

STRUCTURAL ENGINEERING APPLICATIONS OF ARTIFICIAL NEURAL NETWORKS

Muhiddin BAĞCI Gökhan ALTINTAŞ
muhiddin.bagci@bayar.edu.tr gokhan.altintas@bayar.edu.tr
Celal Bayar University, 45140 , Manisa, TURKEY

ABSTRACT

In this study, infilled planar frames and confined reinforced concrete section have been analysed using Artificial Neural Network (ANN). ANN architecture was chosen in which multi layer, feed forward, and back propagation algorithm was used. The training data of infill frame used were provided by a finite element model in which non-linearity of materials and the structural interface were taken into account under increasing lateral load. Using the proposed analytical model (layered model) were generated the training data for confined reinforced concrete section. Analytical technique uses realistic material models for confined and unconfined concrete. After completing the training phase, verification of the performance of the network was carried out using old (included in training phase) and new (not included in training phase) patterns. The controls conducted in the test phase. The findings of this exercise show that the ANN algorithm can be successfully and easily used within reasonable accuracy in order to decrease computational time in finding infill frame and the moment-curvature relationships of reinforced concrete sections.

Key words: Artificial Neural Network, Finite Elements Method, Infilled Frame, Confined Reinforced Concrete Section, Moment-Curvature.

ÖZET

Bu çalışmada, Yapay Sinir Ağları (ANN) kullanılarak dolgu çerçeveler ve sargılı beton kesitlerin analizi yapılmıştır. ANN mimarisi için çok tabakalı ileri beslemeli geri yayımlı algoritma kullanılmıştır. Dolgu duvarlı çerçeve eğitim verileri elde edilirken ara yüzey ve malzeme bakımından doğrusal olmayan etkilerin de dikkate alındığı sonlu elemanlar yöntemi kullanılmıştır. Sargılı beton kesitlerde önerilen analitik model (tabakalı yaklaşım) kullanılarak eğitim seti oluşturulmuştur. Analitik tekniklerde sargılı ve sargısız betonun dikkate alındığı daha gerçekçi malzeme modelleri kullanılmıştır. Eğitim seti oluşturulduktan sonra, ağ performansının kullanılan veya yeni verilerle yakınsama işlemi gerçekleştirilmiştir. Kontroller yapılan test işlemleriyle gerçekleştirilmiştir. Bu çalışma bulguları, Yapay Sinir

Ađı algoritmalarının başarılı ve kolay bir şekilde, hesap zamanını da azaltarak, dolgulu çerçeve ve betonarme kesitlerin moment-eđrilik hesabında kullanılabileceđini göstermektedir.

Anahtar kelimeler: Yapay Sinir ađları, sonlu elemanlar yöntemi, dolgulu çerçeve , sargılı betonarme kesit, moment –eđrilik.

1. INTRODUCTION

The mathematical models have been widely applied for the analysis of infilled frame. Holmes M (1) modelled the infill effect occurring in an infilled frame without considering the effects on the interface between frame and infill. In studies conducted by Smith BS (2), the approach of diagonal compression strut was dealt with in a more detailed way. Using a finite element model, Mallick DV and Severn RT (3) attained the results without considering the shear effect on the infill frame interface. With a program they prepared, Loo YC and Young Y (4), conducted a linear analysis of the infilled arches in terms of material used. Using a nonlinear finite elements method, Liauw TC and Kwan KH (5) examined a frame with multibay and one-storey. Infilled planar frames have been analysed using artificial neural network by Bađcı and Altintaş (6). The layered model for confined reinforced sections was first used by Pavriz *et al* (7). Moment-curvature relationships of confined concrete sections were investigated by Ersoy U and Özcebe G (8). The generalized delta rule algorithm of artificial neural networks is employed to predict the flexural behavior of Steel Fibre Reinforced Concrete (*SFRC*) T-beams using a computer program developed in C++, Patodi SC and Purani VS (9). For some other examples of ANN applications, the reader is referred to (Jadid MN and Fairbairn DR (10), Berke L and Hajela P (11), Lee *et al* (12), Avdelas *et al* (13), Abdalla and Stavroulakis (14); Karlık *et al* (15).

In this study, the stiffness, moment and shear force values on frame for five different height of infill wall are calculated using finite elements method (FEM). The behavior values of confined reinforced concrete sections subjected to flexure and axial load are obtained by using analytical solution (layered model). The calculated key values are used in training a multi-layer, feed forward, back propagation artificial neural network (ANN). The outcomes of training phase were then tested using the data set reserved for this the network purpose. The findings of this exercise have shown that the ANN algorithm can be successfully and easily used within reasonable accuracy in order to decrease computational time in infilled frame and confined section problems.

2. ARTIFICIAL NEURAL NETWORKS APPROACH

An alternative to the conventional numerical techniques is presented in this section by employing an artificial neural network algorithm, computational time is drastically reduced compared to the conventional numerical techniques. ANN's are capable of self-organization and knowledge learning. Ability to perform tasks involving nonlinear relationships and noise-immunity make ANN a good candidate for classification and prediction.

The ANN system is applied with multi-layer perception, feed forward, back propagation algorithm by supervised training. Back-propagation is a time consuming algorithm. The processing units are arranged in layers. Each ANN has an input layer, number of hidden layers and an output layer. The input vector representing the pattern to be recognized is incident on the input layer and distributed to subsequent hidden layers and finally to the output layer via weighted connections. The pattern of connectivity and the number of processing units in each layer may vary with some constraints. No communication is permitted between the processing units in a higher layer. At the forward feeding phase, neurones at the input layer transfer the data values directly to the hidden layer. Each neuron in the network operates by taking the sum of its weighted inputs and passing the result through a nonlinear activation function (transfer function). Generally, the sigmoid function is chosen as the nonlinear activation function.

3. PARAMETRIC STUDIES

Dimensions of infilled frame given by Fiorato AC and Sözen M (17) in Fig. 1 are shown, and the materials properties are listed in Tab. 1. The lateral load (P) was applied at the top left hand corner of the frame in Fig. 1a in 20 increments of 10 kN each.

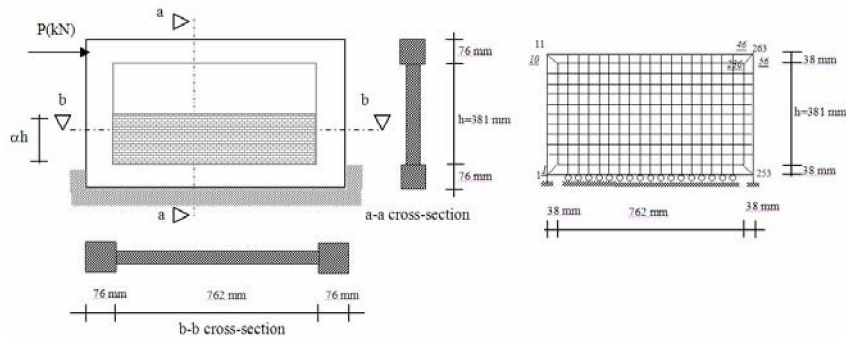


Figure 1a. Frame-infill wall 1b. Mesh model of with full infill wall

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Table 1. Properties of material

	Modulus of elasticity (kN/m ²)	Compression Strength (kN/m ²)	Tension Strength (kN/m ²)	Poisson Ratio
Frame	2.85x10 ⁷	3.1x10 ⁴	3x10 ³	0.2
Infill	1.7x10 ⁷	3.1x10 ⁴	2.8x10 ³	0.2

The wall was modelled mesh of quadrilateral-shaped isoparametric plane stress elements as shown in Figure 1b. The results of a numerical study are given in Tab. 2, with respect to whether the infill fills the space among the frame. Infill height is αh with α being ranging from 0 and 1 ($\alpha=1$, $\alpha=0.8$, $\alpha=0.6$, $\alpha=0.4$, $\alpha=0.2$ and bare).

Table 2. Results of FEM

Infill height	Load-P (kN)	Stiffness (infill / no infill)	Left column shear force / lateral load	Left column moment (Infill / no infill)	Infill height	Load-P (kN)	Stiffness (infill / no infill)	Left column shear force /lateral load	Left column Moment (Infill / no infill)	
h	10	5,65700	0,19000	0,19000	0,4h	10	1,3140	0,51400	0,87900	
	20	5,65700	0,19000	0,19000		20	1,2570	0,54200	0,91900	
	30	5,65700	0,19000	0,19000		30	1,2170	0,55000	0,93800	
	40	5,65700	0,19000	0,19000		40	1,2050	0,55200	0,94700	
	50	5,57100	0,19000	0,19000		50	1,2000	0,56000	0,94700	
	0,8h	160	3,62800	0,33000	0,40200	0,2h	160	1,0970	0,54200	0,97600
		170	3,58800	0,34000	0,40200		170	1,0910	0,53800	0,97600
		180	3,54200	0,35000	0,41400		180	1,0850	0,53800	0,97600
		190	3,51400	0,36000	0,42000		190	1,0850	0,53300	0,97600
		200	3,45700	0,37000	0,42000		200	1,0850	0,53300	0,97600
0,6h		10	3,14800	0,53000	0,49500	Bare	10	1,05700	0,51000	0,97900
		20	2,98200	0,57000	0,52500		20	1,04800	0,51000	0,98900
		30	2,76500	0,61900	0,56100		30	1,04000	0,51000	0,99000
		40	2,64000	0,64700	0,59800		40	1,02500	0,51000	0,99000
		50	2,55400	0,66600	0,60300		50	1,00000	0,51000	0,99000
	0,4h	160	1,76000	0,66600	0,76800	Bare	160	1,00000	0,51000	1,00000
		170	1,71400	0,66300	0,77900		170	1,00000	0,51000	1,00000
		180	1,67400	0,66000	0,79800		180	1,00000	0,51000	1,00000
		190	1,62800	0,65700	0,79800		190	1,00000	0,51000	1,00000
		200	1,58800	0,65000	0,80400		200	1,00000	0,51000	1,00000
10		2,00000	0,53000	0,70400	10		1,00000	0,50000	1,00000	
0,2h	20	1,85100	0,57000	0,75400	Bare	20	1,00000	0,50000	1,00000	
	30	1,76000	0,59000	0,79000		30	1,00000	0,50000	1,00000	
	40	1,68500	0,61000	0,81100		40	1,00000	0,50000	1,00000	
	50	1,66200	0,62300	0,83100		50	1,00000	0,50000	1,00000	
	160	1,31400	0,59500	0,91400		160	1,00000	0,50000	1,00000	

170	1,30200	0,59000	0,91400	170	1,00000	0,50000	1,00000
180	1,28500	0,58800	0,92300	180	1,00000	0,50000	1,00000
190	1,26800	0,58400	0,92300	190	1,00000	0,50000	1,00000
200	1,25700	0,58000	0,92300	200	1,00000	0,50000	1,00000

In order to obtain a clearer understanding of the behaviour of the frame-wall system response to the lateral force, several different variables were monitored at each loading step, though only a small fraction of the results are reported here. These important results are presented in the form of a standardized. The secant stiffness of the frame-wall system, expressed as a multiple of the stiffness of the bare frame (for which α is equal to zero) is depicted in Tab. 2. This is defined as the ratio of the horizontal displacement at the same load level for the bare frame. The shear force at the top of the column where the load is acting in Fig.1a, expressed as a fraction of the lateral load is shown in Tab. 2. The moment at the top of the column where the load is acting in Fig.1a, normalized with respect to the moment at the same location for the bare frame, has been presented in Tab.2.

It has been seen that the effect of infill gets clear only when it reaches at 0.4 for the value at the initial step of loading, though the stiffness of, infilled frame reaches at 5.7 fold, a rather high number, local failures occurring in the infill as a result of increasing dimensionless load, leads to a decrease in the overall stiffness of the system.

Shear strength of the column increases with the height of infill. When the height of infill reached at the value of 0.8h, it was seen that the shear force of the column was 50 % higher than the shear force it carries when it was a bare frame. In this case, “short column” verifies its effect. When the height of infill was organised at the height of storey, it was seen that it was useful in term of shear strength of column.

Input parameters are lateral load (P) and height of infill (αh) values. Output parameters are stiffness (infill /no infill), shear force / lateral load and moment (infill / no infill) at the loaded column. As it is known, in neural network applications, the input values and output values can be reduced to the values between 0-1. That is the normalization process, which is done in this work dividing P's by 220 and dividing αh 's by 1.1h. The output values were also divided by 5.7 stiffness ratio, 0.7 shear force ratio and 1.1 moment ratio, which were the highest values that we used in our application. Training was performed for the heights of wall h, 0.8h, 0.6h, 0.4h, 0.2h and bare and for loads of frame 10, 40, 70, 110, 150,190. As known, the general aim in the training process is to teach the relations between input and output values to the program and to obtain good answers to different input values with the possible lowest error rates.

Values obtained from the numerical procedure (FEM) are used in the network training. A special code was used for ANN exercise by Karlık, B *et al* (17). It is adapted and fitted to our application with some changes. ANN architecture with multi-layered, forward feeding and backward propagation algorithm was chosen for the training. The ANN architecture used is a 2:9:9:3 multi-layer architecture as shown in Fig. 2.

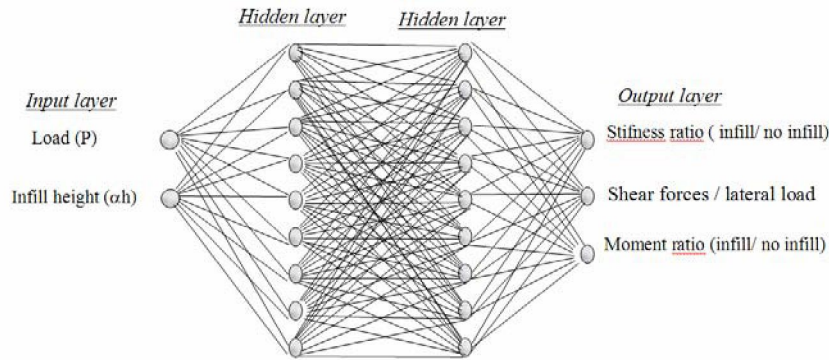


Figure 2. Network Architecture for infilled frame

Exact and ANN values of output are compared in Tab. 3 for various αh and P values. For these training values, the ANN algorithm produced results with average error $\sum \frac{|FEM - ANN|}{ANN}$ / number of output less than 0.2 %. The maximum value for FEM / ANN is about 1.0351 in 0.4h infill height and 70 kN load value.

Table 3. The results of ANN and FEM in training

Infill Height	Lateral load kN	Solution Method	Stiffness ratio (Infill / no infill)	FEM/ ANN	Left column Shear force/lateral load	FEM/ ANN	Left column Moment ratio (Infill / bare)	FEM/ ANN
h	10	FEM	5.65699	0.9977	0.18999	0.9984	0.19000	1.0246
		ANN	5.67016		0.19030		0.18543	
	40	FEM	5.65699	1.0136	0.18999	1.0004	0.19000	0.9650
		ANN	5.58108		0.18992		0.19688	
	70	FEM	4.77100	0.9960	0.21499	0.9963	0.25199	1.0191
		ANN	4.79018		0.21580		0.24728	
	110	FEM	3.97100	1.0105	0.28000	0.9961	0.34500	0.9858
		ANN	3.92982		0.28110		0.34998	
	150	FEM	3.66800	0.9976	0.31999	0.9859	0.39299	1.0051
		ANN	3.67685		0.32458		0.39100	
	190	FEM	3.51399	1.0034	0.35999	0.9830	0.42000	0.9942
		ANN	3.50218		0.36621		0.42245	
10	FEM	3.14800	0.9996	0.52999	1.0010	0.49500	0.9935	
	ANN	3.14932		0.52945		0.49826		

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0.8h	40	FEM	2.64000	1.0004	0.64699	0.9957	0.59800	1.0080
		ANN	2.63882		0.64981		0.59322	
	70	FEM	2.38000	0.9923	0.69000	1.0067	0.63299	0.9901
		ANN	2.39853		0.68539		0.63932	
	110	FEM	2.06800	1.0093	0.69000	1.0082	0.69999	1.0009
		ANN	2.04899		0.68438		0.69937	
0.6h	150	FEM	1.80000	0.9923	0.67400	0.9988	0.75699	1.0050
		ANN	1.81405		0.67482		0.75320	
	190	FEM	1.62799	1.0110	0.65700	0.9978	0.79799	0.9955
		ANN	1.61035		0.65845		0.80154	
	10	FEM	2.00000	1.0097	0.52999	1.0015	0.70400	1.0034
		ANN	1.98080		0.52918		0.70163	
0.4	40	FEM	1.68499	1.0184	0.60999	1.0091	0.81099	1.0034
		ANN	1.65441		0.60451		0.80825	
	70	FEM	1.58799	0.9914	0.62799	0.9952	0.84700	0.9963
		ANN	1.60180		0.63103		0.85013	
	110	FEM	1.44500	0.9884	0.61899	0.9995	0.88500	1.0020
		ANN	1.46194		0.61932		0.88322	
0.2h	150	FEM	1.34199	0.9902	0.59999	1.0000	0.90400	0.9964
		ANN	1.35234	4	0.59997		0.90729	
	190	FEM	1.26799	0.9934	0.58399	1.0032	0.92299	0.9969
		ANN	1.27637		0.58211		0.92590	
	10	FEM	1.31400	0.9688	0.51399	0.9915	0.87899	0.9887
		ANN	1.35626		0.51841		0.88908	
Bare	40	FEM	1.20500	1.0073	0.55200	0.9992	0.94700	1.0067
		ANN	1.19623		0.55243		0.94073	
	70	FEM	1.18800	1.0351	0.55700	1.0031	0.95700	0.9993
		ANN	1.14772		0.55525		0.95764	
	110	FEM	1.14199	1.0259	0.55000	1.0055	0.96599	0.9984
		ANN	1.11313		0.54698		0.96755	
Bare	150	FEM	1.10800	1.0106	0.54199	1.0035	0.97599	1.0033
		ANN	1.09635		0.54013		0.97278	
	190	FEM	1.08499	0.9981	0.53299	0.9956	0.97599	0.9999
		ANN	1.08706		0.53534		0.97613	
	10	FEM	1.05699	0.9928	0.51000	1.0084	0.97900	1.0023
		ANN	1.06466		0.50576		0.97675	
Bare	40	FEM	1.02499	1.0116	0.51000	0.9911	0.99000	0.9981
		ANN	1.01327		0.51457		0.99184	
	70	FEM	0.99999	0.9999	0.51000	0.9931	0.99999	1.0037
		ANN	1.00007		0.51354		0.99633	
	110	FEM	0.99999	1.0044	0.51000	0.9975	0.99999	1.0018
		ANN	0.99560		0.51126		0.99820	
Bare	150	FEM	0.99999	1.0035	0.51000	0.9987	0.99999	1.0018
		ANN	0.99658		0.51065		0.99824	
	190	FEM	0.99999	0.9992	0.51000	0.9975	0.99999	1.0027
		ANN	1.00092		0.51128		0.99726	
	10	FEM	0.99999	0.9883	0.49999	1.0021	0.99999	1.0020
		ANN	1.01186		0.49895		0.99798	
Bare	40	FEM	0.99999	1.0003	0.49999	0.9984	0.99999	0.9979
		ANN	0.99971		0.50082		1.00260	
	70	FEM	0.99999	1.0013	0.49999	0.9994	0.99999	0.9971
		ANN	0.99865		0.50030		1.00295	
	110	FEM	0.99999	1.0014	0.49999	1.0005	0.99999	0.9997
		ANN	0.99875		0.49976		1.00302	
Bare	150	FEM	0.99999	1.0029	0.49999	1.0000	0.99999	0.9973
		ANN	0.99706		0.49999		1.00266	
	190	FEM	0.99999	1.0050	0.49999	0.9980	0.99999	0.9980
		ANN	0.99506		0.50099		1.00196	

In Fig. 3, the mean square errors (MSE) in training versus iteration numbers are shown for problem. After 1600 iterations, the mean square errors dropped drastically. For more than 15000 iterations, our architecture 2:9:9:3 used in the analysis possesses the lowest total error values.

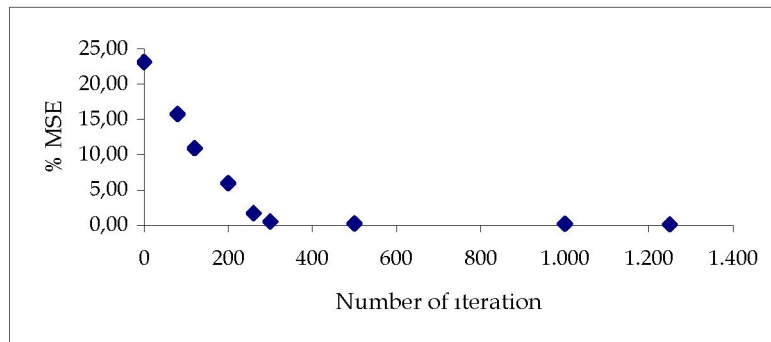


Figure 3. Mean Square Errors (MSE) based on iteration numbers for infilled frame

Different input values were applied to the program for testing the neural network and the results were obtained in milliseconds. Testing was performed for height of wall h and for load values of frame 20, 60, 100, 140, 180. In Tab. 4, we compare the test phase results of ANN and FEM.

Table 4. Test Phase Results for infilled frame

Height of Infill wall	Load P kN	Method	Stiffness ratio (Infilled / no infill)	FEM / ANN	Left column shear force /lateral load	FEM / ANN	Left Column Moment ratio (infilled/ no infill)	FEM / ANN
h	20	FEM	5,65700	1.0021	0,19000	1.0215	0,19000	0.993
		ANN	5,64500		0,18600		0,19120	8
	60	FEM	5,18800	0.9937	0,19500	0.9898	0,21400	1.002
		ANN	5,22100		0,19700		0,2134	8
	100	FEM	4,1140	0.9669	0,27000	0.9953	0,32600	1.031
		ANN	4,2550		0,27130		0,31600	6
	140	FEM	3,73100	1.0138	0,31000	1.0038	0,38000	1.019
		ANN	3,68000		0,3088		0,37290	0
	180	FEM	3,54200	1.0022	0,35000	1.0043	0,41400	0.999
		ANN	3,53400		0,3485		0,41485	8

The average % error ($\sum \frac{|FEM - ANN|}{number\ of\ output}$) obtained is obviously about 0.269. The maximum value for FEM / ANN is about 1.0316 in 100 kN load value. From an engineering point of view, these errors are considerably low.

The other parametric study has been conducted to observe the effect of different variables on behavior of confined reinforced section shown in Fig. 4.

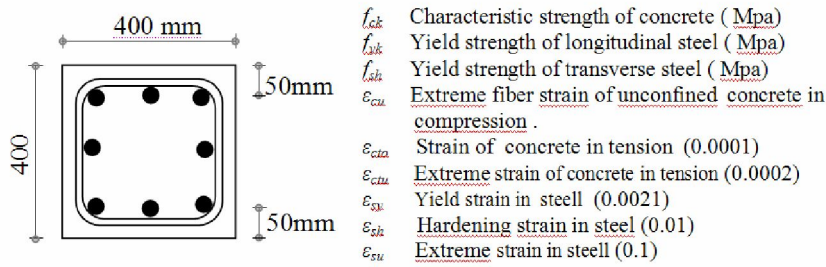


Figure 4. The cross-section considered in analyses.

Variables selected to incorporate in the expression of moment-curvature are compressive strength of concrete (f_{ck}), the ratio of the axial load to the axial load capacity (N/N_o), yield strength in transverse reinforcement (f_{sh}), space of transverse reinforcement (s), diameter of transverse reinforcement (\emptyset), ratio of longitudinal steel (ρ), yield strength of longitudinal steel (f_{yk}) as shown in Tab. 5. Where TY, TH, CvC, CoC , ϵ , M are yield in tension, hardening of reinforcing in tension , cover crushing, core crushing, strain at maximum moment, and maximum moment, respectively.

The results obtained from Tab.5 demonstrates no very significant effect on Moment capacity from compressive strength (f_{ck}) in case of pure bending ($N=0$). The compressive strength becomes effective with increasing axial load. Maximum moment capacity shows changes of $\pm 25\%$ due to $\pm 25\%$ compressive strength variation. The increasing compressive strength causes the decrease in ductility.

As level of the axial load (N/N_o) on the cross-section increases, ductility decreases. Increase in ductility with decreasing axial load is very significant. It is interesting to note that, although the section considered is well confined, the behavior becomes very brittle under high levels of axial load. The upper limits imposed on axial loads in seismic codes results from such considerations.

Table 5. The results according to different variables of confined concrete section

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No	Variable properties							Curvature (rad/m)				ϵ_{cu}	M (kN-m)
	f_{sh} (Mpa)	N/N _c (N)	f_{sh} (Mpa)	s (cm)	\emptyset (mm)	ρ	f_{yk} (Mpa)	TY	TH	CvC	CoC		
1	30	0	420	15	8	0.02	420	0.0085	0.0365	0.0321	0.0492	0.0125	241.0
2	20	0	420	15	8	0.02	420	0.0105	-	0.0245	0.0350	0.0125	228.2
3	16	0	420	15	8	0.02	420	0.0093	0.0363	0.0212	0.0323	0.0125	222.4
4	30	0.25	420	15	8	0.02	420	0.0112	-	0.0120	0.0141	0.0028	350.1
5	20	0.25	420	15	8	0.02	420	0.0171	-	0.0115	0.0125	0.0032	296.2
6	16	0.25	420	15	8	0.02	420	0.0167	-	0.0112	0.0118	0.0032	236.9
-	-	-	-	-	-	-	-	-	-	-	-	-	-
-	-	-	-	-	-	-	-	-	-	-	-	-	-
42	30	0.25	420	15	8	0.008	420	0.0122	0.0494	0.0141	0.0178	0.0034	191.1
43	30	0.5	420	15	8	0.008	420	0.0165	-	0.0084	-	0.0038	214.0
44	30	0.75	420	15	8	0.008	420	-	-	0.0058	-	0.0030	166.5
45	30	0	420	15	8	0.011	320	0.0061	0.0251	0.0494	0.0918	0.0024	90.5
46	30	0	420	15	8	0.011	220	0.0057	0.0235	0.0630	0.1261	0.0026	63.3
47	30	0.25	420	15	8	0.011	320	0.0087	0.0393	0.0142	0.0159	0.0034	190.7
48	30	0.25	420	15	8	0.011	220	0.0075	0.0311	0.0148	0.0164	0.0028	166.9
49	30	0.5	420	15	8	0.011	320	0.0137	-	0.0083	0.0093	0.0032	214.9
50	30	0.5	420	15	8	0.011	220	0.0104	-	0.0084	0.0094	0.0028	196.7
51	30	0.75	420	15	8	0.011	320	0.0151	-	0.0058	0.0065	0.0030	163.7
52	30	0.75	420	15	8	0.011	220	0.0124	-	0.0059	0.0067	0.0030	157.8

It is seen that yield strength in transverse reinforcement (f_{sh}) has no effect on behavior for all levels of axial load. The spacing of the lateral reinforcement (s) in the confined section is ineffective on behavior at low level of axial load. The maximum moment capacity and ductility increase when spacing of the lateral reinforcement is reduced with increasing axial load. As ductility increases with diameter of transverse reinforcement (\emptyset), it has no very effect on moment capacity. The crushing of core concrete delays with increasing diameter of transverse reinforcement. The diameter of transverse reinforcement becomes effective with the increasing axial load. The quantity of longitudinal reinforcement (ρ) has an important effect on behavior of the confined section. Maximum moment capacity causes increasing 10% due to a the quantity of longitudinal reinforcement variation 30%. The quantity of longitudinal reinforcement has very significant effect on behavior at low level axial load. The moment capacity decreases with the higher axial load. The quantity of longitudinal reinforcement is ineffective on ductility. The yield strength of longitudinal bar (f_{yk}) is effective parameter in case of pure bending. Maximum moment capacity causes changing $\pm 10\%$ due to a yield strength of longitudinal reinforcement variation $\pm 30\%$.

In this study , a neural network program which was written by Karlık *et al.* (17) in PASCAL was used . It is adapted and fitted to our application with some changes. Seven variables for input and six variables for output values were considered in the application. As known, the general aim in the training process is to teach the relations between input and output values to the program and to obtain good answers to different input values with the possible lowest error rates. Input variables are compressive strength of concrete (f_{ck}), load level (N/N_o), yield strength of transverse steel (f_{sh}), spacing of transverse steel (s), diameter of transverse steel (\emptyset), quantity of longitudinal bar (ρ), yield strength of longitudinal bar (f_{yk}). Output variables are yield in tension (TY), hardening of reinforcing in tension (TH), cover crushing (CvC), core crushing (CoC), strain at maximum moment (ϵ) and maximum moment capacity. As it is known, in neural network applications, the input values and output values can be normalized to the values between 0-1.

A neural network system is applied with multi-layer perception feed forward and back-propagation algorithm by supervised training. After some trials with low number of training iterations, it is seen that the best results were obtained with learning rate α of 0.7, and momentum value μ of 0.9. The number of nodes in the hidden layer was changed for new trials. 1000 iterations were performed for each node number between 1 and 0, and the errors were obtained from the program per 100 iterations. The changes in % error values of 1000 iterations due to the number of hidden layer nodes are shown in Fig 5. Finally, the lowest errors were obtained in the order of 7:12:13:6 which means 7 input values, 12 and 13 nodes in hidden layers and 6 output value. Thus, the network architecture would be as in Fig 6

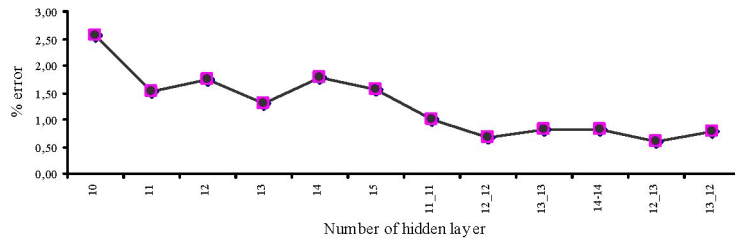


Figure 5. The error changes due to the number of nodes in the hidden layer 1000 iterations.

The training iterations were increased to 5000. So, we obtained as low as 0.07% average errors, which is reasonably good for ANN applications. The

change in errors can be seen in Fig. 7. Then the ANN program is tested with sample values that were not used in the training.

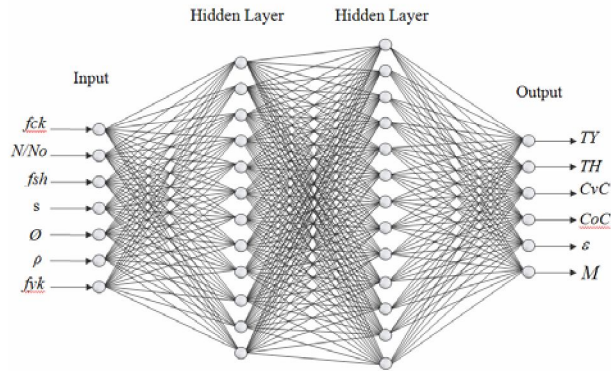


Figure 6. ANN architecture for confined sections

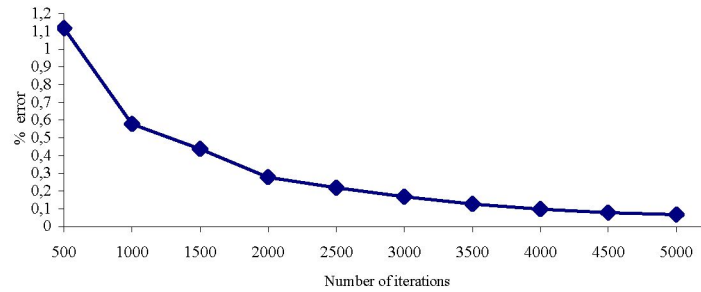


Figure 7. The error change at ANN architecture (7:12:13:6) for confined sections

ANN values of output are compared in Tab. 6. The average error between analytical and ANN ($\frac{|Analytical - ANN|}{ANN}$) is produced less than 0.2 %. The maximum difference (Analytical / ANN) for TY, TH, CvC, CoC, ε and M is about 0.965, 0.978, 1.039, 0.961 , 0.962 , and 0.976 , respectively. From an engineering point of view, these errors are considered low.

Table 6. Training process and results for confined sections

No	Method	TY	Analytical/ ANN	TH	Analytical/ ANN	CvC	Analytical/ ANN	CoC	Analytical/ ANN	ϵ	Analytical/ ANN	M	Analytical/ ANN
1	Analytical	0.00850	1,016	0.03650	0.987	0.03210	1,023	0.04920	1,004	0.01250	1,006	241.00	0.996
	ANN	0.00836		0.03697		0.03139		0.04902		0.01242		241.99	
2	Analytical	0.01050	1,001	-	-	0.02450	1,006	0.03500	0.995	0.01250	0.988	228.20	0.997
	ANN	0.01049				0.02434		0.03516		0.01265		228.86	
5	Analytical	0.01710	1,004	-	-	0.01150	1,027	0.01250	0.977	0.00320	1,005	296.20	1,003
	ANN	0.01702				0.01119		0.01280		0.00318		295.29	
6	Analytical	0.01670	0.999	-	-	0.01120	0.966	0.01180	0.993	0.00320	0.993	236.90	0.995
	ANN	0.01671				0.01159		0.01188		0.00322		238.05	
8	Analytical	0.02640	0.999	-	-	0.00770	1,029	0.00810	0.983	0.00400	1,002	279.20	0.995
	ANN	0.02643				0.00748		0.00824		0.00399		280.52	
9	Analytical	0.02630	1,000	-	-	0.00760	0.996	0.00790	1,023	0.00400	1,000	253.10	1,002
	ANN	0.0263				0.00762		0.00772		0.00400		252.70	
47	Analytical	0.00870	0.966	0.03930	1,011	0.01420	1,031	0.01590	0.969	0.00340	1,018	190.70	0.991
	ANN	0.00900		0.03886		0.01376		0.01641		0.00334		192.42	
48	Analytical	0.00750	1,011	0.03110	0.996	0.01480	1,002	0.01640	0.982	0.00280	0.987	166.90	1,005
	ANN	0.00741		0.03121		0.01476		0.01660		0.00283		166.02	
49	Analytical	0.01370	1,004	-	-	0.00830	0.972	0.00930	1,029	0.00320	1,013	214.90	0.999
	ANN	0.01364				0.00853		0.00909		0.00315		215.06	
50	Analytical	0.01040	0.995	-	-	0.00840	1,022	0.00940	1,018	0.00280	0.984	196.70	1,004
	ANN	0.01045				0.00822		0.00923		0.00284		195.85	
51	Analytical	0.01510	1,005	-	-	0.00580	0.963	0.00650	0.961	0.00300	0.997	163.70	0.994
	ANN	0.01502				0.00602		0.00676		0.00301		164.71	
52	Analytical	0.01240	0.992	-	-	0.00590	0.995	0.00670	0.972	0.00300	1,006	157.80	1,005
	ANN	0.01250				0.00593		0.00689		0.00298		157.09	

The ANN program is tested with sample values that were not used in the training. Different input values were applied to the program for testing the neural network and the results were obtained in milliseconds. A comparison of test and analytical values is given in Tab. 7. The average error $(\frac{|Analytical - ANN|}{ANN})$ obtained is obviously about 0.33%. The maximum difference (Analytical / ANN) for TY, TH, CvC, CoC, ϵ and M is about 0.967, 0.966, 0.972, 0.968, 0.991, and 0.992, respectively. From an engineering point of view, these errors are considered low.

Table 7. Testing process and results for confined sections

No	Method	TY	Analy. / ANN	TH	Analy. / ANN	CvC	Analy. / ANN	CoC	Analy. / ANN	ϵ	Analy. / ANN	M	Analy. / ANN
3	Analytical	0.0093	0.987	0.0363	0.966	0.0212	1.025	0.0323	1.031	0.0125	0.999	222.40	0.992
	ANN	0.0094		0.0375		0.0206		0.0313		0.0125		224.18	
4	Analytical	0.0112	1.014	-	-	0.0120	0.976	0.0141	0.968	0.0028	1.004	350.10	1.005
	ANN	0.0110				0.0122		0.0145		0.0027		348.19	
7	Analytical	0.0251	1.001	-	-	0.0079	0.972	0.0089	1.032	0.0032	0.997	342.40	1.000
	ANN	0.0250				0.0081		0.0086		0.0032		342.33	
12	Analytical	-	-	-	-	0.0048	1.024	0.0059	1.021	0.0036	1.002	173.80	0.994
	ANN	-	-	-	-	0.0046		0.0057		0.0035		174.08	
15	Analytical	0.0082	0.986	0.0337	1.004	0.0390	1.009	0.0646	0.988	0.0100	0.999	135.30	1.008
	ANN	0.0083		0.0335		0.0386		0.0654		0.0100		134.19	
17	Analytical	0.0115	0.992	0.0520	1.012	0.0133	0.979	0.0151	0.975	0.0034	0.991	214.30	0.998
	ANN	0.0115		0.0513		0.0135		0.0154		0.0034		214.79	
24	Analytical	0.0208	0.967	-	-	0.0081	0.978	-	-	0.0038	0.991	222.70	0.992
	ANN	0.0215				0.0082				0.0038		224.44	

4. CONCLUSIONS

In this paper, an alternative numerical and analytical techniques, an ANN algorithm is used in the analysis of infilled frame and confined reinforced section. Neural simulation of numerical and analytical procedure are given in this study. To reduce the calculation time of the microprocessor of system, a new computer program is used by the ANN method, which gives answer in milliseconds. ANN architecture was chosen in which multi layer, feed forward, and back propagation algorithm is used. The training data of infill frame are provided by a finite element model in which non-linearity of materials and the structural interface were taken into account under increasing lateral load. For the inelastic static analysis, an incremental iterative procedure is adopted. Using the proposed analytical model (layered model) are generated the training data for confined reinforced concrete section. Developed model is using layered modeling technique and capable of taking into account; crushing of cover and core concrete, strain hardening of steel and effect of confinement on core concrete. After completing the training phase, verification of the performance of the network was carried out using old (included in training phase) and new (not included in training phase) patterns. The controls conducted in the test phase.

ANN algorithms can not of course replace totally the conventional numerical and analytical techniques, since they need some key values for training. However, in the analysis infilled frame and confined reinforced sections, they can be implemented as an efficient supplementary tool reducing drastically the computational cost. Modeling process in neural network is more direct, since there is no necessity to specify a mathematical relationship between input and output variables. The trained ANN is able to produce quick results in the analysis of infilled frame and confined reinforced section with the same degree of accuracy as numerical and analytical model. Therefore, the trained ANN may be used in practice for the design of infilled frame and confined cross section as an alternative to the time consuming numerical and analytical procedure.

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