

# Technology and Algorithms for Monitoring of the Technical Condition of High-Rise Buildings, Construction and Strategic Objects in Seismically Active Regions by Means of Sets of Informative Attributes

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**Abstract**— Problems of monitoring of seismic stability and technical condition of high-rise buildings, building structures and strategic objects in seismically active regions at early stages of fault origin with application of known methods of calculation of dispersion, correlation, spectral, static and dynamic characteristics have been analyzed. Technologies and algorithms have been offered for solving of this problem with application of robust sets of informative attributes.

**Keywords**— seismic stability; noise; signal; informative attributes; correlation

## I. INTRODUCTION

It is known that a system of monitoring of seismic stability and prediction of changes in the technical condition of high-rise buildings and building structures generally has to contain the following subsystems: primary sensors subsystem; primary data transmission and collection subsystem; subsystem for processing of obtained data and submitting the processing results to the specialized service [1].

Primary data transmission and collection subsystem is to provide data digitalization and transmission from all sensors to the local server, where all data is stored. Data digitalization provides acceptable resolution and frequency for each type of sensors. The server receives, processes received requests and provides only authorized external access. The subsystem for data processing and submittal contains the software providing visualized representation of processed primary data for the operator. Operator position subsystem provides information on the state of the control object by operator's request.

Only correct and adequate processing of signals that come from sensors measuring vibration, oscillation, tilts, deflation, rolls, strain in building structures, etc. and their timely submittal to the operator will ensure carrying out of operational complex of measures on preventing early wear, damage, and defects, such as cracks, bends, tilts, deformation, deflation, etc., and allow controlling physical ageing and obsolescence. On the other hand, in most cases for many high-rise buildings, there

are certain troubles in prediction of changes in the object condition at early stages of fault origin with application of known methods of calculation of dispersion, correlation, spectral, static and dynamic characteristics. They allow one to detect only explicit faults at best. Analysis of emergency origin demonstrates that emergency situations are always preceded by hidden microfaults that emerge as microwears, microsagging, microvibration, microcracks, etc. in some units of the investigated building structure under. Their timely detection makes it possible to predict possible changes in the condition of a building structure, which can be used for warning and prevention of grave failures. The paper thereby considers one of alternative solutions to the problem of monitoring of seismic stability and the technical condition of high-rise buildings and building structures in seismically active regions with application of technology and methods for development of robust sets of informative attributes.

## II. PROBLEM STATEMENT

As is known, prediction process can be generally represented as a combination of three elements: 1) pattern set  $Z$  formed from estimates of statistical characteristics, auto- and cross-correlation functions, spectral characteristics, static and dynamic characteristic corresponding to each  $i$  state of all  $k$  of possible states of the building structure; 2)  $V$  formed from current similar informative attributes that carry information on the current state; 3) rules of identification of  $F$  that compares each element of set  $Z$  to an element of set  $V$ , and vice versa, compares each element of set  $V$  to an element of set  $Z$ . The totality of elements of  $Z$  and  $V$  forms data support of prediction subsystem.

In this case, set  $Z_X$  corresponding to the normal state of a building structure, when signals  $X_i(t)$  are received from sensors, can be represented as follows:

$$Z_X = \begin{bmatrix} D(\varepsilon_1)=0 & D(\varepsilon_2)=0 & \dots & D(\varepsilon_n)=0 \\ R_{X_1 X_1}(\mu) & R_{X_1 X_2}(\mu) & \dots & R_{X_1 X_n}(\mu) \\ R_{X_2 X_1}(\mu) & R_{X_2 X_2}(\mu) & \dots & R_{X_2 X_n}(\mu) \\ \dots & \dots & \dots & \dots \\ R_{X_n X_1}(\mu) & R_{X_n X_2}(\mu) & \dots & R_{X_n X_n}(\mu) \\ a_{11} & a_{12} & \dots & a_{1n} \\ b_{11} & b_{12} & \dots & b_{1n} \\ a_{21} & a_{22} & \dots & a_{2n} \\ b_{21} & b_{22} & \dots & b_{2n} \\ \dots & \dots & \dots & \dots \\ a_{k1} & a_{k2} & \dots & a_{kn} \\ b_{k1} & b_{k2} & \dots & b_{kn} \\ c_{11} & c_{12} & \dots & c_{1n} \\ c_{21} & c_{22} & \dots & c_{2n} \\ \dots & \dots & \dots & \dots \\ c_{m1} & c_{m2} & \dots & c_{mn} \\ W_{11} & W_{12} & \dots & W_{1n} \\ W_{21} & W_{22} & \dots & W_{2n} \\ \dots & \dots & \dots & \dots \\ W_{m1} & W_{m2} & \dots & W_{mn} \end{bmatrix} \quad (1)$$

where  $D(\varepsilon_i)=0$  is the value of variance of noise  $\varepsilon_i(t)$ , which in the normal operation of the building structure equals zero;  $R_{X_i X_j}(\mu)$ ,  $i, j = \overline{1, n}$  are estimates of auto- and cross-correlation functions;  $a_{ij}$ ,  $b_{ij}$ ,  $i = \overline{1, k}$ ,  $j = \overline{1, n}$  are Fourier spectral expansion coefficients;  $c_{ij}$ ,  $i = \overline{1, m}$ ,  $j = \overline{1, n}$  are coefficients of results of solving static identification problem;  $W_{ij}$ ,  $i = \overline{1, m}$ ,  $j = \overline{1, n}$  are transfer functions;  $n$  is the quantity of input parameters,  $m$  is the quantity of output parameters,  $k$  is the quantity of coefficient in Fourier series.

Sets, which are similar to set  $Z_X$ , are composed for each deviation from the normal state of the building structure and allow predicting one or another failure state as a result of identification.

However, signals  $g_i(t) = X_i(t) + \varepsilon_i(t)$  received from sensors measuring vibration, oscillation, tilts, deflation, rolls, etc. are in most cases distorted with noise, i.e. stationary state, normalcy of distribution law are violated in those signals,

correlation between the useful signal and the noise is absent, etc. Then, instead of set  $Z_X$ , set  $Z_g$  is obtained, elements of which contain noise errors:

$$Z_g = \begin{bmatrix} D(\varepsilon_1) & D(\varepsilon_2) & \dots & D(\varepsilon_n) \\ R_{g_1 g_1}(\mu) & R_{g_1 g_2}(\mu) & \dots & R_{g_1 g_n}(\mu) \\ R_{g_2 g_1}(\mu) & R_{g_2 g_2}(\mu) & \dots & R_{g_2 g_n}(\mu) \\ \dots & \dots & \dots & \dots \\ R_{g_n g_1}(\mu) & R_{g_n g_2}(\mu) & \dots & R_{g_n g_n}(\mu) \\ a_{11}^* & a_{12}^* & \dots & a_{1n}^* \\ b_{11}^* & b_{12}^* & \dots & b_{1n}^* \\ a_{21}^* & a_{22}^* & \dots & a_{2n}^* \\ b_{21}^* & b_{22}^* & \dots & b_{2n}^* \\ \dots & \dots & \dots & \dots \\ a_{k1}^* & a_{k2}^* & \dots & a_{kn}^* \\ b_{k1}^* & b_{k2}^* & \dots & b_{kn}^* \\ c_{11}^* & c_{12}^* & \dots & c_{1n}^* \\ c_{12}^* & c_{22}^* & \dots & c_{2n}^* \\ \dots & \dots & \dots & \dots \\ c_{m1}^* & c_{m2}^* & \dots & c_{mn}^* \\ W_{11}^* & W_{12}^* & \dots & W_{1n}^* \\ W_{21}^* & W_{22}^* & \dots & W_{2n}^* \\ \dots & \dots & \dots & \dots \\ W_{m1}^* & W_{m2}^* & \dots & W_{mn}^* \end{bmatrix} \quad (2)$$

where  $D(\varepsilon_i) \neq 0$  is the value of variance of noise  $\varepsilon_i(t)$ , which is different from zero in the presence of noise;

$R_{g_i g_j}(\mu) = R_{X_i X_j}(\mu) + \Lambda_{X_i X_j}(\mu)$ ,  $i, j = \overline{1, n}$  are estimates of auto- and cross-correlation functions of noisy signals,  $\Lambda_{X_i X_j}(\mu)$  is the value of errors of estimates  $R_{g_i g_j}(\mu)$ ;  $a_{ij}^* = a_{ij} + \lambda_{a_{ij}}$ ,  $b_{ij}^* = b_{ij} + \lambda_{b_{ij}}$ ,  $i = \overline{1, k}$ ,  $j = \overline{1, n}$  are Fourier spectral expansion coefficients for noisy signals,  $\lambda_{a_{ij}}$ ,  $\lambda_{b_{ij}}$  is the value of errors of coefficients  $a_{ij}$ ,  $b_{ij}$ ;  $c_{ij}^* = c_{ij} + \lambda_{c_{ij}}$ ,  $i = \overline{1, m}$ ,  $j = \overline{1, n}$  are coefficients of results of solving identification problem of noisy signals static,  $\lambda_{c_{ij}}$  is

the value of error  $c_{ij}$ ;  $W_{ij}^* = W_{ij} + \lambda_{W_{ij}}$ ,  $i = \overline{1, m}$ ,  $j = \overline{1, n}$  are transfer functions of noisy signals,  $\lambda_{W_{ij}}$  is the value of error of estimates of are transfer functions  $W_{ij}$ ;  $n$  is the quantity of input parameters,  $m$  is the quantity of output parameters,  $k$  is the quantity of coefficient in Fourier series.

Building of sets  $V_{g_i}$ , which characterize the current state of the construction object, presents similar difficulties.

Works [1-8] therefore offer algorithms for robust correlation and spectral monitoring, monitoring with application of noise characteristics, as well as algorithms for improvement of conditioning of correlation matrices in solving of static identification problems and problems of dynamics of high-rise buildings, construction and strategic objects in seismically active regions. Using those algorithms, one can build robust matrices  $Z_X^R$ ,  $V_{X_i}^R$ , elements of which are close to elements of matrices  $Z_X$ ,  $V_{X_i}$ . Considered below are algorithms for building robust matrices  $Z_X^R$ ,  $V_{X_i}^R$ .

### III. TECHNOLOGY AND ALGORITHMS FOR MONITORING OF HIGH-RISE BUILDINGS, CONSTRUCTION AND STRATEGIC OBJECTS IN SEISMICALLY ACTIVE REGIONS BY MEANS OF SETS OF INFORMATIVE ATTRIBUTES

Robust matrices  $Z_X^R$ ,  $V_{X_i}^R$  should be built in four stages. At the first stage, estimates of values of noise variances  $D^*(\varepsilon_i)$  and robust estimates of auto- and cross-correlation functions  $R_{X_i X_i}^R(\mu)$ . Robust coefficients  $a_n^R$ ,  $b_n^R$  of Fourier spectral expansion are calculated at the second stage. At the third stage, with application of robust correlation matrices  $\bar{R}_{XX}^R(0)$ ,  $\bar{R}_{XY}^R(0)$  formed from robust estimates of auto- and cross-correlation functions  $R_{X_i X_i}^R(0)$ ,  $R_{X_i Y}^R(0)$ , static identification problem is solved and robust coefficients  $c_{ij}^R$  are calculated. At the fourth stage, with application of robust correlation matrices  $\bar{R}_{XX}^R(\mu)$ ,  $\bar{R}_{XY}^R(\mu)$  formed from robust estimates of auto- and cross-correlation functions  $R_{X_i X_i}^R(\mu)$ ,  $R_{X_i Y}^R(\mu)$ , dynamic identification problem is solved and robust  $W_{ij}^R$  transfer functions are calculated.

#### First stage

Calculation of values of noise variances  $D^*(\varepsilon_i)$  and robust estimates of auto- and cross-correlation functions  $R_{X_i X_i}^R(\mu)$ .

1. Values of autocorrelation functions  $R_{g_i g_i}(\mu)$ ,  $i = \overline{1, n}$  at time shift  $\mu = 0$  are calculated from the following formula:

$$R_{g_i g_i}(\mu) = \frac{1}{N} \sum_{k=1}^N g_i(k\Delta t) g_i(k\Delta t) \quad (3)$$

2. Values of autocorrelation functions  $R_{g_i g_i}(\mu)$ ,  $i = \overline{1, n}$  at time shift  $\mu = 1 \cdot i\Delta t$  are calculated from the following formula:

$$R_{g_i g_i}(\mu) = \frac{1}{N} \sum_{k=1}^N g_i(k\Delta t) g_i((k+1)\Delta t) \quad (4)$$

3. Values of autocorrelation functions  $R_{g_i g_i}(\mu)$ ,  $i = \overline{1, n}$  at time shift  $\mu = 2 \cdot i\Delta t$  are calculated from the following formula:

$$R_{g_i g_i}(\mu) = \frac{1}{N} \sum_{k=1}^N g_i(k\Delta t) g_i((k+2)\Delta t) \quad (5)$$

4. Values of variances  $D^*(\varepsilon_i)$  of noises  $\varepsilon_i(t)$  are calculated from the following formula:

$$D^*(\varepsilon_i) = R_{g_i g_i}(\mu = 0 \cdot \Delta t) - 2 R_{g_i g_i}(\mu = 1 \cdot \Delta t) + R_{g_i g_i}(\mu = 2 \cdot \Delta t) \quad (6)$$

5. Robust estimates of autocorrelation function  $R_{X_i X_i}^R(\mu = 0)$  are calculated by means of the following formula:

$$R_{X_i X_i}^R(\mu = 0) = R_{g_i g_i}(\mu = 0) - D^*(\varepsilon_i) \quad (7)$$

#### Second stage

Calculation of robust coefficients  $a_n^R$ ,  $b_n^R$  of Fourier spectral expansion.

Robust estimates  $a_n^R$  are determined in the following way.

- Noise variance  $D^*(\varepsilon)$  and the mean value of relative error of readings  $\bar{\lambda}_{rel}$  are determined.
- Values  $\Pi^+$ ,  $\Pi^-$ ,  $N^+$  and  $N^-$  are determined.
- Conditions  $N^+ = N^-$  and  $\Pi^+ = \Pi^-$  are checked, during fulfillment of which application of conventional algorithms is recommended.
- When conditions  $N^+ \neq N^-$  and  $\Pi^+ = \Pi^-$  hold true, formula for determination of robust estimates  $a_n^R$  is represented as follows:

$$a_n^R = \frac{2}{N} \left\{ \sum_{i=1}^N \overset{\circ}{g}(i\Delta t) \cos n\omega(i\Delta t) - \frac{1}{4} |N_{a_n^+} - N_{a_n^-}| A(i\Delta t) \right\}$$

where

$$A(i\Delta t) = \frac{\overset{\circ}{g}(i\Delta t) \cos n\omega(i\Delta t)}{\bar{\lambda}_{rel}} \quad (8)$$

- When conditions  $N^+ > N^-$  and  $\Pi^+ \neq \Pi^-$  hold true, estimates  $a_n^R$  are determined from the expression

$$a_n^R = \frac{2}{N} \left\{ \sum_{i=1}^N \overset{\circ}{g}(i\Delta t) \cos n\omega(i\Delta t) - \frac{1}{4} (N_{a_n^+} - N_{a_n^-}) A^+(i\Delta t) - \frac{1}{2} [N - (N_{a_n^+} - N_{a_n^-})] [A^+(i\Delta t) - A^-(i\Delta t)] \right\}, \omega \eta \varepsilon \rho \varepsilon \quad A(i\Delta t) = \frac{\overset{\circ}{g}(i\Delta t) \cos n\omega(i\Delta t)}{\bar{\lambda}_{rel}}$$

$$A^+(i\Delta t) = \frac{\overset{\circ}{g}(i\Delta t) \cos n\omega(i\Delta t)}{\bar{\lambda}_{rel}} \quad (9)$$

$$A^-(i\Delta t) = \frac{\overset{\circ}{g}(i\Delta t) \cos n\omega(i\Delta t)}{\bar{\lambda}_{rel}}$$

- If  $N^+ < N^-$  and  $\Pi^+ \neq \Pi^-$  take place, estimates  $a_n^R$  are determined from the expressions:

$$a_n^R = \frac{2}{N} \left\{ \sum_{i=1}^N \overset{\circ}{g}(i\Delta t) \cos n\omega(i\Delta t) - \frac{1}{4} (N_{a_n^-} - N_{a_n^+}) A(i\Delta t) - \frac{1}{2} [N - (N_{a_n^-} - N_{a_n^+})] [A^+(i\Delta t) - A^-(i\Delta t)] \right\} \quad (10)$$

- If conditions  $N^+ = N^-$  and  $\Pi^+ \neq \Pi^-$  hold true, estimates  $a_n^R$  are determined from the formula

$$a_n^R = \frac{2}{N} \left\{ \sum_{i=1}^N \overset{\circ}{g}(i\Delta t) \cos n\omega(i\Delta t) - \frac{1}{2} N [A^+(i\Delta t) - A^-(i\Delta t)] \right\} \quad (11)$$

Robust estimates  $b_n^R$  are determined in the following way.

- Noise variance  $D^*(\varepsilon)$  and the mean value of relative error of readings  $\bar{\lambda}_{rel}$  are determined.
- Values  $\Pi^+$ ,  $\Pi^-$ ,  $N^+$  and  $N^-$  are determined.
- Conditions  $N^+ = N^-$  and  $\Pi^+ = \Pi^-$  are checked, during fulfillment of which application of conventional algorithms is recommended.
- When conditions  $N^+ \neq N^-$  and  $\Pi^+ = \Pi^-$  hold true, formula for determination of robust estimates  $b_n^R$  is represented as follows:

$$b_n^R = \frac{2}{N} \left\{ \sum_{i=1}^N \overset{\circ}{g}(i\Delta t) \sin n\omega(i\Delta t) - \frac{1}{4} |N_{b_n^+} - N_{b_n^-}| B(i\Delta t) \right\}$$

where

$$B(i\Delta t) = \frac{\overset{\circ}{g}(i\Delta t) \sin n\omega(i\Delta t)}{\bar{\lambda}_{rel}} \quad (12)$$

- When conditions  $N^+ > N^-$  and  $\Pi^+ \neq \Pi^-$  hold true, estimates  $b_n^R$  are determined from the expression

$$b_n^R = \frac{2}{N} \left\{ \sum_{i=1}^N \overset{\circ}{g}(i\Delta t) \sin n\omega(i\Delta t) - \frac{1}{4} (N_{b_n^+} - N_{b_n^-}) B^+(i\Delta t) - \frac{1}{2} [N - (N_{b_n^+} - N_{b_n^-})] [B^+(i\Delta t) - B^-(i\Delta t)] \right\}, \omega \eta \varepsilon \rho \varepsilon \quad B(i\Delta t) = \frac{\overset{\circ}{g}(i\Delta t) \sin n\omega(i\Delta t)}{\bar{\lambda}_{rel}}$$

$$B^+(i\Delta t) = \frac{\overset{\circ}{g}(i\Delta t) \sin n\omega(i\Delta t)}{\bar{\lambda}_{rel}},$$

$$B^-(i\Delta t) = \frac{\overset{\circ}{g}(i\Delta t) \sin n\omega(i\Delta t)}{\bar{\lambda}_{rel}} \quad (13)$$

6. If  $N^+ < N^-$  and  $\Pi^+ \neq \Pi^-$  take place, estimates  $b_n^R$  are determined from the expressions:

$$b_n^R = \frac{2}{N} \left\{ \sum_{i=1}^N g(i\Delta t) \sin n\omega(i\Delta t) - \frac{1}{4} (N_{b_n^-} - N_{b_n^+}) B(i\Delta t) - \frac{1}{2} [N - (N_{b_n^-} - N_{b_n^+})] [B^+(i\Delta t) - B^-(i\Delta t)] \right\} \quad (14)$$

7. If conditions  $N^+ = N^-$  and  $\Pi^+ \neq \Pi^-$  hold true, estimates  $b_n^R$  are determined from the formula

$$b_n^R = \frac{2}{N} \left\{ \sum_{i=1}^N g(i\Delta t) \sin n\omega(i\Delta t) - \frac{1}{2} N [B^+(i\Delta t) - B^-(i\Delta t)] \right\} \quad (15)$$

Third stage.

Building robust correlation matrices  $\bar{R}_{XX}^R(0)$ ,  $\bar{R}_{XY}^R(0)$ , solving static identification problem and calculation of robust coefficients  $c_{ij}^R$  of correlation functions  $R_{X_i X_i}^R(\mu)$ .

1. Values of autocorrelation functions  $R_{g_i g_i}(\mu)$ ,  $i = \overline{1, n}$  at time shift  $\mu = 0$  are calculated from the following formula:

$$R_{g_i g_i}(\mu) = \frac{1}{N} \sum_{k=1}^N g_i(k\Delta t) g_i(k\Delta t) \quad (16)$$

2. Values of autocorrelation functions  $R_{g_i g_i}(\mu)$ ,  $i = \overline{1, n}$  at time shift  $\mu = 1 \cdot i\Delta t$  are calculated from the following formula:

$$R_{g_i g_i}(\mu) = \frac{1}{N} \sum_{k=1}^N g_i(k\Delta t) g_i((k+1)\Delta t) \quad (17)$$

3. Values of autocorrelation functions  $R_{g_i g_i}(\mu)$ ,  $i = \overline{1, n}$  at time shift  $\mu = 2 \cdot i\Delta t$  are calculated from the following formula:

$$R_{g_i g_i}(\mu) = \frac{1}{N} \sum_{k=1}^N g_i(k\Delta t) g_i((k+2)\Delta t) \quad (18)$$

4. Values of variances  $D^*(\varepsilon_i)$  of noises  $\varepsilon_i(t)$  are calculated from the following formula:

$$D^*(\varepsilon_i) = R_{g_i g_i}(\mu = 0 \cdot \Delta t) - 2 R_{g_i g_i}(\mu = 1 \cdot \Delta t) + R_{g_i g_i}(\mu = 2 \cdot \Delta t) \quad (19)$$

5. Robust estimates of autocorrelation function  $R_{X_i X_i}^R(\mu = 0)$  are calculated by means of the following formula:

$$R_{X_i X_i}^R(\mu = 0) = R_{g_i g_i}(\mu = 0) - D^*(\varepsilon_i) \quad (20)$$

6. Robust correlation matrix  $\bar{R}_{XX}^R(0)$  is formed by means of the following expression:

$$\bar{R}_{XX}^R(0) = \begin{bmatrix} R_{g_1 g_1}(\mu = 0) - D^*(\varepsilon_1) & R_{g_1 g_2}(\mu = 0) & \dots & R_{g_1 g_n}(\mu = 0) \\ R_{g_2 g_1}(\mu = 0) & R_{g_2 g_2}(\mu = 0) - D^*(\varepsilon_2) & \dots & R_{g_2 g_n}(\mu = 0) \\ \dots & \dots & \dots & \dots \\ R_{g_n g_1}(\mu = 0) & R_{g_n g_2}(\mu = 0) & \dots & R_{g_n g_n}(\mu = 0) - D^*(\varepsilon_n) \end{bmatrix} \approx \begin{bmatrix} R_{X_1 X_1}^R(0) & R_{X_1 X_2}^R(0) & \dots & R_{X_1 X_n}^R(0) \\ R_{X_2 X_1}^R(0) & R_{X_2 X_2}^R(0) & \dots & R_{X_2 X_n}^R(0) \\ \dots & \dots & \dots & \dots \\ R_{X_n X_1}^R(0) & R_{X_n X_2}^R(0) & \dots & R_{X_n X_n}^R(0) \end{bmatrix} \approx \bar{R}_{XX}^R(0) \quad (21)$$

7. Similarly, correlation matrix  $\bar{R}_{XY}^R(0)$  is formed.

8. The following matrix equation is solved

$$\bar{R}_{XX}^R(0) \cdot \bar{C}^R = \bar{R}_{XY}^R(0) \quad (22)$$

and robust coefficients  $c_{ij}^R$  of static identification equation are calculated from the expression

$$\bar{C}^R = \left[ \bar{R}_{XX}^R(0) \right]^{-1} \bar{R}_{XY}^R(0) \quad (23)$$

Fourth stage.

Building robust correlation matrices  $\bar{R}_{XX}^R(\mu)$ ,  $\bar{R}_{XY}^R(\mu)$ , solving dynamic identification problem and calculation of robust transfer functions  $\bar{W}_{ij}^R$ .

1. Value of autocorrelation functions  $R_{gg}(\mu)$  at time shift  $\mu=0$  is calculated from the following formula:

$$R_{gg}(\mu) = \frac{1}{N} \sum_{i=1}^N g(i\Delta t) g(i\Delta t) \quad (24)$$

2. Value of autocorrelation functions  $R_{gg}(\mu)$  at time shift  $\mu = 1 \cdot i\Delta t$  is calculated from the following formula:

$$R_{gg}(\mu) = \frac{1}{N} \sum_{i=1}^N g(i\Delta t) g((i+1)\Delta t) \quad (25)$$

3. Value of autocorrelation functions  $R_{gg}(\mu)$  at time shift  $\mu = 2 \cdot i\Delta t$  is calculated from the following formula:

$$R_{gg}(\mu) = \frac{1}{N} \sum_{i=1}^N g(i\Delta t) g((i+2)\Delta t) \quad (26)$$

4. Value of variances  $D^*(\varepsilon)$  of noises is calculated from the following formula:

$$D^*(\varepsilon) = R_{gg}(\mu = 0 \cdot \Delta t) - 2 R_{gg}(\mu = 1 \cdot \Delta t) + R_{gg}(\mu = 2 \cdot \Delta t) \quad (27)$$

5. Robust estimates of autocorrelation function  $R_{gg}^R(\mu)$  are calculated by means of the following formula:

$$R_{gg}^R(\mu = 0) = R_{gg}(\mu = 0) - D^*(\varepsilon) \quad (28)$$

6. Robust correlation matrix  $\bar{R}_{XX}^R(0)$  is formed by means of the following expression:

$$\begin{aligned} \bar{R}_{XX}^R(\mu) = & \begin{pmatrix} R_{gg}(0) - D^*(\varepsilon) & R_{gg}(\Delta t) & \dots & R_{gg}[(N-1)\Delta t] \\ R_{gg}(\Delta t) & R_{gg}(0) - D^*(\varepsilon) & \dots & R_{gg}[(N-2)\Delta t] \\ \dots & \dots & \dots & \dots \\ R_{gg}[(N-1)\Delta t] & R_{gg}[(N-2)\Delta t] & \dots & R_{gg}(0) - D^*(\varepsilon) \end{pmatrix} \\ \approx & \begin{pmatrix} R_{XX}(0) & R_{XX}(\Delta t) & \dots & R_{XX}[(N-1)\Delta t] \\ R_{XX}(\Delta t) & R_{XX}(0) & \dots & R_{XX}[(N-2)\Delta t] \\ \dots & \dots & \dots & \dots \\ R_{XX}[(N-1)\Delta t] & R_{XX}[(N-2)\Delta t] & \dots & R_{XX}(0) \end{pmatrix} \\ \approx & \bar{R}_{XX}^R(\mu) \end{aligned} \quad (29)$$

7. Similarly, correlation matrix  $\bar{R}_{XY}^R(\mu)$  is formed.

8. The following matrix equation is solved

$$\bar{R}_{XX}^R(\mu) \bar{W}(\mu) = \bar{R}_{XY}^R(\mu) \quad (30)$$

and robust transfer functions  $\bar{W}_{ij}^R$  of matrix equation of dynamic identification are calculated from the expression

$$\bar{W}_{ij}^R = \left[ \bar{R}_{XX}^R(\mu) \right]^{-1} \bar{R}_{XY}^R(\mu) \quad (31)$$

After all four stages are complete, robustness conditions are provided, i.e. the following equalities hold true:

$$D^*(\varepsilon_i) \approx D(\varepsilon_i), \quad (32)$$

$$R_{g_i g_j}^R(\mu) \approx R_{X_i X_j}(\mu), \quad (33)$$

$$a_{ij}^R \approx a_{ij}, \quad b_{ij}^R \approx b_{ij}, \quad (34)$$

$$c_{ij}^R \approx c_{ij}, \quad W_{ij}^R \approx W_{ij} \quad (35)$$

It allows forming robust correlation matrices  $Z_X^R, V_{X_i}^R$

$$V_{X_i}^R \approx V_{X_i} \quad (38)$$

Thus, as a result of application of robust technology for formation of state matrices  $Z_X^R, V_{X_i}^R$ , a possibility arises to detect faults at early stages for reliable prediction of the technical condition of high-rise buildings or building structures.

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$$Z_X^R = \begin{bmatrix} D^*(\varepsilon_1) & D^*(\varepsilon_2) & \dots & D^*(\varepsilon_n) \\ R_{X_1 X_1}^R(\mu) & R_{X_1 X_2}^R(\mu) & \dots & R_{X_1 X_n}^R(\mu) \\ R_{X_2 X_1}^R(\mu) & R_{X_2 X_2}^R(\mu) & \dots & R_{X_2 X_n}^R(\mu) \\ \dots & \dots & \dots & \dots \\ R_{X_n X_1}^R(\mu) & R_{X_n X_2}^R(\mu) & \dots & R_{X_n X_n}^R(\mu) \\ a_{11}^R & a_{12}^R & \dots & a_{1n}^R \\ b_{11}^R & b_{12}^R & \dots & b_{1n}^R \\ a_{21}^R & a_{22}^R & \dots & a_{2n}^R \\ b_{21}^R & b_{22}^R & \dots & b_{2n}^R \\ \dots & \dots & \dots & \dots \\ a_{k1}^R & a_{k2}^R & \dots & a_{kn}^R \\ b_{k1}^R & b_{k2}^R & \dots & b_{kn}^R \\ c_{11}^R & c_{12}^R & \dots & c_{1n}^R \\ c_{12}^R & c_{22}^R & \dots & c_{2n}^R \\ \dots & \dots & \dots & \dots \\ c_{m1}^R & c_{m2}^R & \dots & c_{mn}^R \\ W_{11}^R & W_{12}^R & \dots & W_{1n}^R \\ W_{21}^R & W_{22}^R & \dots & W_{2n}^R \\ \dots & \dots & \dots & \dots \\ W_{m1}^R & W_{m2}^R & \dots & W_{mn}^R \\ \dots & \dots & \dots & \dots \end{bmatrix} \quad (36)$$

for which the following equalities hold true:

$$Z_X^R \approx Z_X \quad (37)$$