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APPLICATION OF DEEP LEARNING NEURAL NETWORKS FOR MAPPING CRACKING PATTERNS OF MASONRY PANELS WITH OPENINGS

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KEYWORDS

This paper describes the use of a deep learning neural network (NN) in combination with cellular automata (CA) method to direct prediction of the cracking patterns of masonry panels with openings subjected to lateral loading. The Moore CA neighbourhood model was used to establish the CA numerical model for masonry panels. One masonry panel with an opening was chosen as a base panel to predict the cracking pattern of a new (hypothetical unseen) panel based on establishing similar zones. Also different sizes of base and unseen panels can be used to predict crack formation of one another. The deep learning NN, in this study, was represented by back-propagation NN with two hidden layers. CA numerical model along with dimensions of a panel composed the training data for the NN. Using the cracking pattern of the base panel as the output data, the NN modeled the cracking pattern for an unseen panel. The predictions from the NN have been validated using number of experimental data of masonry wall panels with different sizes.

KEYWORDS: *cellular automata, neural network, masonry, cracking pattern*

INTRODUCTION

In recent years, artificial neural networks have become one of the most successful and reliable structures for solving wide variety of practical problems related to different fields. The development of neural networks was inspired by biological nervous systems, basically by the

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working of a human brain. Consequently neural networks are composed of simple elements operating in parallel (neurons). The connections between neurons largely determine the network function and while performing a particular function by adjusting the values of the connections (weights) between elements a neural network can be trained. The ability to train make it possible for neural networks (NNs) to find solutions for the problems, which cannot be solved easily with traditional methods and for those which do not have a solution yet. This sets up the research process to a new stage. Also, for practical purposes the standard simpler algorithms and methods are still preferred, and many researchers are looking for a way to make them more reliable, but the idea that neural networks can reach much better results due to the ability of improving itself with more training data [1] inspires more and more researchers [2].

In the past years interest of applying artificial intelligence solutions to investigate masonry structures behavior has risen. Notably Zhou G. C. used cellular automata (CA) techniques to improve standard finite element method by applying a new strength/stiffness corrector [3]. Behavior of brick masonry walls subjected to concentric or eccentric vertical loading was estimated by an artificial NN [4]. This study proved to be suitable for use by practitioners both for designing and testing masonry walls made of cement mortar and clay bricks. A back-propagation NN in combination with CA implied the capacity of modeling the variation in material properties of the masonry structure in prediction of the cracking pattern of masonry wallet loaded vertically in different orientations [5]. The proposed methodology was based on CA model and experimental data of recorded cracking at zones. Employment of a NN for approximation of masonry failure surface under biaxial stress [1; 6] achieved great performance in fitting the average values of the experimental data with small training error. Furthermore, the authors proclaim that the proposed NN managed to give valuable information about angles that have not been investigated before. By using a database of masonry shear walls an accurate artificial NN model was built to predict in plane shear strength of masonry panels strengthened by Fiber Reinforced Polymer systems [7]. The proposed model was also able to express mechanical cooperation of the layers involved in shear forces. Artificial NNs and adaptive neuro-fuzzy inference systems (ANFIS) were used to determine the compressive strength of ungrouted concrete hollow block masonry prisms [8]. The results from the models developed in this study showed that ANFIS model provided slightly better performance than the artificial NN model; however both models achieved results that closely agreed with the experimental values.

The progress of NNs in investigation masonry behaviour mentioned above confirms its capability in the structural analysis. Nonetheless only few studies embody the use of NNs in the approximation of masonry structures behavior. This article presents an attempt to predict crack propagation of masonry panels with openings by using a NN and CA method combined. An effort to map cracking patterns of laterally loaded masonry wall panels with openings was already made [9]. But in that case the research was based on displacements of CA cells calculated from finite element method. The application of a NN into mapping cracking patterns of masonry panels with openings was realized in this study for the first time.

EXPERIMENTAL DATA

The methodology introduced in this study was validated by the experimental data of masonry wall panels with openings tested by Dr. Chong [10]. The experimental data is presented by six panels of three restrain conditions: free, simply supported and fully restrained. The dimensions and boundary conditions for every panel are listed in Table 1. All the masonry panels were made from the same materials, following common engineering procedure.

Table 1: The experimental data properties

Panel	**Size dimensions (mm)**	**Opening dimensions (mm)**	**Edge boundary condition**			
			Top	Left	Right	Bottom
SB01	5615×2475	-	Free	Simply-supported	Simply-supported	Fully restrict
SB02	5615×2475	2260×1125	Free	Simply-supported	Simply-supported	Fully restrict
SB03	5615×2475	2935×525	Free	Simply-supported	Simply-supported	Fully restrict
SB04	5615×2475	910×2025	Free	Simply-supported	Simply-supported	Fully restrict
SB05	5615×2475	-	Free	Simply-supported	Simply-supported	Fully restrict
SB06	2900×2450	-	Simply-supported	Simply-supported	Simply-supported	Fully restrict
SB07	2900×2450	900×900	Simply-supported	Simply-supported	Simply-supported	Fully restrict

CELLULAR AUTOMATA MODELING

The Moore CA model that comprises eight cells surrounding a central cell (Figure 1) was chosen in this study. The choice was made according to an assumption that eight neighbourhood model closely represents a three-dimensional system [11].

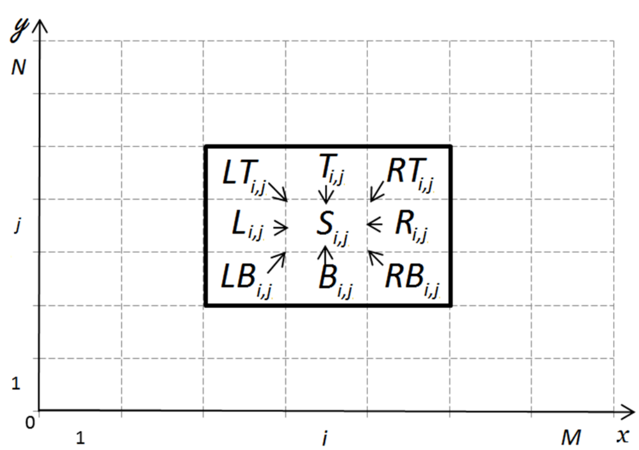


Figure 1: Moor CA model in two dimensional system

State value of a cell $S_{i,j}$ was described by formula (1). The transition functions (2) – (9) represent the boundary effect on the cell.

$$S_{i,j} = \frac{L_{i,j} + R_{i,j} + T_{i,j} + B_{i,j} + LT_{i,j} + RT_{i,j} + LB_{i,j} + RB_{i,j}}{8} \tag{1}$$

$(i = 1,2,\ldots,M;\ j = 1,2,\ldots,N)$

$$L_{i,j} = L_{i,j-1} + \eta(1 - L_{i,j-1}) \qquad (i = 1,2,\ldots,M;\ j = 1,2,\ldots N) \tag{2}$$

$$R_{i,j} = R_{i,j+1} + \eta(1 - R_{i,j+1}) \qquad (i = 1,2,\ldots,M;\ j = N, N\text{-}1,\ldots,1) \tag{3}$$

$$B_{i,j} = B_{i+1,j} + \eta(1 - B_{i+1,j}) \qquad (i{=}M,M\text{-}1,\ldots,1;\ j = 1,2,\ldots,N) \tag{4}$$

$$T_{i,j} = T_{i-1,j} + \eta(1 - T_{i-1,j}) \qquad (i = 1,2,\ldots,M;\ j = 1,2,\ldots,N) \tag{5}$$

$$LT_{i,j} = LT_{i-1,j-1} + \eta(1 - LT_{i-1,j-1}) \qquad (i = 1,2,\ldots,M;\ j = 1,2,\ldots,N) \tag{6}$$

$$RT_{i,j} = RT_{i-1,j+1} + \eta(1 - RT_{i-1,j+1}) \qquad (i = 1,2,\ldots,M;\ j = N, N\text{-}1,\ldots,1) \tag{7}$$

$$LB_{i,j} = LB_{i+1,j-1} + \eta(1 - LB_{i+1,j-1}) \qquad (i = M,M\text{-}1,\ldots,1;\ j = 1,2,\ldots,N) \tag{8}$$

$$RB_{i,j} = RB_{i+1,j+1} + \eta(1 - RB_{i+1,j+1}) \qquad (i = M,M\text{-}1,\ldots,1;\ j = N, N\text{-}1,\ldots,1) \tag{9}$$

Where η - coefficient of transition, whose value is 0.2 based on Zhou G. C. [3]; M and N are numbers of columns (x-direction) and rows (y-direction) on the panels and their cracking patterns after the division on cells; $L_{i,j}$, $R_{i,j}$, $B_{i,j}$, $T_{i,j}$, $LT_{i,j}$, $RT_{i,j}$, $LB_{i,}$, $RB_{i,j}$ – indicate the effect of left, right, bottom, top, left-top, right-top, left-bottom and right-bottom boundaries effect on a cell in [i,j] zone, respectively.

The initial values $L_{i,0}$, $R_{i,N+1}$, $B_{0,j}$, $T_{M+1,}j$, $LT_{M+1,0}$, $RT_{M+1,N+1}$, $LB_{0,0}$ and $RB_{0,N+1}$ for the transition functions were chosen according to principles of numerical difference and the verification of zone similarity [3; 12]. The idea of the numerical difference stated in the mentioned literature is to achieve as large difference between the state values of zones from different initial values as possible.

Boundary types

According to literature [3; 12] the initial values for simply-supported and fully restricted edges are 0.2 and 0.4 respectively. In this research the value of free edge boundary was chosen to be 0.001. The initial values for right-top, left-top, right-bottom and left-bottom edges were calculated according to equations (10) – (13).

$$LT_{M+1,0} = \frac{L_{1,0} + T_{1,N+1}}{2} \tag{10}$$

$$RT_{M+1,N+1} = \frac{R_{M+1,N} + T_{M,N+1}}{2} \tag{11}$$

$$LB_{0,0} = \frac{L_{0,1} + B_{1,0}}{2} \tag{12}$$

$$RB_{M+1,0} = \frac{R_{M+1,1} + B_{M,0}}{2} \tag{13}$$

Size effect

The size effect is one of the important factors that affect the failure propagation. If dimensions of base and new (unseen) panel are different the CA model of a new panel should be adjusted according to correlation coefficient [11] for the height (14) and for the length (15).

$$\mu_h = h_{new} / h_{base} \tag{14}$$

$$\mu_l = l_{new} / l_{base} \tag{15}$$

where l_{new}, l_{base} – width of new and base panels, respectively; h_{new}, h_{base} – height of the new and the base panel, respectively; μ_l– the correlation coefficient for the length direction (i.e., the left and right boundaries); μ_h – the correlation coefficient of the height direction (i.e., the top and bottom boundaries).

In that case the correlation coefficient λ for the transition functions is defined by formula (16):

$$\lambda = \mu_l \mu_h \tag{16}$$

Same rules are applied for the ratio of opening dimensions of a new panel to the opening dimensions of the base panel. It is assumed that inside the opening the state values of cells are zeros, but the initial boundary values should be applied according to the size effect (14) – (15) with substitution of heights and lengths of panels to heights and lengths of their openings. For example, for SB02 as base panel and SB03 as a new panel according to Table 1 the correlation coefficients for SB03 opening will be as in equation (17) – (18).

$$\mu_h = \frac{525}{1125} \approx 0.5 \tag{17}$$

$$\mu_l = \frac{2935}{2260} \approx 1.3 \tag{18}$$

Hence the boundary value of a free edge 0.001 multiplying by the related coefficient in approximation will be: 0.0005 for top and bottom edges; 0.0013 for left and right edges; 0.0009 for left-top, left-bottom, right-top and right-bottom edges according to the equations (14) – (15).

NEURAL NETWORK APPLICATION

What is a deep learning neural network is still a matter of discussion. In general, term deep learning purports a new way of training neural networks composed of multiple non-linear transformations that aim at learning features from higher levels of the hierarchy formed by the composition of lower level features [13].

The neural network in this study is presented by a feed-forward backpropagation network with two hidden layers (Figure 2). The Levenberg-Marquardt training algorithm was chosen as it is proved to be one of the most efficient algorithms suited for small- and medium-sized problems [14].

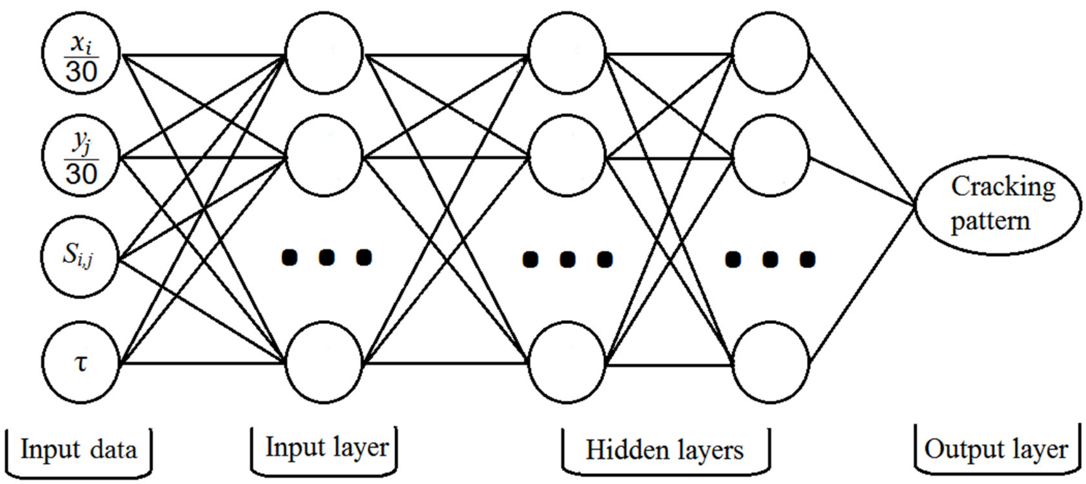


Figure 2: Proposed back-propagation NN

Input and training data

The location of a single cell on the pattern matters. For the study the tested panels (CA models) and their cracking patterns were divided into 30 cells in the x and y directions. That is 900 cells overall. The size of panels was normalized as 1×1. Therefore every cell on the pattern had 1/30 × 1/30 dimensions according to the number of cells on the pattern. To investigate the effect of opening dimensions to the crack propagation ratio τ of dimensions of the opening on a panel to its dimensions (19) was included in the training (percentage of opening). Hence the input data (vector) for the NN was represented by normalized location x_i/30 and y_i/30 for every cell, state values of the cells $S_{i,j}$ and ratio τ.

$$\tau = \frac{h_0 \cdot l_0}{h \cdot l} \tag{19}$$

where h_0, l_0 – height and length of an opening of the panel respectively; h, l – height and length of the panel respectively.

Transfer function

Transfer function for both hidden layers was chosen to be hyperbolic tangent function. The function returns a matrix of elements in the interval [-1, 1].

Output data

To make cracking patterns comprehensible for the artificial intelligence they were modified to a 0-1 numerical model, where 1 meant crack and 0 – no crack. Similarly with the CA models cracking patterns were divided into 30 cells in the x and y directions. The example of modification of experimental cracking pattern to numerical is shown on the Figure 3.

a) b)

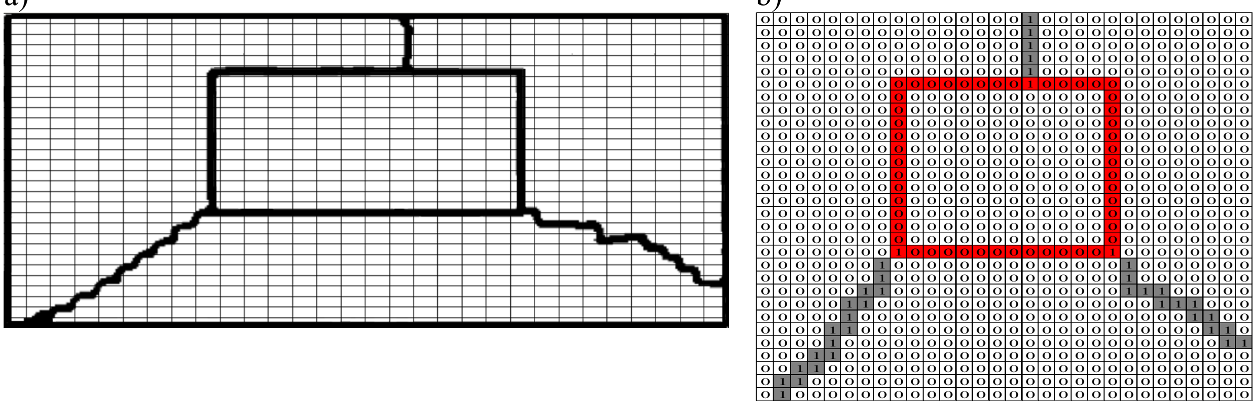


Figure 3: SB02 a) experimental and b) numerical cracking patterns

Results of the experimentation

The results for the prediction of crack propagation depend on the choice of a base panel. The experiments of this research showed that for panels with an opening it is better to choose a panel with an opening as a base panel. The following Table 2 shows the results of the NN prediction where SB02 panel was used as the base.

From the Table 2 it can be seen that prediction goes good for panels with the same dimensions, but lacks the accuracy when new panel has smaller size. The situation is true in experiments when SB03 and SB04 are used as base panel. Whereas experiments with SB07 as base panel cannot give results with good accuracy for panels with bigger size (Table 3).

Table 2: Predicted cracking patterns with SB02 as the base panel

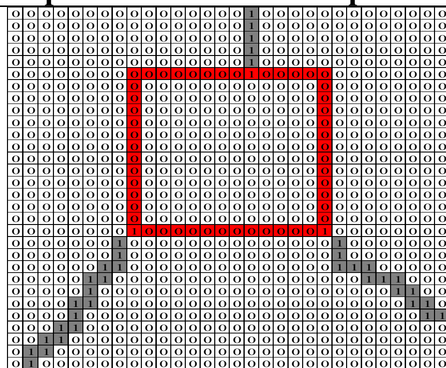
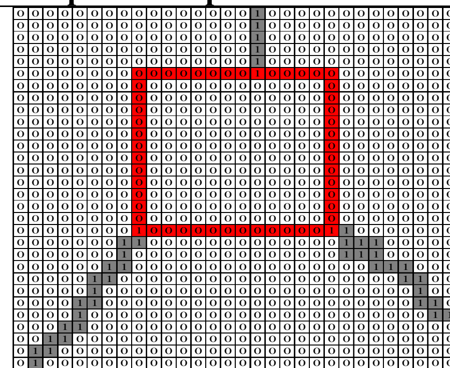
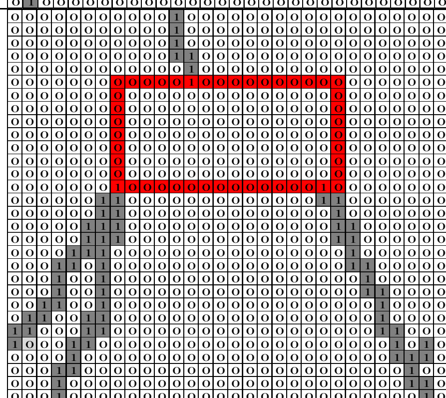
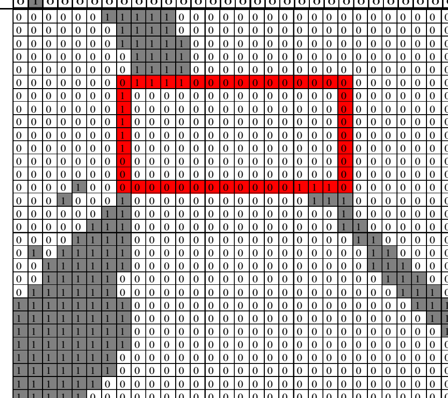
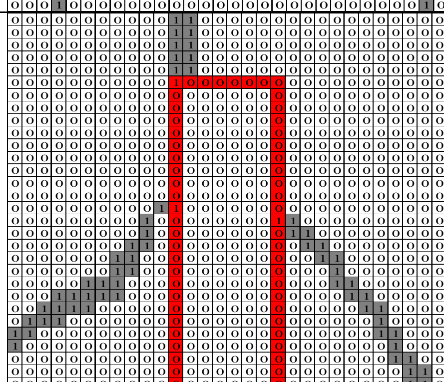
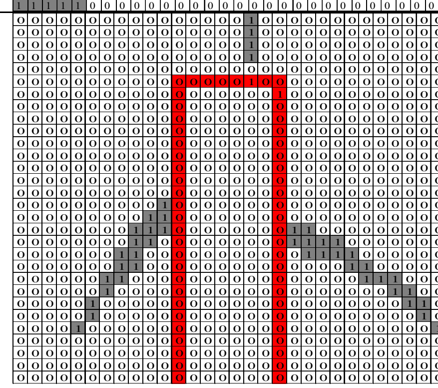
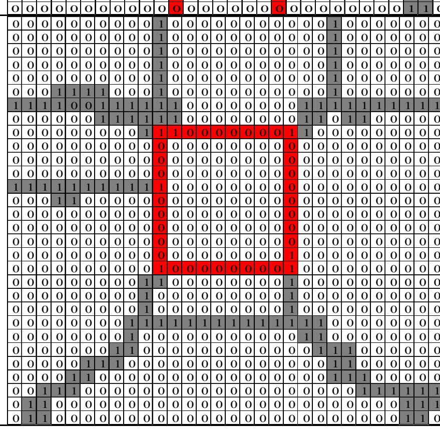
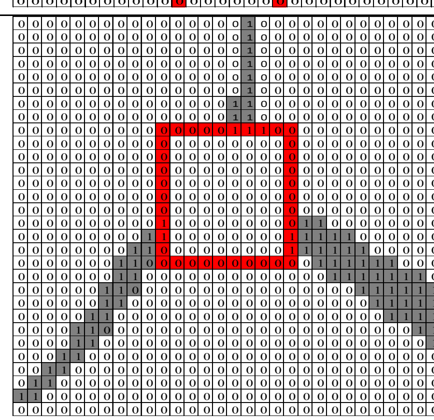
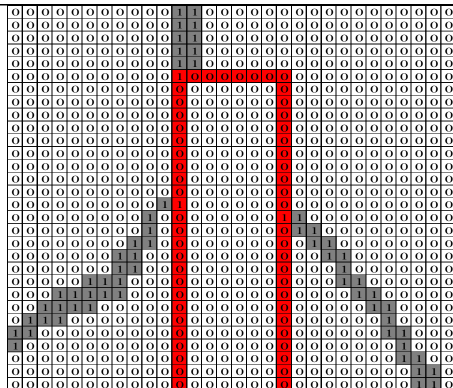
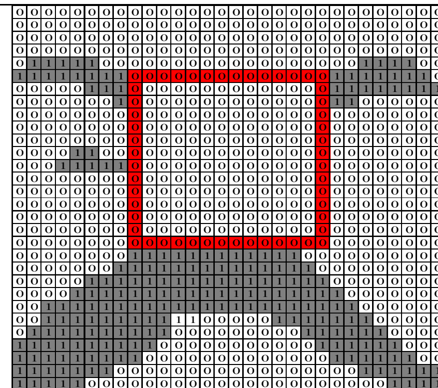
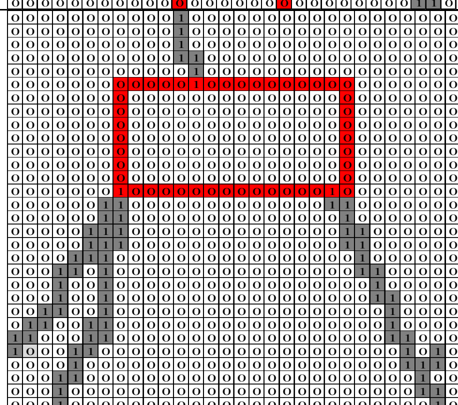
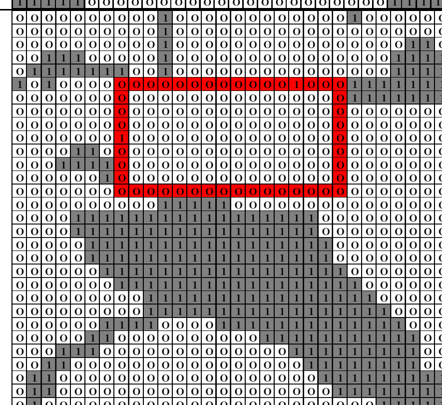
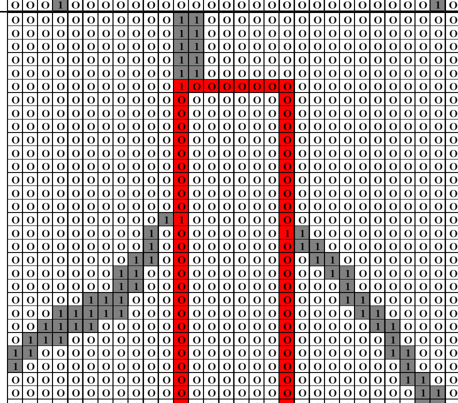
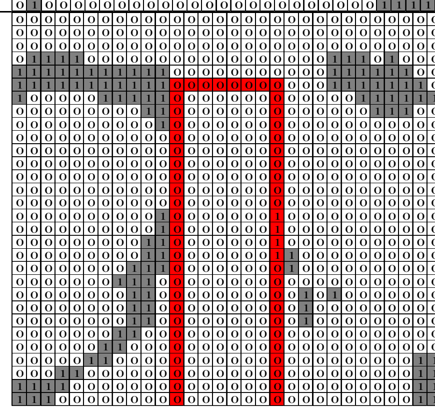
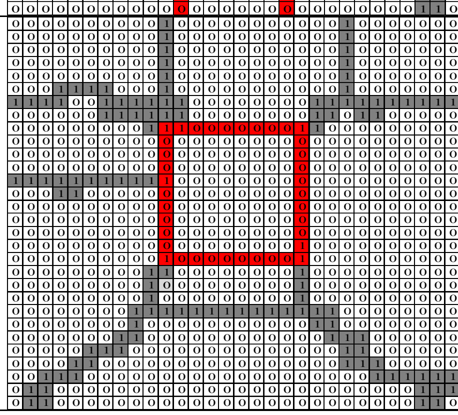
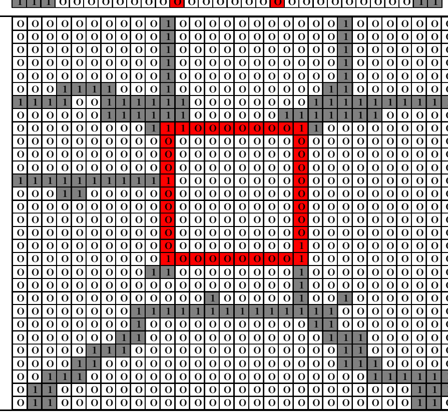
Panel type	Experimental numerical pattern	NN predicted pattern
SB02		
SB03		
SB04		
SB07		

Table 3: Predicted cracking patterns with SB07 as the base panel

Panel type	Experimental numerical pattern	NN predicted pattern
SB02		
SB03		
SB04		
SB07		

CONCLUSIONS AND SUGGESTIONS

This study corroborates the statement that NNs and CA can be used for mapping cracking patterns [5]. CA model for new panel in this study was built considering the difference of its dimensions and opening to those of the base panel. Hence the new boundary value different from zero for free edge was used. The results show the capacity of a NN to predict cracking patterns of masonry panels with different dimensions, but accuracy of the results depends on the training data. Notably the results of the experiments where base panel and new panel had even sizes were more accurate. That indicates the need in deeper investigation of the size effect on the accuracy of NN prediction. For this purpose training data should be reconsidered. Notably, in this study training data was gathered from experimental data of one base panel. But nature of NNs testifies that with more training data the results of the prediction can be improved. Therefore this technique can produce reliable and accurate prediction of failure pattern of laterally loaded masonry panels, by quantifying variation in masonry properties and properly modeling the effect of panel boundaries on the overall response of the panel subjected to lateral loading. Proved to be reliable trained NN allows studying masonry structures that have not been studied yet. Thereby the complex mechanical behavior of masonry material can be studied without expensive experiments and in shorter time. It provides an advanced tool for people to pursue the optimal engineering structure design.

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