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A Combined Finite Element Analysis and Artificial Neural Network Approach for Diagnostics of Building Cross-Sections Weakened with Stress Concentrators

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Abstract

Introduction. The study is dedicated to developing a new method for identifying defects in building structures with stress concentrators. The method is based on the integration of shadow ultrasonic testing with deep learning algorithms, which would enable accurate diagnosis with reliably identifying the geometric characteristics of defects.

Materials and Methods. A finite element model of an area with an angular point and damping layers made of metal with a flexible coating was used. An ultrasonic actuator and receiver were placed on the opposite edges. Numerical experiments with changes in the geometry and materials of the area and defect parameters were conducted on a distributed computing system. The resulting signals were converted into spectrograms which were used in order to train a convolutional neural network that establishes a connection between the spectrogram and the defect parameters.

Results. An extensive dataset of spectrograms has been formed. The trained neural network has displayed the ability to accurately identify the key defect parameters based on a spectrogram such as size, position, and orientation. Verification of the method has shown that it outperforms the traditional methods of ultrasonic signal analysis in terms of its accuracy and speed.

Discussion and Conclusion. The hybrid approach for non-destructive testing in complex geometric conditions has been proven to be effective. The major advantage is automated and intelligent data analysis reducing a degree of subjectivity. The practical significance is the creation of a prototype adaptive diagnostic system. Prospects are related to further training on experimental data and integration into portable systems for monitoring structures.

Keywords: building structures, non-destructive testing, ultrasonic diagnostics, stress concentrator, shadow method, deep learning, convolutional neural network, finite element modeling, defect identification, spectrogram

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Оригинальное эмпирическое исследование

Комбинированный подход конечно-элементного анализа и искусственных нейронных сетей для диагностики сечений строительных конструкций, ослабленных концентраторами напряжений

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Аннотация

Введение. Исследование посвящено разработке нового метода идентификации дефектов в строительных конструкциях с концентраторами напряжений. Метод основан на интеграции теневого ультразвукового контроля с алгоритмами глубокого обучения, что позволит достичь точной диагностики с достоверным определением геометрических характеристик дефектов.

Материалы и методы. Использовалась конечно-элементная модель области с угловой точкой и демпфирующими слоями из металла с гибким покрытием. Ультразвуковой актуатор и приемник размещались на противоположных гранях. На распределенной вычислительной системе проведены численные эксперименты с варьированием геометрии и материалов области и параметров дефектов. Полученные сигналы преобразованы в спектрограммы, которые использовались для обучения сверточной нейронной сети, устанавливающей связь между спектрограммой и параметрами дефекта.

Результаты исследования. Сформирован обширный датасет спектрограмм. Обученная нейронная сеть продемонстрировала способность с высокой точностью определять по спектрограмме ключевые параметры дефекта: размер, положение и ориентацию. Верификация метода показала, что он превосходит по точности и скорости традиционные методы анализа ультразвуковых сигналов.

Обсуждение и заключение. Подтверждена эффективность гибридного подхода для неразрушающего контроля в сложных геометрических условиях. Основное преимущество — автоматизированный и интеллектуальный анализ данных, снижающий субъективность. Практическая значимость — создание прототипа адаптивной диагностической системы. Перспективы связаны с дообучением на экспериментальных данных и интеграцией в портативные комплексы для мониторинга конструкций.

Ключевые слова: строительные конструкции, неразрушающий контроль, ультразвуковая диагностика, концентратор напряжений, теневой метод, глубокое обучение, сверточная нейронная сеть, конечно-элементное моделирование, идентификация дефектов, спектрогра мма.

Благодарности. Авторы выражают благодарность редакции и рецензентам за внимательное отношение к статье и указанные замечания, которые позволили повысить ее качество.

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Introduction. The fundamental scientific task this study is aimed at addressing is to investigate the problems of strength and reliability of critical elements of building structures taking into account internal stress concentrators (defects). In order to tackle this research problem, an integrated approach has been implemented consisting in the following. At the first stage, the sections of structural elements are diagnosed in order to identify technological or operational defects. At the second stage, the problems of deformable solid mechanics are solved for these elements taking into account the identified defects, and conclusions are made as regards their operability [1, 2].

The initial formulation of the problem at the first stage is analyzing forced oscillations of a region with an angular point within the framework of elasticity theory described by the corresponding system of equations:

$$\sigma_{ij,j} = \rho \ddot{u}_i,$$
$$\sigma_{ij} = c_{ijkl} u_{k,l}.$$

The desired functions are the components of the displacement vector u_i (i = 1, 2, 3), the system of equations relates them to the stress tensor through elastic constants c_{ijkl} and material density ρ, complimented by the boundary conditions

$$u_i|_{S_u} = u_i^{(0)}$$
$$\sigma_{ij}n_j|_{S_t} = p_i$$
$$\sigma_{ij}n_j|_{S_d} = q_i$$

The boundary conditions are identified on surfaces S_u (specified by the displacements $u_i^{(0)}$), S_t (specified by the loads p_i, q_i, taking into account the normal n_i) and S_d representing the surface of the crack rupture itself in a direction parallel to the axis of the application.

The detection of defects, which include cracks and impurities, is an inverse geometric problem in the mechanics of a deformable solid [3], where it is required to identify the contours of defects, including their shape, location and size, which directly determines the boundaries of the shores S_d.

In the initial formulation, it is assumed that the crack banks are not in contact with each other and are stress-free, which corresponds to the condition

$$q_i = 0.$$

The inverse problem of identifying the boundaries of a defect cannot be solved solely on the basis of boundary conditions due to its incorrectness. In order to ensure the stability of the solution, additional experimental data is being used – the amplitude-time characteristics (ATCs) of the displacement field $\bar{U}$ recorded on a free surface.

$$X: u_i = U_i(\bar{x}_j, t).$$

Here t is the duration of the time interval [0, T] of the signal recording, N is the total number of the control nodes $\bar{x}_j$ on the surface S_t where ATCs were being measured.

Materials and Methods. The paper analyzes a model (Fig. 1) of an area with an angular point with a coating that contains an internal defect. The location areas of the actuator and sensors are indicated.

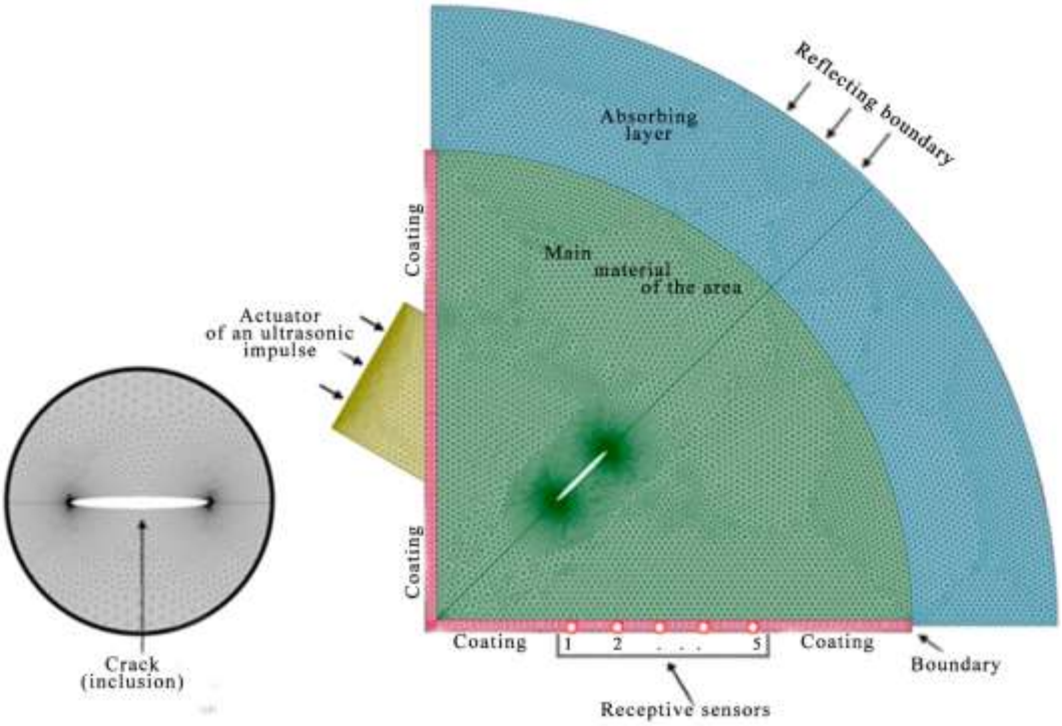


Fig. 1. Investigated model of a structure with an angular point

The ANSYS Mechanical application software package version 2023 R1 was used for numerical modeling, which allows simulations of complex physical phenomena including structural mechanics [4].

The Explicit Dynamics package module serves as a tool for modeling elastic wave propagation, demonstrating a high level of accuracy in complex and heterogeneous materials. An important element of such calculations are special absorbing layers that are used in finite element analysis to implement non-reflective boundary conditions and minimize parasitic reflections of waves. They are designed in order to approximate an infinite region by simulating the behavior of waves when they interact with an infinite medium. The main functional aim of the absorbing layers is to suppress reflections of wave energy from artificial boundaries of the computational domain, which can lead to non-physical results and disruption of the stability of the solution.

From a methodological standpoint, the approach used is based on the approximation of the desired functions using piecewise polynomial basis functions. The algorithmic implementation of the method is focused on performing calculations for models with a significant number of degrees of freedom [5]. The basic dependent variables defining the mathematical model of the module are velocity and deformation. The Rayleigh damping model is used in order to mathematically describe dissipative processes.

The method is based on solving a system of equations describing the behavior of a linear elastic medium.

$$\rho\frac{\partial v}{\partial t} - \operatorname{div} S = F_v$$

$$2\frac{\partial E}{\partial t} - [\nabla v + (\nabla v)^T] = 0$$

$$S = C{:}\,\epsilon$$

The system describes the law of conservation of momentum (equation of motion), where v is the vector of the velocity; ρ is the density of the material; S is the Cauchy stress tensor; S is the resulting superficial force; F_v is the vector of external volumetric forces; a kinematic ratio relating the rate of change of deformations (ϵ is the deformation tensor) with the velocity gradient and generalized Hooke's law (C is the elasticity tensor).

The propagation velocities of elastic waves in a continuous medium are directly dependent on its mechanical properties, i.e., the Young's modulus (E) and the Poisson's ratio (v). This relation for the longitudinal velocities (c_p) and transverse (c_s) waves is mathematically expressed with the following ratios:

$$c_p = \sqrt{\frac{E(1-v)}{\rho(1+v)(1-2v)}}, c_s = \sqrt{\frac{E}{2\rho(1+v)}}.$$

The use of an explicit integration scheme calls for a special setting of internal boundary conditions in the area of the connection between the coating and the base material, particularly in the presence of angular points. These conditions are formulated taking into account a surge in the physical and mechanical characteristics at the contact of dissimilar materials. They ensure the continuity of the velocity field and the equality of the normal components of the voltage vector.:

$$v_1 - v_2 = 0,$$

$$(S_1 - S_2)n = 0,$$

where indices «1» and «2» denote the values of the parameters on the opposite sides of the interface and n is a unit vector of the normal to it.

An absorbing layer is used in the model to suppress unwanted reflections from the boundaries of the calculated area. Its algorithm combines use of the three methods: scaling coordinates, applying filters, and applying simple non-reflective conditions. In the model the cylindrical geometry of the absorbing layer was chosen due to its symmetrical location relative to the angular point of the area under study. The configuration of the absorbing layer in a cylindrical coordinate system ensures isotropic absorption of wave energy regardless of the direction of its propagation. This approach minimizes the effect of reflection of waves from the artificial boundaries of the computational domain returning their energy back to the domain.

In spite of the high efficiency of the absorbing layer technique for suppressing spurious boundary reflections, its application is faced with a few limitations. Some properties of the media being modelled might cause premature reflection of waves on internal inhomogeneities prior to their interaction with the damping layer. An additional factor is the increased computational costs, particularly expressed in tasks with a large number of degrees of freedom. Thus the decision on the implementation of absorbing layers calls for a preliminary analysis and is to be justified by the specific features of the problem at hand.

In order to ensure minimal reflection of wave disturbances from the geometry feature in the form of an angular point on the right boundary of the structure (Fig. 1), a special boundary condition is implemented. It minimizes wave reflection by matching the properties of the boundary with the medium enabling longitudinal and transverse waves to leave the modeling area unhindered. The combined application of this condition with the technique of absorbing layers forms a highly efficient absorption mechanism for most possible angles of incidence of waves.

Correct modeling of the propagation of ultrasonic waves in elastic media calls for adequate discretization of the computational domain [6]. The accuracy and stability of the solution are mostly determined by the parameters of the finite element grid which are to be in compliance with a number of criteria. The key requirement is to provide a spatial resolution sufficient to approximate the shortest wavelength component of the wave field. To this end, the maximum characteristic size of the grid element (h) must be less than the minimum wavelength of the wave being modelled (λ_{min}). This condition can be formalized with the following ratio:

$$h \leq \lambda_{min} / n,$$

where n is the number of elements per wavelength determined with the order of the finite elements used and the required accuracy (as a rule, $n \geq 6$–10 for linear elements, the value $n = 5$ is normally used).

Special requirements are regarding the discretization of areas adjacent to the boundaries of the materials. In order to describe the processes of reflection and wave passage in a correct way, a local increase in the density of the grid is essential. A mandatory stage of the model preparation is verification of the grid quality. The critical parameters are the distortion level of the elements and their aspect ratio. Exceeding the permissible limits for these parameters might lead to a deterioration in the conditionality of the system of equations as well as numerical variance. The spatial sampling parameters are determined with the wave properties of the elastic medium, while the key factor is the mode with the highest phase velocity. The minimum wavelength is a critical parameter in the construction of the grid λ_p associated with this mode that sets the required spatial resolution. For the explicit integration scheme used in the Explicit Dynamics module, the use of higher-order approximation elements requires that the maximum size of the element is in compliance with the following criteria:

$$h_{max} = \frac{\lambda_{max}}{1{,}5} = \frac{c_{max}}{1{,}5 \cdot f_{max}},$$

where f_{max} is the upper limit of the frequency range to be resolved during modelling of wave processes.

The geometric parameterization of the mesh should adequately approximate the features of the structure, including the curved boundaries of an elliptical defect localized in the vicinity of an angular point. The details of the grid in the vicinity of the vertices of this defect are shown in Fig. 1 (the lower left fragment). The curvature coefficient settings used in the model ensure high-quality geometry approximation that is in compliance with the requirements of the applied numerical method.

The stability of the explicit integration scheme used in this work is identified using the Courant-Friedrichs-Levy criterion that sets a strict limit on the size of the calculated time step. The global time step is limited by the minimum value in the computational domain of the ratio of the characteristic size of the final element to the propagation velocity of the fastest volume wave c_p . Thus, the permissible time interval is determined by the smallest size of the grid element.

The spatial discretization criteria for each component of the composite structure are established based on the dispersion characteristics of the material, particularly the propagation velocity of the dominant elastic mode. This makes it necessary to use an adaptive grid with an increased density of elements in areas of wave field concentration, i.e., the defect localization and acoustic input area.

Based on the calculated dependencies, the carrier frequency of the probing pulse was set at 0.5 MHz. The exciting signal is formed in the form of a sinusoidal fill modulated by the Henning window function and is set by the following boundary conditions:

$$Sn = F_A(t), F_A = -p(t)n.$$

The optimization of the computational process and modelling parameters made it possible to conduct the necessary number of numerical experiments within the limited time. Fig. 1 shows the geometric configuration of the computational domain whose parameters are provided in Table 1. The model includes a two-component structure consisting of an aluminum alloy coating and a steel substrate forming an area of angular singularity.

Research Results. In order to increase the stability of the solution, additional experimental data is used in the work — the displacement fields of the ATCs recorded in a free surface. The set of specified data allows a defect to be identified. The suggested approach, which integrates the shadow ultrasound method and deep learning algorithms, allows not only defects, but also the geometric parameters of areas with an angular point to be identified. This combined solution demonstrates a significant superiority in velocity, accuracy and reliability over the traditional methods of non-destructive testing [6].

In order to verify the accuracy and increase the reliability of the technique, a finite element model describing the propagation of ultrasonic waves has been developed. In order to minimize the distorting effect of parasitic reflections, special damping layers have been introduced into the model to absorb these signals and to prevent them from propagating in the area with an angular point. Based on this model, a shadow ultrasound scanning method is implemented, where the transducer and receiver are located on the opposite sides of an object being monitored.

In order to form a training sample in a distributed computing environment, a series of numerical experiments has been performed, suggesting a multivariate solution to problems with changing geometric parameters: location of a signal source and receiver, as well as configuration of an internal defect. The training sample for the neural network model is based on parametric finite element analysis. In compliance with the methodology in [7, 8], a balanced data set has been formed, including modelling results with variations in the geometric parameters of the system. The obtained data set was used in order to train a neural network model whose task was the binary classification of a defect and regression of its spatial characteristics.

The ranges of parameter variation included: the defect length — 5–25 mm (20 discrete values); defect width — 0.5–2.5 mm (20 values); defect position — 5–50 mm (20 values); actuator position — 0–80 mm (20 values).

Table 1

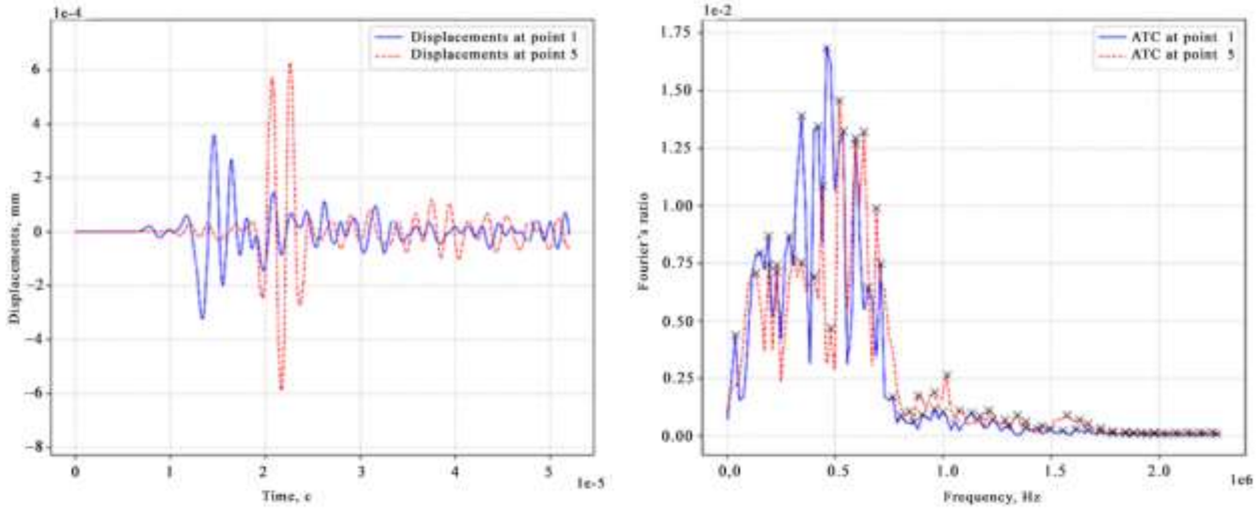
Main parameters of the finite element model made of steel with aluminum alloy coating

Parameter	Value
Opening angle of the area with an angular point	90 °
Coating thickness	1 mm
Size of the area with an angular point	150 mm
Crack length	20 mm
Crack thickness	2 mm
Crack distance from an angular point	30 мм
Actuator and receiver distance from an angular point	25 mm
Velocity of propagation of a longitudinal wave in the coating	6 197 m/sec
Velocity of propagation of a longitudinal wave in the body of the area with an angular point	5 778 m/sec
Coating density	2.7 g/cm^3
Density of the body of the area with an angular point	7.85 g/cm^3
Young's module of the coating	70 GPa
Young's module of the body of the area with an angular point	200 GPa
Poisson's ratio of the coating	0.33
Poisson's ratio of the body of the area with an angular point	0.29
Frequency of an ultrasonic signal	0.5 MHz

In compliance with the accepted methodology, intact models that did not contain defects were analyzed in 5% of cases. The elements of the training sample were represented by means of spectrograms generated using the fast Fourier transform (FFT) algorithm. The obtained spectrograms represent the frequency content of the signals and are used as input data for training a neural network model.

The joint registration of acoustic responses in five measuring positions (Fig. 1) allowed us to form a representative database, including 15,500 implementations for samples with defects and 780 implementations for reference samples with no defects. The physical nature of the phenomenon under study excludes the possibility of making use of the input data augmentation algorithms. The adequacy of the model was checked on a control subsample that made up 20% of the total experimental data.

The temporal realizations of acoustic signals received at the monitoring points are shown in Fig. 2*a*, and their spectral characteristics are shown in Fig. 2*b*. The target variables of the model are geometric descriptors of the defect and a binary classifier for its detection. This set of features is used in order to design the training vectors fed to the input of a neural network architecture.



a) *b)*

Fig. 2. Acoustic signal analysis: *a* — amplitude-time characteristic (time realization); *b* — amplitude-frequency characteristic (spectrum)

Fig. 3 shows the spectrograms of the signals recorded at various control points on the surface of the area with an angular point. The recording was carried out with synchronous movement of the source and receiver of ultrasonic vibrations along the edges of the area under study. Visual analysis of spectrograms demonstrates their significant informative value for solving the problem of defect identification.

The analysis of the spectrograms at control points 1–5 reveals a pronounced acoustic shadow area resulting from the presence of an internal defect. The spatial and temporal features of the propagation of wave fields recorded during the experiment are the basis for creating a training dataset of a neural network architecture.

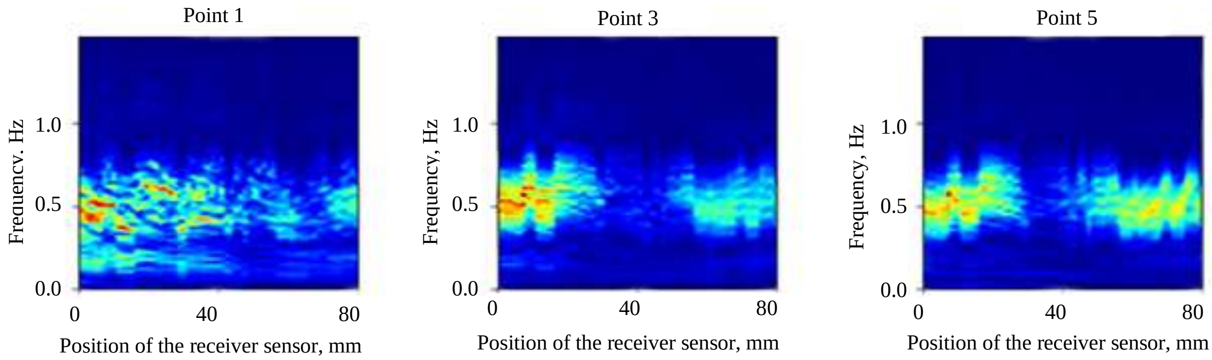


Fig. 3. Spectrograms of a signal received at 3 different points on the surface of the area with an angular point

The paper presents the architecture of a convolutional neural network (CNN) designed for image classification [5]. The network model accepts two-dimensional pixel intensity matrices with a size of 60×120 as the input. The input data is transformed by means of a three-stage hierarchical structure. At each stage of this hierarchy, a convolutional operation is applied followed by a nonlinear transformation using the ReLU function, and then a subsampling operation to reduce the spatial dimension of the generated features. The number of filters in the convolutional layers is consistently reduced from 64 to 32 and 16, respectively, which provides a hierarchical allocation of features of different levels of abstraction. After the convolutional layers, the spatial data structure is transformed in order to ensure compatibility with fully connected layers. The final stage of processing is a fully connected hidden layer containing 512 neurons with ReLU nonlinearity that is trained in order to identify complex dependencies between high-level features. The fully connected layer, also known as the dense layer, is an essential component of the CNN. These layers follow the convolutional and unifying layers in the CNN architecture and serve to combine the information extracted by the convolutional layers into a single output signal.

The output layer of the network is formed by five neurons and a Softmax activation function that provides a probabilistic distribution across target classes. Each neuron corresponds to a separate characteristic of the defect: two of them implement a binary classification of the fact of the defect in the control area, whereas the other three are regression neurons encoding, respectively, the length of the defect, the width of the crack and the coordinate of its position relative to the vertex of an angular point. The total number of trainable parameters of the suggested architecture is 559,285.

The mean square error (MSE) was chosen as the optimization objective function. The experiments have shown that satisfactory model quality is achieved following 30 training epochs. The stabilization of the learning process is ensured by a balanced composition of the training sample and use of batch normalization layers [9] that accelerate convergence and act as a regularizer reducing the risk of overfitting.

An experimental assessment of the operability of the trained neural network model was carried out on a control sample with a capacity of 2,500 samples. The input space of the model consisted of the frequency characteristics generated during finite element modeling of the ultrasonic flaw detection process. The output interface of the model combined a defect detector (binary classification) and predictors of its spatial characteristics (regression problem).

Discussion and Conclusion. The accuracy of the regression estimation of the crack width was analyzed by means of the suggested model (Fig. 4). The analysis of dependencies showed that as the crack width increases, so does the prediction accuracy subsequently stabilizing in the upper part of the range under study. The calculation of the mean square error for this parameter demonstrated that its value is not over 5% for the opening angle of the controlled area $\alpha = 60°$ and 10 % — for $\alpha = 120°$.

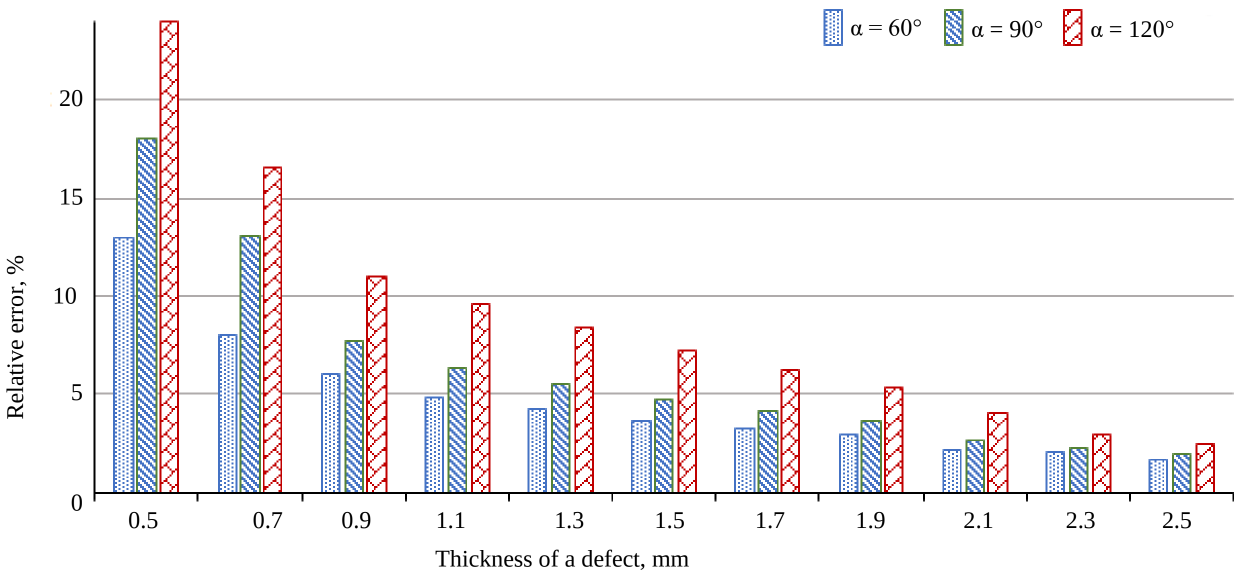


Fig. 4. Error in identifying the thickness of the defect at α = 60°, α = 90° and α = 120°

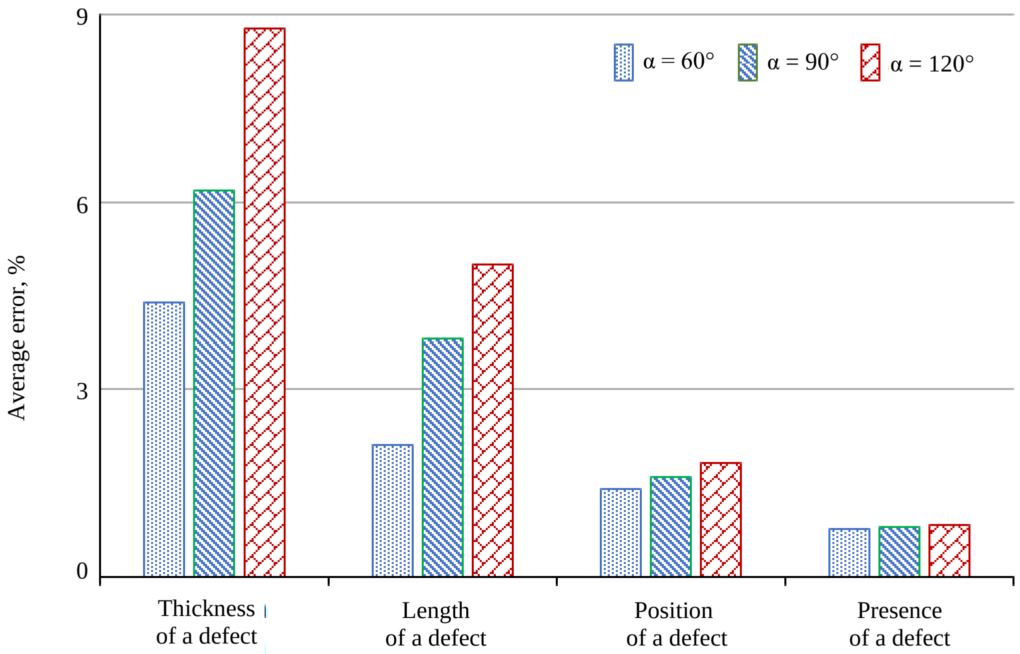


Fig. 5. Average errors of the CNN for identifying the defect characteristics for different angles of the model area opening (60°, 90° and 120°)

The obtained data confirm the prospects of using ultrasonic monitoring models using high-frequency probing signals, as well as with alternative schemes of acoustic transducers, which opens up avenues for further improvement of the accuracy of identifying geometric parameters of defects.

The analysis demonstrates the limited effect of the opening angle of the controlled area (α) on the accuracy of the neural network model (Fig. 5).

The statistical analysis has enabled us to find out that the change in the angle α is not the dominant source of error. Its contribution to the total error in identifying the coordinates of the defect relative to the vertex of the angle is significantly lower compared to the other factors considered. The highest accuracy of the technique is attained for the small values, which confirms its effectiveness and high reliability in the control of structural elements with an angular point.

An increase in the accuracy of the neuromodel has been attained by processing the input data and further training it on the synthesized numerical experiments [10–12]. The developed method demonstrates a high degree of reliability in detecting defects in areas with an angular point with coatings with a capacity to continuously improve diagnostic characteristics. Combining the shadow ultrasound scanning method with deep machine learning technologies, the technique provides a faster and more reliable tools of detecting defects and has prospects to be applied in a broad range of areas [7].

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