# Methods of diagnostic of pipe mechanical damage using functional analysis, neural networks and method of finite elements

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***Abstract:*** *The main goal of the study is to analyze methods and diagnose mechanical damage to the pipeline using functional analysis, neural networks and the finite element method. In the work, mathematical formulations of the corresponding geometrical inverse problems of the theory of shells on reconstruction of defects of lateral surface are formulated according to measurement data obtained from sensors located in a given section of the shell. The statement was given and a method for solving inverse geometric problems for a shell of Tymoshenko type was developed. The authors have offered methods for solving inverse geometric problems of identifying volumetric and crack-like defects in extended underground structures and pipelines based on the analysis of responses to unsteady elastic-wave perturbations using the mathematical apparatus of wavelet signal transformation, the finite element modeling method and intelligent software system based on neural network.*

***Key Words:*** *ballistics, inverse problems, regularization method, variation principle, Euler equation*

## 1. INTRODUCTION

In order to increase the reliability and safety of engineering structures and constructions, over the past few decades, various methods for detecting damage and monitoring systems have been intensively developed. In this regard, the development of highly effective, easy-to-use, precise and structurally non-destructive diagnostic system that could replace traditional diagnostic procedures is of great importance for solving many problems with maintenance of engineering structures. In addition, determining the level of safety of a structure throughout its entire service life is important not only for safe operation, but also to decrease maintenance and preventive maintenance to prevent damage.

The development of diagnostic methods was done on the basis of mathematical modeling of technical facilities and devices within the linear elasticity theory, and fluid dynamics of the acoustic approximation [1], [2], [3], [4], [5], [6], [7], [8], [9], [10], [11]. The research of heat propagation problems and development of cracks were provided in [12], [13], [14], [15], [16], [17], [18], [19], [20], [21], [22].

The problems under consideration were mathematically formulated in the form of corresponding initial-boundary value problems. The objectives of searching and identifying structural defects can be mathematically formulated as geometric inverse problems of theory of elasticity, the solution of which is associated with difficulties in overcoming their incorrectness. One of the approaches to solving inverse problems of theory of elasticity, which has gained wide popularity recently, is a combination of finite element methods and artificial neural networks.

The highest difficulty in developing a diagnostic system is the creation of a technique for recognizing the type, size and intensity of damage [23], [24], [25], [26], [27], [28], [29]. For these purposes, the development and creation of an artificial neural network in combination with damage database was proposed.

Using finite element modeling, the initial state of the damage database was formed, which contains the structural dynamic responses of the system to some specific forms of damage. The created state of the damage database will be used for initial training of artificial neural network. In order to reduce the number of initial states without losing the required precision, the wavelet transform of responses was used to extract irregularities delivered by defects.

The first scientific and technical objective in developing a system for detecting structural damage using a neural network is the formation of the initial state of the damage database, which will be used as input to the learning process of artificial neural network. To perform this task, it was proposed to use the finite element modeling method. In this case, the initial state of the damage database should contain, as far as possible, the most complete information about structural response of the structure to certain damage. For this, a wavelet decomposition of the structural response was used.

Damage to the structure was modeled by decrease in stiffness, which depends on the size and location of the damage in the structure. In order to obtain a data set for the initial training of artificial neural network, the stiffness reduction coefficients of the elements were assumed to be random numbers between 0 and 1.

The location of the damaged structural element was also assumed to be random. In addition, a defect may be modeled using several finite elements.

After the initial state of the damage database is formed, the training process of the artificial neural network was carried out, which continues until the result of artificial neural network meets the desired goal or until the work of artificial neural network reaches the expected accuracy of the output result.

This accuracy can be estimated by the least squares error method. A trained network, having received new, previously unknown analysis results, shall be able to correctly recognize the defect parameters.

The input for training an artificial neural network may be converted using wavelet transform, which improves the reconstruction process. The issues of artificial neural network architecture, ways of presenting training information and the influence of defect sizes on the accuracy and time of their identification have also been studied.

## 2. METHODOLOGY

A circular cylindrical shell of length $L$ *is considered*, having a through defect of arbitrary shape bounded by curve $G$. A predetermined load $f(\tau)$ acts on the left end $z = 0$ of shell. At the initial instant of time, the shell is in unperturbed state and in a certain section of the shell, for example, when measuring equipment (signal receiver) is located at $x = L$ (Fig. 1). It is required to determine the location and shape of the defect from identified signal data.

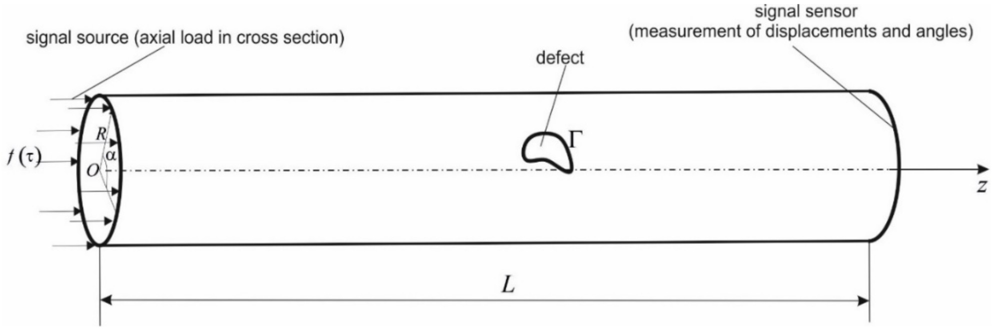


Fig. 1 - A shell with defect

The Tymoshenko equation of motion of the shell has the form [14], Eq. (1):

$$\ddot{W} = LW + P \tag{1}$$

where $W = (u, v, w, \chi_\alpha, \chi_z)^T$ is displacement vector ($u, v, w$ are angular, axial and normal displacements, $\chi_\alpha, \chi_z$ are angles of rotation of the sections due to shear deformations), $\boldsymbol{P} = (q_u, q_v, p, 0,0)^T$ is pressure vector, $L = \left(L_{ij}\right)_{5\times5}$ is operator matrix, Eqs. (2-18):

$$L_{11} = \frac{\partial^2}{\partial\alpha^2} + \eta^2\left(\frac{\partial^2}{\partial z^2} - k^2\right) \tag{2}$$

$$L_{12} = (1 - \eta^2)\frac{\partial^2}{\partial\alpha\partial z} = L_{21} \tag{3}$$

$$L_{13} = -L_{13} = (1 + \eta^2 k^2)\frac{\partial}{\partial\alpha} \tag{4}$$

$$L_{14} = -\gamma^2\frac{\partial^2}{\partial\alpha^2} + \eta^2 k^2 \tag{5}$$

$$L_{15} = \gamma^2(2\eta^2 - 1)\frac{\partial^2}{\partial\alpha\partial z} = \gamma^2 L_{51} \tag{6}$$

$$L_{22} = \eta^2\frac{\partial^2}{\partial\alpha^2} + \frac{\partial^2}{\partial z^2} \tag{7}$$

$$L_{23} = (1 - 2\eta^2)\frac{\partial}{\partial z} = -L_{32} \tag{8}$$

$$L_{24} = -\gamma^2\eta^2\frac{\partial^2}{\partial\alpha\partial z} \tag{9}$$

$$L_{25} = -\gamma^2\eta^2\frac{\partial^2}{\partial\alpha^2} = \gamma^2 L_{52} \tag{10}$$

$$L_{33} = \eta^2 k^2 \left( \frac{\partial^2}{\partial \alpha^2} + \frac{\partial^2}{\partial z^2} \right) - 1 \tag{11}$$

$$L_{34} = \eta^2 k^2 \frac{\partial}{\partial \alpha} \tag{12}$$

$$L_{41} = -\frac{\partial^2}{\partial \alpha^2} + \eta^2 \gamma^{-2} \tag{13}$$

$$L_{42} = -\eta^2 \frac{\partial^2}{\partial \alpha \partial z} \tag{14}$$

$$L_{43} = -\eta^2 k^2 \gamma^{-2} \frac{\partial}{\partial \alpha} \tag{15}$$

$$L_{44} = \frac{\partial^2}{\partial \alpha^2} + \eta^2 \frac{\partial^2}{\partial z^2} - \eta^2 k^2 \gamma^{-2} \tag{16}$$

$$L_{45} = (1 - \eta^2) \frac{\partial^2}{\partial \alpha \partial z} = L_{54} \tag{17}$$

$$L_{55} = \eta^2 \frac{\partial^2}{\partial \alpha^2} + \frac{\partial^2}{\partial z^2} - \eta^2 k^2 \gamma^{-2} \tag{18}$$

The system of dimensionless quantities (bar denotes dimensional parameters), Eqs. (19-36)

$$z = \frac{z}{R} \tag{19}$$

$$\tau = \frac{c_1 t}{R} \tag{20}$$

$$u = \frac{u'}{R} \tag{21}$$

$$v = \frac{v'}{R} \tag{22}$$

$$w = \frac{w'}{R} \tag{23}$$

$$c_1^2 = \frac{\lambda + 2\mu}{\rho} \tag{24}$$

$$c_2^2 = \frac{\mu}{\rho} \tag{25}$$

$$\eta^2 = \frac{c_2^2}{c_1^2} \tag{26}$$

$$p = \frac{p'}{\sigma} \tag{27}$$

$$q_\alpha = \frac{q'_\alpha}{\sigma} \tag{28}$$

$$q_z = \frac{q'_z}{\sigma} \tag{29}$$

$$\sigma = \frac{\rho h c_1^2}{R} \tag{30}$$

$$\gamma^2 = \frac{h^2}{12R^2} \tag{31}$$

$$L = \frac{L'}{R} \tag{32}$$

$$\kappa_{\xi\zeta} = R\kappa'_{\xi\zeta} \tag{33}$$

$$T_{\xi\zeta} = \frac{T'_{\xi\zeta}}{h(\lambda + 2\mu)} \tag{34}$$

$$M_{\xi\zeta} = \frac{M'_{\xi\zeta}R}{I(\lambda + 2\mu)} \tag{35}$$

$$Q_\xi = \frac{Q'_\xi}{\mu h k^2}\ (\xi, \zeta = \alpha, z) \tag{36}$$

where, $R$ is the radius and thickness of the shell; $\tau$ ia dimensionless time; $c_1, c_2$ are the velocities of waves of tension-compression and shear in the shell material; $\lambda$, $\mu$, $\rho$ are Lame elastic parameters, and the density of the shell material; $T_{\xi\zeta}$, $M_{\xi\zeta}$ and $Q_\xi$ are tangential forces, moments and cutting forces.

Physical relationships, Eqs. (37-45):

$$T_{\alpha\alpha} = \varepsilon_{\alpha\alpha} - \kappa_{\alpha\alpha} + (1 - 2\eta^2)(\varepsilon_{zz} - \kappa_{zz}) \tag{37}$$

$$T_{z\alpha} = 2\eta^2\varepsilon_{z\alpha} \tag{38}$$

$$T_{zz} = \varepsilon_{zz} + (1 - 2\eta^2)\varepsilon_{\alpha\alpha} \tag{39}$$

$$T_{\alpha z} = 2\eta^2(\varepsilon_{\alpha z} - \kappa_{\alpha z}) \tag{40}$$

$$M_{\alpha\alpha} = \kappa_{\alpha\alpha} + (1 - 2\eta^2)\kappa_{zz} \tag{41}$$

$$M_{zz} = \kappa_{zz} + (1 - 2\eta^2)\kappa_{\alpha\alpha} \tag{42}$$

$$M_{\alpha z} = 2\eta^2\kappa_{\alpha z} \tag{43}$$

$$Q_\alpha = \theta_\alpha \tag{44}$$

$$Q_z = \theta_z \tag{45}$$

Kinematic relationships, Eqs. (46-53):

$$\varepsilon_{\alpha\alpha} = \frac{\partial u}{\partial \alpha} + w \tag{46}$$

$$\varepsilon_{zz} = \frac{\partial v}{\partial z} \tag{47}$$

$$\varepsilon_{\alpha z} = \frac{1}{2}\left(\frac{\partial u}{\partial z} + \frac{\partial v}{\partial \alpha}\right) \tag{48}$$

$$\kappa_{\alpha\alpha} = \frac{\partial}{\partial \alpha}(\chi_\alpha - u) - w \tag{49}$$

$$\kappa_{zz} = \frac{\partial \chi_z}{\partial z} \tag{50}$$

$$\kappa_{\alpha z} = \frac{1}{2}\left[\frac{\partial}{\partial \alpha}(\chi_z - v) + \frac{\partial \chi_\alpha}{\partial z}\right] \tag{51}$$

$$\theta_\alpha = \chi_\alpha - u + \frac{\partial w}{\partial \alpha} \tag{52}$$

$$\theta_z = \chi_z + \frac{\partial w}{\partial z} \tag{53}$$

where $\varepsilon_{\xi\zeta}$, $\kappa_{\xi\zeta}$ are components of the strain tensors and changes in curvature. Initial conditions, Eq. (54):

$$u|_{\tau=0} = \dot{u}|_{\tau=0} = v|_{\tau=0} = \dot{v}|_{\tau=0} = w|_{\tau=0} = \dot{w}|_{\tau=0} = \chi_\alpha|_{\tau=0} = \dot{\chi}_\alpha|_{\tau=0} = \chi_z|_{\tau=0} = \dot{\chi}_z|_{\tau=0} = 0 \tag{54}$$

It can be assumed that the defect is end-to-end, then the conditions of the free edge are satisfied on the defect contour, Eq. (55):

$$T_{\alpha\alpha}|_\Gamma = T_{z\alpha}|_\Gamma = T_{\alpha z}|_\Gamma = T_{zz}|_\Gamma = M_{\alpha\alpha}|_\Gamma = M_{z\alpha}|_\Gamma = M_{zz}|_\Gamma = Q_\alpha|_\Gamma = Q_z|_\Gamma = 0 \tag{55}$$

We assume that the source of force disturbances is specified in the shell section, Eq. (56):

$$q_z|_{z=0} = f(\tau) \tag{56}$$

We also assume that the displacements and rotation angles in section $z = L$ are known, Eqs. (57-61):

$$u|_{z=L} = U(\tau) \tag{57}$$

$$v|_{z=L} = V(\alpha, \tau) \tag{58}$$

$$w|_{z=L} = W(\alpha, \tau) \tag{59}$$

$$\chi_\alpha|_{z=L} = X_\alpha(\alpha, \tau) \tag{60}$$

$$\chi_z|_{z=L} = X_z(\alpha, \tau) \tag{61}$$

## 3. RESULTS AND DISCUSSIONS

It may be assumed that the solution of the direct problem for a shell having some “standard” defect is known.

As such a defect, we take a curved square centered at a point $(\alpha_*, z_*)$ and with sides $\Delta z = \Delta\alpha$. Furthermore, the values $\alpha_*, z_*, \Delta z$ are the defect parameters (Fig. 2).

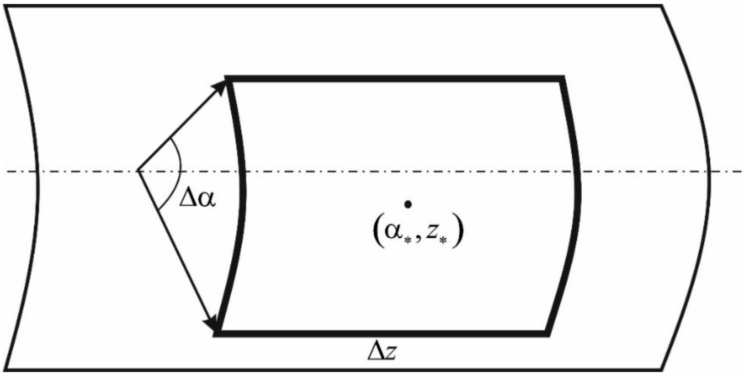

Fig. 2 - “Standard defect”

Let us denote $W_*(\alpha,\tau;\alpha_*,z_*,\Delta z)=W|_{z=L}$ as the displacement vector in the section $z=L$. It is dependent on the angular coordinate, time and defect parameters. Let us introduce the residual functional, which for a fixed time $\tau$ is the functional defined on a finite-dimensional set of defect parameters ( $\widetilde{W}(\alpha,t)$ is the displacement vector in the shell section $z=L$ with desired defect), Eq. (62):

$$\Phi_0(\alpha_*,z_*,\Delta z)=\int_0^{\tau}\int_0^{2\pi}\left|\widetilde{W}(\alpha,t)-W_*(\alpha,t;\alpha_*,z_*,\Delta z)\right|^2 d\alpha dt \tag{62}$$

We shall formulate the problem of determining the approximate position and shape of defect as follows.

In the first stage (iteration zero) by minimizing the residual functional (62) set by parameters $\alpha_*,z_*,\Delta z$, that characterize the defect in zero approximation (Fig. 3).

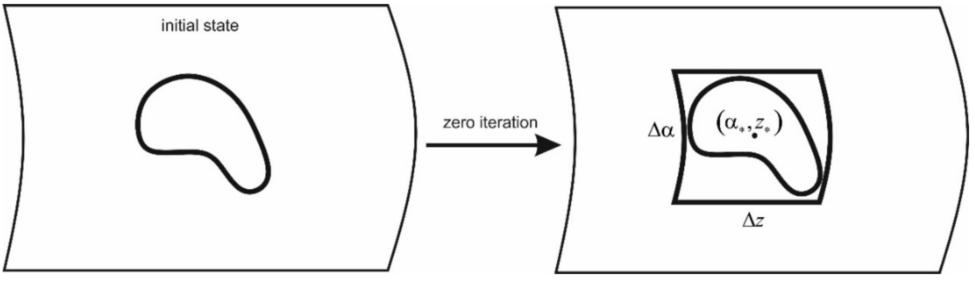

Fig. 3 - Zero iteration

The next step is represented by the procedure for clarifying the defect contour. For this, the method of regularizing functional on finite-dimensional sets is used.

The defect contour is approximately replaced by broken line with a given number of nodes (Fig. 4).

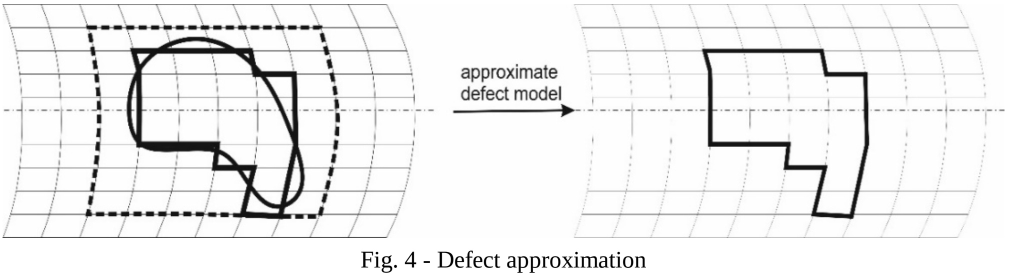

Fig. 4 - Defect approximation

The approximation of the contour $2n$ is determined by spatial coordinates of its nodal points. Again, we construct the residual functional, depending on $2n$ of desired parameters of the contour, Eq. (63):

$$\Phi_k(\alpha_1, \alpha_2, \dots, \alpha_n, z_1, z_2, \dots, z_n) = \int_0^{\tau} \int_0^{2\pi} \left| \widetilde{W}(\alpha, t) - W_k(\alpha, t; \alpha_1, \alpha_2, \dots, \alpha_n, z_1, z_2, \dots, z_n) \right|^2 d\alpha dt \quad (63)$$

At zero iteration, we place the unknown nodes of approximation of the defect on sides of the curved square (Fig. 5).

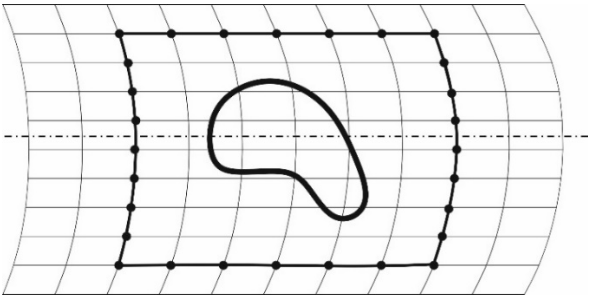

Fig. 5 - Approximation Nodes at Zero Iteration

Then, an iterative procedure of the Newton-Gauss method is organized, at each step of which we obtain the next approximate positions of the nodes. The procedure is repeated until the specified accuracy $\varepsilon$ will be achieved, Eq. (64):

$$\Phi_k(\alpha_1, \alpha_2, \dots, \alpha_n, z_1, z_2, \dots, z_n) \le \varepsilon \quad (64)$$

Second iteration process (Fig. 6):

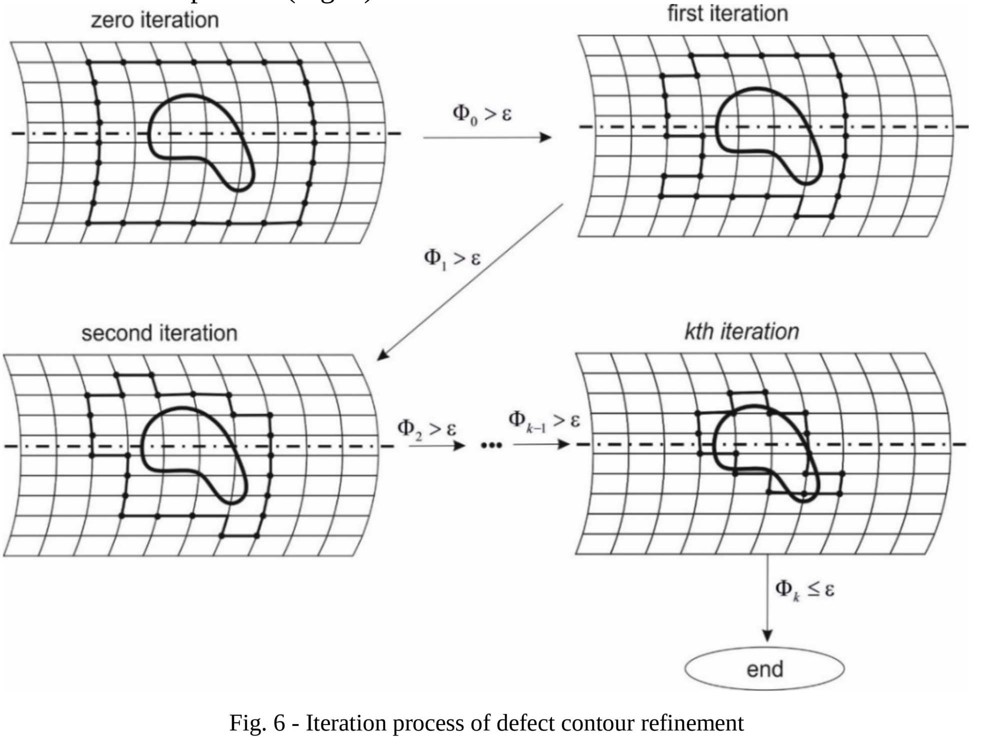



Fig. 6 - Iteration process of defect contour refinement

To effectively resolve the complex problems of diagnosis and identification, the urgent task is to develop a universal method suitable for recognizing defects in complex piping systems (heating mains, heating and gas supply lines for communal facilities, etc.).

A universal approach based on the finite element method, wavelet transform, and artificial neural network has been suggested to solve these important problems.

The general scheme of the method is:

1. Creation of finite element models with damage, solving direct problems for pipelines with defects, and organizing database containing structural responses (speeds of longitudinal displacements) at the points of fixing of virtual sensors.

2. Processing the results of virtual experiments by means of discrete wavelet analysis. In this case, feature vectors are formed corresponding to the signal from some type of defect.

3. Development of the structure of artificial neural network. The choice of its type, number of layers, number of neurons for each layer.

4. Organizing database of training samples.

5. Implementation of artificial neural network model and computer learning algorithm.

6. Development of training algorithms for artificial neural network.

7. Neural network training.

8. Verification of work and testing of neural network for correct recognition of defects of some type.

When forming the signal base, defects such as metal loss were considered with their geometric parameters changed in a wide range:

- depth of the defect;
- length (size in the axial direction);
- disclosure (size in circumferential direction);
- position on pipe (external/internal).

The velocities of longitudinal displacements of shell surface in the fixing zone of the virtual sensor were taken as recognizable signal.

As an exciting signal, a triangular pulse of longitudinal pressure of unit amplitude was used in the same section of pipeline, where a sensor for measuring the velocity of longitudinal displacements was fixed (Figs. 7-8).

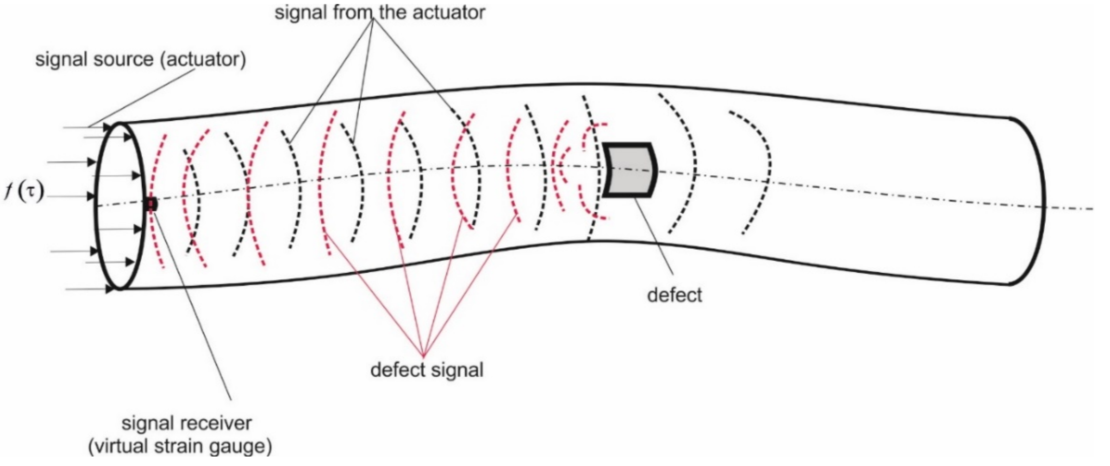


Fig. 7 - The virtual experiment diagram

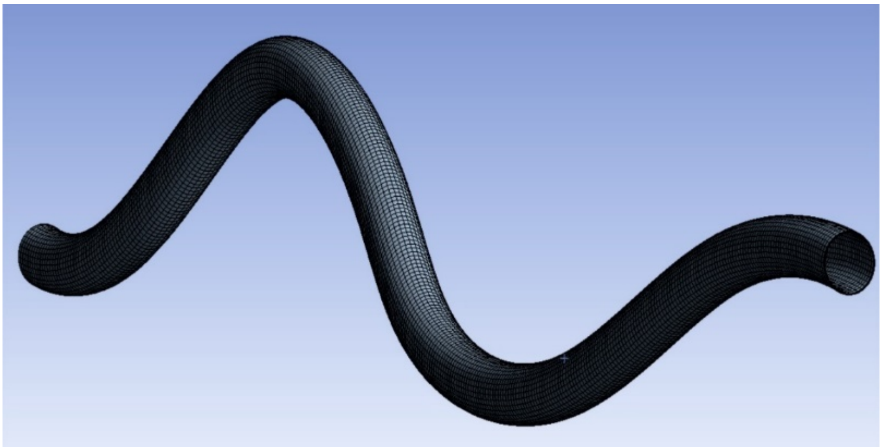

Fig. 8 - The finite-element model of pipeline with complex geometry

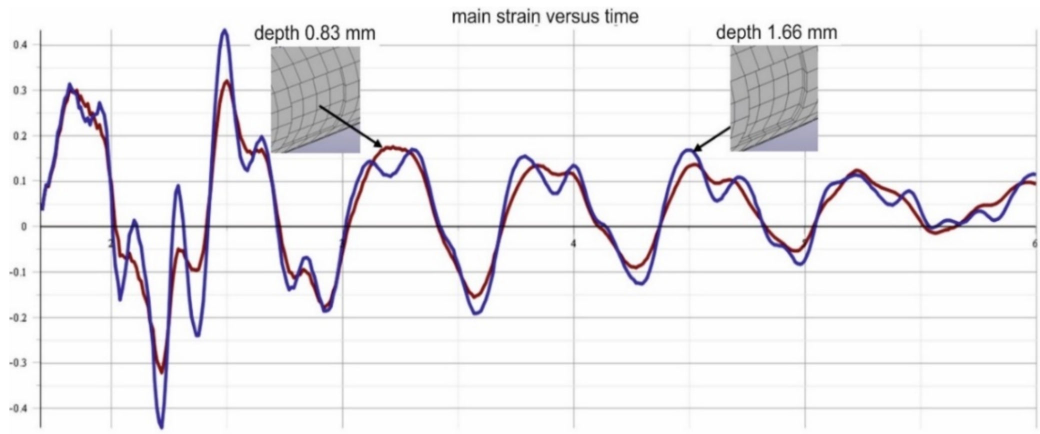


Fig. 9 - Registration of signals from various defects

Figure 9 depicts time dependences of the main stresses obtained from virtual strain sensor for two defects of the same size but different depths. Visually there is a significant difference in results, which allows us to classify them.

## 4. CONCLUSIONS

With the purpose of solving the inverse geometric problems of defect identification in pipelines, two approaches were developed. The first is a phenomenological approach based on rigorous description of the mechanics of interaction of generated unsteady wave fields and the object with the defect. It consists in development of mathematical formulations and methods for solving unsteady geometrically inverse problems based on theory of Timoshenko type shell, functional analysis, and numerical methods.

The second approach is based on methods for classifying structural responses of the studied object to effects of unsteady disturbances. Hence, the geometrically inverse problem can be formulated as the problem of recognizing defect by its characteristic features, which are extracted from the corresponding signal (structural response) recorded by measuring sensors. To solve the classification problem, it was proposed to use artificial neural network with learning process based on the algorithm of backpropagation of error.

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