2. Причинами образования трещин в монолитных железобетонных стенах БРПЗ являются конструктивные решения проекта, не обеспечивающие прочность и трещиностойкость строительных конструкций на действие эксплуатационных нагрузок, наличие в строительных конструкциях ряда вышеупомянутых дефектов, а также возникновение усилий от вынужденных деформаций (температурно-усадочных и осадочных).

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FULL CONNECTED NEURAL-NETWORK FOR SIMULATION OF EXTANTION IN SELF-STRESSED MONOLITIC SLABS ON GROUND

Introduction. In the article the strategy of interdisciplinary convergence of mechanics and artificial intelligence is illustrated. The article presents the results of calculating displacements in self-stressed monolithic slabs on ground obtained using a trained fully connected neural network. The empirical results of displacements in slabs on ground, displacements calculated according to the physicomechanical model, and obtained using a neural network are represented. The inspiration brought us to study neural networks modeling biological neural networks are follow: neural networks can autonomously detect patterns hidden in phenomena and can identify parameters on complex behavioral tracks of different physical systems. The authors describe in detail the developed and trained fully connected neural network.

Existed methods of calculation of deformable state in slabs on ground. In the article, a physical-mechanical model of the stressed-strain state (SSS) of the slab on ground was presented and the results of numerous laboratory and field tests of the slabs were given. At the same time well known that existing methods for calculating such structures from expansion forced deformations, for certain time intervals, do not always assess the deformed state of the slabs with high accuracy. The displacements in slabs were determined based on the equilibrium equation recorded for the infinitesimal part of slab. A general differential equation describing the displacements of the slab has a view:

$$\frac{d^2u}{dx^2} - \frac{\tau(u)}{E_C \cdot h} = 0 \tag{1}$$

Solution of equation (2) with respect to displacements *u*, under the following initial conditions: $x = L/2$; $u = 0$; $x = 0$, is presented as:

$$u = -\frac{1}{\beta} \cdot \left(\frac{\sigma_{C0}}{E_{C,t}} + \varepsilon_0(t, t_0) \right) \cdot \frac{\sinh \beta \left(\frac{L}{2} - x \right)}{\cosh \beta \left(\frac{L}{2} \right)} \tag{2}$$

where: *u* – absolute displacement in the slab; $\varepsilon_0(t, t_0)$ – deformation of free expansion of concrete; $\varepsilon_{C,t}$ – elastic deformation of concrete; $E_{C,t}$ – modulus of elasticity of concrete, σ_{C0} – internal axial stress; $\sigma_{C0}/E_{C,t}$ – elastic component of relative deformations of concrete; β – coefficient depending on the characteristics of the contact of the slab with the base, the modulus of elasticity, the geometry of the plate.

As practice has shown, the physical mechanical model, although it approached significantly to empirical data, but starting from certain time intervals (after 72 hours of hardening), demonstrates slightly overestimated results. In order to clarify the characteristics of SSS, we developed and trained (on the available experimental data) an artificial neural network (ANN) of a fully connected architecture with four incoming neurons, five hidden layers and eight neurons of the output layer. Each of the eight output layer neurons learned to "see" the displacements of slab at a specific coordinate.

ANN and Parameter Recognition. Approach which employs computational models that mimic the architectural, structural, or functional aspects of biological neural networks, such as the human brain are known from the middle of the XX century. It consists of multiple processing elements called neurons, which are connected to each other by links. A popular method of training of multilayer perceptron is the back-propagation (BP) algorithm, which includes as a special case the least mean squares (MS) algorithm.

Presently some scholars are proposing ANN to be widely used with deep learning model as an important part of the efficient target detection algorithm. ANN plays role of a feature extractor in the target detection algorithm. This scheme allows to computers autonomously capture experience from massive amounts of knowledge.

Full connection of neurons. In a brain, neutrons link with each other which are convenient for information transmission. In a neural network, full connection layer also means many links. In the fully connected layer, each neuron relates to all neurons in former layer and next layer. It means that each neuron in fully connected layer can capture the global information of data. ANN can extract the underlying reflection from input to output with just addition and multiplication operation. So, a well-trained network can respond quickly without mechanical computation. Because the number of parameters of ANN is large, an efficient large-scale matrix solve method is needed. Gradient decent makes it possible to train a network easily. To evaluate the parameters, loss function is introduced. Loss function is proposed to evaluate the gap between the true label (target) and the prediction given by neural network. Thus, the process of training neural network becomes an optimization problem which aim is to minimize the loss. As a function of activation of neurons, the «Relu» function inserted into the Python software language profile was used.

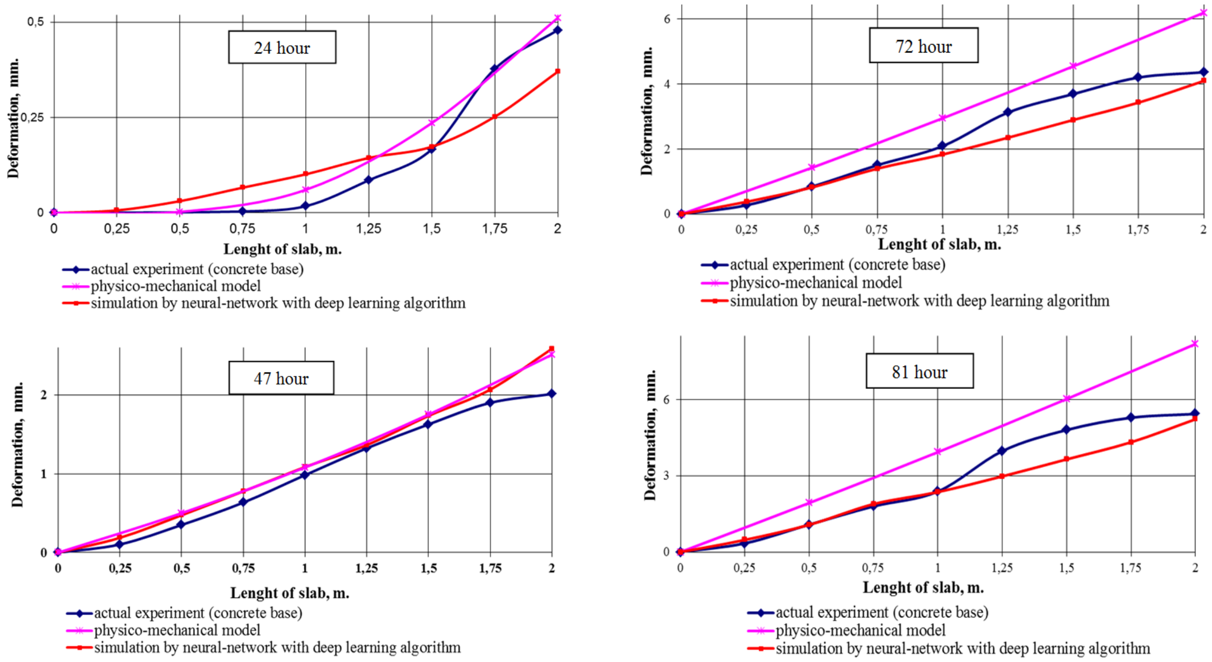

Fig. 1 – Diagram of displacements.

Conclusion. In paper has been verified the feasibility of using trained neural network to identify physical parameters. It is not difficult to notice a significant improvement in the predictive power of the neural network with respect to (w.r.t) the physicomechanical model over time. C_u - coefficient of variation or u_{calc} / u_{exp} ratio for the moment of time - 81 hour, obtained by the neural network decreased by 30% w.r.t. the physicomechanical model. Coefficient of variation of the error vector decreased too (on 24%).

To improvement the proper design of slabs on ground, AI aided method is universal and promising. In addition, this makes it possible to promote prognostic methods of description of stress-strain state condition in such slabs. ANN with deep learning algorithm proved that it can be implemented in other engineering problems. If the data richness of the training set continues to increase, the prediction accuracy of this neural network will be further improved and as wanted to believe be involved in good application prospects.