Neural-Network Applications for Analysis of Infilled Frame

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Abstract

The modelling of infilled frames is complex due to the large number of variables as well as the non-linear material behaviour involved. Artificial Neural Network (ANN) is found to be a tool capable of solving such problems. This has led to the increasing use of ANN for analysing infilled reinforced concrete frames. This paper reports the details of a study conducted using ANN for predicting the failure of an infilled reinforced concrete infilled frame subjected to lateral loading. Using the data generated based on analytical solutions, the ANN model was trained. The so trained model was tested for different set of input parameters and the output values were compared with the actual values based on analytical results. The agreement was found to be good.

Keywords:. Artificial Neural Network (ANN), Infilled Frame, Equivalent strut method

1. INTRODUCTION

The principle behind Artificial Neural Networks is the functioning of the human brain. Different areas in engineering and technology use this technique for solving complex problems. In civil engineering, it is successfully applied to areas like optimal design of structures, earthquake characterization, damage detection etc. It is found to be efficient for analysing structures which are otherwise very difficult to analyse due to various constraints. Different approaches have been used in the past to analyse the infilled-framed structures. In general, the theoretical studies were followed by experiments to evaluate the reliability of the proposed method. In most of the experimental investigations, only models are used since testing of prototype structures will be costly, time consuming and laborious. The infill walls are used as partitions and / or architectural elements. The presence of infill is usually neglected in conventional designs. Since the interaction between the frame and the infill plays an important role in the stiffness and strength of infilled frames, a method in which the infill portion is neglected will not be a realistic one.

Maurizio Papia [1998] used numerical analysis to examine the behaviour of infilled frames subjected to horizontal loads. Stafford Smith [1962] studied the behaviour of infilled frames subjected to inplane loading, by replacing the infill by an equivalent strut and considering the infill neither as an integral part nor bonded to the frame. Stafford Smith and Carter [1969] considered the possibility of failure occurring either by diagonal cracking or by crushing of infill. By an analogy with the behaviour of beam on elastic foundation, the contact length was expressed as a function of λh, where λ is a non-dimensional parameter. The method was evaluated by testing a three-storey prototype building. The estimated values agreed well with the experimental results. A six-storey steel frame with rigid joints was analysed by Jenkins [1995] using ANN. He concluded that ANNs could be used for the analysis provided the training data is sufficient and the number of units in the hidden layer is adequate to represent the internal features and relationships connecting input and output values. Muralikrishna and Gangadharam [1999] investigated a single bay single storey portal frame subjected to inplane nodal loads and demonstrated that ANN can accommodate the non-linear behaviour of infill/frame materials as well as their non-homogeneity and, the uncertainties like lack of fit at the frame/infill.

2. ARTIFICIAL NEURAL NETWORKS

The present study is concerned with the prediction of the collapse load and the displacement of infilled reinforced concrete frames under lateral loading using ANN .For this, a five storey building with number of bays ranging from one to five is considered. The data for training and testing were formed using analytical results.For generating the data analytically, equivalent strut method was used. The database consists of 63 sets of results, of which 55 sets were used for training the network, and the remaining 8 were used for testing

2.1. Equivalent Strut Method

The design method based on equivalent strut concept developed by Stafford Smith and Carter [1969] is used here for the analysis. This method predicts the lateral strength and stiffness of the brick infilled composite frame .

The stiffness and strength of an infilled panel depend not only on its dimensions and physical properties but also on its length of contact with the surrounding frames. The length of contact α is governed by the relative stiffness of the infill and the frame and Stafford Smith and Carter [1969] suggest an approximate relation,

$$\frac{\alpha}{h} = \frac{\pi}{2\lambda h} \tag{1}$$

in which h= height of storey and λh = a non- dimensional parameter expressing the relative stiffness of the frame and the infill ,

$$\lambda h = \sqrt[4]{\frac{E_m\, t \sin 2\theta}{4E_c\, I_c\, h}} \tag{2}$$

where Em = Young's modulus of elasticity of infill, t = Thickness of infill, h1 = Height of infill ,Ic = Second moment of area of the column, Ec = Young's modulus of elasticity of column concrete and θ = Slope of the infill diagonal to the horizontal.

The relative stiffness parameter λh provides the key to the estimation of an infilled frame's behaviour, and it therefore assumes a prominent role in the development and presentation of the methods for predicting the strength and stiffness.

In estimating the lateral strength of an infilled frame, it is necessary to find the weakest of the various modes of failure of the frame and the infill. The possible failure modes of the frame include the tensile failure of the columns and beams, shear failure of the column and, joint failure between the column and the beam.

An approximate method to determine the strength, based on these modes, is to analyse the forces in the equivalent pin-jointed frame subjected to known horizontal loading, assuming the infills to be replaced by diagonal struts. The calculated tensile load in the column and beam and the shearing components of the load in the diagonal struts may then be compared with the respective strengths of the columns and beams. Assuming the frame has adequate strength, the brick infill may fail by one of the following modes.

-Tension cracking of the mortar joints and masonry

-Shear cracking along the interface between the bricks and mortar (bed joints)

-Local crushing of the masonry at the mortar in one of the compressed corners of the infill.

2.1.1 Diagonal cracking of infill

The diagonal tensile strength of masonry may be assumed to be equal to the tensile strength of the mortar in all cases where the mortar has lower tensile strength than the individual bricks. Using the curves relating the width of the of the equivalent strut and the nondimensional parameter λh given by Stafford Smith and Carter [1969] , the diagonal cracking tensile strength of brickwork was obtained by Govindan [1986] as

$$\frac{R_t}{f_t\, h\, t} = 3.1\left(\frac{l^l}{h^l}\right)^{0.98} (\lambda\, h)^{-0.1\left(\frac{l^l}{h^l}\right)^{0.48}} \qquad (3)$$

where Rt = Diagonal load on the infill to cause cracking, ft = Tensile stress of the infill and l1 = length of infill.

2.1.2. Shear strength of infill

The resistance of masonry to shear stresses is usually considered to be provided by the combined action of the bond, shear strength and the friction between the masonry and mortar. Using the design curves given by Stafford Smith and Carter [1969], the following relationship was derived by Govindan [1986] for calculating the shear failure load of the infill.

$$\frac{R_s}{f_s\,h\,t} = 1.65\left(\frac{l'}{h'}\right)^{0.6} (\lambda\,h)^{-0.05\left(\frac{l'}{h'}\right)^{0.50}} \qquad (4)$$

where Rs = Diagonal load on the infill to cause shear failure of infill and fs = Maximum shear stress of the infill.

2.1.3. Compressive failure

After cracking in the brick infill due to shear and/or tension, it has been observed from experiments that the corner region of the infill, where crushing takes place generally extends along the column contact length α. Based on this, Stafford Smith and Carter [1969] developed an approximate formula for the diagonal compressive strength

$$Rc = \alpha\ t\ \mathrm{Sec}\theta\ fm \qquad (5)$$

where Rc = Compressive failure load and fm = Compressive stress of the infill. Substituting the value of α, the compressive failure load can be expressed in the nondimensional form as

$$\frac{R_c}{f_m\,h\,t} = \frac{\pi}{2\,\lambda\,h}\sec\theta \qquad (6)$$

. For a given infilled frame, λh can be calculated and these expressions can be used to obtain the failure load corresponding to the infill for any aspect ratio, l_l / h_l .

Unit load method has been used for calculating the deflection of the frames. The equivalent strut width for each individual panel in a multistory building varies with the applied loading and consequently, the stiffness of the structure decreases as the lateral load increases. The stiffness of the equivalent frame for any value of load can be determined by considering appropriate equivalent widths of the diagonal struts for the particular load and computing $\Sigma \frac{FUL}{AE}$. It is often useful to know the total lateral displacement at a particular loading. Based on the Mechanics of materials approach, the horizontal displacement under any load as given by Stafford Smith and Carter [1969] is

$$\delta H = H\,\Sigma f\,\frac{FUL}{A_I E} + \frac{H^2}{2H_c}\,\Sigma s\,\frac{FUL}{AE}\,\frac{A_I - A_C}{A_I . A_C} \qquad (7)$$

where δH = total horizontal displacement under applied load, H = Applied load, Σf = Summation sign for all beams and columns in the frame including diagonal strut, Σs = Summation sign for all diagonal struts only, F= force in members due to applied load H, U = Force in members due to unit load applied, at the point and in the direction in which displacement is required, AI = Initial cross-sectional area of members, including diagonal strut when H/Hc=0. Ac = Cross-sectional area of diagonal struts when H/Hc=1 in critical panel, all others proportioned accordingly, E= Modulus of elasticity of frame members and infill, Hc = Horizontal load, to cause crushing in the critical panel infill, determined from the appropriate value of Rc / (fm. h t) for the particular value of λh, L=Length of member.

2.2. Identification of Parameters

Based on a critical study of the parameters affecting the strength and stiffness of infilled frames, ten major parameters were identified. They are; aspect ratio, number of bays, area of column, column steel, column stirrups, area of beam, beam steel, type of concrete, type of steel used for the construction and a non-dimensional parameter λh representing the infill behaviour. Concrete of grades C20, C25, C30, C35 and steel of grade S420 and S500 are used in the analysis. Hence the number of nodes or processing elements in the input layer of the network comes to 14 representing the ten parameters listed above plus the four extra grades for concrete and steel considered. The output layer consists of three nodes for the collapse loads corresponding to frame as well as infill and the top storey displacement of the frame at the verge of failure.

Table 1. Range of Values for Data Base

Parameter	Symbol	Range
Aspect ratio	l/h	1 to 2.5
No.of bays	B	1 to 5
Area of column	Ac	0.02 to 0.15
Area of column steel	Acst	0.0068 to 0.0100
Area of beam	Ab	0.05 to 0.12 m2
Area of beam steel	Abst	0.000315 to
Area of stirrups	Asv	0.000195 to 0.00113 m2
Non-dimensional characteristic length parameter	Λh	2 to 15
Grade of concrete	C20,C25,C30 and	20, 25, 30 and 35

Grade of steel	S420,S500	420, 500 MPa

2.3 Configuration of the Network

2.3.1 Selection of error tolerance

A numerical study of training and testing of the network was done keeping the error tolerance values as 0.1, 0.01 and 0.001.For an error tolerance of 0.1, the number of cycles required is less: but the results are less accurate. In the case of 0.001, even though the accuracy is high, the numbers of cycles required are very high. Hence, keeping in mind the number of cycles required for convergence together with the accuracy needed for training and testing, the error tolerance was chosen as 0.01.

2.3.2 Selection of number of hidden layers.

The first step in the configuration of the network is the selection of the number of hidden layers to be used. The parametric study is made to find out the optimum number of hidden layers as well as the number of nodes for the present problem. With one hidden layer, the architecture is able to attain the required error tolerance of 0.01 within 5000 cycles considered for all the combinations of neurons considered. The network with one hidden layers having the 14-10-3 architecture is chosen since it reaches the required error tolerance with the least number of cycles, which in turn will reduce the CPU time requirement.

2.3.3 Selection of learning rate and momentum parameters

For the chosen architecture of 14-10-3, the number of cycles required to reach the desired error tolerance of 0.01 are computed for different learning rates and momentum parameters. The results are shown in Table 2. From the table, it can be seen that a learning rate of 0.7 and momentum parameter of 0.9 are the optimum values since only this combination requires the minimum number of cycles to achieve the required error tolerance. Hence, these values are used in the analysis.

2.3.4 Training of the network

Using the 14-10-3 architecture and the learning rate, momentum parameter values of 0.7, 0.9 , the network is trained and then tested. For training the network, totally 55 data set are used which are listed under Table 2. These data sets were generated analytically using the equivalent strut method.

Table 2. Data Set Used Training

INPUT														*OUTPUT*		
B	*l/h*	*S420*	*S500*	*C20*	*C25*	*C30*	*C35*	*Ac*	*Ab*	*Acst*	*Abst*	*λh*	*Asv*	*C-F*	*C-I*	*Δ*
1	1	1	0	1	0	0	0	0.02	0.02	0.0068	0.000315	2	0.000195	18.8	89.34	25.467
1	1	1	0	0	1	0	0	0.06	0.05	0.0214	0.001030	6	0.000503	61.1	186.9	34.896
1	1	1	0	0	1	0	0	0.06	0.05	0.0214	0.001030	10	0.000503	61.1	136.80	35.769
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5	1.5	0	1	0	0	1	0	0.11	0.08	0.0357	0.001730	10	0.000785	826	766.7	121.133
5	2	0	1	0	0	1	0	0.11	0.08	0.0357	0.001730	4	0.000785	1035	547	70.98
5	2	0	1	0	0	1	0	0.11	0.08	0.0357	0.001730	8	0.000785	1035	899	142.049

NOT: C-F = Collapse load corresponding to frame in kN , C-I= Collapse load corresponding to infill in kN, Δ= Displacement of frame at the top level under collapse load in mm.

2.3.5 Testing of the network

The network, after being trained, is tested with 8 data sets.. The data sets used for testing the network are shown in Table 3.

Table 3. Data Set Used Testing

INPUT														*OUTPUT*		
B	*l/h*	*S420*	*S500*	*C20*	*C25*	*C30*	*C35*	*Ac*	*Ab*	*Acst*	*Abst*	*λh*	*Asv*	*C-F*	*C-I*	*Δ*
2	1	1	0	0	1	0	0	0.05	0.05	0.0214	0.001030	6	0.000503	148	301.1	61.383
2	2.5	0	1	0	0	1	0	0.11	0.08	0.0357	0.001730	4	0.000785	546	217.6	28.237
3	1.5	1	0	0	1	0	0	0.06	0.05	0.0214	0.001030	6	0.000503	322	612.4	42.905
3	2	0	1	0	0	1	0	0.11	0.08	0.0357	0.001730	8	0.000785	658	515.2	81.409
4	1	1	0	1	0	0	0	0.02	0.02	0.0068	0.000315	2	0.000195	101	281.3	11.115
4	1.5	1	0	0	1	0	0	0.06	0.05	0.0214	0.001030	2	0.000503	429	394.3	46.650
5	2	0	1	0	0	1	0	0.11	0.08	0.0357	0.001730	8	0.000785	1035	899	142.049
5	2.5	0	1	0	0	0	1	0.15	0.12	0.0510	0.002500	15	0.001130	1795	700.6	110.669

3. RESULTS and DISCUSSION

The collapse load and displacement predicted using ANN is compared with the actual values in Fig.1. In these figures, the diagonal lines represent a one to one correspondence, that is, when the predicted and the actual values are identical.

The results clearly show that for the frame and infill failure, the collapse load values predicted using neural network vary only marginally (the maximum variation is only 4%) from the actual values for the data formed using equivalent strut method. In the case of the displacement of the frame under collapse load, the predicted values using neural network vary only marginally (maximum of 5%) from the actual values, be it based on experiments or equivalent strut method. It can be stated that overall the prediction is very good.

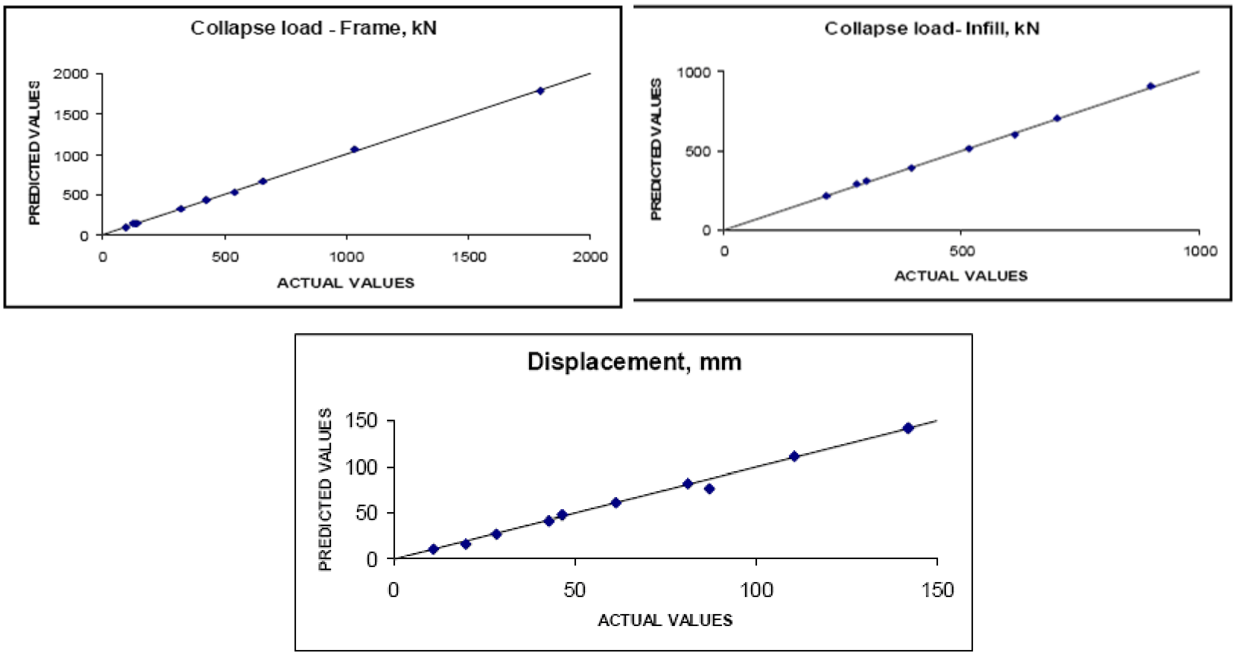

Figure 1. Comparison of predicted and actual values.

4. CONCLUSION

The conventional analysis of infilled frames is complex due to the large number of parameters and the non-linear behaviour involved. Hence, the practice is to ignore the contribution from the infill and analyse the structure as a bare frame. However, it is well known that the infill affects the behaviour of the structure significantly. In this context, Artificial Neural Network is increasingly used effectively as a tool for the analysis of infilled reinforced concrete frames. In this paper, a multilayer feed forward network with back propagation algorithm has been adopted to model a five storey infilled frame with number of bays ranging from one to five. The training patterns were generated using the equivalent strut method with different modes of failures in the frame and infill to arrive at the collapse load for the infill and frame as well as the displacements. The performance of the network has been demonstrated by comparing the output with the analytically generated values. Based on the investigation, it can be stated that ANN models can predict the behaviour of infilled frames efficiently.

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