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Neural network technology for identifying defect sizes in half-plane based on time and positional scanning

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Introduction. The selected research topic urgency is due to the need for a quick assessment of the condition and reliability of materials used in various designs. The work objective was to study parameters of the influence of the defect on the response of the surface of the medium to the shock effect. The solution to the inverse problem of restoring the radius of a defect is based on the combination of a computational approach and the use of artificial neural networks (ANN). The authors have developed a technique for restoring the parameters of a defect based on the computational modeling and ANN.
Materials and Methods. The problem is solved in the flat setting through the finite element method (FEM). In this paper, we used the linear equations of the elasticity theory with allowance for energy dissipation. The finite element method implemented in the *ANSYS* package was used as a method for solving the boundary value problem. *MATLAB* complex was used as a simulation of the application process (ANN).
Results. A finite element model of a layered structure has been developed in a flat formulation of the problem in the *ANSYS* package. The problem of determining unsteady vibrations under pulsed loading for different radius variations of the defect is solved. Positional scanning of the research object is applied. Graphical dependences of the vibration amplitudes of points on the surface on the defect radius are plotted.
Discussion and Conclusions. As a result of studying the dependences of vibration responses on the defect radius, the authors have developed an approach to restore this parameter in a flat structure based on a combination of the FEM and ANN. The research has shown that the amount of data used is sufficient for successful training of the constructed ANN model and identification of a hidden defect in the structure.

Keywords: flat layered structure, defect, non-destructive diagnostics, *FE* modeling, impulse action, unsteady oscillations, surface waves, artificial neural networks, positional scanning, amplitude-time characteristics.

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Introduction. There is an extensive list of various building and bridge structures, premises, foundations, soils, composite materials that are used under different conditions. Structures can have a sufficiently long service life and defects of various configurations: cracks, cavities, inclusions, corrosive changes in the structure, dimples, etc. As a result, unforeseen pre-emergency conditions and structural failures may occur.

This fact determines the need for using various methods of non-destructive testing [1–2]. Some directions in the development of single methods for fault diagnosing defects in various objects are presented in [3–10]. The methods are based on the collection and analysis of certain structural parameters, which are the response to its loading. Vibration displacement of certain points of the surface under impulse loading of structure oscillations can be one of such parameters. In this case, a wave front propagates from the place of excitation of oscillations, exciting the displacement of points and oscillations of all structural elements. The problem can be reduced to considering measuring the velocity constants of wave field propagation. Based on the analysis of publications in foreign literature, it can be stated that experimental studies show a clear tendency to operate with the "velocity measuring" technique [11–12].

The application of specialized devices, which are located at certain points of the object and collect information on various vibration parameters, are described in [13−14]. This technique assumes positional, time and frequency scanning of the study objects. The most attractive is using acoustic sensors and receivers installed on the outer surface of the structure. These sensors can record signals reflected from defects. The use of diagnostic systems and complexes requires the development of software, which provides the primary analysis of the signal. In the case of fine instrument tuning, for example, when using special processing algorithms for analyzing the reflected signal, the software identifies the region of imperfection of the structure. The corresponding software can be developed from using an artificial neural network (ANN) [15]. The application of ANN in problems of reconstruction of the damaged state of structural elements is described in [16–26]. The use of various architectures and ANN algorithms is described in [16–20]. The paper [21] considers the determination of defects in anisotropic plates using ANN. In [22], the authors pointed out the advantages of identification methods that do not require preliminary construction of a mathematical model of the research object.

In this paper, a method for reconstructing the diameter of a circular defect located in the half-plane of a layered structure is developed. Defects of this kind can often occur under the opening of the upper soil layers in the form of compaction of stone structures under the pavement layers. The elastic modulus and density of such structures can differ multi-fold from the basic parameters of the layer. In the mathematical setting, the problem is reduced to solving the inverse geometric problem of the elasticity theory [27]. The construction of an algorithm for recovering information on an object localized in a certain place is considered. For this, the application of the FE method, the analysis of the results of surface waves, and the correlation analysis of the dependence of the parameters of the defect on the wave field of the response using ANN, is considered.

Materials and Methods. An approach, whose purpose is to restore information on the parameters of the region of imperfection of the structure based on the analysis of the impact response of the surface of the medium, is proposed. The analysis is carried out on the basis of the developed algorithms with a combination of the computational approach and the use of ANN. A laminated material is considered as a sample.

Loading of the structure by impulse impact is carried out at a certain distance from the area under study, and the sensors recording vibrations are located in certain positions and sequences in the linear direction of this area. Lateral and longitudinal vibrations can be measured. Of interest is the period of time when waves reflected from the ends of the simulated section of the structure do not have time to reach the sensor. In this way, simulation of field operating conditions of a layered structure of the subgrade is simulated. The analysis of the measured amplitude-time characteristics (ATC) shows the possibility of their use in inverse problems of defect recovery.

As a tool for solving the inverse problem of reconstructing defect parameters, ANN are used, which were originally designed to solve the problems of determining nonlinear dependencies in multidimensional data arrays. Unlike other algorithms, ANNs are not programmed, but trained on a set of data for the investigated design parameters. Training samples are built through solving direct problems in the *ANSYS FE* package. The trained network, having received new, previously unknown analysis results, is able to correctly recognize the parameters of the defect.

Effective applications of analytical and numerical modeling, which correlate sufficiently well with the recoverable parameters of structural elements, are presented in [28–34].

Formulation of the problem. The problem is solved in a flat formulation using the finite element method (FEM). In this paper, we use linear equations of the elasticity theory with allowance for energy dissipation adopted in the *ANSYS* package [34−35].

For an elastic medium:

$$\rho\ddot{u}_i + \alpha\rho\dot{u}_i - \sigma_{ij,j} = f_i \, ;$$

$$\sigma_{ij} = c_{ijkl}(\varepsilon_{kl} + \beta\dot{\varepsilon}_{kl}) \, ;$$

$$\varepsilon_{kl} = \frac{u_{k,l} + u_{l,k}}{2},$$

where ρ is material density; u_i — components of the vector-function of displacements; $\sigma_{i,j}$ — mechanical stress tensor components; f_i — components of the density vector of mass forces; ε_{kl} — strain tensor components; c_{ijkl} — components of the fourth-rank tensor of elastic moduli; α — nonnegative damping coefficients (in *ANSYS*).

Let us consider fully the mechanical boundary conditions. When defining mechanical boundary conditions, the body boundary is represented as a union of non-intersecting regions $S = S_u S_t S_{ut}$, on which the following conditions are set:

— the condition for fixing the border or specified displacements:

$$u_i|_{S_u} = u_i^0,$$

— the condition of force action, at which the components of the vector of mechanical stresses are given:

$$t_i = \sigma_{ij} n_j\big|_{S_t} = p_i,$$

— the condition of smooth contact with an absolutely rigid solid, the equality to zero of normal displacements and tangential stresses:

$$u_n = u_i n_i|_{S_{ut}} = 0, t_i^{(k)} = \sigma_{ij} n_j \tau_i^{(k)}\big|_{S_{ut}} = 0.$$

Description of the model. A layered construction is considered. The upper layer is rigidly linked to the underlying half-space (Fig. 1). Layer 1 contains a defect in the form of a circular configuration centered at a certain depth. The properties of the material are presented in Table 1. The defect is located at a depth of Y_{loc} = 1.5 m subsurface and at a distance of X_{loc} = 2 m from the point P_1 of application of a single pulsed P_t (Fig. 1) loading. Impulse loading depends linearly on the time of load application (τ = 0.003 s), which corresponds to the parameters of real shock loading (Fig. 2). The field of surface displacements as a result of a short-term impulse action is considered as an input parameter. The radius of the defect varies in calculations as: R_i = 0; 0.25; 0.3; 0.35; 0.4; 0.45; 0.5 m. The basic objective is to determine the functional dependence of the defect radius on the oscillation responses measured at certain points of the structure based on the use of ANN.

Table 1

Layer options

No.	Name	Thickness, *m*	E, GPa	ρ, kg/m³	*ν*	Attenuation coefficient
1	Layer 1	5	0.1	2000	0.33	0.001
2	Underlying layer	0.1	0.1	2000	0.33	0.1
3	Defect R_i	X_{CENTER}=2 Y_{CENTER}=−1.5	1	2000	0.33	0.001

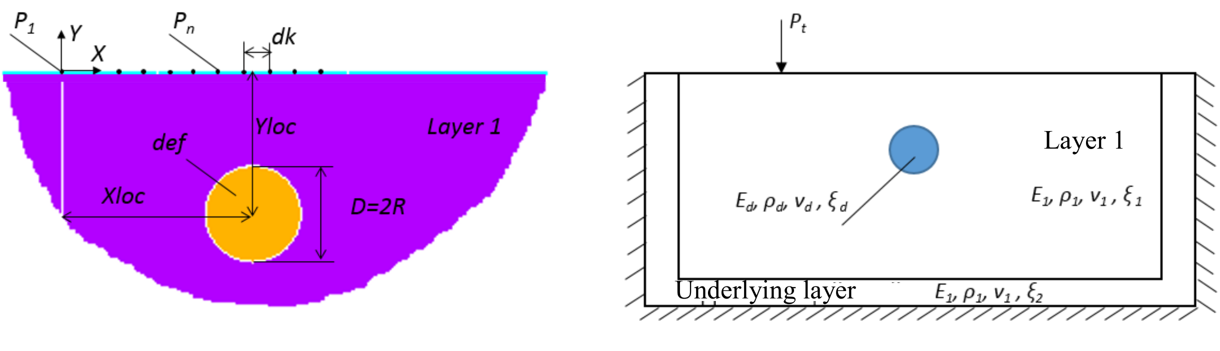


Fig. 1. Layered construction model with inner circular defect:
(a) description of the region with imperfection; *(b)* layered structure model schematic

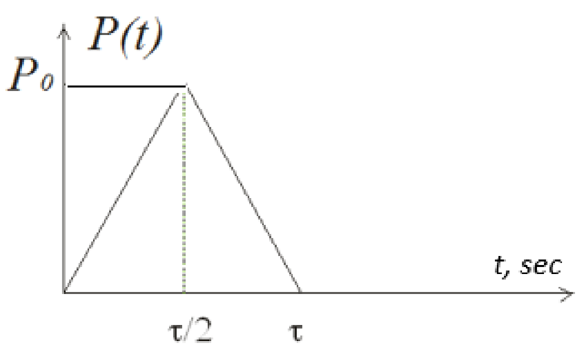


Fig. 2. Dependence of impulse load P on loading time

***FE* modeling.** Modeling of a flat structure (*10 m* wide) with a defect was carried out in the *ANSYS FE* complex: elements of the *PLANE82* type with triangular and quadrangular configurations with plane deformation (*3950* nodes and *1890* finite elements) were used for modeling. The outer layer of the structure (underlying) had high damping coefficients, but retained the basic properties of layer 1. The analyzed time was selected such that the impulse from the extreme boundaries of the structure did not return back. This was achieved by fixing the time of a sharp increase in the vibration amplitudes at the outer boundary of layer 1. The shock load was applied at the point P_t on the surface of the structure.

As a result of impulse loading, transverse and longitudinal wave displacements of points occur both on the surface of the structure and throughout its entire volume. An example of the form of transverse vibrations of the structure at time t = 0.01 s is shown in Fig. 3. Control points (40 points) are located on the surface at a distance of dk = *0.1 m* from each other (Fig. 1). The simulation of the distribution of points on the surface displays a true picture of measurements. The first measuring point is located at a distance of *0.1 m* from the place of impact.

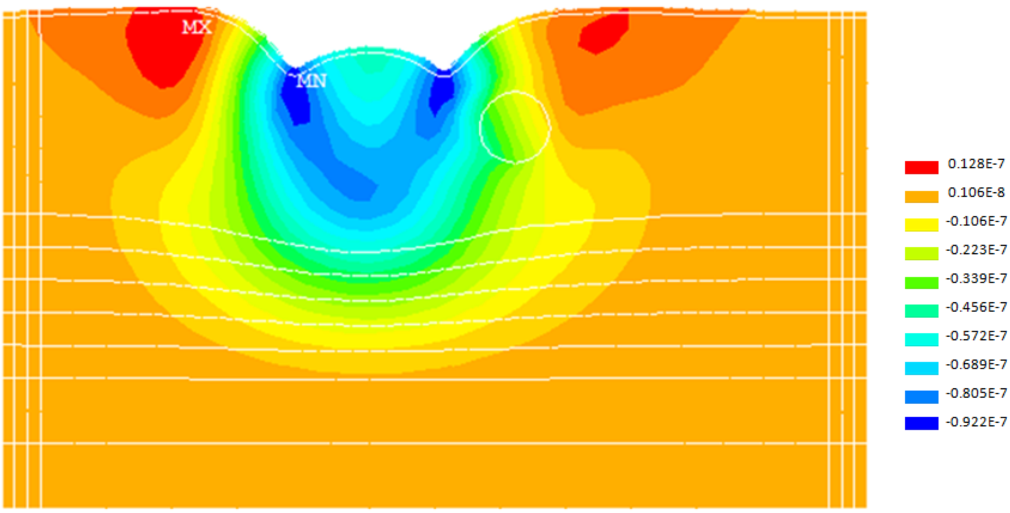


Fig. 3. Wave displacements along thickness of the structure at $t = 0.01$ *s*

Fig. 4, 5 show the results of calculating the transverse displacements (direction OY) at various points of the surface. In the process of solving the problem, the transverse displacements were calculated at the control points of the structure in the time interval t = 0–0.1 s. Of special interest is the field of displacements of points of the surface layer in the time interval t = 0–0.04 s. At this time, the primary form of the layered structure deflections is formed, and there are no vibration responses from the excitation of the outer structure layers.

Fig. 5 shows the maximum values of vibration amplitudes depending on the time of their registration. The analysis shows that they have an exponential approximate trend. For the same measurement positions of the amplitude maxima, there are discrepancies in the vibration amplitudes depending on the value of the radius of the defect.

At the next stage, relative values of the displacement of amplitudes д ΔU_y (a), the velocity ΔV_y (b) and the acceleration ΔA_y (c) were calculated for the points N_p=1–40. These relative values were calculated as the difference between the current indicator of the maximum amplitude for the point at R_i (at i=2–7) and the amplitude of the vibration parameter at a defect size $R_1=0$ *(no defect in the structure)*:

$$\Delta U_{yi}=U_{yi}-U_{y1};$$

$$\Delta V_{yi}=V_{yi}-V_{y1};$$

$$\Delta A_{yi}=A_{yi}-A_{y1}.$$

Fig. 6 shows three-dimensional graphs representing the dependences of the relative magnitudes of the displacement of the amplitudes ΔU_y (a), the velocity ΔV_y (b) and the acceleration ΔA_y (c) for points N_p=1–40 on the surface of the structure and a variant of the radius R_i of the defect.

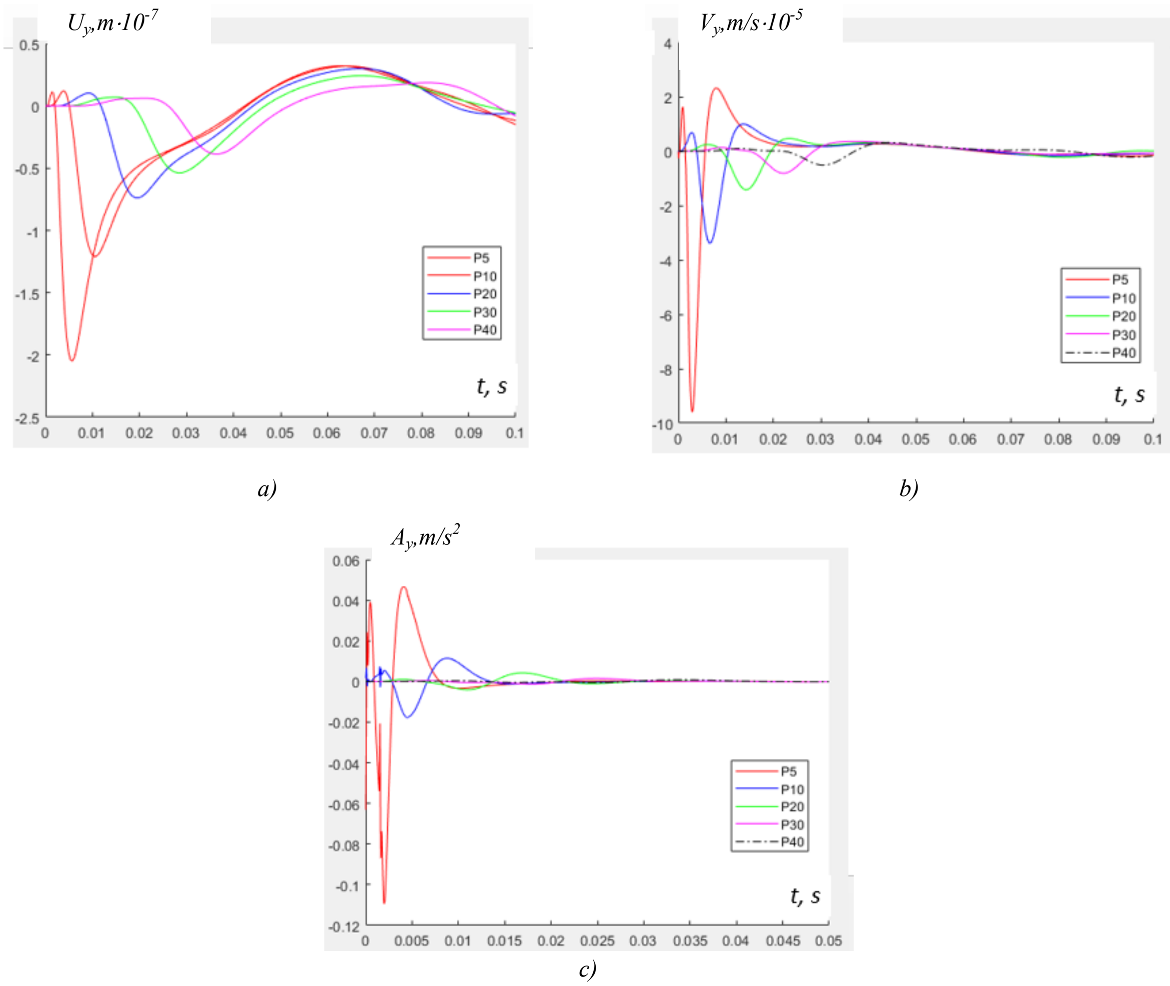


Fig. 4. Amplitudes of displacements U_y *(a)*, velocity V_y *(b)* and acceleration A_y *(c)* depending on time for points 1-40 on the surface of the structure

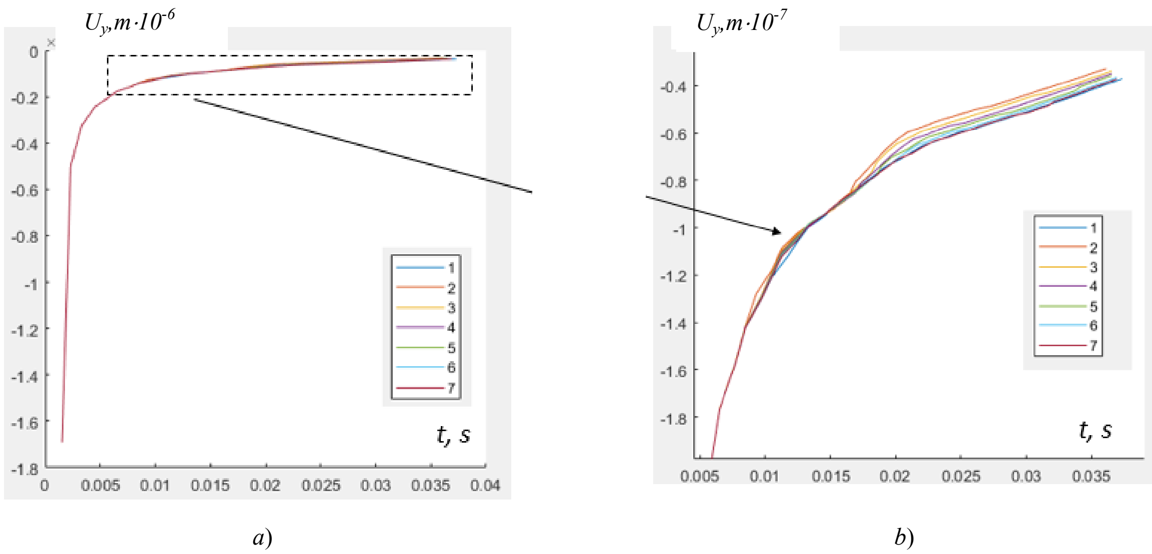
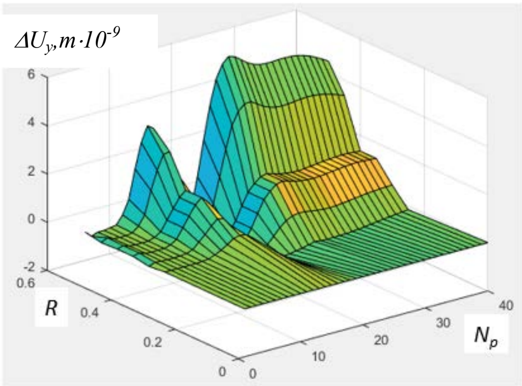
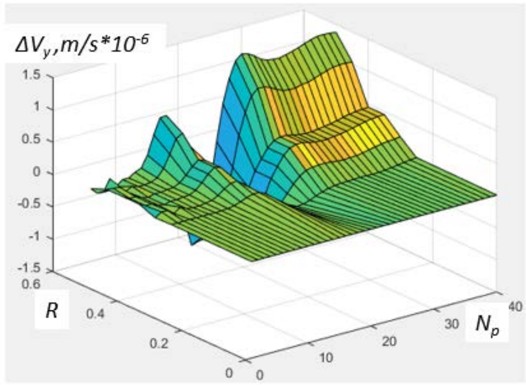


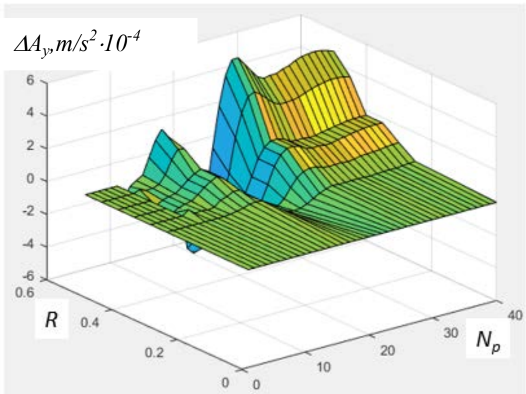
Fig. 5. Dependences of maximum displacements*: (a)* on time for points 1-40 on the surface of the structure for seven variants of the radius of the defect; *(b)* for the selected range of amplitudes



a)



b)



c)

Fig. 6. Relative values of displacement amplitudes ΔU_y *(a)*, velocity ΔV_y *(b)* and acceleration ΔA_y *(c)* for points N_p = 1-40 on the surface of the structure and variant of radius R_i of the defect

The center of the defect was located under the point P_{20}. The analysis of these graphs shows that on the left and right in the vicinity of the defect, knees of the curves of the maximum oscillation amplitudes of the relative values of the displacement ΔU_y, velocity ΔV_y and acceleration ΔA_y occur. This tendency persists for all variations in the radius of the defect R_i. Thus, this sign can be an indicator of the location of the defect.

In practice, such effects can be achieved through positional scanning during registration and processing of vibration amplitudes. The curves of the relative indices of displacement, velocity and acceleration in the vicinity of the defect correlate sufficiently well with the size of the defect.

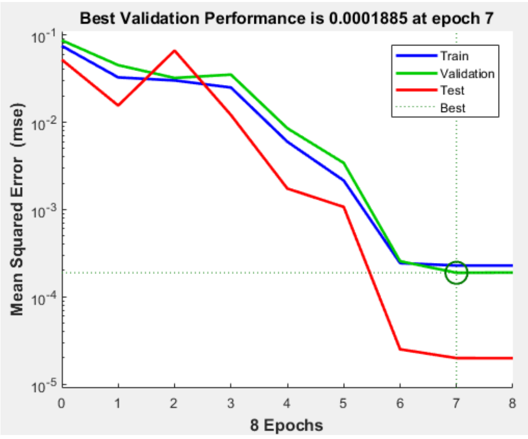
The use of neural network technologies in the problem of identifying the size of a hidden defect. Let us establish a connection between velocity, acceleration, and vibration amplitudes propagating in the layered structure, and the radius of the defect $R_{i.}$. Based on the data obtained at the *FE* modeling stage, a training set is formed with the help of which the constructed ANN model is trained.

As a result of the numerical solution to a number of direct problems in the *ANSYS FE* software package, data were obtained for 40 points on the surface of the layered structure with variations in the radius of the defect $R_{i.}$ with a calculation error within *3%*. For each set of 40 values, the corresponding defect radius was set. The prepared training vectors contained the relative values of the oscillation amplitudes $\Delta U_y(N_{pi})$, of the velocity $\Delta V_y(N_{pi}$, and acceleration $\Delta A_y(N_{pi})$ as the input values, and the defect radius as the output values.

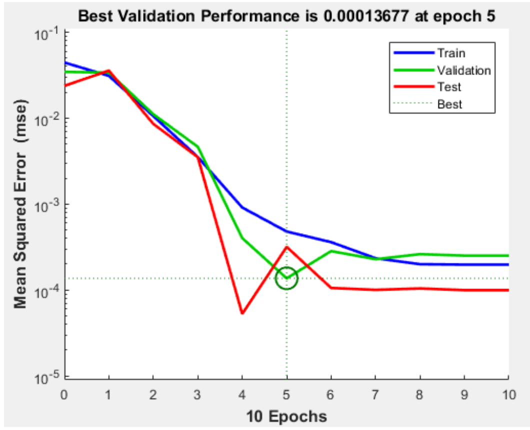
A total of 100 numerical experiments were carried out. Thus, the training set consists of 100 vectors for each type of the investigated parameter ΔU_y, ΔV_y и ΔA_y. All data used in training the neural network are normalized and are on the interval [0, 1].

To identify the radius of a defective inclusion, a fully connected multilayered ANN model was used, simulated in the *Matlab* complex. The ANN model contained 1 layer, consisted of 40 input neurons and 1 output neuron. Sigmoid was chosen as the input activation function, and a linear dependence was established as the output activation function. The network was trained using an error backpropagation algorithm based on the Levenberg-Marquardt optimization [37].

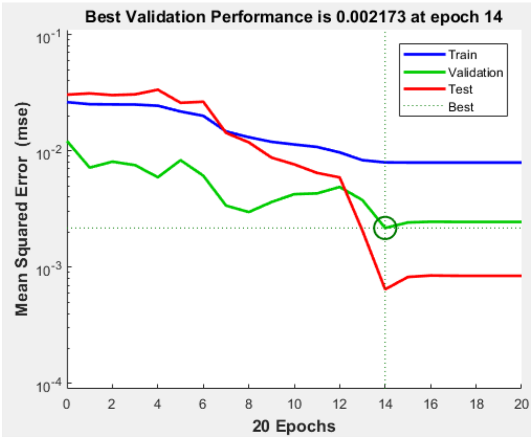
The loss function was characterized by the mean square error (MSE). For the training and test set, 100 vectors were constructed from the indicators of the relative values of the oscillation amplitudes ΔU_y, velocity ΔV_y and acceleration ΔA_y. The correlation of these parameters to the radius of the defect is found. It was established that 8, 10 and 20 learning epochs for the corresponding indicators are sufficient to achieve the required level of the ANN performance. Fig. 7 shows the dependence of the root mean square error on the number of learning epochs of the ANN model. The analysis shows that when learning of more than 8 epochs is reached for all relative parameters of vibration amplitudes, the MSE changes insignificantly



a)



b)



c)

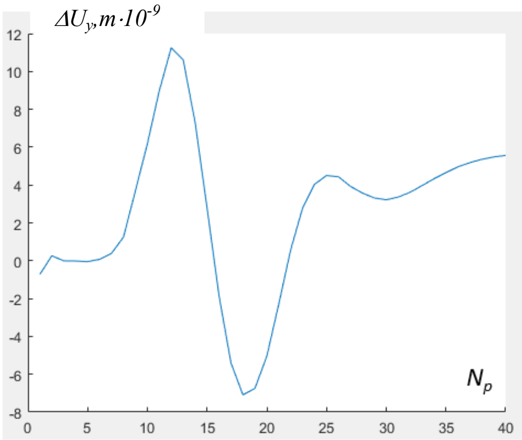
Fig. 7. Change in the MSE of the ANN operation under its training based on the relative values of the oscillations: *(a)* amplitudes ΔU_y, *(b)* velocity ΔV_y, and (*c*) acceleration ΔA_y

Table 2

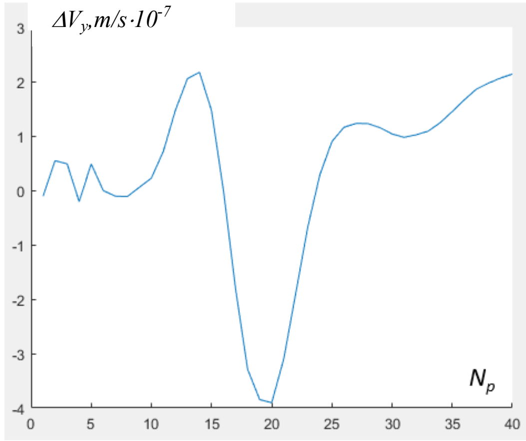
Calculation accuracy evaluation

ANN applied	Relative error, %
ΔU_y	0.50
ΔV_y	3.03
ΔA_y	16.70

Testing the ANN dependences obtained. For a selective assessment of the restoration of the defect radius index R_i, sets of vibration amplitude parameters were performed, and their relative values were obtained. Graphical display of the results of three test sets for the relative values of vibration amplitudes ΔU_y *(a)*, velocity ΔV_y *(b)* and acceleration ΔA_y *(c)* are shown in Fig. 8. These indicators of the sets were substituted into the corresponding ANN, and the values of the radius of the defect were calculated. Table 2 shows the calculated error of the restored radius R of the defect. The analysis shows that the least accurate is the restoration of the radius from the acceleration parameters. At this, the average relative error in recovering the parameter of the radius R of the defect based on the data of the vibration amplitudes ΔU_y and the velocity ΔV_y does not exceed 5%.



a)



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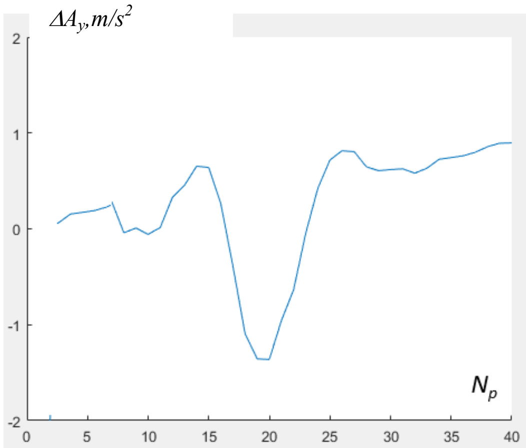

c)

Fig. 8. Set of calculated relative values of vibration amplitudes ΔU_y *(a)*, velocity ΔV_y *(b)* and acceleration ΔA_y *(c)*

Discussion and Conclusions. The problem on reconstructing the radius of a defect based on the application of simulation modeling of oscillations in the *ANSYS* finite element complex and ANN in the *MATLAB* complex is considered. The results of unsteady oscillations of a half-plane with a circular internal defect are obtained. The transverse displacements are calculated at the control points of the structure during the propagation of a wave from a pulsed loading. As a result, an approach was developed to restore the radius of a defect in a structure based on a combination of the FEM and ANN. The best configuration of the ANN architecture consisting of 1 hidden and 1 output layers included 40 input neurons and 1 output neuron.

The study has shown that the amount of data used is sufficient for successful training of the constructed model and identification of a hidden defect in the structure. In addition, the relative accuracy of determining the radius of the defect inside layer 1, in the case of using the values of amplitudes of displacement oscillations and velocity, is more than 99%.

Thus, the constructed ANN algorithms can be successfully applied to assess the stratification of layered structures using temporal and positional scanning when oscillations are excited from a far zone.

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