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CRACK PATTERN PRIDICTION OF LATERALLY LOADED PANELS WITH OPENINGS BASED ON ANN METHOD

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In this paper a Back Propagation Neural Network (BPNN) is used to predict crack pattern for masonry panels with opening subjected to lateral loading. The cellular automata method is used to digitalize the panels, including two steps----dividing a panel into a certain number of cells and calculating cell state values by Von Neumann neighborhood model. These digitalized values are used as input data of NN model respectively. All the experimental data is collected, including panel's configuration, material property, opening ratio and location, state values, crack pattern. The NN model is trained repeatedly, taking part of the data as a training set, to determine parameters. And the rest data is taken to check the model. Well-trained NN model can predict the crack pattern of any other panel. The results show that NN method is suitable for prediction of crack pattern. Comparing the two ways of prediction, the Fragility Coefficient Method gets a more precise pattern. The predicted cracks are distributed successively in some specific areas, especially in high similarity, compared with experimental crack pattern.

Keywords: Cellular Automata, Digitalization, Weakness, Fragility Coefficient, Back-Propagation Neural Network.

1 INTRODUCTION

For traditional masonry structure, the lateral force is an unneglectable load, such as great wind pressure could not be ignored for damages on some special buildings. Other lateral forces, like explosion (Varma 1997), cyclic lateral force (Davidson 1985), and out-of-plane shaking force (Tu 2010), are also taking effect on the behavior of themselves. Golding (1991) and Sinha (2001) took deep researches on the design of laterally loaded masonry. One of the key research topics is the failure model. In this paper, an artificial neural network (ANN) model is built to predict the crack pattern of laterally-loaded panels with different openings. And all the original statistics are from Chong's experiments (1997). To accomplish the prediction, firstly digitalize the panels by cellular automata (CA) technique. Secondly the generated data and other aspects which concern the crack distribution are treated as the input data of the ANN model. Crack status (cracked or non-cracking) as the output data of the ANN model. Taking some one panel as the base panel, it's CA model and crack status are used to train the ANN model. Then, using the trained ANN model to predict other panels. This method could reflect the main crack distribution, but it still has imperfections such as the disappeared tiny cracks. So, this paper gives an innovative concept, the fragility coefficient.

2 BACK PROPAGATION NEURAL NETWORK ARCHITECTURE

The BPNN contains input layer, hidden layers, and output layer. Input layer contains 11 nodes totally (shown in Figure 1), in which 9 nodes are the state values of one cell (shown in Figure 2), and the other two are the x and y coordinates (these two parameters were used especially for panels with different size, and it's not mentioned in this paper). There are two hidden layers, 18 nodes in the first layer and 10 nodes in the second one. For the direct prediction method (DPM), Output layer means the crack pattern of matrix type, only including two separate digits, 0 for non-cracking cells and 1 for cracked ones. Considering the fragility coefficient, Output layer is different from DPM's, continuous values between 0 to 1. Figure 3 describes the relationship between the DPM and the fragility coefficient method (FCM). Activation function is logsig.

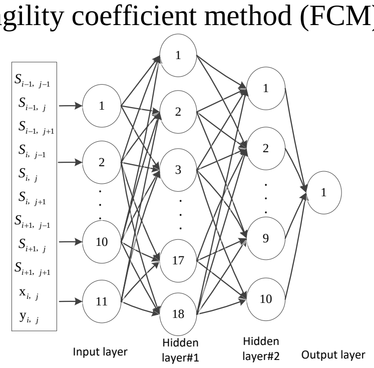


Figure 1. The BPNN model

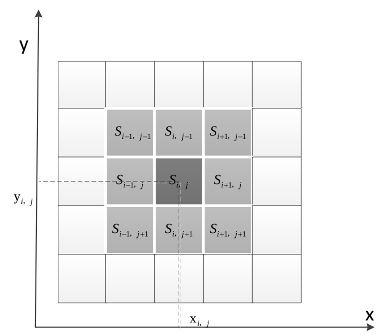


Figure 2. The state value by Moore model of CA

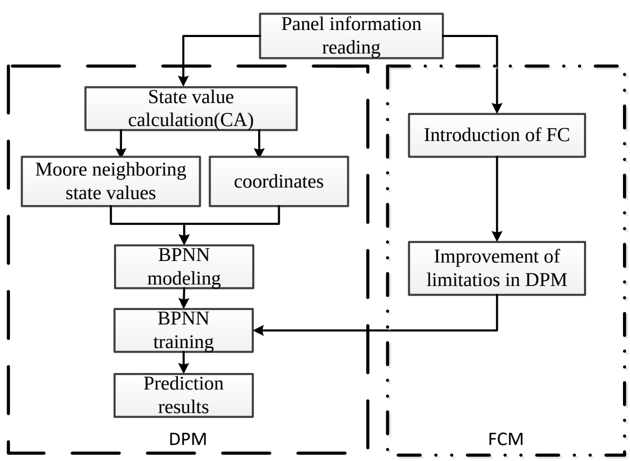
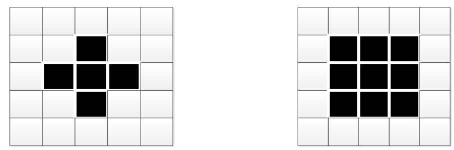


Figure 3. Introduction of two methods

3 BACK PROPAGATION NEURAL NETWORK MODEL

3. 1 Panel information digitalization

CA is a localized and dynamic system both in time and space. Cell is a basic unit of a CA system. Every cell has its unique state value, which could reflect the corresponding location's potential information (Adamska 2010; Maja 2010; Morita 2018). The state value of a cell is not only decided by itself, but also these cells around it. These cells are called neighborhoods. There're two main neighborhood models, Von Neumann neighborhoods and Moore neighborhoods showing in Figure 4.



(a) Von Neumann (b) Moore

Figure 4. Two neighborhood models

3.1.1 Selection of the state values

The state value of a panel is calculated by Von Neumann neighborhoods as following:

$$
\begin{aligned}
&L_{si,j}=1-L_{i,j}, L_{i,j}=L_{i,j-1}+\eta(1-L_{i,j-1}), \quad (i = 1,2,\ldots,M;\ j = 1,\ 2,\ldots,N)\\
&R_{si,j}=1-R_{i,j}, R_{i,j}=R_{i,j-1}+\eta(1-R_{i,j-1}), (i = 1,2,\ldots,M;\ j = N,\ N-1,\ldots,1)\\
&B_{si,j}=1-B_{i,j}, B_{i,j}=B_{i-1,j}+\eta(1-B_{i-1,j}), (i = M,\ M-1;\ j = 1,\ 2,\ldots,\ N)\\
&T_{si,j}=1-T_{i,j}, T_{i,j}=T_{i+1,j}+\eta(1-T_{i+1,j}), (i = 1,2,\ldots,M;\ j = 1,\ 2,\ldots,N)
\end{aligned} \tag{1}
$$

Where $L_{si,j}$, $T_{si,j}$, $B_{si,j}$, $R_{si,j}$ are state values calculated by constraint transiting from left, top, bottom and right side. $L_{i,0}$, $T_{0,j}$, $B_{M+1,j}$, $R_{i,N+1}$ are the initial values of $L_{i,j}$, $T_{i,j}$, $B_{i,j}$, $R_{i,j}$, which reflect the constraint on each border. M, N are the numbers of rows and columns of the zoning area. And η is coefficient of transition (Zhang 2010 and Huang 2013).

The state value $S_{i,j}$ of each cell is defined as the average value from its four neighboring cells:

$$
S_{i,\ j}=\frac{\left(L_{i,j}+R_{i.j}+T_{i,j}+B_{i,j}\right)}{4}\left(i=1,\ 2\ldots M,\ j=1,\ 2\ \ldots,N\right) \tag{2}
$$

3.1.2 Division of the panel with opening

During the digitalization of panel with opening, there is a bit flaw, that is loss of continuity near the opening. Due to its importance to the NN training, division again is needed absolutely. And the way of division for a representing panel, taking Panel SB02 for example, is shown in Figure 5. According to this division method, all panels can be divided into four parts and the zoning data are shown in Table1. Taking Area I-VIII-VII for an example, the state value is calculated by transiting the left, top and bottom side constraints. Each parameter is expressed in Figure 6.

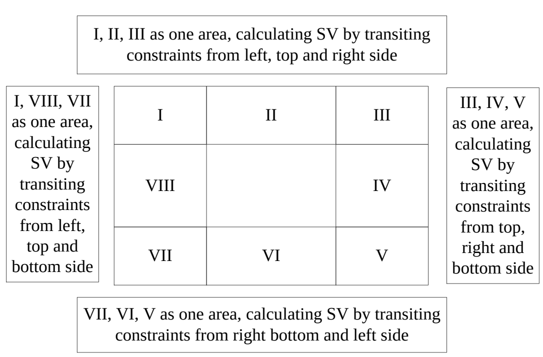


Figure 5. Panel division

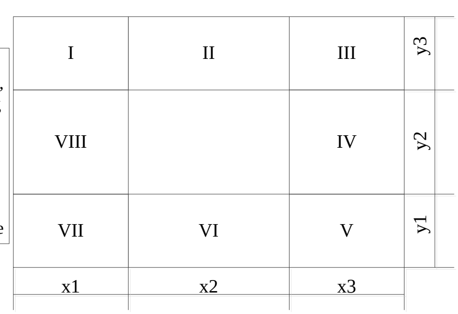


Figure 6. Parameters from division

Table 1. Sizes of panel division (mm)

size	SB01	SB02	SB03	SB04	SB05	SB06	SB07	SB09
x1	2808	1677	1340	2352	2808	1450	1000	3815
x2	0	2260	2935	910	0	0	900	900
x3	2808	1677	1340	2352	2808	1450	1000	900
y1	1238	900	1500	0	1238	1225	900	900
y2	0	1125	525	2025	0	0	900	900
y3	1238	450	450	450	1238	1225	650	675

3. 2 The fragility coefficient of the panel with opening

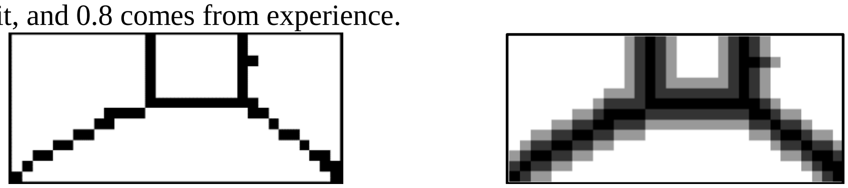
Unlike the homogeneous materials like steels, masonry panels are made up of building blocks (like bricks) and bonder (like mortar), which gives them the variability that is another factor influencing the working performance besides material itself and load case.

The data from the previous experiment is not accurate enough to choose a base panel. The information the base panel representing could not stand for the scientific and general law. On the other hand, predicted crack patterns of other panels may show great differences from the actual ones due to the influence of the masonry's variability. To alleviate the influence, Fragility Coefficient (FC) is proposed to make comparison of the DPM method.

Fragility Coefficient: a parameter that shows whether a unit within the panel is apt to crack or not. To realize it, Formula (3) is proposed to calculate FC, referring to the feature of inverse proportional function. With an experimental crack pattern, the FC data could be achieved by programming. Figure 6 shows the FC distribution of Panel SB05.

$$\mu = \frac{0.8}{|x_i - x_p| + |y_i - y_p|} \tag{3}$$

Where x_i, y_i are x and y coordinates of the calculating unit, x_p, y_p are x and y coordinates of the reference unit, and 0.8 comes from experience.



(a) Experimental crack pattern (b) FC distribution

Figure 6. Panel SB05

4 BPNN TRAINING AND RESULTS

With all data preparation and BPNN model, this study selects different representative base panels in the two methods to compare two prediction results. In each method, a base panel with 512(16×32, from one base panel) groups of data are used to train the BPNN. In DPM, Panel SB02 is used as the base panel. And Panel SB05 is the base one in FCM. Training process of the DPM (as an example) is shown in figure 7. Predicted crack pattern of other panels from SB01 to SB09 are shown in the Table 2.

According to comparison of prediction results, it can be found that there're still distinct similarities and differences, although both methods have the same BPNN model. It should be further analyzed:

- Both predicted crack patterns can generally reflect the main location and spreading direction of actual crack.
- In DPM, predicted cracks are located on top of the opening, spreading along the vertical

symmetrical axis, such as Panel SB03 and SB04. Due to complexity of crack, the prediction results are disappeared someone crack, except Panel SB04.

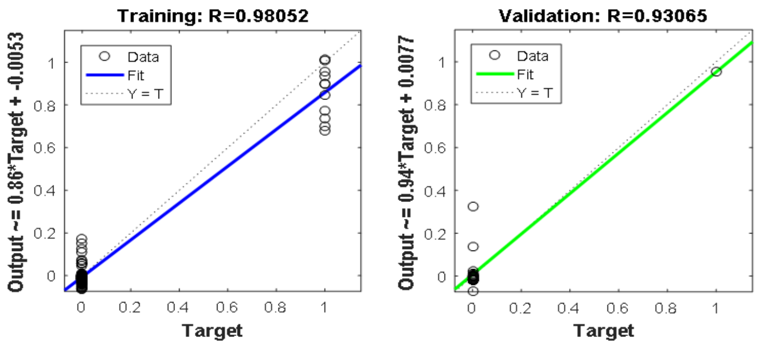
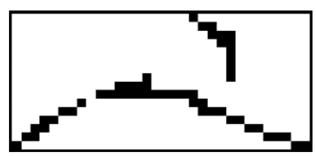
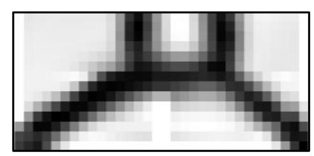
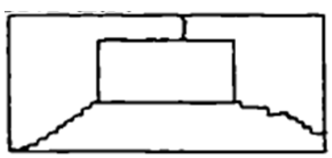
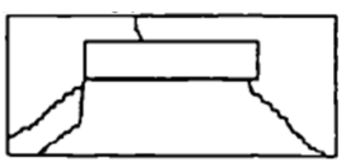
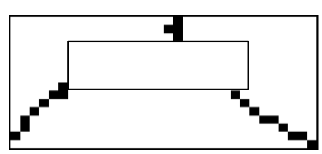
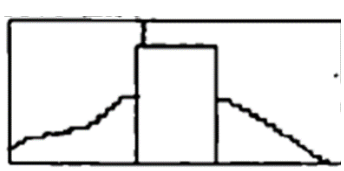
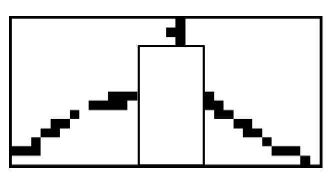
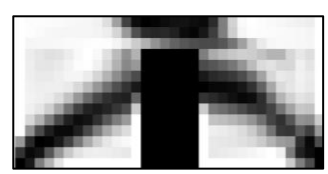
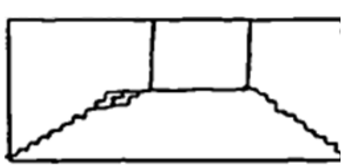
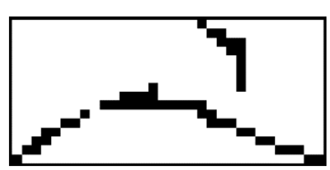
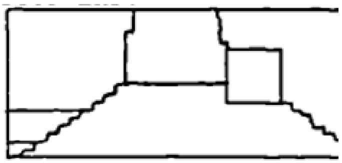
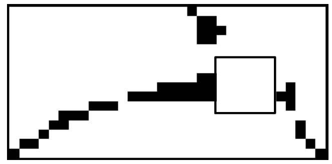
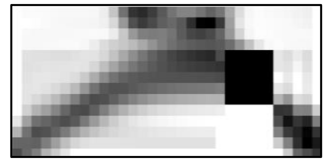


Figure 7. Training of the BPNN

- In FCM, a black rectangular area means the opening of panel, and the shadow means location and spreading direction of actual crack. That is, this area contains all potential cracks.

Table 2. Prediction result

Panel No.	Experimented crack pattern	Predicted crack patterns	
		DPM	FCM
SB01			
SB02		Base Panel	
SB03			
SB04			
SB05			Base Panel

Panel No.	Experimented crack pattern	Predicted crack patterns	
		DPM	FCM
SB09			

5 CONCLUSION

This paper presents that BPNN predicts the crack pattern of the masonry panels with opening. Comparing two methods of prediction, we have the following conclusions:

- Although only one panel is used for training, with the science of digitalization, different panels have the same feature in state value, giving BPNN the basis to decide a unit is cracked or not. So it can make the prediction of crack pattern of the masonry panels with opening easy to come true.
- FC is presented to describe the location and spreading direction of actual crack. It's better than DPM, for including abundant information about potential crack pattern.
- Proposed division of panel with opening is a specialized targeted method about digitalization. It is an effective and worthy method to analyze in future.

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