APPLICATION OF CONVOLUTIONAL NEURAL NETWORK IN PREDICTING FORCED DISPLACEMENTS IN MONOLITHIC SELF-STRESSED SLABS ON THE BASE

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Problem statement

The first step of CNN is to intelligently search for solutions to offset in the test slabs (the slab that tests the predictive ability of the neural network). However, there is no information about the displacements of the central hole area in the slab when training the neural network.

To this end, the solution obtained using the closed form of the strip slabs [1] was used to determine the displacement of the slab length on the characteristic points, and different geometric forms of the plate were formed in the next stage.

Basic assumptions

In some cases, even during the design phase, the slab structure may have holes of different shapes on the outline (Fig. 1). For example, when installing floor slabs in production building workshops, nuclear power plant machinery workshops, other facilities, and existing facilities, the behavior of the slabs in the envelop hole area must be considered in advance.

Solving these problems by determining the state of displacement and stress-strain condition (SSC) is either very difficult or impossible.

Figure 1. Design of slabs with different shapes [2, 3]

Application of Convolutional Neural Networks in base slab design

The advantage of neural network models is to detect nonlinear relationships between inputs and outputs without assuming any functional dependencies between them [4].

CNN combine three methods of image processing. This is to use a local receptor field for each neuron in the convolutional layer, forming a convolutional layer as a set of cards, where neurons have the same synaptic connections and there is a subsampling layer map, thereby improving the network's resistance to distortion [5, 6, 7, 8].

1.Preparing training samples

Two types of data were used: one was to "break" the grid node topology of the slab, and the other was the shape parameters of the perforated slab; The second type includes the geometric characteristics of the entire slab, the physical and mechanical properties of self-stressed concrete, and the characteristics of the contact layer in the slab-base system.

In order to obtain the parameters, the slab on base is marked on points (nodes) 11x11. Each node in the grid is defined with a distance value from the center of the slab and corresponding displacement. The displacement of grid nodes is used as the target output values of convolutional network. The data is recorded in matrix form. The data is stored in a separate directory with [.csv] files (each of the 14 directories contains 21 subdirectories containing coordinates and displacement files).

2.Concatenation of CNN with a fully-connected neural network

Technically speaking, this task is similar to image conversion. Therefore, we used the PIX to PIX architecture [9]. The PIX to PIX architecture consists of two units: an encoder and a decoder, with connections between them.

In this study each example has additional feature vectors. These characteristics are the connections between the displacement of each point in the strip plate with self-stressing concrete physical and mechanical properties established during physical experiments: H, $f^{m}_{c,cube}$, $\tau_{1,R(t)}$, $u_{1,R(t)}$, σ_{CE}, ε_0 (Fig. 3). Among them: H – slab height, [m]; $f^{m}_{c,cube}$– average guaranteed compressive strength of normal weight concrete, [MPa]; $\tau_{1,R(t)}$ – shear stress (peak point in the graph, [MPa]) determined by method; $u_{1,R(t)}$– slab offset corresponding to the maximum tangential stress in contact with the slab and base, [m]; σ_{CE}– self-stressing in concrete [MPa]; ε_0– free expansion relative deformation of concrete determined by the method.

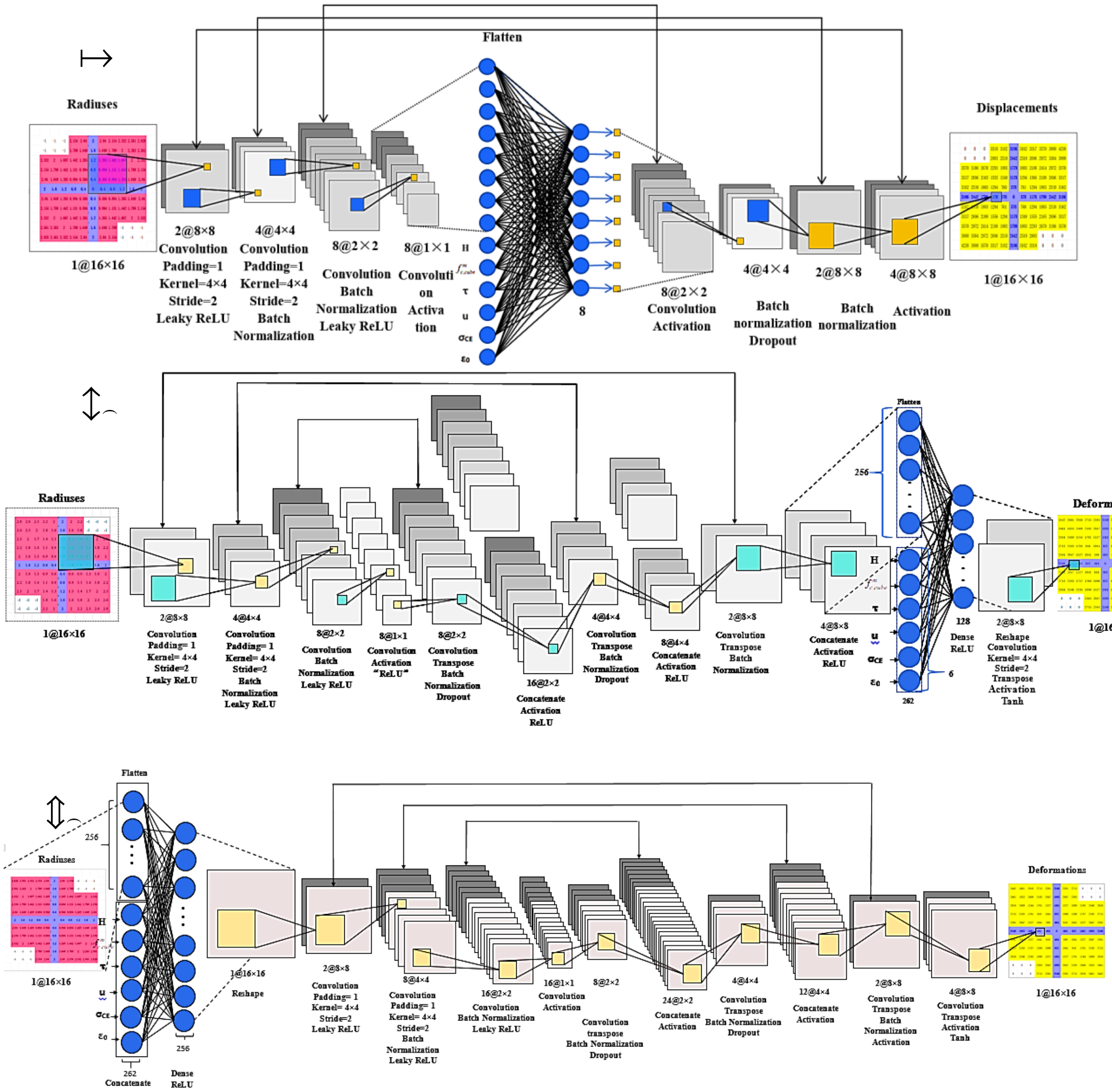

Figure 3. Neural network with PIX to PIX architecture: a) Model I – Connection before decoder, b) Model II – Connection after decoder, c) Model III – Connection before encoder

Due to the particularity of PIX to PIX, the two-dimensional CNN data (describing the geometric structure of the slab grid nodes) was increased to 16x16 (estimated 256 features) before submission for training. In this study, it was decided to encode holes using "0". Among all models, 1000 learning epochs were specified, 70% of the raw data (randomly) was selected as the baseline data for the training set, and 30% of the data was retained for model quality checks.

3.Mechanism of operation of ANN and filter

Each filter neuron is considered as an operator that changes the input data [9, 10]. The ANN input receives the values of the grid nodes, and the signal at the neuron output is determined as follows:

$$y_i = f_{act}\left(\sum x_i \cdot w_i + b\right), \tag{2}$$

Where x and y are the input and output signals of the neural network, w is the weight parameter of the synapse, b is the displacement, the neuron activation functions – LeakyReLu for the encoder and ReLu for the decoder, the activation of the last layer was carried out using the function Tanh.

4.Normalization

All data fed to the input and output of the convolutional neural network was normalized using batch normalization. The essence of this method is that some layers of the neural network receive data that is pre-processed and has zero mathematical expectation and unit variance [11].

5.ANN performance quality criteria

The loss function was defined as:

$$E = \frac{1}{n}\sum \left|Y_{target} - Y_{predicted}\right|, \tag{3}$$

where n is the number of examples, Y_{target} – the actual initial data, $Y_{predicted}$ – the predicted values of the predicted parameter.

6.Parametric optimization, gradient descent algorithm

The stochastic optimization method "Adam" was used as an optimizer. Adam [12] is a first-order gradient algorithm for stochastic objective functions based on adaptive lower-order moment estimators [13].

The goal of parametric optimization is to find the minimum value of the loss function E. At each iteration, the algorithm updates the weight parameters. Thus, using the gradient information, the optimal path to achieve the global minimum on the loss hypersurface is determined.

7.Results of displacements in slabs with central holes

Physical-mechanical, geometric parameters of the slabs are depicted in fig 6a-g.

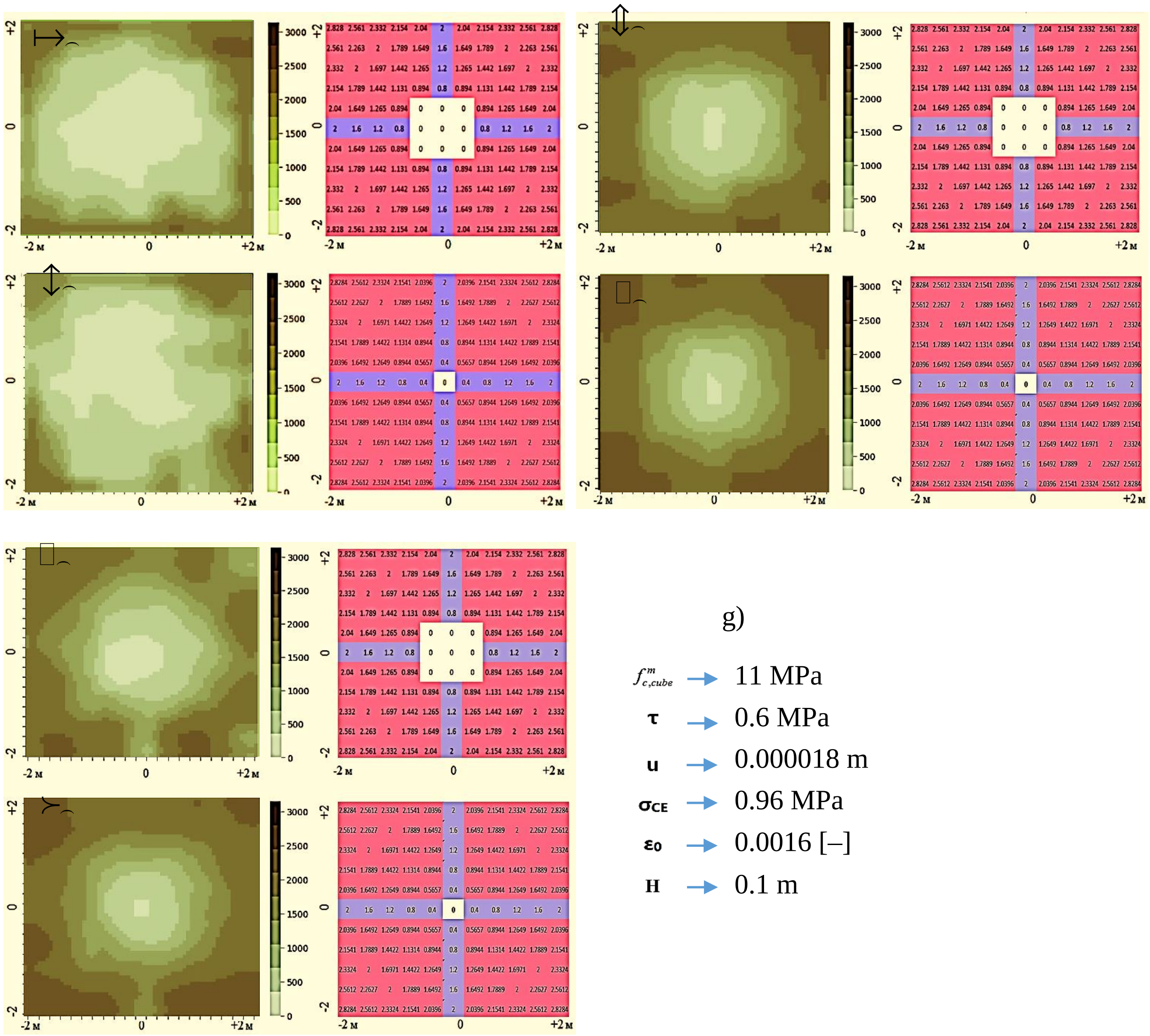

Figure 6 – Displacements in slabs with central holes:
a) model I, central hole 0.8x0.8 m, b) hole 0.4x0.4 m; c) model II, central hole 0.8x0.8 m;
d) hole 0.4x0.4 m; e) model III, central hole 0.8x0.8 m, f) hole 0.4x0.4 m;
g) physical-mechanical, geometric parameters of slabs

Conclusions

Three models are created to test the quality of prediction of slab displacements. The relative error for a full-body slab using model I was 47,87 %, the absolute error – 143,16 %; for model II – 5,2 % and 14,94 % respectively; for model III – 8,9 % and 17,8 % respectively.

We assume that model I has the worst predictive ability because of the way of concatenation after the encoder. In models II, and III concatenations were performed after the decoder, and before the encoder respectively and the predictive ability is significantly better. This is primarily due to the peculiarity of connecting the two neural networks into a system. Such encoding seems to facilitate the training of the convolutional network, which is evident from the comparison of loss diagrams in models II and III. At the same time, model III appears to be the most adequate compared to the predictions of model II (despite the fact that model II has a smaller relative error in predicting displacements in the full-body slab), as it better predicts displacements near the larger center hole.

The developed neural network, trained on 189 samples, quite confidently predicts displacements in slabs with a central hole, using data from only peripheral cuts. If increase the training sample, the relative and absolute errors and losses can be reduced.

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