considerable accuracy. However, the real vibration signals received from vibration sensors of offshore platform arrive with certain noise $\varepsilon(t)$, meaning that

$$g(t)=X(t)+\varepsilon(t).$$

In this case, the values of a_n and b_n are calculated from the formulas

$$a_n=\frac{2}{T}\int_0^T\left[x(t)+\varepsilon(t)\right]\cos n\omega t\mathrm{d}t=$$

$$=\frac{2}{T}\int_0^T\left[x(t)\cos n\omega t\mathrm{d}t+\varepsilon(t)\cos n\omega t\mathrm{d}t\right]\mathrm{d}t,$$

$$b_n=\frac{2}{T}\int_0^T\left[x(t)+\varepsilon(t)\right]\sin n\omega t\mathrm{d}t=$$

$$=\frac{2}{T}\int_0^T\left[x(t)\ \sin n\omega t\mathrm{d}t+\varepsilon(t)\sin n\omega t\mathrm{d}t\right]\mathrm{d}t. \tag{9}$$

Despite the obvious differences in expressions (8) and (9), when conditions (1)–(4) hold, the positive and negative errors cancel out, and the estimates of a_n and b_n, calculated from formulas (8) and (9), match.

However, when conditions (1)–(3) do not hold and conditions (4)–(6) occur, the errors λ_{a_n} and λ_{b_n} appear in the sought-after estimates. These can be calculated from the expressions

$$\lambda_{a_n}=\sum_{i=1}^{N^+}\int_{t_1}^{t_{i+1}}\varepsilon(t)\cos n\omega t\mathrm{d}t-\sum_{i=1}^{N^-}\int_{t_1}^{t_{i+1}}\varepsilon(t)\cos n\omega t\mathrm{d}t,$$

$$\lambda_{b_n}=\sum_{i=1}^{N^+}\int_{t_1}^{t_{i+1}}\varepsilon(t)\sin n\omega t\mathrm{d}t-\sum_{i=1}^{N^-}\int_{t_1}^{t_{i+1}}\varepsilon(t)\sin n\omega t\mathrm{d}t, \tag{10}$$

where t_1 and t_{i+1} are the beginning and the end, respectively, of the i-th positive half-cycle of both $\cos n\omega t$ and $\sin n\omega t$, t_{i+1} and t_{i+2} are the beginning and the end, respectively, of the negative half-cycle both of $\cos n\omega t$ and $\sin n\omega t$, and N^- are the numbers of the positive and negative half-cycles, respectively, of both $\cos n\omega t$ and $\sin n\omega t$.

Obviously, to improve the reliability of the monitoring results of the vibration conditions of offshore platforms using spectral analysis technologies for noisy vibration signals $g(t)$, it is necessary to develop algorithms that provide robust estimates of a_n and b_n by eliminating the influences of the errors λ_{a_n} and λ_{b_n}.

Let us consider this issue in further detail. Assume that a sufficiently long observation time T is selected to realise the noisy vibration signal $g(t)=X(t)+\varepsilon(t)$. Assuming that the functions $X(t)$ and $\varepsilon(t)$ can be represented as sampled stationary centred random signals with zero mathematical expectations, the formulas for calculating the coefficients a_n and b_n are as follows:

$$a_n=\frac{2}{N}\sum_{i=1}^{N}\left[X(i\Delta t)+\varepsilon(i\Delta t)\right]\cos n\omega(i\Delta t)=$$

$$=\frac{2}{N}\sum_{i=1}^{N}X(i\Delta t)\cos n\omega(i\Delta t)+$$

$$+\left[\sum_{i=1}^{N^+}\varepsilon(i\Delta t)\ \cos n\omega(i\Delta t)-\sum_{i=1}^{N^-}\varepsilon(i\Delta t)\cos n\omega(i\Delta t)\right]=$$

$$=\frac{2}{N}\sum_{i=1}^{N}\left[X(i\Delta t)\cos n\omega(i\Delta t)+\lambda_{a_n}\right],$$

$$b_n=\frac{2}{N}\sum_{i=1}^{N}\left[X(i\Delta t)+\varepsilon(i\Delta t)\right]\sin n\omega(i\Delta t)=$$

$$=\frac{2}{N}\sum_{i=1}^{N}X(i\Delta t)\sin n\omega(i\Delta t)+$$

$$+\left[\sum_{i=1}^{N^+}\varepsilon(i\Delta t)\sin n\omega(i\Delta t)-\sum_{i=1}^{N^-}\varepsilon(i\Delta t)\sin n\omega(i\Delta t)\right]=$$

$$=\frac{2}{N}\sum_{i=1}^{N}\left[X(i\Delta t)\sin n\omega(i\Delta t)+\lambda_{b_n}\right]. \tag{11}$$

where $X(i\Delta t)$ and $\varepsilon(i\Delta t)$ are the samples of the signal $X(t)$ and the noise $\varepsilon(t)$ at the sampling moments $t_0,t_1,...,t_i,...,t_N$ with an interval of Δt, respectively.

It is clear that in this case, as long as conditions (1)–(4) hold, the positive and negative N^- errors of the pair products $\varepsilon(i\Delta t)\cos n\omega(i\Delta t)$ and $\varepsilon(i\Delta t)\sin n\omega(i\Delta t)$ will cancel out. However, for cases in which a facility goes into an emergency state, as a correlation appears between the useful signal $X(t)$ and the noise $\varepsilon(t)$, the errors λ_{a_n} and λ_{b_n} also appear, and their values grow as the correlation grows. As a result, in some cases, the estimates of the errors λ_{a_n} and λ_{b_n} that are caused by the effects of the noise $\varepsilon(t)$ are commensurate with the sought-after coefficients a_n and b_n, which results in monitoring errors for the control object's technical conditions.

In consideration of the above, we examine a possible option for ensuring the robustness of the estimates a_n and b_n based on balancing the positive and negative errors of their respective pair products. Assume that the samples of the noise $\varepsilon(i\Delta t)$ of the sum signal $g(i\Delta t)$ are known. In this case, the value of the error $\lambda(i\Delta t)$ of each pair product $g(i\Delta t)\cos n\omega(i\Delta t)$ and $g(i\Delta t)\sin n\omega(i\Delta t)$ can be calculated with the formulae

$$\begin{aligned}&\lambda_{a_n}(i\Delta t)=\left(\varepsilon(i\Delta t)\cos n\omega(i\Delta t)\right),\\&\lambda_{b_n}(i\Delta t)=\left(\varepsilon(i\Delta t)\sin n\omega(i\Delta t)\right).\end{aligned}\qquad(12)$$

Estimates of the mean absolute errors $\lambda(i\Delta t)$ can be calculated from the formulae

$$\begin{aligned}&\overline{\lambda_{a_n}(i\Delta t)}=\overline{\left(\varepsilon(i\Delta t)\cos n\omega(i\Delta t)\right)},\\&\overline{\lambda_{b_n}(i\Delta t)}=\overline{\left(\varepsilon(i\Delta t)\sin n\omega(i\Delta t)\right)}.\end{aligned}\qquad(13)$$

However, according to expression (12), to calculate the errors λ_{a_n} and λ_{b_n}, it is necessary to determine the samples of the noise $\varepsilon(i\Delta t)$, which is practically impossible. According to our previous work [16], it is both possible and appropriate to achieve this by utilizing technology for calculating the estimate of the noise variance D_ε from the expression

$$D_\varepsilon\approx\frac{1}{N}\sum_{i=1}^{N}\left[\begin{array}{l}g(i\Delta t)g(i\Delta t)-2g(i\Delta t)g((i+1)\Delta t)+\\+g((i+2)\Delta t)g(i\Delta t)\end{array}\right].\qquad(14)$$

that can be represented as

$$\begin{aligned}D_\varepsilon&\approx\frac{1}{N}\sum_{i=1}^{N}g(i\Delta t)g(i\Delta t)-\\&-\sum_{i=1}^{N}2g(i\Delta t)g((i+1)\Delta t)+\sum_{i=1}^{N}g(i\Delta t)g((i+2)\Delta t)=\\&=\frac{1}{N}\sum_{i=1}^{N}\left[X(i\Delta t)+\varepsilon(i\Delta t)\right]\left[X(i\Delta t)+\varepsilon(i\Delta t)\right]-\\&-\frac{1}{N}\sum_{i=1}^{N}2\left[X(i\Delta t)+\varepsilon(i\Delta t)\right]\times\\&\times\left[X((i+1)\Delta t)\varepsilon((i+1)\Delta t)\right]+\frac{1}{N}\sum_{i=1}^{N}\left[X(i\Delta t)+\varepsilon(i\Delta t)\right]\times\\&\times\left[X((i+2)\Delta t)+\varepsilon((i+2)\Delta t)\right]=\\&=R_{XX}(0)+R_{X\varepsilon}(0)+R_{\varepsilon X}(0)+R_{\varepsilon\varepsilon}(0)-\\&-2R_{XX}(\Delta t)-2R_{X\varepsilon}(\Delta t)-2R_{\varepsilon X}(\Delta t)-2R_{\varepsilon\varepsilon}(\Delta t)+\\&+R_{XX}(2\Delta t)+R_{X\varepsilon}(2\Delta t)+R_{\varepsilon X}(2\Delta t)+R_{\varepsilon\varepsilon}(2\Delta t).\end{aligned}\qquad(15)$$

In this case, if both the stationarity and normality conditions of the distribution law hold for the signal $g(i\Delta t)=X(i\Delta t)+\varepsilon(i\Delta t)$, the following equalities will hold as well:

$$\begin{cases}R_{X\varepsilon}(0)=\dfrac{1}{N}\sum\limits_{i=1}^{N}X(i\Delta t)\varepsilon(i\Delta t)\neq 0,\\R_{\varepsilon X}(0)=\dfrac{1}{N}\sum\limits_{i=1}^{N}\varepsilon(i\Delta t)X(i\Delta t)\neq 0,\\R_{\varepsilon\varepsilon}(0)=\dfrac{1}{N}\sum\limits_{i=1}^{N}\varepsilon(i\Delta t)\varepsilon(i\Delta t)\neq 0,\\R_{XX}(0)+R_{XX}(2\Delta t)-2R_{XX}(\Delta t)\approx 0,\\R_{\varepsilon\varepsilon}(\Delta t)=\dfrac{1}{N}\sum\limits_{i=1}^{N}\varepsilon(i\Delta t)\varepsilon((i+1)\Delta t)\approx 0,\\R_{\varepsilon\varepsilon}(2\Delta t)=\dfrac{1}{N}\sum\limits_{i=1}^{N}\varepsilon(i\Delta t)\varepsilon((i+2)\Delta t)\approx 0,\\R_{X\varepsilon}(\Delta t)=\dfrac{1}{N}\sum\limits_{i=1}^{N}X(i\Delta t)\varepsilon((i+1)\Delta t)\approx 0,\\R_{X\varepsilon}(2\Delta t)=\dfrac{1}{N}\sum\limits_{i=1}^{N}X(i\Delta t)\varepsilon((i+2)\Delta t)\approx 0,\\R_{\varepsilon X}(\Delta t)=\dfrac{1}{N}\sum\limits_{i=1}^{N}\varepsilon(i\Delta t)X((i+1)\Delta t)\approx 0,\\R_{\varepsilon X}(2\Delta t)=\dfrac{1}{N}\sum\limits_{i=1}^{N}\varepsilon(i\Delta t)X((i+2)\Delta t)\approx 0.\end{cases}\qquad(16)$$

Therefore, on the right-hand side of formula (14), we get

$$\begin{aligned}&D_\varepsilon\approx R_{X\varepsilon}(0)+R_{\varepsilon X}(0)+R_{\varepsilon\varepsilon}(0)\approx\\&\approx 2R_{X\varepsilon}(0)+D_{\varepsilon\varepsilon}\approx D_\varepsilon=\frac{1}{N}\sum_{i=1}^{N}\varepsilon^2(i\Delta t),\end{aligned}\qquad(17)$$

which demonstrates that the estimate for the noise variance $\varepsilon(i\Delta t)$ of the vibration signal $g(i\Delta t)$ can be calculated from expression (14). Assuming that both

$$\begin{aligned}&\varepsilon'(i\Delta t)=\\&=g(i\Delta t)\left[g(i\Delta t)-2g(i+1)\Delta t-2g(i+2)\Delta t\right],\end{aligned}\qquad(18)$$

$$\begin{aligned}&\varepsilon(i\Delta t)\approx\varepsilon^e(i\Delta t)=\\&=\operatorname{sgn}\varepsilon'(i\Delta t)\sqrt{\left|g(i\Delta t)\left[g(i\Delta t)-2g(i+1)\Delta t-2g(i+2)\Delta t\right]\right|}=\\&=\operatorname{sgn}\varepsilon'(i\Delta t)\sqrt{\left|\varepsilon'(i\Delta t)\right|}\end{aligned}\qquad(19)$$

and

$$\begin{aligned}&D_\varepsilon=\frac{1}{N}\sum_{i=1}^{N}\varepsilon^2(i\Delta t)\approx\frac{1}{N}\sum_{i=1}^{N}\varepsilon^{e2}(i\Delta t)=\\&=\frac{1}{N}\sum_{i=1}^{N}\left|g(i\Delta t)\left[g(i\Delta t)+g(i+2)\Delta t-2g(i+1)\Delta t\right]\right|,\end{aligned}\qquad(20)$$

the formula for calculating the mean value of $\varepsilon(i\Delta t)$ can be reduced to the calculation of the mean value of $\varepsilon^e(i\Delta t)$:

$$\overline{\varepsilon(i\Delta t)}\approx\overline{\varepsilon^e(i\Delta t)}=\frac{1}{N}\sum_{i=1}^{N}\varepsilon^e(i\Delta t).$$

In this case, expression (13) can be represented as follows:

$$\begin{aligned}&\overline{\lambda_{a_n}(i\Delta t)}=\overline{\left(\varepsilon^e(i\Delta t)\cos n\omega(i\Delta t)\right(},\\&\overline{\lambda_{b_n}(i\Delta t)}=\overline{\left(\varepsilon^e(i\Delta t)\sin n\omega(i\Delta t)\right(},\end{aligned}\qquad(21)$$

and it can be used to calculate the approximate values for the unknown errors of the estimates for a_n and b_n using the expressions

$$\lambda_{a_n} = \left[\frac{N^+_{a_n} - N^-_{a_n}}{N} \overline{\lambda_a(i\Delta t)} \right],$$

$$\lambda_{b_n} = \left[\frac{N^+_{b_n} - N^-_{b_n}}{N} \overline{\lambda_b(i\Delta t)} \right], \quad (22)$$

where N^- are the numbers of positive and negative micro-errors, respectively, in both of the pair products $g(i\Delta t)\cos n\omega(i\Delta t)$ and N_{q_0}.

As a result, the robustness of the estimates a^R_n and b^R_n can be assured by balancing the positive and negative errors using the formulae

$$a^R_n = \frac{2}{N}\sum_{i=1}^{N}\left[g(i\Delta t)\cos n\omega(i\Delta t) - \lambda_{a_n} \right],$$

$$b^R_n = \frac{2}{N}\sum_{i=1}^{N}\left[g(i\Delta t)\sin n\omega(i\Delta t) - \lambda_{b_n} \right]. \quad (23)$$

Therefore, the use of these robust algorithms makes enhancing the reliability of the results of monitoring for changes in the vibration conditions of offshore platforms possible.

In the following paragraphs, we demonstrate the validity of the proposed technology through the results of a computational experiment conducted in the MATLAB computing environment.

In the experiment, a noisy signal $g(i\Delta t)$ consisting of the useful signal

$$X(i\Delta t) = A\sin\omega(i\Delta t)$$

with a number of samples $N = 5000$, an amplitude $g_0(i\Delta t)$, a period $T = 2$ ms, a cyclic frequency $\omega = \pi$, a sampling period

$$\Delta t = \frac{T}{N} = \frac{2}{5000},$$

and noise $\varepsilon(i\Delta t)$ was generated in the form of a random function following a normal distribution law, with a useful signal variance $D_X = 50.005$, and with a noise variance $D_\varepsilon = 9.0205$.

After that, an array was formed from the samples of the noise $\varepsilon(i\Delta t)$ that were generated by a random variable generator. In addition, an array of samples of $\varepsilon'(i\Delta t)$ was created from the samples of $g(i\Delta t) = X(i\Delta t) + \varepsilon(i\Delta t)$ using formula (18). Then, using formula (11), traditional estimates of the spectral characteristics a_n and b_n of the noisy signal $g(i\Delta t)$ were calculated, and an array of samples of $\varepsilon^e(i\Delta t)$ was created from formula (19). Then, using formulas (21) and (22), both the estimates of $\overline{\lambda_a(i\Delta t)}$ and $\overline{\lambda_b(i\Delta t)}$ and the estimates of the errors λ_{a_n} and λ_{b_n} were calculated. Finally, robust estimates for a^R_n and b^R_n were calculated from formula (23).

In the experiment, for the spectra n=1, 2, 3, 4, the values of the estimates a_n and b_n were close to zero. However, when $n = 5$ (i. e., the period length was 0.5 ms), sudden changes were observed in the values of the estimates a_5 and b_5 that were calculated via traditional technologies. The results of this experimental case are shown in Table 1.

Table 1

Results of the computational experiment for calculating robust estimates of the spectral characteristics

a_5	0.0023
b_5	9.9682
$\overline{\lambda_a(i\Delta t)}$	0.1435
$\overline{\lambda_b(i\Delta t)}$	0.0673
λ_{a_5}	0.014
λ_{b_5}	0.0558
a^R_5	0.0051
b^R_5	9.8565

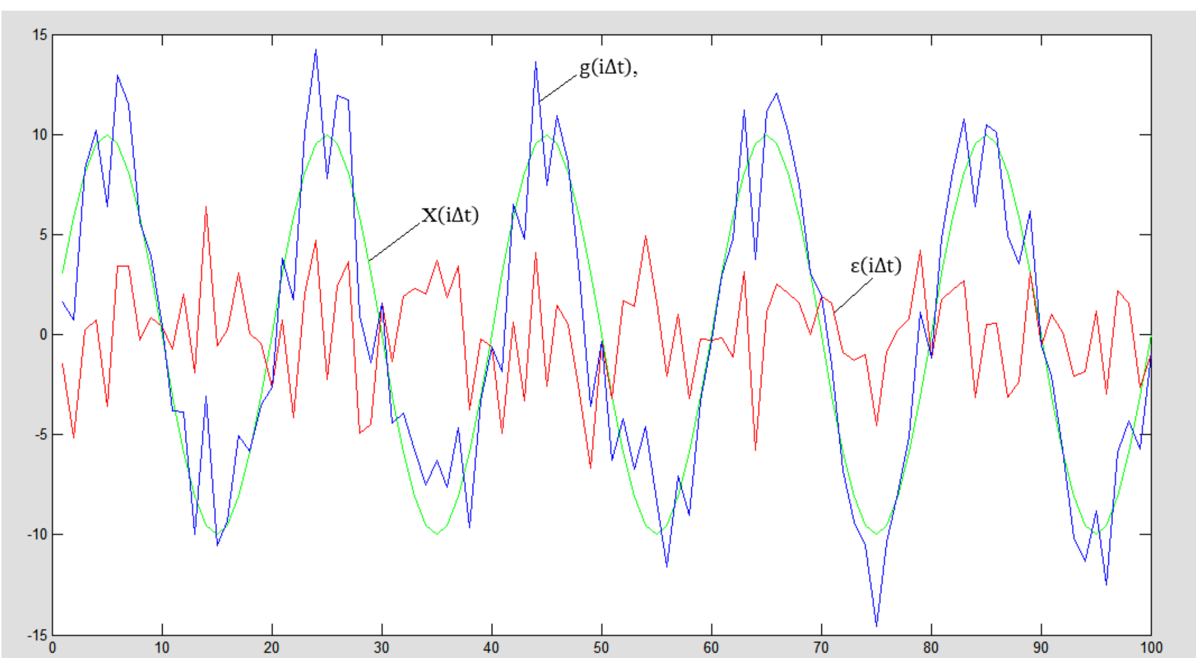

Fig. 1. Diagram of first 100 samples of useful signal $X(i\Delta t)$, noise $\varepsilon(i\Delta t)$, and sum noisy signal $g(i\Delta t)$

As Table 1 shows, the robust estimates of a_n^R and b_n^R calculated from formula (23) turned out to be close to the estimates of a_n of b_n calculated from the traditional formula (11), which confirms the reliability and validity of the proposed technology.

5. Technologies for calculating estimates of spectral characteristics of vibration signal noise

Our research has revealed that the onsets of changes in the vibration conditions of offshore platforms resulting from the births of various defects primarily affect the spectrum of the noise $\varepsilon(i\Delta t)$ of the vibration signal $g(i\Delta t)$. Therefore, in order to provide reliable monitoring of the beginning of latency period T_1, it is logical to use estimates of the spectral characteristics of the noise $\varepsilon(i\Delta t)$ as informative attributes [16–18]. Considering the expressions (18)–(21), the algorithms for spectral analysis of the noise $\varepsilon(i\Delta t)$ of the vibration signal $g(i\Delta t)$ can be represented as

$$a_{n_\varepsilon} = \frac{2}{N}\sum_{i=1}^{N}\varepsilon(i\Delta t)\cos n\omega(i\Delta t) \approx$$
$$\approx \frac{2}{N}\sum_{i=1}^{N}\varepsilon^{e}(i\Delta t)\cos n\omega(i\Delta t),$$

$$b_{n_\varepsilon} = \frac{2}{N}\sum_{i=1}^{N}\varepsilon(i\Delta t)\sin n\omega(i\Delta t) \approx$$
$$\approx \frac{2}{N}\sum_{i=1}^{N}\varepsilon^{e}(i\Delta t)\sin n\omega(i\Delta t). \qquad (24)$$

Assuming that

$$\operatorname{sgn} g(i\Delta t) = \operatorname{sgn} X(i\Delta t) = \begin{cases} +1 & \text{if } g(i\Delta t) > 0, \\ 0 & \text{if } g(i\Delta t) = 0, \\ -1 & \text{if } g(i\Delta t) < 0, \end{cases} \qquad (25)$$

and taking into account formulae (18) and (19), expression (24) can be written as follows:

$$a_{n_\varepsilon} \approx \frac{2}{N}\sum_{i=1}^{N}\operatorname{sgn}\varepsilon'(i\Delta t)\sqrt{\left|g(i\Delta t)\left[g(i\Delta t)+g(i+2)\Delta t-2g(i+1)\Delta t\right]\right|}\cos n\omega(i\Delta t) =$$
$$= \frac{2}{N}\sum_{i=1}^{N}\operatorname{sgn}\varepsilon'(i\Delta t)\sqrt{\left|\varepsilon'(i\Delta t)\right|}\cos n\omega(i\Delta t),$$

$$b_{n_\varepsilon} \approx \frac{2}{N}\sum_{i=1}^{N}\operatorname{sgn}\varepsilon'(i\Delta t)\sqrt{\left|g(i\Delta t)\left[g(i\Delta t)+g(i+2)\Delta t-2g(i+1)\Delta t\right]\right|}\sin n\omega(i\Delta t) = b_{5_2}. \quad (26)$$

Thus, the robust estimates of a_{n_ε} and b_{n_ε} obtained from expression (23) make it possible to register the onset of defect formation during period T_1. However, using expression (26) in control systems makes it possible to register the beginning of the latency period T_1, representing the platform's transition into an emergency state, by calculating the estimates of the spectral characteristics of the noise $\varepsilon(i\Delta t)$ of the vibration signal $g(i\Delta t)$.

An analysis of other possible options for calculating the estimates of the spectral characteristics of the noise has shown that, by taking into account expressions (24)–(26), the algorithms for calculating the estimates $a_{n\varepsilon}$ and $b_{n\varepsilon}$ of the relay spectral characteristics of the noise $\varepsilon(i\Delta t)$ of the vibration signal $g(i\Delta t)$ can be represented by

$$a^{*}_{n_\varepsilon} \approx \frac{1}{N}\sum_{i=1}^{N}\operatorname{sgn}\varepsilon(i\Delta t)\cos n\omega(i\Delta t) =$$
$$= \frac{2}{N}\sum_{i=1}^{N}\operatorname{sgn}\varepsilon'(i\Delta t)\sqrt{\left|g(i\Delta t)\left[g(i\Delta t)+g(i+2)\Delta t-2g(i+1)\Delta t\right]\right|}\cos n\omega(i\Delta t) =$$
$$= \frac{2}{N}\sum_{i=1}^{N}\operatorname{sgn}\varepsilon'(i\Delta t)\sqrt{\left|\varepsilon'(i\Delta t)\right|}\cos n\omega(i\Delta t),$$

$$b^{*}_{n_\varepsilon} \approx \frac{1}{N}\sum_{i=1}^{N}\operatorname{sgn}\varepsilon(i\Delta t)\sin n\omega(i\Delta t) =$$
$$= \frac{2}{N}\sum_{i=1}^{N}\operatorname{sgn}\varepsilon'(i\Delta t)\sqrt{\left|g(i\Delta t)\left[g(i\Delta t)+g(i+2)\Delta t-2g(i+1)\Delta t\right]\right|}\sin n\omega(i\Delta t) = b_{5_2}. \quad (27)$$

Our research has also demonstrated that, in addition to the above, noise sign spectral analysis technology can be used to solve our problem with the expressions

$$a'_{n_\varepsilon} = \frac{1}{N}\sum_{i=1}^{N}\operatorname{sgn}\varepsilon(i\Delta t)\operatorname{sgn}\cos n\omega(i\Delta t) =$$
$$= \frac{2}{N}\sum_{i=1}^{N}\operatorname{sgn}\varepsilon'(i\Delta t)\sqrt{\left|g(i\Delta t)\left[g(i\Delta t)+g(i+2)\Delta t-2g(i+1)\Delta t\right]\right|}\operatorname{sgn}\cos n\omega(i\Delta t) =$$
$$= \frac{2}{N}\sum_{i=1}^{N}\operatorname{sgn}\sqrt{\left|\varepsilon'(i\Delta t)\right|}\operatorname{sgn}\cos n\omega(i\Delta t),$$

$$b'_{n_\varepsilon} = \frac{1}{N}\sum_{i=1}^{N}\operatorname{sgn}\varepsilon(i\Delta t)\operatorname{sgn}\sin n\omega(i\Delta t) =$$
$$= \frac{2}{N}\sum_{i=1}^{N}\operatorname{sgn}\varepsilon'(i\Delta t)\sqrt{\left|g(i\Delta t)\left[g(i\Delta t)+g(i+2)\Delta t-2g(i+1)\Delta t\right]\right|}\operatorname{sgn}\sin n\omega(i\Delta t) =$$
$$= \frac{2}{N}\sum_{i=1}^{N}\operatorname{sgn}\sqrt{\left|\varepsilon'(i\Delta t)\right|}\operatorname{sgn}\sin n\omega(i\Delta t). \qquad (28)$$

It is clear that the estimates of $a'_{n\varepsilon}$ and $b'_{n\varepsilon}$ obtained from these expressions will be different from zero only in the presence of a correlation between $X(i\Delta t)$ and $\varepsilon(i\Delta t)$. The distinctive features of this technology are that it is easily implementable in terms of hardware and that it can be used to signal the starting moment of period T_1.

Considering how extremely important monitoring the formation of defects that precede accidents on offshore platforms is, it is advisable to duplicate the indication of the beginning of period T_1 by estimating the spectral characteristics of the noise $\varepsilon(i\Delta t)$, with indication occurring the moment that a correlation between the useful vibration signal and its noise appears. An analysis of the characteristics of possible solutions to this problem has shown that, in addition to the above algorithms, it is expedient to utilise the algorithm for calculating the estimate of the relay cross-correlation function $R_{X\varepsilon}(\mu)$ between $X(i\Delta t)$ and $\varepsilon(i\Delta t)$ of the noisy vibration signal $g(i\Delta t)$. In [3], the authors show that the estimate of the relay cross-correlation function $R_{X\varepsilon}(0)$ between $\varepsilon(i\Delta t)$ and $X(i\Delta t)$ can be calculated with the following formula:

$$D_\varepsilon(0)\approx\frac{1}{N}\sum_{1}^{N}\begin{bmatrix}\operatorname{sgn} g(i\Delta t)g(i\Delta t)-2\operatorname{sgn} g(i\Delta t)g((i+1)\Delta t)+\\+\operatorname{sgn} g(i\Delta t)g((i+2)\Delta t)\end{bmatrix}. \quad (29)$$

Expanding the right-hand side of this formula and taking into account that

$$\operatorname{sgn} g(i\Delta t)=\operatorname{sgn} X(i\Delta t), \quad (30)$$

expression (29) can be written as

$$R^*_{X\varepsilon}(0)=\frac{1}{N}\sum_{i=1}^{N}\Big[\big[\operatorname{sgn} X(i\Delta t)X(i\Delta t)+\operatorname{sgn} X(i\Delta t)\varepsilon(i\Delta t)\big]$$
$$-2\big[\operatorname{sgn} X(i\Delta t)X((i+1)\Delta t+\operatorname{sgn} X(i\Delta t)\varepsilon((i+1)\Delta t)\big]+$$
$$+\big[\operatorname{sgn} X(i\Delta t)X((i+2)\Delta t+\operatorname{sgn} X(i\Delta t)\varepsilon((i+2)\Delta t)\big]\Big]. \quad (31)$$

If both the stationarity and normality conditions of the distribution law are then satisfied, we can assume that

$$\left.\begin{aligned}&R^*_{X\varepsilon}(0)=\frac{1}{N}\sum_{i=1}^{N}\operatorname{sgn} X(i\Delta t)\varepsilon(i\Delta t)\neq 0 \text{ where } R^*_{X\varepsilon}(\Delta t)=\frac{1}{N}\sum_{i=1}^{N}\operatorname{sgn} X(i\Delta t)\varepsilon((i+1)\Delta t)=0,\\&\frac{1}{N}\sum_{i=1}^{N}\operatorname{sgn} X(i\Delta t)X(i\Delta t)+\frac{1}{N}\sum_{i=1}^{N}\operatorname{sgn} X(i\Delta t)X((i+2)\Delta t)-\frac{1}{N}\sum_{i=1}^{N}2\operatorname{sgn} X(i\Delta t)X((i+1)\Delta t)\approx 0,\\&R^*_{X\varepsilon}(\Delta t)=\frac{1}{N}\sum_{i=1}^{N}\operatorname{sgn} X(i\Delta t)\varepsilon((i+1)\Delta t)\approx 0,\ R^*_{X\varepsilon}(2\Delta t)=\frac{1}{N}\sum_{i=1}^{N}\operatorname{sgn} X(i\Delta t)\varepsilon((i+2)\Delta t)\approx 0.\end{aligned}\right\} \quad (32)$$

As a result, we attain the expression

$$D^*_\varepsilon(0)=R_{X\varepsilon}(0)=$$
$$=\frac{1}{N}\sum_{i=1}^{N}\operatorname{sgn} X(i\Delta t)\varepsilon(i\Delta t)=\frac{1}{N}\sum_{i=1}^{N}\operatorname{sgn} g(i\Delta t)\varepsilon(i\Delta t).$$

Formula (29) provides us with an estimate of the relay cross-correlation function $R^*_{X\varepsilon}(0)$ between the useful signal $X(i\Delta t)$ and the noise $\varepsilon(i\Delta t)$, meaning that

$$R^*_{X\varepsilon}(0)=$$
$$=\frac{1}{N}\sum_{i=1}^{N}\operatorname{sgn} g(i\Delta t)[g(i\Delta t)+g((i+2)\Delta t)-2g((i+1)\Delta t)]. \quad (33)$$

The most distinctive feature of this algorithm is that the estimate of $R^*_{X\varepsilon}(0)$ is equal to zero during normal platform operation. However, as various defects arise, when a correlation appears between $X(i\Delta t)$ and $\varepsilon(i\Delta t)$, the estimate diverges from zero and makes it possible to both reliably register and signal the onset of a facility's transition into an emergency state. Therefore, the estimates of a_{n_ε}, b_{n_ε}, $a^*_{n\varepsilon}$, $b^*_{n\varepsilon}$, $a'_{n\varepsilon 1}$, $b'_{n\varepsilon 1}$ and $R^*_{X\varepsilon}(0)$ mirror their respective counterparts. As the defect develops, the values of the estimates of a_{n_ε}, b_{n_ε}, $a^*_{n\varepsilon}$ and $b^*_{n\varepsilon}$ grow, which allows for control of not only the start but also the dynamics of change in the facility's emergency state.

Fig. 2 is a photograph of our semi-natural experiment, showing both the vibration sensor and the monitor displaying the signal received during the experiment.

To verify the reliability of this technology, we present the results of a semi-natural experiment including the use of our monitoring system, in which various defects were simulated. The noisy signals $g_1(i\Delta t)$, $g_2(i\Delta t)$, $g_3(i\Delta t)$, and $g_4(i\Delta t)$ consisting of both the useful signals $X_1(i\Delta t)$, $X_2(i\Delta t)$, $X_3(i\Delta t)$ and $X_4(i\Delta t)$ and the noise functions $\varepsilon_1(i\Delta t)$, $\varepsilon_2(i\Delta t)$, $\varepsilon_3(i\Delta t)$ and $\varepsilon_4(i\Delta t)$, respectively, were received at the outputs of the vibration sensors (Fig. 2). The estimates of the cross-correlation function between the useful signals $X_1(i\Delta t)$, $X_2(i\Delta t)$, $X_3(i\Delta t)$ and $X_4(i\Delta t)$ and the noise functions $\varepsilon_1(i\Delta t)$, $\varepsilon_2(i\Delta t)$, $\varepsilon_3(i\Delta t)$ and $\varepsilon_4(i\Delta t)$, respectively, assumed different values for the occurrences of different defects. During the experiments, it became clear that for the spectra n=1, 2, 3, 4, the values of the estimates $a_{n_{\varepsilon_i}}$ and $b_{n_{\varepsilon_i}}$ were close to zero. However, when n=5 (i. e., when the period was 0.5 ms), estimates of the spectral characteristics of the noise began increasing in conjunction with the estimates of the cross-correlation function $R_{X\varepsilon}$ for different defects. The results of one of the many experiments are shown in Table 2.

As Table 2 shows, different estimates of the cross-correlation function $R_{X\varepsilon}$ were obtained depending on the specific nature each defect, which, in turn, affected the estimates $a_{5_{\varepsilon_1}}$, $a_{5_{\varepsilon_2}}$, $a_{5_{\varepsilon_3}}$, $a_{5_{\varepsilon_4}}$, $b_{5_{\varepsilon_1}}$, $b_{5_{\varepsilon_2}}$, $b_{n_{\varepsilon_3}}$ and $b_{5_{\varepsilon_4}}$ of the spectral characteristics of the noise. The results of numerous similar experiments found these estimates to be reliable indicators of the beginning of the latency period of a platform's transition into an emergency state.

Thus, when typical defects began to emerge in the elements of a platform as a result of the correlation appearing between $X(i\Delta t)$ and $\varepsilon(i\Delta t)$, both the estimate $R^*_{X\varepsilon}(0)$ and the spectral characteristics $a_{n\varepsilon}$, $b_{n\varepsilon}$, $a_{n\varepsilon}$, $b_{n\varepsilon}$, $a'_{n\varepsilon}$ and $b'_{n\varepsilon}$ of the noise $\varepsilon(i\Delta t)$ deviated from zero. In the absence of a correlation between $\varepsilon(i\Delta t)$ and $X(i\Delta t)$, these estimates were equal to zero. Consequently, they can be used as reliable alternative informative attributes for the timely monitoring of the beginning of period T_1.

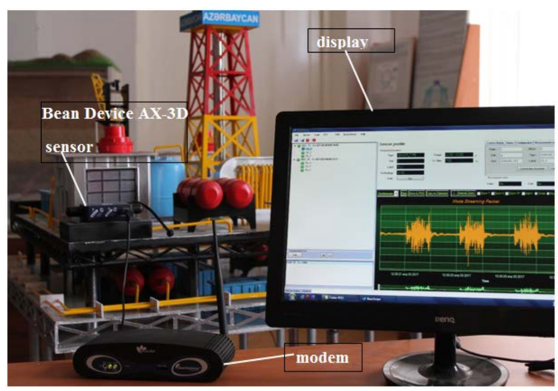

Fig. 2. Intelligent system for monitoring the technical conditions of offshore platforms and test bench for semi-natural experiments

Table 2

Results of a computational experiment for calculating estimates of the spectral characteristics of the noise $\varepsilon(i\Delta t)$ of the vibration signal $g(i\Delta t)$

Estimate/noise	ε_1	ε_2	ε_3	ε_4
$a_{5_{\varepsilon_i}}$	0.066	0.264	1.211	2.574
$b_{5_{\varepsilon_i}}$	0.024	0.138	0.854	1.745
$R_{X\varepsilon}$	0.252	1.008	4.032	9.072

6. Operating principles of the spectral noise subsystem for monitoring the onset of changes in the vibration conditions of offshore platforms

The operating principles of the subsystem performing the noise monitoring of the technical conditions of offshore platforms are described in detail in [1]. Here, we discuss forming additional reference sets of informative attributes consisting of the estimates of the spectral characteristics $a_{n\varepsilon}$, $b_{n\varepsilon}$, $a^*_{n\varepsilon}$, $b^*_{n\varepsilon}$, $a'_{n\varepsilon}$, $b'_{n\varepsilon}$, D_ε and $R^*_{X\varepsilon}(0)$ of the vibration signals obtained from expressions (14), (17), (23), (26)–(29) and (33).

Note that the number of these reference sets depends on the number of vibration sensors installed in either the main sections or the most vulnerable "informative" structures of platforms. Naturally, as the number of subsystems increases, the system becomes more complicated. However, a lower number of subsystems increases the probability of delays occurring in the indication of faults. The optimization of the number of sensors is not considered in this paper, but a preliminary analysis shows that the number of sensors used should be at least 15–20. For a large number of sensors, the nonnegative garrote approach, described in detail in [19–24], is recommended. In general, the process of selecting a sensor is determined by the conditions of its application. Structural frequency monitoring systems most commonly use sensors for [21, 22]:

– vibration displacement;
– vibration velocity;
– vibration acceleration.

Sensors in the first category characterise the control object's position, sensors in the second category characterise the rate of change of the object's displacement with respect to time, and sensors in the third category characterise the rate of change in velocity. These three parameters characterizing vibration are interrelated, and by controlling, for example, vibration acceleration via either single or double integration, it is easy to calculate the remaining two parameters.

The use of these three types of sensors is based on the need to control vibrations at facilities with different frequency characteristics. Vibration displacement sensors are well-proven to be effective in the low-frequency region, vibration velocity sensors are usually used for medium-frequency facilities, and vibration acceleration sensors are usually used for high-frequency ones.

Our analysis of the possible applications of vibration sensors in monitoring the technical conditions of offshore platforms found Bean Device AX-3D sensors the most suitable. These sensors can be easily installed at the most vulnerable points of a platform's structure (Fig. 1). Measurement information is collected from these sensors via Wi-Fi using the Bean CetanWay Controller. The Wi-Fi signals emanating from the Bean Device AX-3D sensor carry ranges of up to 650 m, which is sufficient for the typical sizes of offshore platforms. The technical parameters of the Bean Device AX-3D sensor are described in [23].

During the operation of the intelligent system for monitoring the technical conditions of platforms shown in Fig. 2, reference sets consisting of the estimates of the vibration signal noise characteristics are generated in the first stage of training. This means that for each kind of platform vibration conditions, including during calm weather, moderate wind, strong wind, a hurricane, a drilling rig operating, or others, a reference set W_{ε_j} of informative attributes is created:

$$W_{\varepsilon_j}=\begin{cases} a_{n(1)}, b_{n(1)}, a_{n_\varepsilon(1)}, b_{n_\varepsilon(1)}, a^*_{n_\varepsilon(1)}, b^*_{n_\varepsilon(1)}, a'_{n_\varepsilon(1)}, b'_{n_\varepsilon(1)}, R_{X_\varepsilon(1)}, \\ a_{n(2)}, b_{n(2)}, a_{n_\varepsilon(2)}, b_{n_\varepsilon(2)}, a^*_{n_\varepsilon(2)}, b^*_{n_\varepsilon(2)}, a'_{n_\varepsilon(2)}, b'_{n_\varepsilon(2)}, R_{X_\varepsilon(2)}, \\ \vdots \\ a_{n(20)}, b_{n(20)}, a_{n_\varepsilon(20)}, b_{n_\varepsilon(20)}, a^*_{n_\varepsilon(20)}, b^*_{n_\varepsilon(20)}, a'_{n_\varepsilon(20)}, b'_{n_\varepsilon(20)}, R_{X_\varepsilon(20)}. \end{cases}$$

After this training, in a similar way to the system described in [1], our system switches to monitoring mode, in which combinations of the current spectral characteristic estimates of the vibrating signal noise received from the corresponding sensors are calculated via the same technologies. Then these are compared with all of the elements of the reference sets. The current estimates that differ from their respective reference elements by values exceeding an established threshold are singled out. If no such element is detected, then it is assumed that the platform's vibration conditions are stable. When such an element is detected, it is located based on its vibration sensor address in order to be diagnosed by maintenance and repair personnel. The methods described in [25–28] can be used to locate damage in the platform's structure.

Our experiments have shown that the reliability of spectral noise monitoring results depends primarily on the noise sampling interval selection. This is because changes in marine weather conditions affect the vibration conditions both of individual structural elements and of each platform as a whole, altering the spectra of both the noise and the useful vibration signal. Since the estimates of the spectral characteristics of the noise $\varepsilon(i\Delta t)$ of the vibration signal $g(i\Delta t)$ contain the diagnostic information, adaptive calculation of the sampling interval Δt_ε is required [29, 30]. Therefore, the sampling interval Δt_ε is calculated in the monitoring system in real time in order to obtain the estimates of the spectral characteristics of the noise $\varepsilon(i\Delta t)$ with sufficient accuracy. This is achieved by making use of the frequency properties of the least significant bit $q_0(i\Delta t)$ of the samples $g(i\Delta t)$ that forms during the analogue-to-digital conversion of the vibration signal $g(i\Delta t)$.

To accomplish this, the signal $g(t)$ is converted into digital code with a frequency f_v that considerably exceeds the sampling frequency f_c found using the traditional method (i. e., $f_v \gg f_c$) [15, 29].

In this case, the sampling interval Δt_v, calculated from the formula

$$\Delta t_v = \frac{1}{f_v}, \tag{34}$$

proves to be considerably smaller than the sampling frequency Δt_g of the vibration signal $g(i\Delta t)$, meaning that

$$\Delta t_g \gg \Delta t_\varepsilon. \tag{35}$$

As a result, the following inequality between the sampling frequency $f_X = f_g$ and the frequency f_v arises:

$$\left.\begin{aligned} f_v &\gg f_X, \\ \Delta t_v &\ll \Delta t_X. \end{aligned}\right\} \tag{36}$$

Therefore, there is a high probability that the bit values of the samples of the signal $g(i\Delta t)$ will be repeated in each subsequent step of the analogue-to-digital conversion, and the following equality arises:

$$[X(i\Delta t)] \approx P[X((i+1)\Delta t)] \approx 1, \qquad (37)$$

where P is the probability sign.

In the process of analogue-to-digital conversion with the frequency f_v, the frequency f_{q_0} affected by the spectrum of the noise $\varepsilon(i\Delta t)$ is determined by the number of transitions N_{q_0} of the least significant bit $q_0(i\Delta t)$ of sample $g(i\Delta t)$ from one-state to zero-state per unit time. For this case, both the number N_{q_0} and the total number of samples N of the vibration signal $g(i\Delta t)$ are determined. Then, the following expression can be used in the calculation of both the frequency f_{q_0} and the sampling interval Δt_ε using software:

$$f_{q_0} \approx \frac{N_{q_0}}{N} f_v. \qquad (38)$$

Therefore, software calculation of the monitoring system's sampling interval Δt_e of the noise is reduced to the following:

1) The vibration signal $g(i\Delta t)$ is converted into digital code with an excess frequency f_v during the observation time T, and a file is generated from N of its samples.

2) The number of samples Nq_0 for which the least significant bit $q_0(i\Delta t)$ of sample $g(i\Delta t)$ differs from the least significant bits $\mathrm{q}_0((i+1)\Delta t)$ and $\mathrm{q}_0((i-1)\Delta t)$ of the adjacent samples $g(i+1)\Delta t$ and $g(i-1)\Delta t$, respectively, calculated using software. Then, using the correlations

$$f_{q_0} = \frac{N_{q_0}}{N} f_v; \quad \Delta t_\varepsilon \le \frac{1}{f_{q_0}},$$

f_{q_0} and Δt_ε are calculated.

For instance, at the sampling frequency $f_v = 10000$ Hz for $N = 10000$, if N_{q_0} is equal to 1000 samples, then the frequencies

$$f_{q_0} = \frac{N_{q_0}}{N} \text{ and } f_v = \frac{1000}{10000} 10000 = 1000 \text{ Hz},$$

and the interval Δt is

$$\Delta t_\varepsilon \le \frac{1}{f_{q_0}} = \frac{1}{1000} = 0.001 \text{ s}.$$

Our experiments have shown that such a calculation of the sampling interval Δt_ε is easily programmable, and during the encoding of the vibration signals $g(i\Delta t)$, it is easy to determine the noise sampling frequency that corresponds to the high-frequency spectrum of the noise $\varepsilon(i\Delta t)$ of the sum signal $g(i\Delta t)$. It has been established that the spectral noise monitoring of the vibration conditions is effective within a sampling frequency f_{q_0} range of 2000–3000 Hz. Because of the simplicity of the implementation of this technology, it carries the prospect of wide practical application, which is of particular importance.

7. Discussion of research results

Comparing with traditional algorithms and technologies, which are effective under the condition that there is no correlation between the useful signal and the noise, the use of the offered technology for monitoring the condition of offshore platforms prevents delays in malfunction reporting and catastrophic accidents.

The algorithms and technologies of spectral analysis of both vibration signal and its noise proposed in this paper increase the reliability of monitoring the beginning of a latent period of transition to an emergency state of offshore platforms. This feature helps to improve the effectiveness of the control systems of offshore platforms.

In the article [1] we proposed noise technologies for monitoring changes in vibration condition of offshore platforms by means of the sets of combinations of informative attributes. Improved technologies of spectral analysis of vibration signal and its noise proposed in this article give the opportunity to identify the beginning of a latent period of transition to an emergency state of offshore platforms.

Control of the vibration state of oil-gas objects functioning in sea conditions is the task of paramount importance in the creation of control systems of such objects. Another important area of implementation of the given technology is the control of the vibration state of drilling rigs. By means of this it is possible to determine the beginning of the latent period of the failures. This problem will be discussed in another article.

8. Conclusions

1. During the operation of an offshore platform, changes in weather conditions affect the vibration conditions both of the individual structural elements and of the platform as a whole, which leads to changes in the spectra of both the noise $\varepsilon(i\Delta t)$ and the useful vibration signal $X(i\Delta t)$ received from the corresponding vibration sensors. In addition, because we need to calculate the estimates of the spectral characteristics of the noise $\varepsilon(i\Delta t)$ of the vibration signal $g(i\Delta t)$ in real time to obtain continuously updated diagnostic information, the sampling interval Δt_ε is calculated by making use of the frequency properties of the least significant bit $q_0(i\Delta t)$ of samples $g_0(i\Delta t)$ that forms during the analogue-to-digital conversion of the vibration signal [29]. The sampling frequency of the noise $\varepsilon(i\Delta t)$ is determined, using the number of transitions N_{q_0} of the least significant bit $q_0(i\Delta t)$ of sample $g(i\Delta t)$ from one-state to zero-state per unit time. In the monitoring process, this procedure is reduced to a software calculation of the correlation between the number of samples N_{q_0} of $g(i\Delta t)$ for which the least significant bit $q_0(i\Delta t)$ differs from the least significant bits $q_0((i+1)\Delta t)$ and $q_0((i-1)\Delta t)$ of the adjacent samples and the total number of samples N of $g(i\Delta t)$. Due to its simplicity of implementation, this technology can find wide practical applications in modern monitoring, diagnostic, and control systems.

2. Offshore platforms and other offshore oil and gas extraction facilities operate under continuous oscillating conditions due to the influence of ocean waves in various weather conditions. In this regard, vibration signals contain most of the information about the technical conditions of a platform. Studies have shown that in terms of the timely registration and signalling of the onsets of faults, the use of spectral analysis technology on the vibration signal noise is the most effective means of achieving this. It should be taken into account that vibration signals develop correlated noise due to the defects emerging in such a facility, which in some cases is the only useful information available about the

beginning of the latency period of the facility's transition into an emergency state. However, the data contained in the noise is lost in existing control systems because of filtering. Therefore, the algorithms and technologies that were proposed in this paper for the spectral analyses of both the noisy vibration signal and its noise in order to increase both the reliability and the validity of the monitoring of the onset of the latency period of transition into an emergency state can contribute to an enhanced operating efficiency for control systems of offshore platforms.

3. The use of traditional algorithms and technologies for the spectral analyses of noisy signals in control and diagnostics systems is effective and expedient under classical conditions, such as stationarity, the normality of the distribution law, and the absence of correlation between the useful signal and the noise. These algorithms have found wide practical applications, as these conditions are met in many industries for the signals received at the outputs of their corresponding sensors. However, in certain cases, correlations are present between the useful signal and the noise. In one of these cases, if a delayed indication of malfunction does not result a state of emergency for the facility, then the use of traditional algorithms can be considered expedient. However, there are many facilities for which a delayed indication of malfunction can entail a catastrophic accident, rendering traditional algorithms inefficient and impractical. For instance, the uses of such systems in monitoring and diagnosing the conditions of offshore platforms leads to delays in malfunction reporting, which can sometimes result in catastrophic accidents.

References

1. Aliev T. A., Alizada T. A., Rzayeva N. E. Noise technologies and systems for monitoring the beginning of the latent period of accidents on fixed platforms // Mechanical Systems and Signal Processing. 2017. Vol. 87. P. 111–123. doi: 10.1016/j.ymssp.2016.10.014
2. Aliev T. A., Alizada T. A., Tahirova Kh. S. Hybrid system of control and diagnostics of the condition of offshore platforms // Journal of Oil Industry. 2000. Issue 1. P. 29–31.
3. Aliev T. Digital Noise Monitoring of Defect Origin. Springer, 2007. doi: 10.1007/978-0-387-71754-8
4. Noise monitoring technology for objects in transition to the emergency state / Aliev T. A., Guluyev G. A., Pashayev F. H., Sadygov A. B. // Mechanical Systems and Signal Processing. 2012. Vol. 27. P. 755–762. doi: 10.1016/j.ymssp.2011.09.005
5. Singpurwalla N. D. Damage Processes. Encyclopedia of Statistics in Quality and Reliability. John Wiley and Sons, Inc., 2008. doi: 10.1002/9780470061572.eqr073
6. Guseynov S. E., Aleksejeva J. V., Andreyev S. A. On one Regularizing Algorithm for Comprehensive Diagnosing of Apparatus, Engines and Machinery // Advanced Materials Research. 2015. Vol. 1117. P. 254–257. doi: 10.4028/www.scientific.net/amr.1117.254
7. Major accidents on oil platforms in 2010–2015. RIA News. URL: https://ria.ru/spravka/20150401/1055996620.html
8. Cho Y., Kwon S., Hwang S. A new approach to developing a conceptual topside process design for an offshore platform // Korean Journal of Chemical Engineering. 2017. Vol. 35, Issue 1. P. 20–33. doi: 10.1007/s11814-017-0258-z
9. Jahanitabar A. A., Bargi K. Time-dependent seismic fragility curves for aging jacket-type offshore platforms subjected to earthquake ground motions // Structure and Infrastructure Engineering. 2017. Vol. 14, Issue 2. P. 192–202. doi: 10.1080/15732479.2017.1343360
10. Chang Z., Yu Y., Qi Y. Study on dynamic characteristics of hydraulic pumping unit on offshore platform // China Ocean Engineering. 2017. Vol. 31, Issue 6. P. 693–699. doi: 10.1007/s13344-017-0079-1
11. Elginoz N., Bas B. Life Cycle Assessment of a multi-use offshore platform: Combining wind and wave energy production // Ocean Engineering. 2017. Vol. 145. P. 430–443. doi: 10.1016/j.oceaneng.2017.09.005
12. Response of nonlinear offshore spar platform under wave and current / Soeb M. R., Islam A. B. M. S., Jumaat M. Z., Huda N., Arzu F. // Ocean Engineering. 2017. Vol. 144. P. 296–304. doi: 10.1016/j.oceaneng.2017.07.042
13. Marino A., Velotto D., Nunziata F. Offshore Metallic Platforms Observation Using Dual-Polarimetric TS-X/TD-X Satellite Imagery: A Case Study in the Gulf of Mexico // IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing. 2017. Vol. 10, Issue 10. P. 4376–4386. doi: 10.1109/jstars.2017.2718584
14. Hu Z., Qin W. Fuzzy Method and Neural Network Model Parallel Implementation of Multi-Layer Neural Network Based on Cloud Computing for Real Time Data Transmission in Large Offshore Platform // Polish Maritime Research. 2017. Vol. 24, Issue s2. P. 39–44. doi: 10.1515/pomr-2017-0062
15. Bendat J. S., Piersol A. G. Engineering Applications of Correlation and Spectral Analysis. 2nd ed. Wiley, 1993.
16. Aliev T. Robust Technology with Analysis of Interference in Signal Processing. Springer, 2003. doi: 10.1007/978-1-4615-0093-3
17. Aliev T. A., Alizada T. A. Robust technology for calculation of the coefficients of the Fourier series of random signals // Automatic Control and Computer Sciences. 2000. Issue 4. P. 18–26.
18. Orsingher E. On the maximum of gaussian fourier series emerging in the analysis of random vibrations // Journal of Applied Probability. 1989. Vol. 26, Issue 01. P. 182–188. doi: 10.2307/3214329
19. Vibro-Detection Applied To Offshore Platforms / Lepert P., Chay M., Heas J. Y., Narzul P. // Offshore Technology Conference. 1980. doi: 10.4043/3918-ms
20. Roitman N., Viero P. F. Detection and Location of Damages in Offshore Platforms: An Application of Some Methods Using Eigenvectors // Proceedings of SPIE – The International Society for Optical Engineering. 1997. P. 1124–1131.
21. Vibrations in Technology. Vol. 5: Handbook / M. D. Genkin (Ed.). Moscow: Mashinostroenie, 1999.
22. Skobelev O. P. Acceleration, Vibration and Shock Sensor Dynamics // Wit Pr/Computational Mechanics. 2000.
23. Wireless accelerometer with built-in data logger. BeanDevice. URL: http://www.beanair.com/wireless-accelerometer-over.html
24. Paynabar K., Jin J., Reed M. P. Informative Sensor and Feature Selection via Hierarchical Nonnegative Garrote // Technometrics. 2015. Vol. 57, Issue 4. P. 514–523. doi: 10.1080/00401706.2014.947383

25. Acoustic emission source location in complex structures using full automatic delta T mapping technique / Al-Jumaili S. K., Pearson M. R., Holford K. M., Eaton M. J., Pullin R. // Mechanical Systems and Signal Processing. 2016. Vol. 72-73. P. 513–524. doi: 10.1016/j.ymssp.2015.11.026
26. Locating acoustic emission sources in complex structures using Gaussian processes / Hensman J., Mills R., Pierce S. G., Worden K., Eaton M. // Mechanical Systems and Signal Processing. 2010. Vol. 24, Issue 1. P. 211–223. doi: 10.1016/j.ymssp.2009.05.018
27. Delta T source location for acoustic emission / Baxter M. G., Pullin R., Holford K. M., Evans S. L. // Mechanical Systems and Signal Processing. 2007. Vol. 21, Issue 3. P. 1512–1520. doi: 10.1016/j.ymssp.2006.05.003
28. Mostafapour A., Davoodi S. A method for acoustic source location in plate-type structures // Mechanical Systems and Signal Processing. 2017. Vol. 93. P. 92–103. doi: 10.1016/j.ymssp.2017.02.006
29. Position-binary and spectral indicators of microchanges in the technical states of control objects / Aliev T. A., Guliev Q. A., Rzaev A. H., Pashaev F. H., Abbasov A. M. // Automatic Control and Computer Sciences. 2009. Vol. 43, Issue 3. P. 156–165. doi: 10.3103/s0146411609030067
30. Mehdiyeva G., Ibrahimov V., Imanova M. General Theory of the Application of Multistep Methods to Calculation of the Energy of Signals. Vol. 348 // Lecture Notes in Electrical Engineering. 2016. P. 1047–1056. doi: 10.1007/978-81-322-2580-5_95

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STUDY OF THE MATHEMATICAL MODELS OF OPTIMAL PARTITIONING FOR PARTICULAR CASES

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Досліджено особливості застосування теорії задач неперервного розбиття множин для випадку, коли вихідна множина є частиною плоскої кривої. Сформульована задача для окремого випадку відомої постановки. Ця задача розв'язана з урахуванням запропонованих обмежень. Виконано обчислювальний експеримент. Зроблено висновки про можливості прикладного застосування розв'язків поставленої задачі

Ключові слова: оптимальне розбиття, неперервна множина, мінімізація, довжина дуги, центр множини, метрика, розташування

Исследованы особенности применения теории задач непрерывного разбиения множеств для случая, когда исходное множество является частью плоской кривой. Сформулирована задача для частного случая известной постановки. Эта задача решена с учётом предложенных ограничений. Проведён вычислительный эксперимент. Сделаны выводы о возможности прикладного применения решения поставленной задачи

Ключевые слова: оптимальное разбиение, непрерывное множество, минимизация, длина дуги, центр множества, метрика, размещение

1. Introduction

Over the past decade, a number of fundamental results have been obtained in the theory of continuous optimal set partitioning problems (OSP). Methods and algorithms for solving multi-product, linear and nonlinear, stochastic and dynamical problems of optimal set partitioning problems with specified and unspecified coordinates of centers of subsets were developed. In addition, solutions to applied problems from the field of monitoring of ecology of industrial regions, territory planning of service spheres and control of social sphere, were obtained. The problems of control of technological processes and the problems, associated with construction of the elements of artificial intelligence systems were united in one direction [1, 4].

A variety of initial data, including information about properties of a set, restrictions on particular parameters of a problem and quality criteria, determines a wide range of applied partitioning problems. This, in turn, makes it possible to speak about the relevance of subsequent research both aimed at the development of the theoretical base, and at the search for solutions to specific problems. The problems of optimal partitioning of a plane curve, which are particular cases of a continuous OSP problem with placement of subsets' centers, are of special interest.

2. Literature review and problem statement

The theory of continuous OSP problems is based on a unified approach, which lies in reducing original infinite-dimensional optimization problems via Lagrange functional to non-smooth, as a rule, finite-dimensional optimization problems. For numerical solution of such problems, effective methods of non-differentiable optimization are used.