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# DETERMINATION OF THERMAL AND SHRINKAGE STRESSES IN MONOLITHIC REINFORCED CONCRETE SLABS BASED ON A SLIDING FOUNDATION USING DEEP LEARNING NEURAL NETWORKS

In certain situations, the design step requires the creation of technological openings of various shapes, while the slab surface may have complex geometry. Determining the stress-strain state in such cases can be very labor-intensive or even impossible. This article presents an alternative method based on the use of 3D convolutional neural networks (CNNs) with a U-Net architecture and 3D Deep Convolutional Generative Adversarial Nets (DC-GAN), which allows for fairly accurate predictions of shrinkage and temperature stresses and displacements in reinforced concrete slabs on a sliding base, in a simpler way compared to finite element methods (FEM). The article highlights the promising potential of using neural net-works in the area of construction design.

**Keywords:** thermal stresses, shrinkage stresses, concrete slabs, neural networks, deep learning.

**Introduction.** Due to the significantly increased use of monolithic concrete in construction, mainly in the manufacture of slabs for various purposes (floor slabs for buildings, bridge decks, overpasses, monolithic floors of industrial enterprises, public buildings and structures), there is a question of finding adequate methods for such structures analysis. These structures provide for very complex geometry, the presence of technological openings of various shapes, as well as special requirements for operation, that is typical for highways, airfield pavements. At nuclear power plants, workshops the behavior of the plate in the area of openings and process circuits throughout the entire life cycle should be taken into account in advance.

Practical realization of slabs on the base is associated with a number of difficulties, first of all, it refers to the evaluation of the initial stress-strain condition (SSC) at hardening and shrinkage (or expansion) of concrete, under the influence of not only the traditional constraint (reinforcement), but also the restricting influence of the base. At present, the existing calculation methods for the forced deformations (temperature, shrinkage) of such structures in some cases do not adequately evaluate the range of factors affecting the SSC of the slab. In the paper [1] the research of slab prototypes is carried out, the state of the question of the accepted parameters of concrete shear on the base is considered, the schemes of the developed shear devices are presented, the research of concrete prototypes under the shear is carried out, the analytical dependences of displacements under shear on the types of bases are obtained. The proposal to approximate the shear curve by a three-line diagram is justified for the "concrete-on-concrete" shear.

Nowadays, the basic normative document regulating for the design of floors of industrial, residential, public, administrative and household buildings in the republic of Belarus is "SN 5.09.01-2020" [2], within the European Union – EN 1992-1-1:2023 [3].

At designing, only two main parameters of concrete floor layers are set: slab thickness and concrete compressive strength class. There is no methodology for calculating stresses in such structures, taking into account the processes of temperature effects, shrinkage, expansion, occurring in concrete during the curing period when the designed layer interacts with the base. In order to exclude the limiting influence of the base on the SSC in slabs built on the base, a sliding layer is used, and to prevent shrinkage phenomena, reinforcement meshes are used.

**The purpose of the paper**

1 To illustrate the possibilities of artificial intelligence in mechanics.

2 To show the possibility of using soft computing with deep learning in design-related tasks.

3 To show the advantages of convolutional neural networks (CNN) in predicting forced displacements and stresses in reinforced slabs on the base.

4 To develop a database of slabs for training neural networks with subsequent integration with available data and data planned to be generated in future stages.

The ultimate goal of the research is to create a slab design method combining the advantages of theoretical models, finite element methods, and biosimilar technologies – a so-called hybrid.

**Soft computing. Artificial neural network.**

Due to recent advances in the field of computing systems and the development of new programming languages for solving complex engineering problems, significant part of researchers proposes to utilize the increased capabilities of soft computing [4–18].

According to the established approach [5], the following directions of soft computing can be distinguished:

1 Problems with fuzzy logic.

2 Problems solved with the help of neural networks (artificial neural networks).

3 Evolutionary modeling (genetic algorithms), etc.

The article [5] claims that the foundation of soft computing lies in its ability to adapt to the vast imprecision of the real world, unlike traditional hard computing.

Lotfi Zadeh formulated the principle of soft computing as follows: "tolerance of imprecision, uncertainty, and partial truth allows for ease of manipulation, robustness, reduced decision-making costs, and a more accurate correspondence to reality." According to [19], the use of neural networks (NN) for modeling is significantly simpler than traditional mathematical models. Although NNs employ mathematical relationships between nodes (neurons) and a process for minimizing learning error, the mathematical formulas themselves are not explicitly presented. Artificial neural networks can effectively predict concrete strength and structural resistance with an error of less than 10 % [19].

Research [4] indicates the potential for using neural networks as an alternative to mathematical models and experiments at the early design stage for quickly assessing the predicted behavior of reinforced concrete slabs under load, as well as for determining their load-bearing capacity and deflections.

The use of neural networks in engineering research significantly simplifies and accelerates computational processes.

**Fundamental prerequisites.** Sometimes, at the design stage, technological openings of various shapes are already made in the slab structure. This is due to the fact that the slabs can be installed in the workshops of industrial buildings, as well as in other premises and existing structures, where it is necessary to think in advance about the behavior of the slab in the places of the openings of the enclosing structures.

There are traditional approaches based on the use of finite element models, but they have certain, and sometimes significant, disadvantages. Among the existing approaches, both advantages and disadvantages can be distinguished as follows: the first approach uses temperature effects to model shrinkage deformations; the second approach does not take into account the nonlinear nature of the kinetics of concrete hardening in the first 28 days; the third approach does not take into account the nonlinear temperature change due to chemical reactions in the initial hardening phase; the fourth – inhomogeneity of the material and its certain anisotropy, which cause nonlinear and non-uniform change of SSC; the fifth – external temperature and humidity processes affecting the course of chemical reactions and distribution of stresses and strains.

**Problem statement.** At this stage, the task was to find an intelligent solution for the stresses and displacements caused by the shrinkage of reinforced concrete slabs with holes of various shapes, as well as monolithic slabs throughout the volume.

**Data preparation for CNN and DCGAN training.** A 5-dimensional matrix was created, it's all input and output parameters were recorded. The matrix consisted of the following dimensions: 1 – sample number, 2 – coordinate "$X$", 3 – coordinate "$Y$", 4 – coordinate "$Z$", 5 – vector of 17 parameters (physical and mechanical characteristics of slab concrete: stress, displacement, distance (radius vector from the center of the slab) to the center of the voxel, shape of the concrete slab, concrete elasticity modulus, Poisson's ratio of concrete, concrete thermal expansion coefficient, free shrinkage deformation of concrete, strength of concrete, shape of reinforcement mesh, elastic modulus of steel, Poisson's ratio of steel, coefficient of thermal expansion of steel, diameter of reinforcement, free deformation of reinforcement at zero temperature, strength of steel, and reinforcement ratio.

The main difference from the investigation [20] was the change in the method of data submission. In this paper, volumetric elements were formed, i.e., due to the peculiarities of the Vox-to-Vox architecture of the neural network, data conversion from 3D coordinate representation to voxel representation was performed (Figure 1). The data were partitioned into 64×64×4 voxels (16384 elements were evaluated) for neural network training before feeding. Thus, coordinates "2", "3", "4" were transformed into "distances", i. e. a vector obtained by calculation the moduli of the radius vectors from the origin to the center point of each 3D voxel (where in the slab is the hole (void) – this parameter was missing). In addition, the concrete and rebar form parameters – "concrete form", "rebar form" – were introduced, which are responsible for the number of the slab from the sample, with information about the shape of this slab, as well as about the number and shape of reinforcement meshes, respectively.

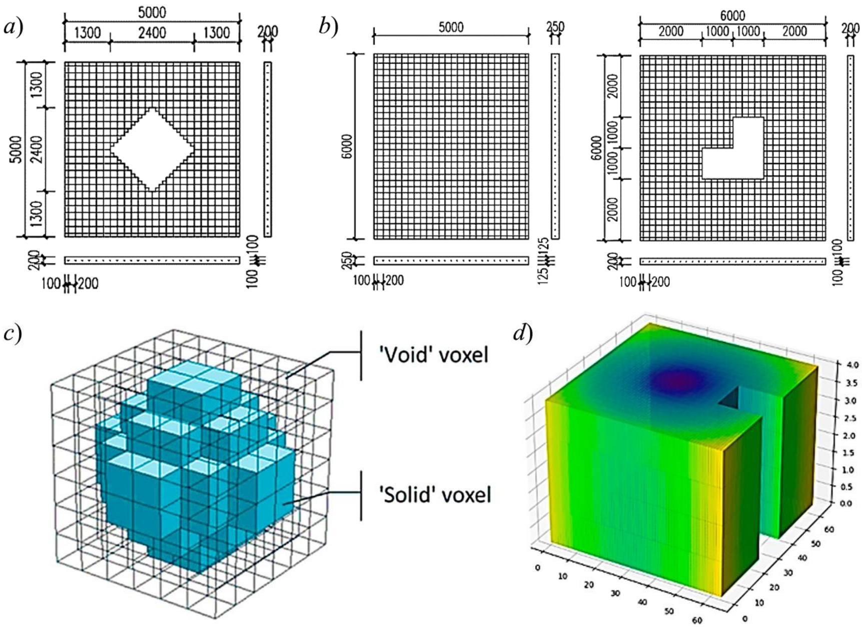


Figure 1 – Reinforced concrete slabs on the base:
*a*, *b* – slabs of different sizes with and without holes;
*c* – volumetric representation of data [21]; *d* – slab in voxel form

Initially, it was possible to vary 12 parameters at different levels: *concrete modulus of elasticity, concrete Poisson's ratio, concrete thermal expansion coefficient, concrete strength, concrete free shrinkage, reinforcement modulus of elasticity, reinforcement Poisson's ratio, reinforcement thermal expansion coefficient, reinforcement diameter, reinforcement relative strain, reinforcement strength, reinforcement coefficient.*

All slabs differed in the shape and location of the openings, as well as in the reinforcement ratio and the number of reinforcement meshes (single and double layer meshes were used). A set of 56 different slabs was developed. Examples of solid slab and slabs with holes are shown at figure 1, *a* – 1, *c*. The training set of 45 slabs has been randomly selected. The testing set included the remaining 11 slabs.

The purpose was to obtain the analysis results of the stress-strain state in the slab all over the volume. There were obtained the stresses and displacements for the CNN and DCGAN approaches in the ABAQUS, then the results were recorded in a feature vector. Just like the input data, where each voxel of the concrete slab was associated with all inherent features of the concrete and the reinforcement voxel with reinforcement features, the output concrete voxels were associated with two parameters, concrete stress and displacement.

**3D-CNN operation with U-Net architecture.** U-Net is commonly used as a standard CNN architecture applicated for image segmentation tasks [22], it can be also suited for regression tasks [23].

It should be noted that the existing literature lacks information on the use of either convolutional or generative adversarial neural networks for predicting the shrinkage of SSC slabs on a base.

The classification of neural networks developed to date is quite extensive. A perceptron with a single hidden layer is a universal approximator, i.e., it is capable of approximating any continuous function with any accuracy if a continuous, monotonically increasing, bounded function is used as the activation function of the neural elements of the hidden layer [24].

Convolutional neural networks, which are a further development of the multilayer perceptron, are widely used for image processing and, unlike the multilayer perceptron, allow to consider the image topology and to preserve predictive properties during shifts, scaling, and other distortions of the input image. Since stresses, deformations or displacements are data structures, they have a similarity to an image when inferred in a certain way. The convolutional and generative-adversarial neural networks used in this paper to achieve the goal.

The encoder works layer by layer: at each step, it "compresses" the two-dimensional matrix using convolution. This compression reduces the number of points in the plate grid by half. However, it doesn't lose important information; on the contrary, it concentrates it, increasing the number of elements that describe key stress features at each grid point. The process continues until all the information is collected into a single final vector (visualized as a 1×1×4 layer of feature maps in Figure 2). Then the reverse transformation to the previous size is started.

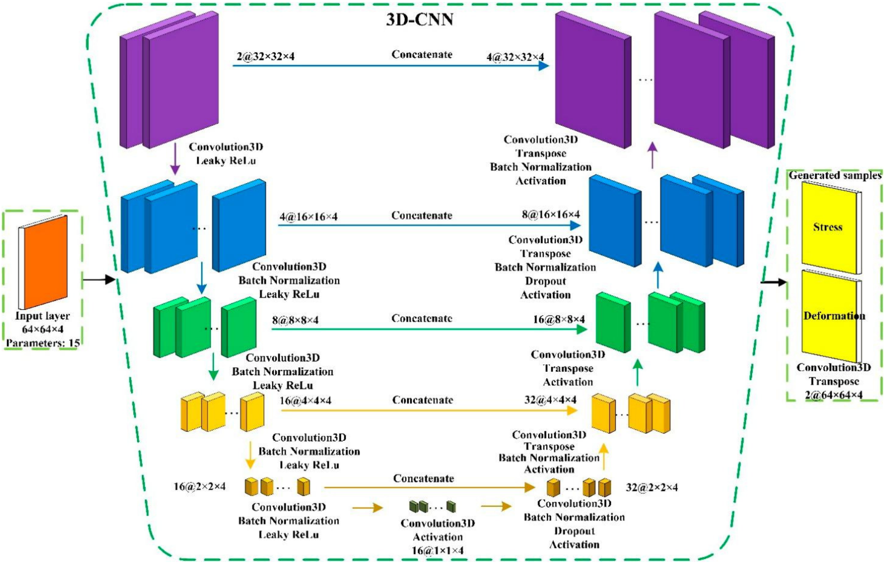


Figure 2 – 3D-CNN convolutional neural network created by the U-Net "Voxel-to-Voxel" architecture using four voxels at the lowest resolution. A feature map with multi-channels is connected to each corresponding parallelepiped. The parameter signature of the map contains the information of the number of channels: it is indicated by the first digit (before @). The map parameter caption shows the map dimensions that are indicated behind the @ sign

**Use of DCGAN (Deep Convolutional Generative Adversarial Nets).** Generative-adversarial networks are a machine learning algorithm, part of the family of generative models and built on a two neural networks combination: *G* – a generative model, that builds the data distribution approximation; , *D* – a discriminative model, that makes an assessment of the probability that the obtained from training data sample is not generated by model *G* (Figure 3). The essence of the model *G* training is to maximize the discriminator *D* error probability. Such networks were first presented in [25].

DCGAN is a modification of the GAN algorithm, which is based on a convolutional neural network. The task of finding a convenient feature representation on large volumes of unlabeled data is one of the most active areas of research. As our own research and studies [26] have shown, using CNN directly did not give good results, so the authors [25], proposed to use this modification of GAN, with restrictions imposed on the convolution layers:

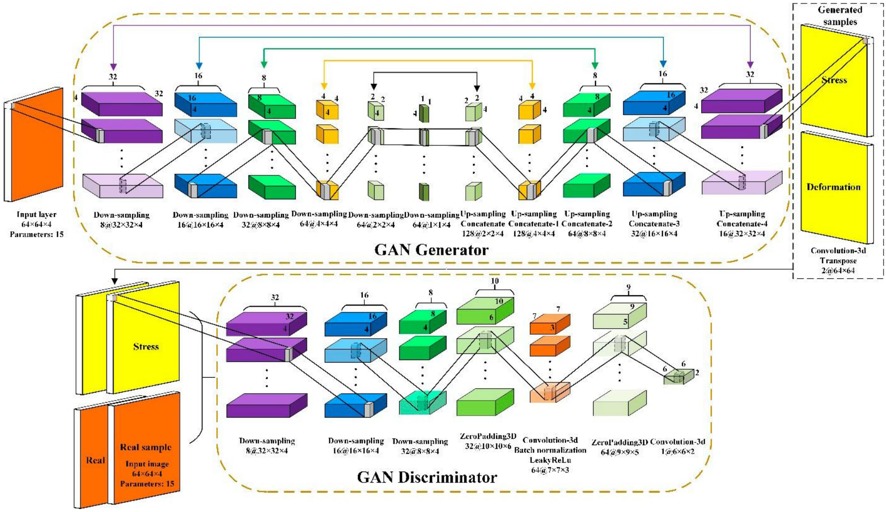


Figure 3 – 3D-DCGAN model based on the Vox-to-Vox Architecture

1) apply *Batch Normalization* to the generator and discriminator, with zero mathematical expectation, and unit variance. Do not use Batch Normalization for the output layer of the generator and input discriminator;

2) exclude all fully connected layers that are not displayed (hidden), especially when transforming architectures from convolutional neural networks (CNNs) to deep learning generative adversarial networks (DCGANs);

3) use *ReLU* as the function for the generator activation for the all considered layers except the last one(the tanh is used);

4) use *LeakyReLU* as the activation function rectifying unit in the discriminator for the all considered layers.

As practice has shown, in addition to the task of object generation, this algorithm also performs well in feature extraction [26].

**Results of neural network operation.** When training the CNN U-Net models, 1000 epochs were assigned. DCGAN training was performed for 10000 epochs. For optimal regularization, 30 % of the raw data was left for model quality check while 70 % was randomly selected from the training set.

**Results of stress and displacement calculations and their analysis.** The general picture of the distribution of training and predicted stresses and displacements in reinforced concrete slabs is shown in Figures 4 and 5. In assessing the accuracy of the stresses and displacement prediction, the well-known mathematical statistics is used: mean absolute error (*MAE*), standard deviation (*RMSE*), Pearson correlation coefficient (*r*), coefficient of determination ($R^2$), calculated in accordance with the procedure given in TCP EN 1990 [27]. The above statistical parameters are summarized in Table 1.

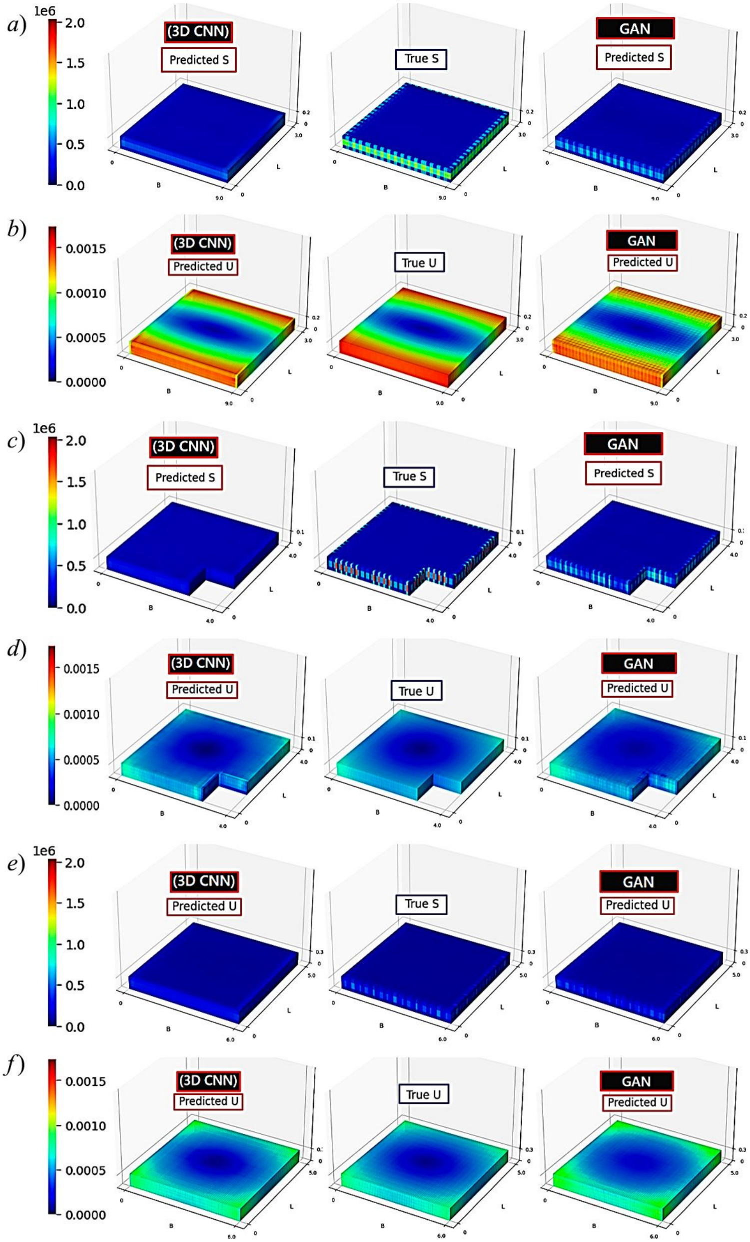


Figure 4 – Shrinkage: *a, c, e* – stresses; *b, d, f* – displacements

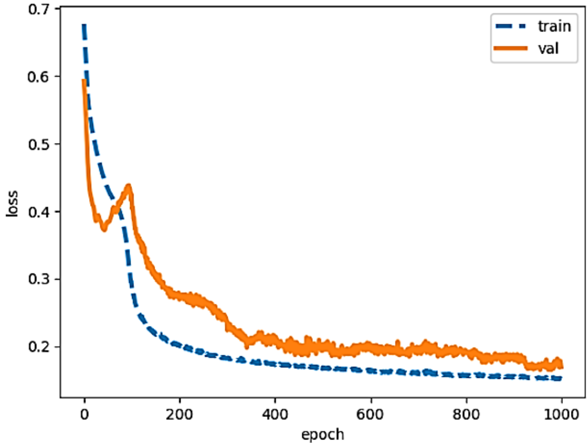


Figure 5 – CNN loss plots

Table 1 – Statistical parameters indicating the accuracy degree for the developed models

| *No.* | *SSC* | *Models* | *RMSE* | *MAE* | *r* | $R^2$ | *b* |
|---|---|---|---|---|---|---|---|
| Slab 1 (a, b) | Displace-ment | CNN | 0.0224 | 0.0123 | 0.9948 | 0.9895 | 1.0016 |
| | | DCGAN | 0.0507 | 0.0432 | 0.9925 | 0.9466 | 0.9180 |
| | Stress | CNN | 0.0715 | 0.0253 | 0.8378 | 0.4089 | 0.6215 |
| | | DCGAN | 0.0649 | 0.0284 | 0.9407 | 0.5133 | 0.5952 |
| Slab 2 (c, d) | Displace-ment | CNN | 0.0162 | 0.0112 | 0.9879 | 0.9700 | 0.9718 |
| | | DCGAN | 0.0262 | 0.0220 | 0.9824 | 0.9219 | 0.9090 |
| | Stress | CNN | 0.0732 | 0.0217 | 0.4896 | 0.2064 | 0.5835 |
| | | DCGAN | 0.0531 | 0.0173 | 0.8317 | 0.5826 | 0.6776 |
| Slab 3 (e, f) | Displac-ement | CNN | 0.0252 | 0.0208 | 0.9947 | 0.9307 | 1.0820 |
| | | DCGAN | 0.0510 | 0.0457 | 0.9814 | 0.7154 | 1.1688 |
| | Stress | CNN | 0.0172 | 0.0099 | 0.8026 | 0.6164 | 0.9994 |
| | | DCGAN | 0.0148 | 0.0100 | 0.8998 | 0.7165 | 1.0927 |

Statistical analysis of the prediction of displacement reliability using CNN and DCGAN shows that the DCGAN model has a slightly higher predictive ability. The slight difference in favor of the prediction ability of the CNN model only concerns displacements (the correlation coefficient for in slabs 1, 2, 3, is higher by: 0.2 %, 0.6 %, 1.4 % respectively). The stresses are better predicted by the DCGAN. For example, for stresses, Pearson's coefficient is higher for slabs 1, 2, 3, by: 10.9 %, 41.1 %, 10.8 %, respectively, than CNN. The coefficient of determination is also higher for the DCGAN model. If we consider the difference in the coefficient values of the same model, between displacements and stresses, the stresses are predicted slightly worse in each case. At the same time, it should be noted that the Pearson coefficient (DCGAN model) on average (for all slabs) gives a value for stresses – 0.891 (CNN – 0.610), for displacements – 0.993 (CNN – 0.992). The mean coefficient of determination (DCGAN model) for stresses is

0.604 (CNN – 0.410) and for displacements 0.861 (CNN – 0.964). Considering the training sample small number, the obtained results demonstrate the predictive ability of the DCGAN model as very high for displacements and average for stresses (it is accepted to consider as good computational models with determination coefficient higher than 0.8 and correlation coefficient higher than 0.9). One of the reasons for the low predictive ability for stresses may be that when modelling reinforced slabs on ABAQUS, due to the difference in the coefficient of thermal expansion and the peculiarities of taking into account the conditions of meshing of reinforcement and concrete, local areas with higher stresses appeared at the end sections of the slabs. In neural network simulation, the stresses in neighboring points were averaged out.

**Conclusions.** According to numerous scientific publications, the use of neural networks to model the behavior of engineering structures demonstrates significant simplification compared to classical mathematical models.

Neural networks can serve as an alternative to both mathematical models and experimental studies in the initial stages of design. They enable rapid prediction of the response of reinforced concrete slabs under loads, determining both the magnitude of forced displacements and the levels of stress and deflection. Thus, neural networks are capable of modeling system behavior with optimized design costs, providing rapid and appropriate solutions in the face of high complexity, uncertainty, and unique situations.

Overall, despite the presence of some statistical indicators with suboptimal values, the predictive ability of a model based on a generative adversarial neural network with voxel-based object interpretation can be assessed as quite high. The authors believe that the reliability of the obtained results can be improved by retraining the neural network on a sample of more samples.

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## ОПРЕДЕЛЕНИЕ ТЕМПЕРАТУРНЫХ И УСАДОЧНЫХ НАПРЯЖЕНИЙ В МОНОЛИТНЫХ ЖЕЛЕЗОБЕТОННЫХ ПЛИТАХ НА СКОЛЬЗЯЩЕМ ОСНОВАНИИ С ИСПОЛЬЗОВАНИЕМ НЕЙРОННЫХ СЕТЕЙ ГЛУБОКОГО ОБУЧЕНИЯ

В некоторых случаях на этапе проектирования требуются технологические проемы различной формы, а поверхность плиты может иметь сложную геометрическую форму. Определение напряженно-деформированного состояния в замкнутом виде в таких случаях весьма трудоемко или даже невозможно. В данной статье представлен альтернативный подход, основанный на использовании 3D сверточных нейронных сетей (CNN) с архитектурой U-Net и 3D глубоких сверточных генеративно-состязательных сетей (DC-GAN), который позволяет достаточно точно прогнозировать усадочные и температурные напряжения и перемещения в железобетонных плитах на скользящем основании, причем более простым способом по сравнению с методом конечных элементов (МКЭ). В статье подчеркивается перспективность использования нейронных сетей в строительном проектировании.

**Ключевые слова:** температурные напряжения, усадочные напряжения, бетонные плиты, нейронные сети, глубокое обучение.

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