

## Intelligent noise control of the state of the rail infrastructure using the technology for forming equivalent noise of noisy signals

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### ABSTRACT

*It is shown in the paper that the technical condition of bridges, tunnels and other objects of railroad tracks is controlled at "certain time intervals", since "continuous control" of objects of all hauls of the railroad tracks is practically impossible. At the same time, the technical condition of objects in seismically active regions can change at any given moment due to the unpredictability of seismic processes. For this reason, the authors consider one of the possible options for "continuous" monitoring of the beginning of changes in the technical condition of the railroad tracks by means of the Noise technologies. In this analysis of the useful signal and the noise that appears because of the vibration caused by the impact of the rolling stock, informative attributes for identifying the technical condition of objects of the railroad tracks are formed. To this end, a technology is proposed for extracting and analyzing the useful vibration signal, the noise of the vibration signal and the cross-correlation function between them. Their estimates here are used as the main carriers of vital diagnostic information, and they are implemented in technical tools that can be easily installed on all objects of the railroad tracks with the purpose of controlling the beginning of changes in their technical condition in real time during the movement of the rolling stock.*

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## 1. Introduction

It is known that rail transport is effectively used to transport large amounts of cargo and passengers over long distances [1, 2]. When transporting large volumes of traffic, significant cost savings are achieved in comparison, for instance, with motor transport. In this regard, the problem of ensuring the reliability and safety of the transportation process becomes increasingly important. It is obvious that the successful solution of this problem depends on the timely detection of deviations of the parameters of rail transport from the specified norms at an early stage of inception, without leading to pre-failure and failure states [3, 4]. To date, to solve this problem, systems for monitoring and diagnosing railroad communications with modern bridges, tunnels, stations, overpasses, crossings and power supply devices have been created. In this case, monitoring can be

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carried out periodically or continuously. It is obvious that with continuous monitoring of the technical condition of a railroad object, the processing of diagnostic information and the issuance of appropriate messages are carried out continuously in time, which provides greater efficiency compared to periodic monitoring. However, the widespread use of continuous monitoring systems in railroad objects requires high costs for implementation and operation. In addition, the existing methods of signal processing are not always effective enough and do not provide an adequate assessment of the situation.

As our research has shown, the solution to such problems as control of the latent period of changes in the technical condition of the railroad tracks, railway bridges, tunnels, crossings, etc. the degree of safety of rail transport can be increased [3, 4]. This is especially important for the rail transport of countries located in seismically active regions. The reason is that weak earthquakes of magnitude 1-3 occur quite often in these regions, affecting the technical condition of the railroad tracks, bridges, tunnels and communications. They usually do not end in great destruction. But each such earthquake is a potential factor contributing to the beginning of a latent period of changes in the technical condition of the object.

In this regard, the application of new, more advanced technologies is of undoubted practical interest. In [5-11], technologies and systems of noise control were developed. This paper discusses the possibility of using noise technologies in the system for ensuring the safety of rail transport in seismically active regions and countries [2-4]. Moreover, when the railway passes through seismically active regions, additional requirements for traffic safety appear. Analysis of the literature [1, 2] on technologies and control systems, taking into account the peculiarities of railroads in seismically active regions, shows that the specificity of the application of noise technologies can improve the safety of this type of transport [5-11]. Therefore, it is advisable to: 1) develop technologies for the separate analysis of the useful component and the noise of noisy vibration signals; 2) create a base of informative attributes of the technical condition of the rail infrastructure; 3) create a subsystem for noise control of the latent period of the onset of faults in the railroad tracks, bridges, tunnels and communications along the entire route. The solution of these three tasks will provide an opportunity to obtain additional information in advance for taking appropriate measures to improve traffic safety in general.

## **2. Problem statement**

It is known that the control of the rail infrastructure involves the use of both means of station, haul and on-board control, as well as means of control and monitoring of track structures, bridge passages, crossings, tunnels, overpasses and power supply devices. However, each of these objects of rail infrastructure and rolling stock loses reliability over time and cannot ensure the safety of transportation.

The systems of periodic control existing today are often operated manually and the obtained data do not always adequately reflect the technical condition of the object. At the same time, intensively developing continuous monitoring systems receive enormous amounts of data, the processing of which is time-consuming and expensive. Therefore, for many technological situations, alarms are false. In addition, the occurrence of a malfunction leads to interruptions in the incoming signals and the appearance of additional noise. For instance, a change for whatever reason in the stress-strain state of a rail, damage to pantographs of electric stock in traction facilities, distortion of information about the actual state of the overhead wire during its preventive heating during anti-icing actions, etc. In addition, in seismically active regions, under the influence of seismic processes, certain changes may take place even a day after the control. In this regard, the problem of creating new alternative solutions in the field of improving the control of the technical condition of the tracks is relevant. Therefore, in addition to the existing ones, it is advisable to

create simple and inexpensive intelligent technical monitoring tools that can be installed as a device signaling the beginning of changes in the technical condition of bridges, tunnels, etc. on the way of the rolling stock. In this case, the information center can receive in real time signals from the corresponding stages, which should be controlled promptly "out of the turn" [1-4]. Consequently, the creation of new intelligent technologies for monitoring the beginning of changes in the technical condition of the railroad tracks in real time is of great practical importance. At the same time, it is advisable to take into account that one of the effective methods for diagnosing the technical condition of elements of the rail infrastructure is based on the use of vibration processes caused by the rolling stock [2-4]. The premise of using the vibration method is due to the fact that a group of diagnostic signs of a dynamic process that occurs during the movement of trains on railroads corresponds to a certain state of the structures in operation.

Suppose that during the movement of the rolling stock, a noisy sampled vibration signal  $g(i\Delta t)$  is obtained at the output of the vibration sensor  $D_v$  installed on the bridge frame. The result of a dynamic process, reflecting the beginning of changes in the technical condition during the movement of the rolling stock, affects the vibration signal  $g(i\Delta t)$ , which consists of the useful vibration signal  $X(i\Delta t)$  and the sum noise  $\varepsilon(i\Delta t)$  of the vibration signal, i.e.:

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

At the same time, it can be assumed that low-frequency vibrations are caused by the technical condition of the track, due to the great weight of the car and rolling stock. At the same time, it can also be assumed that from other factors associated with the technical condition of the rolling stock, in most cases, cause to form high-frequency components. Therefore, it can be assumed that in the sum noisy vibration signal  $g(i\Delta t)$ , the high-frequency components of the noise  $\varepsilon(i\Delta t)$  mainly reflect the technical condition of the track rails, and the useful signal  $X(i\Delta t)$  consisting of low-frequency components and the coefficient of relation between  $X(i\Delta t)$  and  $\varepsilon(i\Delta t)$  to a greater extent reflect information about the technical state of the structure. Consequently, by analyzing the useful vibration signal  $X(i\Delta t)$ , the noise  $\varepsilon(i\Delta t)$  of the sum vibration signal and the relationship between them, it is possible to monitor the beginning of changes in the technical condition of bridges and tunnels in any section of the track during the movement of cars of the rolling stock.

The problem this paper aims to solve is the development of new intelligent technologies and tools for monitoring the technical condition of the railroad track, which, by analyzing vibration noisy signals, allow identifying its pre-failure states in real time without restrictions on the speed of train movement.

In view of the above, to monitor the beginning of changes in the technical condition of bridges, tunnels and other structures of the railroad track during the movement of the rolling stock in real time, it is necessary to create technologies for forming and analyzing equivalent useful vibration signals  $X^e(i\Delta t)$  and equivalent noises  $\varepsilon^e(i\Delta t)$ , which allow obtaining results similar to the results of real useful vibration signals  $X(i\Delta t)$  and noise  $\varepsilon(i\Delta t)$ , i.e. it is necessary to ensure that the following equalities hold:

$$D_X = \frac{1}{N} \sum_{i=1}^N X^2(i\Delta t) \approx \frac{1}{N} \sum_{i=1}^N X^{e2}(i\Delta t) = D_X^e,$$

$$D_\varepsilon = \frac{1}{N} \sum_{i=1}^N \varepsilon^2(i\Delta t) \approx \frac{1}{N} \sum_{i=1}^N \varepsilon^{e2}(i\Delta t) = D_\varepsilon^e,$$

$$R_{XX}(\mu) = \frac{1}{N} \sum_{i=1}^N X(i\Delta t)X((i+\mu)\Delta t) \approx \frac{1}{N} \sum_{i=1}^N X^e(i\Delta t)X^e((i+\mu)\Delta t) \approx R_{X^eX^e}(\mu)$$

$$\begin{aligned}
 R_{\varepsilon}(\mu) &= \frac{1}{N} \sum_{i=1}^N \varepsilon(i\Delta t) \varepsilon((i+\mu)\Delta t) \approx \frac{1}{N} \sum_{i=1}^N \varepsilon^e(i\Delta t) \varepsilon^e((i+\mu)\Delta t) \approx R_{\varepsilon^e \varepsilon^e}(\mu), \\
 R_{X\varepsilon}(\mu) &= \frac{1}{N} \sum_{i=1}^N X(i\Delta t) \varepsilon((i+\mu)\Delta t) \approx \frac{1}{N} \sum_{i=1}^N X^e(i\Delta t) \varepsilon^e((i+\mu)\Delta t) \approx R_{X^e \varepsilon^e}(\mu), \\
 a_{n_x} &= \frac{1}{N} \sum_{i=1}^N \sin n \omega_j X(i\Delta t) \approx a_{n_x}^e \frac{1}{N} \sum_{i=1}^N \sin n \omega_j X^e(i\Delta t) = a_{n_x}^e, \\
 b_{n_x} &= \frac{1}{N} \sum_{i=1}^N \cos n \omega_j X(i\Delta t) \approx b_{n_x}^e \frac{1}{N} \sum_{i=1}^N \cos n \omega_j X^e(i\Delta t) = b_{n_x}^e, \\
 a_{n_\varepsilon}^* &= \frac{1}{N} \sum_{i=1}^N \sin n \omega_j \varepsilon(i\Delta t) \approx a_{n_\varepsilon}^{*e} \frac{1}{N} \sum_{i=1}^N \sin n \omega_j \varepsilon^e(i\Delta t) = a_{n_\varepsilon}^{*e}, \\
 b_{n_\varepsilon}^* &= \frac{1}{N} \sum_{i=1}^N \cos n \omega_j \varepsilon(i\Delta t) \approx b_{n_\varepsilon}^{*e} \frac{1}{N} \sum_{i=1}^N \cos n \omega_j \varepsilon^e(i\Delta t) = b_{n_\varepsilon}^{*e},
 \end{aligned}$$

where  $X(i\Delta t)$ ,  $X^e(i\Delta t)$  are the useful vibration and the equivalent useful vibration;  $\varepsilon(i\Delta t)$ ,  $\varepsilon^e(i\Delta t)$  are the noise of the vibration signal and the equivalent noise;  $R_{XX}(\mu)$ ,  $R_{\varepsilon\varepsilon}(\mu)$ ,  $R_{X^e X^e}(\mu)$ ,  $R_{\varepsilon^e \varepsilon^e}(\mu)$  are the estimates of the correlation functions of the useful signal and the noise and the equivalent correlation functions of the useful signals and equivalent noises;  $a_{n_x}$ ,  $b_{n_x}$ ,  $a_{n_\varepsilon}$ ,  $b_{n_\varepsilon}$ ,  $a_{n_x}^e$ ,  $b_{n_x}^e$ ,  $a_{n_\varepsilon}^{*e}$ ,  $b_{n_\varepsilon}^{*e}$  are the spectral characteristics of useful signals and noises and estimates of spectral characteristics of equivalent useful signals and equivalent noises.

### 3. Algorithms for determining the estimate of the noise variance and the correlation function of the useful vibration signal

In [1], it was shown that the noise variance can be determined from the expression:

$$D_\varepsilon \approx \frac{1}{N} \sum_{i=1}^N [g^2(i\Delta t) - 2g(i\Delta t)g((i+1)\Delta t) + g(i\Delta t)g((i+2)\Delta t)]. \quad (1)$$

The validity of this expression can be verified by expanding the right-hand side into the corresponding terms, i.e.:

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

In this case, if the conditions of stationarity and normality of the distribution law of noisy signals are satisfied, then the following conditions can be considered correct [1, 5-10]:

$$R_{X\varepsilon}(0) \approx \frac{1}{N} \sum_{i=1}^N X(i\Delta t) \varepsilon(i\Delta t) \neq 0,$$

$$\begin{aligned}
 R_{\varepsilon X}(0) &\approx \frac{1}{N} \sum_{i=1}^N \varepsilon(i\Delta t) X(i\Delta t) \neq 0, \\
 R_{\varepsilon\varepsilon}(0) &\approx \frac{1}{N} \sum_{i=1}^N \varepsilon(i\Delta t) \varepsilon(i\Delta t) \neq 0, \\
 R_{XX}(0) + R_{XX}(2\Delta t) - 2R_{XX}(\Delta t) &\approx 0, \\
 R_{\varepsilon\varepsilon}(\Delta t) &\approx \frac{1}{N} \sum_{i=1}^N \varepsilon(i\Delta t) \varepsilon((i+1)\Delta t) \approx 0, \\
 R_{\varepsilon\varepsilon}(2\Delta t) &\approx \frac{1}{N} \sum_{i=1}^N \varepsilon(i\Delta t) \varepsilon((i+2)\Delta t) \approx 0, \\
 R_{X\varepsilon}(\Delta t) &\approx \frac{1}{N} \sum_{i=1}^N X(i\Delta t) \varepsilon((i+1)\Delta t) \approx 0, \\
 R_{X\varepsilon}(2\Delta t) &\approx \frac{1}{N} \sum_{i=1}^N X(i\Delta t) \varepsilon((i+2)\Delta t) \approx 0, \\
 R_{\varepsilon X}(\Delta t) &\approx \frac{1}{N} \sum_{i=1}^N \varepsilon(i\Delta t) X((i+1)\Delta t) \approx 0, \\
 R_{\varepsilon X}(2\Delta t) &\approx \frac{1}{N} \sum_{i=1}^N \varepsilon(i\Delta t) X((i+2)\Delta t) \approx 0.
 \end{aligned} \tag{3}$$

Taking into account (3), in the right-hand side of expression (2) we obtain:

$$D_\varepsilon = R_{X\varepsilon}(0) + R_{\varepsilon X}(0) + R_{\varepsilon\varepsilon}(0) \approx 2R_{X\varepsilon}(0) + R_{\varepsilon\varepsilon}(0).$$

Thus, the estimate of the noise variance  $D_\varepsilon$ , which is determined from formula (1), is the error in the estimate of the correlation function  $R_{gg}(\mu)$  of the vibration signal at  $\mu = 0$ . Therefore, the estimate of the correlation function  $R_{XX}(\mu = 0)$  of the useful vibration signal  $X(i\Delta t)$ , contaminated by the noise  $\varepsilon(i\Delta t)$ , can be determined from the formula:

$$R_{XX}(\mu = 0) = R_{gg}(\mu = 0) - D_\varepsilon = R_{gg}(\mu = 0) - [R_{\varepsilon\varepsilon}(\mu = 0) + 2R_{X\varepsilon}(\mu = 0)].$$

In [5-11], it is shown that the error of the estimate  $R_{gg}(\mu)$  at  $\mu \neq 0$  is an estimate of the cross-correlation function  $R_{X\varepsilon}(\mu)$  between the useful vibration signal  $X(i\Delta t)$  and the noise  $\varepsilon(i\Delta t)$ . Therefore, for this case, the estimate of the correlation function  $R_{XX}(\mu)$  of the useful vibration signal  $X(i\Delta t)$  at  $\mu \neq 0$  can be represented as:

$$R_{XX}(\mu\Delta t) = R_{gg}(\mu\Delta t) - 2R_{X\varepsilon}(\mu\Delta t).$$

Therefore, to reduce the error of the correlation analysis of noisy vibration signals at  $\mu \neq 0$ , it is necessary to determine the estimate  $R_{X\varepsilon}(\mu\Delta t)$ .

In this case, the formula for determining the cross-correlation function between  $X(i\Delta t)$  and  $\varepsilon(i\Delta t)$  at  $\mu \neq 0$  can be represented as:

$$R'_{X\varepsilon}(\mu = \Delta t) \approx \frac{1}{N} \sum_{i=1}^N [g(i\Delta t)g((i+1)\Delta t) - 2g(i\Delta t)g((i+2)\Delta t) + g(i\Delta t)g((i+3)\Delta t)]$$

Expanding the right-hand side of this equality, we obtain:

$$\begin{aligned} & \frac{1}{N} \sum_{i=1}^N [g(i\Delta t)g((i+1)\Delta t)] - \frac{1}{N} \sum_{i=1}^N 2[g(i\Delta t)g((i+2)\Delta t)] + \frac{1}{N} \sum_{i=1}^N [g(i\Delta t)g((i+3)\Delta t)] \approx \\ & \approx \frac{1}{N} \sum_{i=1}^N [X(i\Delta t) + \varepsilon(i\Delta t)][X((i+1)\Delta t) + \varepsilon((i+1)\Delta t)] - \frac{1}{N} \sum_{i=1}^N 2[X(i\Delta t) + \varepsilon(i\Delta t)] \times \\ & \times [X((i+2)\Delta t) + \varepsilon((i+2)\Delta t)] + \frac{1}{N} \sum_{i=1}^N [X(i\Delta t) + \varepsilon(i\Delta t)][X((i+3)\Delta t) + \varepsilon((i+3)\Delta t)] \approx \\ & \approx R_{XX}(\Delta t) + R_{X\varepsilon}(\Delta t) + R_{\varepsilon X}(\Delta t) + R_{\varepsilon\varepsilon}(\Delta t) - 2R_{XX}(2\Delta t) - 2R_{X\varepsilon}(2\Delta t) - 2R_{\varepsilon X}(2\Delta t) - \\ & - 2R_{\varepsilon\varepsilon}(2\Delta t) + R_{XX}(3\Delta t) + R_{X\varepsilon}(3\Delta t) + R_{\varepsilon X}(3\Delta t) + R_{\varepsilon\varepsilon}(3\Delta t). \end{aligned}$$

Under the conditions of stationarity and normality of the distribution law of noisy vibration signals, as well as in the presence of a correlation between  $X(i\Delta t)$  and  $\varepsilon((i+1)\Delta t)$ , assuming the validity of the relations [5-11]

$$\begin{aligned} R_{X\varepsilon}(\Delta t) & \approx \frac{1}{N} \sum_{i=1}^N X(\Delta t)\varepsilon((i+1)\Delta t) \neq 0, \quad R_{\varepsilon X}(\Delta t) \approx \frac{1}{N} \sum_{i=1}^N \varepsilon(i\Delta t)X((i+1)\Delta t) \neq 0 \\ R_{XX}(\Delta t) + R_{XX}(3\Delta t) - 2R_{XX}(2\Delta t) & \approx 0, \quad R_{\varepsilon\varepsilon}(\Delta t) \approx 0, \quad R_{\varepsilon\varepsilon}(3\Delta t) \approx 0, \quad R_{\varepsilon\varepsilon}(2\Delta t) \approx 0 \\ R_{X\varepsilon}(2\Delta t) & \approx \frac{1}{N} \sum_{i=1}^N X(i\Delta t)\varepsilon((i+2)\Delta t) \approx 0, \quad R_{X\varepsilon}(3\Delta t) \approx \frac{1}{N} \sum_{i=1}^N \varepsilon(i\Delta t)X((i+3)\Delta t) \approx 0 \\ R_{\varepsilon X}(2\Delta t) & \approx \frac{1}{N} \sum_{i=1}^N \varepsilon(i\Delta t)X((i+2)\Delta t) \approx 0, \quad R_{\varepsilon X}(3\Delta t) \approx \frac{1}{N} \sum_{i=1}^N \varepsilon(i\Delta t)X((i+3)\Delta t) \approx 0 \end{aligned}$$

we obtain the equality:

$$R'_{X\varepsilon}(\Delta t) \approx R_{X\varepsilon}(\Delta t) + R_{\varepsilon X}(\Delta t) \approx 2R_{X\varepsilon}(\Delta t).$$

Therefore, the estimate of the cross-correlation function  $R_{X\varepsilon}(\Delta t)$  between the useful signal  $X(i\Delta t)$  and the noise  $\varepsilon(i\Delta t)$  at  $\mu = \Delta t$  can be calculated from the expression:

$$R_{X\varepsilon}(\Delta t) \approx \frac{R_{X\varepsilon}(\Delta t)}{2} \approx \frac{1}{2N} \sum_{i=1}^N [g(i\Delta t)g((i+1)\Delta t) - 2g(i\Delta t)g((i+2)\Delta t) + g(i\Delta t)g((i+3)\Delta t)]$$

It is clear that the estimates  $R_{X\varepsilon}(2\Delta t)$ ,  $R_{X\varepsilon}(3\Delta t)$ , ... in the presence of a correlation between  $X(i\Delta t)$  and  $\varepsilon(i\Delta t)$  at  $\mu = 2\Delta t$ ,  $\mu = 3\Delta t$ , ... can also be determined in a similar way. Therefore, at different time shifts  $\mu\Delta t$ ,  $\mu = 1, 2, 3, \dots$ , the estimates  $R_{X\varepsilon}(\mu\Delta t)$  can be determined using a similar expression, i.e.:

$$R_{X\varepsilon}(\mu\Delta t) \approx \frac{1}{2N} \sum_{i=1}^N g(i\Delta t)g((i+\mu)\Delta t) - 2g(i\Delta t)g((i+\mu+1)\Delta t) + g(i\Delta t)g((i+\mu+2)\Delta t) \quad (4)$$

Thus, algorithms and technologies for determining the estimates of the noise variance  $D_\varepsilon$  and the cross-correlation function  $R_{X\varepsilon}(\mu)$  between the useful signal and the noise of the noisy vibration signals  $g(i\Delta t)$  open up the possibility of determining the estimate of the correlation function of the useful vibration signal  $X(i\Delta t)$ , contaminated by the noise  $\varepsilon(i\Delta t)$ , from the expression:

$$R_{XX}(\mu) \approx \begin{cases} R_{gg}(0) - [2R_{X\varepsilon}(0) + R_{\varepsilon\varepsilon}(0)] & \text{when } \mu = 0 \\ R_{gg}(\mu) - 2R_{X\varepsilon}(\mu) & \text{when } \mu \neq 0 \end{cases}$$

where the estimates  $R_{\varepsilon\varepsilon}(0)$  and  $R_{X\varepsilon}(\mu)$  are determined from expressions (1), (4).

#### 4. Algorithms for analysis of noisy vibration signals using equivalent samples of their noises and useful signals

The studies showed that it is possible to control the technical condition of railroad tracks by analyzing noise vibration signals, using the technology for determining the equivalent samples of their noise  $\varepsilon^e(i\Delta t)$  [5-11]. For this purpose, we first consider the possibility of calculating approximate quantities of the samples of the noise  $\varepsilon(i\Delta t)$  of the noisy vibration signals  $g(i\Delta t)$ , which cannot be measured directly. An analysis of possible solutions to this problem demonstrated [5-11] that, using the technology for calculating the estimate of the noise variance  $D_\varepsilon$  from expression (1), instead of immeasurable samples of the noise  $\varepsilon(i\Delta t)$ , we can determine their approximate equivalent values  $\varepsilon^e(i\Delta t)$ . For this purpose, formula (1) is represented in the form:

$$D_\varepsilon = \frac{1}{N} \sum_{i=1}^N \varepsilon^2(i\Delta t) \approx \frac{1}{N} \sum_{i=1}^N g(i\Delta t)[g(i\Delta t) + g((i+2)\Delta t) - 2g((i+1)\Delta t)].$$

Due to this, taking the notation:

$$\varepsilon'(i\Delta t) = g(i\Delta t)[g(i\Delta t) + g((i+2)\Delta t) - 2g((i+1)\Delta t)],$$

$$\text{sgn } \varepsilon'(i\Delta t) = \begin{cases} +1 & \text{when } \varepsilon'(i\Delta t) > 0 \\ 0 & \text{when } \varepsilon'(i\Delta t) = 0, \\ -1 & \text{when } \varepsilon'(i\Delta t) < 0 \end{cases}$$

the formula for calculating the equivalent values of samples of the noise  $\varepsilon^e(i\Delta t)$  can be presented as follows:

$$\begin{aligned} \varepsilon(i\Delta t) \approx \varepsilon^e(i\Delta t) &= \text{sgn } \varepsilon'(i\Delta t) \sqrt{g(i\Delta t)[g(i\Delta t) + g((i+2)\Delta t) - 2g((i+1)\Delta t)]} = \\ &= \text{sgn } \varepsilon'(i\Delta t) \sqrt{|\varepsilon'(i\Delta t)|}. \end{aligned} \quad (5)$$

Here, assuming that the following expression is true [5-11]:

$$D_\varepsilon = \frac{1}{N} \sum_{i=1}^N \varepsilon^2(i\Delta t) \approx \frac{1}{N} \sum_{i=1}^N \varepsilon^{e2}(i\Delta t) = \frac{1}{N} \sum_{i=1}^N |g(i\Delta t)[g(i\Delta t) + g((i+2)\Delta t) - 2g((i+1)\Delta t)]|, \quad (6)$$

the formula for calculating the mean value  $\bar{\varepsilon}(i\Delta t)$  of samples of the noise  $\varepsilon(i\Delta t)$  can be reduced to the calculation of the mean value of the equivalent samples of the noise  $\varepsilon^e(i\Delta t)$ , i.e.:

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

Numerous computational experiments have shown that despite possible deviations of the approximate values of the equivalent samples  $\varepsilon^e(i\Delta t)$  from their true values  $\varepsilon(i\Delta t)$  by the value  $\Delta\varepsilon(i\Delta t) = \varepsilon^e(i\Delta t) - \varepsilon(i\Delta t)$ , the following equality takes place between their estimates:

$$\begin{aligned} P\left\{\frac{1}{N} \sum_{i=1}^N \varepsilon^{e2}(i\Delta t) > \frac{1}{N} \sum_{i=1}^N \varepsilon^2(i\Delta t)\right\} &\approx P\left\{\frac{1}{N} \sum_{i=1}^N \varepsilon^{e2}(i\Delta t) < \frac{1}{N} \sum_{i=1}^N \varepsilon^2(i\Delta t)\right\} = 1, \\ P\left\{\frac{1}{N} \sum_{i=1}^N \varepsilon^e(i\Delta t) > \frac{1}{N} \sum_{i=1}^N \varepsilon(i\Delta t)\right\} &\approx P\left\{\frac{1}{N} \sum_{i=1}^N \varepsilon^e(i\Delta t) < \frac{1}{N} \sum_{i=1}^N \varepsilon(i\Delta t)\right\} = 1. \end{aligned} \quad (7)$$

Both equalities (5)-(7) and our experimental research demonstrate that by means of the equivalent samples of the noise  $\varepsilon^e(i\Delta t)$ , we can get results that are identical to the results of the

analysis of the same vibration signals with known real samples of the noise  $\varepsilon(i\Delta t)$ . To this end, we use the formula:

$$X^e(i\Delta t) \approx g(i\Delta t) - \varepsilon^e(i\Delta t) \approx g(i\Delta t) - \varepsilon(i\Delta t) = X(i\Delta t) \quad (8)$$

to determine the equivalent samples  $X^e(i\Delta t)$  of the useful vibration signal  $X(i\Delta t)$ .

In this case, the possibility also arises, by separating the equivalent noise samples  $\varepsilon^e(i\Delta t)$  from the noisy vibration signal  $g(i\Delta t)$  according to the obtained equivalent values of the samples of the useful signal  $X^e(i\Delta t) = g(i\Delta t) - \varepsilon^e(i\Delta t)$ , to determine the estimates  $R_{xx}^e(\mu)$  and  $R_{xx}^e(0)$  equivalent to the estimates of the correlation functions of the useful vibration signal  $R_{XX}(\mu)$ , i.e.:

$$R_{XX}(\mu) \approx \begin{cases} \frac{1}{N} \sum_{i=1}^N X^e(i\Delta t) X^e(i\Delta t) & \text{when } \mu = 0 \\ \frac{1}{N} \sum_{i=1}^N X^e(i\Delta t) X^e((i + \mu)\Delta t) & \text{when } \mu \neq 0 \end{cases}$$

It is obvious that knowing the equivalent noise samples  $\varepsilon^e(i\Delta t)$  and the useful signal  $X^e(i\Delta t)$ , we can determine the estimates of the cross-correlation function between the useful vibration signal  $X(i\Delta t)$  and the noise  $\varepsilon(i\Delta t)$  from the expression:

$$R_{X\varepsilon}(\mu) \approx \frac{1}{N} \sum_{i=1}^N X(i\Delta t) \varepsilon((i + \mu)\Delta t) \approx \frac{1}{N} \sum_{i=1}^N X^e(i\Delta t) \varepsilon^e((i + \mu)\Delta t).$$

Studies also showed that despite certain errors of the samples  $X_i^e(i\Delta t)$  compared with the samples of useful signals  $X(i\Delta t)$ , with a sufficient duration of the observation time  $T$ , equality (7) holds. Due to this, the following equality is achieved:

$$R_{XX}(\mu) \approx R_{X^e X^e}(\mu), \quad R_{X\varepsilon}(\mu) \approx R_{X^e \varepsilon^e}(\mu),$$

which shows that, using expressions (5)-(8), using equivalent samples of the noise  $\varepsilon^e(i\Delta t)$  and of the useful signal  $X^e(i\Delta t)$ , we can find equivalent estimates of the correlation functions  $R_{X^e X^e}(\mu)$  of the useful signal and the cross-correlation function  $R_{X^e \varepsilon^e}(\mu)$  between the useful signal and the noise, which allow us to solve the problem of monitoring the beginning of changes in the technical condition of the track.

## 5. Spectral technology for the noise control of the beginning of changes in the technical condition of railroad objects

As was mentioned earlier, the beginning of changes in the technical condition of the railroad track and the dynamics of their development are accompanied by the emergence of the noise correlated with the useful signal  $X(i\Delta t)$ . As a result, the sum noise  $\varepsilon(i\Delta t)$  forms, which in the latent period of emergency state of the given section of the track correlates with the useful signal. Therefore, when solving the problem of controlling the beginning and dynamics development of faults, it is advisable to also use estimates of the spectral characteristics of the sum noise  $\varepsilon(i\Delta t)$  as informative attributes. An analysis of possible solutions to this problem showed [5-11] that in a spectral control of the technical condition of the track, it is advisable to replace non-measurable samples of the noise  $\varepsilon(i\Delta t)$  with their approximate equivalent values  $\varepsilon^e(i\Delta t)$ .

Taking into account expressions (5)-(8), the formula for calculating the mean value  $\bar{\varepsilon}(i\Delta t)$  of samples of the noise  $\varepsilon(i\Delta t)$  can be reduced to calculating the mean value of equivalent samples of the noise  $\varepsilon^e(i\Delta t)$ , i.e.



$$\bar{\varepsilon}(i\Delta t) \approx \overline{\varepsilon^e}(i\Delta t) = \frac{1}{N} \sum_{i=1}^N \varepsilon^e(i\Delta t). \quad (9)$$

Due to this, the expression for calculating the estimates of the spectral characteristics of the noise can be represented in the following form:

$$\begin{cases} a_{n_\varepsilon} \approx \frac{2}{N} \sum_{i=1}^N \varepsilon^e(i\Delta t) \cos n\omega(i\Delta t) \\ b_{n_\varepsilon} \approx \frac{2}{N} \sum_{i=1}^N \varepsilon^e(i\Delta t) \sin n\omega(i\Delta t) \end{cases}. \quad (10)$$

Thus, the use of algorithms (9) and (10) opens the possibility for registering the beginning of the latent period of faults, since the estimates  $a_{n_\varepsilon}$  and  $b_{n_\varepsilon}$  will differ from the reference informative attributes only at the beginning of an emergency state. Because of this, the use of the proposed expressions will make it possible to enhance the reliability of the control of the beginning of the latent period of changes in the technical condition of the railroad track.

Studies have shown that the dynamics of development of faults in railroad objects affects the degree of correlation between the samples of the noise  $\varepsilon(i\Delta t)$  and the useful signal. It also affects the change of correlation between samples of the equivalent noise  $\varepsilon^e(i\Delta t)$ . Here the formula for forming the equivalent noise at  $\mu = 1\Delta t$  can be represented in the form:

$$\begin{aligned} \text{sgn } \varepsilon'(i\Delta t) &\approx \sqrt{g(i\Delta t)[g((i+1)\Delta t) + g((i+3)\Delta t) - 2g((i+2)\Delta t)]}, \\ \varepsilon^e((i+1)\Delta t) &= \text{sgn } \varepsilon'(i\Delta t) \sqrt{g(i\Delta t)[g((i+1)\Delta t) + g((i+3)\Delta t) - 2g((i+2)\Delta t)]}. \end{aligned}$$

This expression at  $\mu = 2\Delta t$  will have the form:

$$\varepsilon^e((i+2)\Delta t) = \text{sgn } \varepsilon'(i\Delta t) \sqrt{g(i\Delta t)[g((i+2)\Delta t) + 2g((i+4)\Delta t) - 2g((i+3)\Delta t)]}.$$

At  $\mu = m\Delta t$ , this expression can be written in a generalized form:

$$\varepsilon^e((i+m)\Delta t) = \text{sgn } \varepsilon'(i\Delta t) \sqrt{g(i\Delta t)[g((i+m)\Delta t) + 2g((i+m+2)\Delta t) - 2g((i+m+1)\Delta t)]}.$$

Due to this, based on the results of a spectral analysis of the equivalent  $\varepsilon^e(i\Delta t)$  of the noise  $\varepsilon(i\Delta t)$  at  $\mu = 1\Delta t, 2\Delta t, 3\Delta t, \dots, m\Delta t$ , i.e.  $\varepsilon^e((i+1)\Delta t), \varepsilon^e((i+2)\Delta t), \varepsilon^e((i+3)\Delta t), \dots, \varepsilon^e((i+m)\Delta t)$ , it is possible to control the dynamics of an accident, using the following expressions:

$$\left\{ \begin{array}{l} a_{1\varepsilon}^* \approx \frac{2}{N} \sum_{i=1}^N \varepsilon^e((i+1)\Delta t) \cos n\omega(i\Delta t) \\ b_{1\varepsilon}^* \approx \frac{2}{N} \sum_{i=1}^N \varepsilon^e((i+1)\Delta t) \sin n\omega(i\Delta t) \\ a_{2\varepsilon}^* \approx \frac{2}{N} \sum_{i=1}^N \varepsilon^e((i+2)\Delta t) \cos n\omega(i\Delta t) \\ b_{2\varepsilon}^* \approx \frac{2}{N} \sum_{i=1}^N \varepsilon^e((i+2)\Delta t) \sin n\omega(i\Delta t) \cdot \\ \dots\dots\dots \\ a_{n\varepsilon}^* \approx \frac{2}{N} \sum_{i=1}^N \varepsilon^e((i+n)\Delta t) \cos n\omega(i\Delta t) \\ b_{n\varepsilon}^* \approx \frac{2}{N} \sum_{i=1}^N \varepsilon^e((i+n)\Delta t) \sin n\omega(i\Delta t) \end{array} \right.$$

If the fault is stable, then the estimates of the equivalent noise will repeat. However, in the presence of fault development dynamics, the estimates  $a_{1\varepsilon}^*, b_{1\varepsilon}^*; a_{2\varepsilon}^*, b_{2\varepsilon}^*; \dots; a_{n\varepsilon}^*, b_{n\varepsilon}^*$  will differ from each other over time, and in the case of high dynamics of the development of the defect degree, these differences will be significant.

### 6. Intelligent vibration noise control system

Fig. 1 shows the block diagram of a system for intelligent Noise control of the beginning of changes in the technical condition of railroad track objects. The system consists of the following modules: 1 – vibration sensor; 2 – module of sampling and formation of centered samples of the noise vibration signals  $g(i\Delta t)$ ; 3 – module of sampling and formation of centered samples of the noise vibration signals  $R_{gg}(i\Delta t)$ ; 4 – module of determining the equivalent samples of the useful signal  $X(i\Delta t)$ ; 5 – module of determining the estimates of the equivalent correlation functions of the useful signal  $R_{X^e X^e}(\mu)$  and the cross-correlation function between the useful vibration signal and the noise  $R_{X^e \varepsilon^e}(\mu)$  and the spectral estimates  $a_{nX^e}, b_{nX^e}, a_{n\varepsilon^e}^*, b_{n\varepsilon^e}^*$  of the useful vibration signal  $X(i\Delta t)$  and the noise  $\varepsilon^e(i\Delta t)$ ; 6 – module of formation of current informative attributes consisting of current estimates  $R_{X^e X^e}(\mu)$  and  $R_{X^e \varepsilon^e}(\mu), a_{nX^e}, b_{nX^e}, a_{n\varepsilon^e}^*, b_{n\varepsilon^e}^*, R_{gg}(0)$ ; 7 – learning module; 8 – module of formation of the set of reference informative attributes; 9 – decision-making module; 10 – модуль формирования информации для сигнализации и дистанционной передачи.

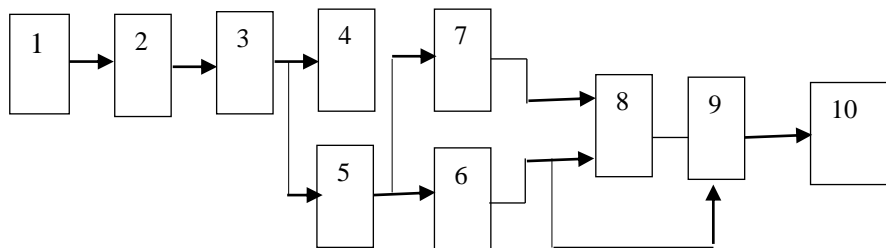


Fig. 1. Intelligent vibration noise control system

The Noise control system operates as follows. At the beginning of the operation, the learning process begins and during the movement of the rolling stock in each control cycle, by means of the appropriate modules, the sampled vibration signal  $g(i\Delta t)$  is analyzed and the obtained estimates  $R_{X^e X^e}(\mu)$ ,  $R_{X^e \varepsilon^e}(\mu)$ ,  $D_{\varepsilon^e}$  are saved as informative attributes. In subsequent cycles, current estimates are compared with previous estimates and only those greater than the previous maximum estimates are kept. As a result, the set  $W_j^e$  forms after a certain time, which consists of maximum estimates of informative attributes. They, i.e.  $R_{X^e X^e}^{\max}(\mu)$ ,  $R_{X^e \varepsilon^e}^{\max}(\mu)$ ,  $D_{\varepsilon^e}^{\max}$  are taken as reference estimates. In the following cycles, this process repeats and similarly forms the subsequent reference set. If the current informative attributes are greater than the maximum reference attributes, then it is assumed that the training for controlling the technical condition of the track object for a given haul is completed. The comparison of current combinations of informative attributes with an element of the set  $W_j^e$  of reference informative attributes begins. If subsequently the current attributes are not greater than the reference ones, then the technical condition of the object is considered unchanged. If current informative features are greater than the reference ones, it is assumed that the beginning of the latent period of changes in the technical condition of the controlled object takes place. At the same time, information is formed in Module 10 to signal the advisability of control of the technical condition of a given track object using traditional methods and technologies. In the case when no change is detected, it is also possible to form and transmit information about the safety of the track objects in this haul.

## **7. Conclusion**

It is shown in the paper that “continuous control” of technical objects of all railroad lines is a difficult and practically impossible task. Therefore, the existing methods, technologies and technical tools provide reliable control of the serviceability of technical objects of all hauls of the track after a certain period of time. It is clear that the smaller this "interval", the greater the security guarantee. However, in real practice, it is impossible to guarantee the complete stability of the technical condition of controlled track objects during these time intervals. This is especially difficult for seismically active regions. Therefore, in order to solve the safety problem on all railroad lines at the indicated time intervals, it is necessary to continuously monitor the beginning of the transition to an emergency state of all technical objects of the track using simple and inexpensive technical tools.

Since in the event of a malfunction, additional noises occur in the vibration signals, the results of processing these signals contain errors that reduce the adequacy of the track control results. Therefore, the formation of the corresponding sets of informative attributes by analyzing vibration signals using correlation and spectral analysis technologies, as well as other traditional technologies, turned out to be ineffective. To eliminate this difficulty, technologies for split analysis of the useful vibration signal, vibration signal noise, and the relationship between them are used in the paper. At the same time, the noise is used as a carrier of diagnostic information, by means of which sets of informative attributes are formed, which make it possible to identify the technical condition of controlled objects.

The paper also proposes one of the possible versions of intelligent technical tools of noise control, which can be easily implemented in all technical objects of the track.

## References

- [1] T.A. Aliev, Noise control of the beginning and development dynamics of accidents, Springer, (2019) 201 p.
- [2] Машины и оборудование для диагностики пути, Региональный центр инновационных технологий, Путьевые машины, применяемые ОАО «РЖД» Конструкция, Теория и расчет. [In Russian: Track machines used by Russian Railways. Construction, theory and calculation. Chapter 11. Machines and equipment for track diagnostics. Regional Center for Innovative Technologies]
- [3] Е.С. Ашпиз, Методы и средства диагностики земляного полотна, Железнодорожный путь, (2013). [In Russian: Y.S. Ashpiz. Methods and tools of roadbed diagnostics. Zheleznodorozhnyi put]
- [4] И.К. Михалкин, О.Б. Симаков, Ю.А. Седелкин, В.В. Атапин, Новые подходы к мониторингу железнодорожного пути, НПЦ ИНФОТРАНС. [In Russian: I.K. Mikhalkin, O.B. Simakov, Y.A. Sedelkin, V.V. Atapin. New approaches to monitoring the railroad track. NPTS INFOTRANS]
- [5] Т.А. Алиев, Н.Ф. Мусаева, Н.Э. Рзаева, А.И. Мамедова, Разработка технологий для уменьшения погрешности традиционных алгоритмов корреляционного анализа зашумленных сигналов, Измерительная техника. No.6 (2020) 9-16. [In Russian: T.A. Aliev, N.F. Musaeva, N.E. Rzayeva, A.I. Mamedova. Developing technologies to reduce the error of traditional algorithms for correlation analysis of noisy signals. Izmeritelnaya tekhnika]  
<https://doi.org/10.32446/0368-1025it.2020-6-9-16>
- [6] Т.А. Алиев, Н.Ф. Мусаева, Н.Э. Рзаева, А.И. Мамедова, Technologies for forming equivalent noises of noisy signals and their use, Journal of automation and information sciences, No.5 (2020) pp.1-12.  
<https://doi.org/10.1615/JAutomatInfScien.v52.i5.10>
- [7] Т.А. Алиев, Т.А. Babayev, Т.А. Alizada, Н.Э. Rzayeva, Noise control of the beginning and development dynamics of faults in the running gear of the rolling stock, Transport problems. 9 No.10 (2019) pp.87-95.
- [8] Т.А. Алиев, Н. Ahmedov, Т. Babayev, Т. Alizada, Е. Manafov, N. Zohra-bov, A. Mammadova, Using fuzzy set theory and noise analysis technologies to enhance validity and reliability of control of the condition of the running gear of rolling stock, 15-18 October 2019, "Transport bridge Europe-Asia" V Georgian-Polish International scientific-technical conference. Kutaisi.
- [9] Т.А. Алиев, Т. Babayev, Т. Alizada, N. Rzayeva, Possibilities of application of noise technology in railroad operation safety systems in seismically active regions, 26-28 June 2019, The Silesian university of technology, Transport problems, XI International scientific conference. Katowice, Poland
- [10] Т.А. Алиев, Н.Ф. Мусаева, Б.И. Газызаде, Технологии мониторинга динамики развития повреждений на буровых установках с использованием моментов высоких порядков помехи, Мехатроника, автоматизация, управление, Москва. 21 No.4 (2020) 213-223 [In Russian: T.A. Aliev, N.F. Musaeva, B.I. Gazizade, Technologies for monitoring the dynamics of damage development in drilling rigs using high-order moments of the noise, Mekhatronika, avtomatizatsiya, upravlenie]
- [11] Т.А. Алиев, Н.Ф. Мусаева, М.Т. Сулейманова, Алгоритмы построения доверительного интервала для математического ожидания помехи и их применение для контроля динамики развития аварий, Мехатроника, автоматизация, управление, Москва. 21 No.9 (2020) 521-529 [In Russian: T.A. Aliev, N.F. Musaeva, M.T. Suleymanova, Algorithms for constructing the confidence interval for the mathematical expectation of the noise and their application in the control of the dynamics of accident development, Mekhatronika, avtomatizatsiya, upravlenie]