Structural Engineering Applications of Artificial Neural Networks

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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.

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

1. INTRODUCTION

The mathematical models have been widely applied for the analysis of infilled frame. Holmes M (1961) 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 (1962), the approach of diagonal compression strut was dealt with in a more detailed way. Using a finite element model, Mallick DV and Severn RT (1967) attained the results without considering the shear effect on the infill frame interface. With a program they prepared. Infilled planar frames have been analysed using artificial neural network by Bağcı and Altintaş (2006). The layered model for confined reinforced sections was first used by Pavriz et al (1991). Moment-curvature relationships of confined concrete sections were investigated by Ersoy U and Özcebe G (1997). For some other examples of ANN applications, the reader is referred to (Jadid MN and Fairbairn DR (1996), Lee et al (1992), Avdelas et al (1995), Karlık et al (1998).

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. PARAMETRIC STUDIES

Dimensions of infilled frame given by Fiorato AC and Sözen M (1973) 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.

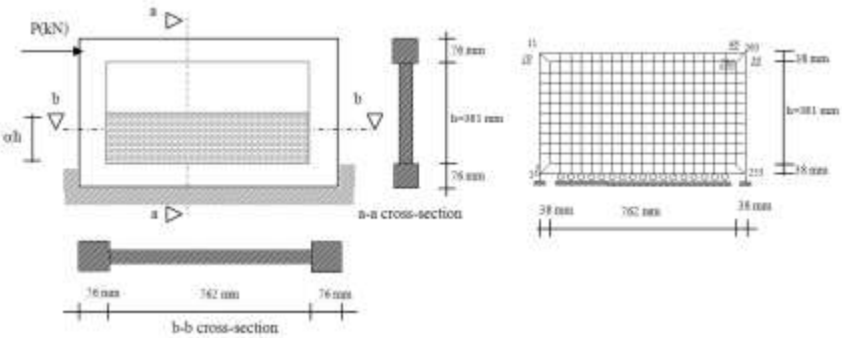

Figure 1a. Frame-infill wall 1b. Mesh model of with full infill wall

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 (α=1, α=0.8, α=0.6, α=0.4, α=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
	.	.	.	.		.	.	.	.
	.	.	.	.		.	.	.	.

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. 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.

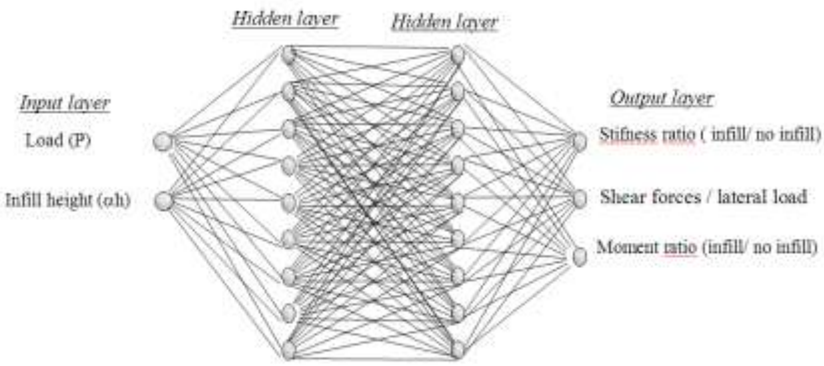

Figure 2. Network Architecture for infilled frame

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	1.01.91
		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	

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.

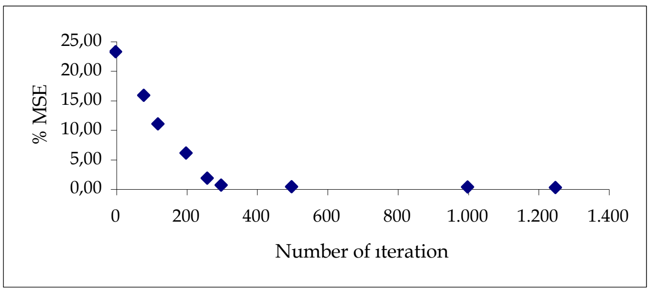

Figure 3. Mean Square Errors (MSE) based on iteration numbers for infilled frame

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
	20	FEM	5,65700	1.0021	0,19000	1.0215	0,19000	0.9938
		ANN	5,64500		0,18600		0,19120	
	60	FEM	5,18800	0.9937	0,19500	0.9898	0,21400	1.0028
		ANN	5,22100		0,19700		0,2134	
h	100	FEM	4,1140	0.9669	0,27000	0.9953	0,32600	1.0316
		ANN	4,2550		0,27130		0,31600	
	140	FEM	3,73100	1.0138	0,31000	1.0038	0,38000	1.0190
		ANN	3,68000		0,3088		0,37290	
	180	FEM	3,54200	1.0022	0,35000	1.0043	0,41400	0.9998
		ANN	3,53400		0.3485		0,41485	

The average % error ($\sum \frac{|FEM - ANN| / ANN}{number\, of\, output}$) 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.

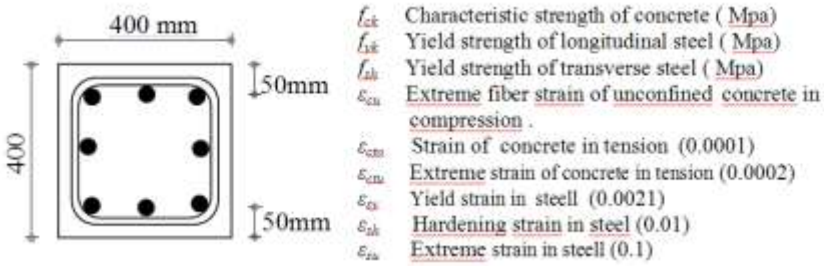

Figure 4. The cross-section considered in analyses.

Variables selected to incorporate in the expression of moment-curvature are compressive strength of concrete (fck), the ratio of the axial load to the axial load capacity (N/No), yield strength in transverse reinforcement (fsh), space of transverse reinforcement (s), diameter of transverse reinforcement (Ø), ratio of longitudinal steel (ρ), yield strength of longitudinal steel (fyk) 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 (fck) in case of pure bending (N=0). The compressive strength becomes effective with increasing axial load. Maximum moment capacity shows changes of ±25% due to ±25% compressive strength variation. The increasing compressive strength causes the decrease in ductility.

As level of the axial load (N/No) 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

Variable properties								Curvature (rad/m)				ε_{cu}	M (kN-m)
No	f_{ck} (Mpa)	N/N_o (N)	f_{sh} (Mpa)	s (cm)	Ø (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 (fsh) 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 (Ø), 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 (fyk) is effective parameter in case of pure bending. Maximum moment capacity causes changing ±10% due to a yield strength of longitudinal reinforcement variation ±30%.

In this study , a neural network program which was written by Karlık et al. (1998) in PASCAL was used . Seven variables for input and six variables for output values were considered in the application. As it is known, in neural network applications, the input values and output values can be normalized to the values between 0-1. 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 chances 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

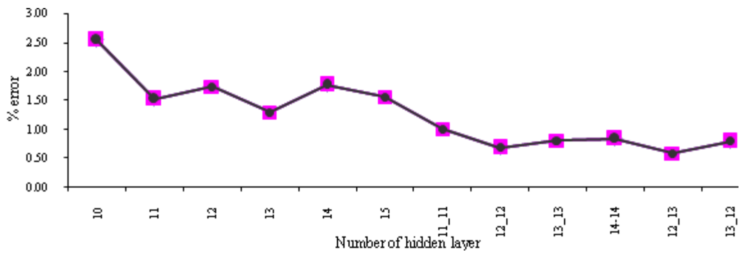

Figure 5. The error changes due to the number of nodes in the hidden layer 1000 iterations.

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..

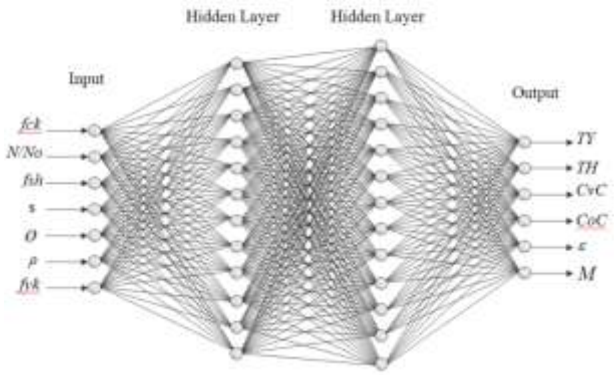

Figure 6. ANN architecture for confined sections

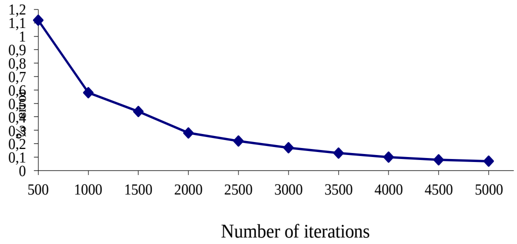

Figure 7. The error change at ANN architecture (7:12:13:6) for confined sections

ANN values of output are compared in Tab. 6. The average error between analytical and ANN ($\dfrac{|Analytical - ANN|/ANN}{number of\ solution}$) 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 1	ε	Analytical/ ANN	M	Analytical/ ANN
1	Analytical ANN	0.00850 0.00836	1,016	0.03650 0.03697	0,987	0.03210 0.03139	1,023	0.04920 0.04902	1,004	0.01250 0.01242	1,006	241.00 241.99	0,996
2	Analytical ANN	0.01050 0.01049	1,001	- -	-	0.02450 0.02434	1,006	0.03500 0.03518	0,995	0.01250 0.01265	0,988	228.20 228.86	0,997
5	Analytical ANN	0.01750 0.01702	1,004	- -	-	0.01150 0.01119	1,027	0.01250 0.01280	0,977	0.00320 0.00318	1,005	296.20 295.29	1,063
6	Analytical ANN	0.01670 0.01671	0,999	- -	-	0.01120 0.01159	0,966	0.01180 0.01188	0,993	0.00320 0.00322	0,993	236.90 238.05	0,995
8	Analytical ANN	0.02640 0.02643	0,999	- -	-	0.00770 0.00748	1,029	0.00810 0.00824	0,983	0.00400 0.00399	1,002	279.20 280.52	0,995
9	Analytical ANN	0.02630 0.0263	1,000	- -	-	0.00760 0.00762	0,996	0.00790 0.00772	1,023	0.00400 0.00400	1,000	253.10 252.70	1,002
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47	Analytical ANN	0.00870 0.00900	0,966	0.03930 0.03886	1,011	0.01420 0.01376	1,031	0.01590 0.01641	0,969	0.00340 0.00334	1,018	190.70 192.42	0,991
48	Analytical ANN	0.00750 0.00741	1,011	0.03110 0.03121	0,996	0.01480 0.01476	1,002	0.01640 0.01660	0,982	0.00280 0.00283	0,987	166.90 166.02	1,005
49	Analytical ANN	0.01370 0.01384	1,004	- -	-	0.00830 0.00853	0,972	0.00930 0.00909	1,029	0.00320 0.00315	1,013	214.90 215.06	0,999
50	Analytical ANN	0.01040 0.01045	0,995	- -	-	0.00840 0.00822	1,022	0.00940 0.00923	1,018	0.00280 0.00284	0,984	196.70 195.85	1,004
51	Analytical ANN	0.01510 0.01502	1,005	- -	-	0.00580 0.00602	0,963	0.00650 0.00676	0,961	0.00300 0.00301	0,997	163.70 164.71	0,994
52	Analytical ANN	0.01240 0.01250	0,992	- -	-	0.00590 0.00593	0,995	0.00670 0.00689	0,972	0.00300 0.00298	1,006	157.80 157.09	1,005

A comparison of test and analytical values is given in Tab. 7. The average error ($\dfrac{|Analytical - ANN|/ANN}{number of\ solution}$) 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 ANN	0.0093 0.0094	0.987	0.0363 0.0375	0.966	0.0212 0.0206	1.025	0.0323 0.0313	1.031	0.0125 0.0125	0.999	222.40 224.18	0.992
4	Analytical ANN	0.0112 0.0110	1.014	- -	-	0.0120 0.0122	0.976	0.0141 0.0145	0.968	0.0028 0.0027	1.004	350.30 348.19	1.005
7	Analytical ANN	0.0251 0.0250	1.003	- -	-	0.0079 0.0081	0.972	0.0089 0.0086	1.032	0.0032 0.0032	0.997	342.40 342.33	1.000
12	Analytical ANN	- -	-	- -	-	0.0048 0.0046	1.024	0.0059 0.0057	1.021	0.0036 0.0035	1.002	173.80 174.08	0.994
15	Analytical ANN	0.0082 0.0083	0.986	0.0337 0.0335	1.004	0.0390 0.0386	1.009	0.0646 0.0654	0.988	0.0100 0.0100	0.999	135.30 134.19	1.008
17	Analytical ANN	0.0115 0.0115	0.992	0.0520 0.0513	1.012	0.0133 0.0135	0.979	0.0151 0.0154	0.975	0.0034 0.0034	0.991	214.30 214.79	0.998
24	Analytical ANN	0.0208 0.0215	0.967	- -	-	0.0081 0.0082	0.978	- -	-	0.0038 0.0038	0.991	222.70 224.44	0.992

4. CONCLUSION

In this paper, an alternative numerical and analytical technique, an ANN algorithm is used in the analysis of infilled frame and confined reinforced section. Neural simulation of numerical and analytical procedure is 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 on alternative to the time consuming numerical and analytical procedure.

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