STRENGTH AND DEFORMATION CAPACITY OF STRUCTURAL ELEMENTS UNDER HORIZONTAL LOADING

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ABSTRACT :

Understanding the behavior of structural elements under in-plane horizontal loading is essential for any performance based design procedure. That applies especially to columns and walls as main lateral load resisting elements. There are many parameters that influence the prediction of the elements behavior, especially at the ultimate stage. The outlined problem presents an ideal example where neural networks (artificial intelligence) can be used.

An extensive library of tested columns and walls has been collected. Work on that database considers devising a protocol of presenting the research data in the performance form. The relationship between qualitative performance description and engineering parameters that can be considered in design has been established. The use of neural networks, taught on the collected data base, enables development of improved procedures for assessment of strength and deformation capacities of the columns and walls at all performance levels. It enables prognostic behavior of the lateral load resisting elements under horizontal in-plane loading. The element geometry and material data are used for input and performance behavior of the elements is obtained as the output of such an expert system that can be used as problem solver.

The work on the collected data base increases the understanding of element behavior, their performance at various demand levels and eliminates complicated detailing that were encouraged by lack of knowledge. That is in direct support of development a multi level performance design methodology for structural systems.

KEYWORDS: Neural networks, Performance based design procedure, Seismic capacity, Reinforced concrete columns and walls, Experimental database;

1. INTRODUCTION

Civil and structural engineers, in their attempt to improve the analysis, design and control of the behavior of both built and natural systems have shown much interest in the modeling of the behavior of physical processes. Since the behavior of reinforced concrete columns and walls with nonhomogeneous, nonisotropic and nonlinear material under a multiaxial state of stress may be difficult to establish theoretically, test data are often used to develop empirical and semi empirical approaches. The quantitative determination of strength and performance capability of structural elements is of vital importance for the vulnerability assessment of existing buildings as well as for effective performance based design of earthquake resistant new buildings.

The work was motivated due to a great deal of uncertainty in the estimation of the seismic capacity of wall and frame structures. In spite of extensive experimental studies there is still a lack of understanding about the dependence of observed behavior on variables such as cross-sectional shape, amount of vertical and horizontal reinforcement, axial compression, loading histories, etc. Evaluation of performance capability of walls and columns based on the stress-strain properties of material does not easily represent true behavior due to many unknown parameters (bond-slip of reinforcement, crushing and spalling of concrete, etc.). Empirical approach seems to be more appropriate, as many unpredictable parameters are included in the closed form empirical expressions. However, a comparative study of various models will often show that the models are effective only to interpret their own experimental results or data used.

Non-linear response of reinforced concrete (RC) is caused by cracking, plastic deformations in compression and crushing of the concrete and plastic deformations of the reinforcement. Other, usually less important, time-independent non-linearity arises from bond slip between steel and concrete, aggregate interlock of cracked concrete and dowel action. Many mathematical models for non-linear finite element (FE) analysis of reinforced concrete structures were proposed. A number of computer programs are also available for non-linear analysis of reinforced concrete. The constitutive models and plasticity models used in these programs, however, are different, and it is generally not straightforward to apply these models. Some of the input parameters are fictive and need an adjustment.

On the other hand, inherent in the concept of Performance Levels and Ranges is the assumption that performance can be measured using analytical results such as story drift ratios or strength and ductility demands on individual components or elements. To enable structural verification at the selected Performance Level, stiffness, strength, and ductility characteristics of many common elements and components have to be derived, from laboratory tests and analytical studies, and put in a standard format.

Because of that, the intended aim of this study is to explore the feasibility of using neural network in predicting the performance capability of specific vertical structural elements, which have a very favorable lateral load resistance. Over 100 experimental test results were collected from the literature of rectangular and spiral reinforced concrete columns as well as of nearly 300 reinforced concrete walls, all tested under concentric horizontal loading. A multilayer functional link neural network was used for training and testing the experimental data. It was found that the neural network model could reasonably capture the underlying behavior of confined reinforced concrete columns and walls, because it provided instantaneous result once it is properly trained and tested.

2. NEURAL NETWORKS

Neural networks, as part of the field of artificial intelligence, have nowadays quite extensive usage in scientific research as well as in a broad range of practical applications, including classification, pattern recognition, function approximation, optimization, prediction, evaluation of state and automatic control. An artificial neural network consists of a number of processing elements, logically arranged into two or more layers and interacts with each other via weighted connections to constitute a network. The remarkable computational characteristics of neural networks are their ability to learn functional relationships from training examples and to discover patterns and regularities in data through self-organization. Applied software package was “NeuroShell2” Ward System Co [1]. Using NeuroShell2 software program, we created operable problem solving application called neural network (NN) without programming in order to predict the behavior of reinforced concrete structural columns and walls subjected to horizontal loading. The neural network has been trained through learning on the example patterns.

2.1. Neural Network Architecture

Experimental database used in the study was compiled from the available literature and includes data from laboratory tests carried out on reinforced concrete walls and columns. Work on that database considers devising a protocol of presenting the research data in the performance form. Relationship between qualitative performance description and engineering parameters considered in design is established. The inputs of the created neural networks are geometrical and material properties, reinforcement ratios and loading. Output variables are those, which have an important role in performance evaluation, like drift (δ), displacements (d), shear strength (V) and mode of failure. A set of neural networks were devised and tested until the output results satisfied the set up quality criteria, and the one that gave best overall results was used later on.

The learning process primarily involves the determination of connection weight matrices and the pattern of the connections, and application of the learning rule that the neural network obtains the desired relationship embedded in the training data. Analyzing the various training patterns, we have selected the type and neural network architecture that gave the best estimation results. We also analyzed the influence of database arrangement on the estimation of results. Finally, back propagation network architecture with multiple hidden slabs and different activation functions was chosen (Figure 2.1).

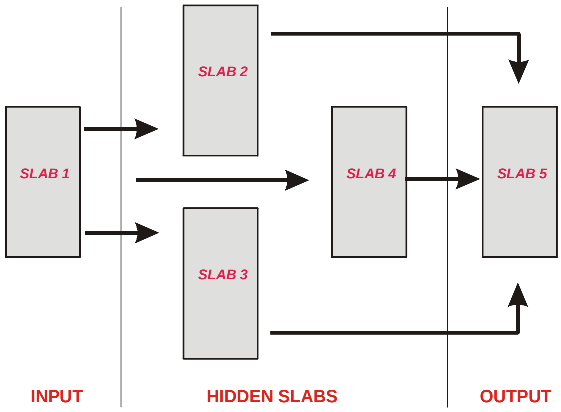

Figure 2.1 Neural network architecture scheme

3. APPLICATION OF NEURAL NETWORK TO RC COLUMNS

3.1. The experimental database

The database used in this study includes data from the PEER Structural Performance Database. This database builds on previous work at the National Institute of Standards and Technology. The original NIST database described 107 tests of rectangular reinforced columns and 92 tests of spiral-reinforced concrete columns; for this research, we have used 91 rectangular columns and 30 spiral-reinforced [6].

3.1.1. Input variables

Based on theoretical background and available database, the following variables were chosen as input variables influencing structural columns behavior subjected to in plane horizontal loading:
f_c - characteristic compressive strength of concrete (MPa), P - axial load (kN), B - column width (mm), H - column depth (mm), L - length of equivalent cantilever (mm), ϕ_L- diameter of longitudinal reinforcement bars (mm), n_L- number of longitudinal reinforcement bars, a - clear cover (mm), ρ_l - longitudinal reinforcement ratio, f_{yl} - yield stress of longitudinal reinforcement(MPa), ϕ_T- bar diameter of transverse reinforcement (mm), ρ_t - transverse reinforcement ratio, f_{yt} - yield stress of transverse reinforcement (MPa).

3.1.2. Output variables

The following variables were chosen as output variables describing structural columns behavior subjected to in plane horizontal loading:
F_y - yield shear force, d_y - yield displacement, F_u - ultimate shear force, d_u - ultimate displacement, Failure type (F - flexure 1; S - shear 2; flexure - shear 3).

3.2. Neural networks training models

We used a regular three-layer back propagation network with two slabs in the hidden layer. Input variables are in slab 1 with 13 neurons. Hidden slabs 2, 3 and 4, had 5 neurons each. Output variables are in element 5. For every output variable, we created one neural network. The network learning rate (the amount of weight modification) was set to 0,1, momentum factor (the proportion of the last weight change that is added into the new weight change) was set to 0,1, while the initial weights (describing connection strengths between the neurons) were set to 0,3. The network randomly chooses the training patterns. Missing data values were replaced using average of the minimum and maximum values. We used a 20% production set to test the network's results with data the network has never "seen" before. The remainder of the pattern file (80%) formed a training set.

Table 3.1 Neural network training models overview

Neural network	*Number of examples*	*Column type*	*Complete input variables*	*Number of inputs*	*Outputs*
NN-01-C	121	R, S	complete	13	Fy
NN-02-C	121	R,S	complete	13	dy
NN-03-C	121	R,S	complete	13	Fu
NN-04-C	121	R,S	complete	13	du
NN-05-C	121	R,S	complete	13	Failure type

3.3. Test examples

The selected test columns geometrical and material properties are shown in Table 3.2 and on Figure 3.1.

Table 3.2 Test columns geometrical and material properties (input variables)

Test Columns	*1 (RO)*	*2 (RI)*	*3 (R)*	*4 (RI)*	*5 (R)*	*6 (RI)*
Specimen name	*10*	*20*	*40*	*60*	*90*	*4*
f'c (MPa)	40,00	25,60	19,80	115,80	29,20	23,50
P (kN)	1920,00	819,00	406,00	1176,00	267,00	4265,00
B (mm)	400,00	400,00	160,00	200,00	305,00	550,00
H (mm)	400,00	400,00	160,00	200,00	305,00	550,00
L (mm)	1600,00	1600,00	1600,00	500,00	1676,00	1200,00
ϕ_L (mm)	16,00	20,00	9,50	12,70	22,00	24,00
n_L	12,00	8,00	8,00	12,00	4,00	12,00
a (mm)	13,00	40,00	12,50	9,00	32,00	38,00
ρ_l	0,0151	0,0157	0,0222	0,0380	0,0163	0,0179
f_{yl} (MPa)	446,00	474,00	341,00	399,60	367,00	375,00
ϕ_T (mm)	6,00	12,00	5,00	6,00	9,50	12,00
ρ_t	0,0057	0,0255	0,0073	0,0161	0,0154	0,0350
f_{yt} (MPa)	255,00	333,00	559,00	328,40	363,00	294,00

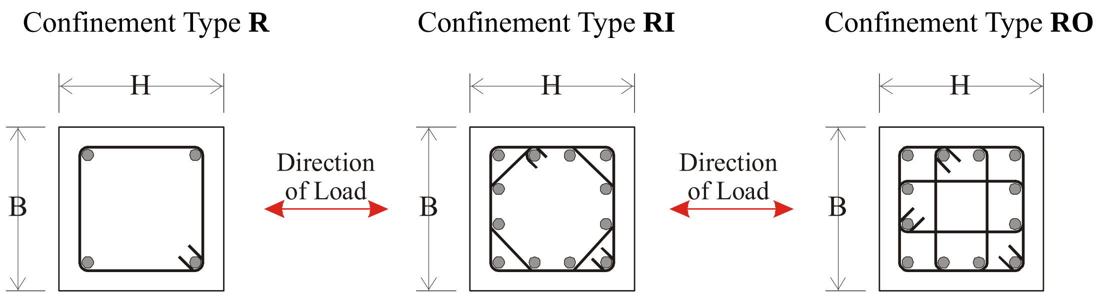

Figure 3.1 Test columns geometrical properties and confinement types

3.4. Test results

The quality of chosen neural network is tested on the columns left out from the original database. The prediction and experimental data were reasonably close, as we can see at following figures.

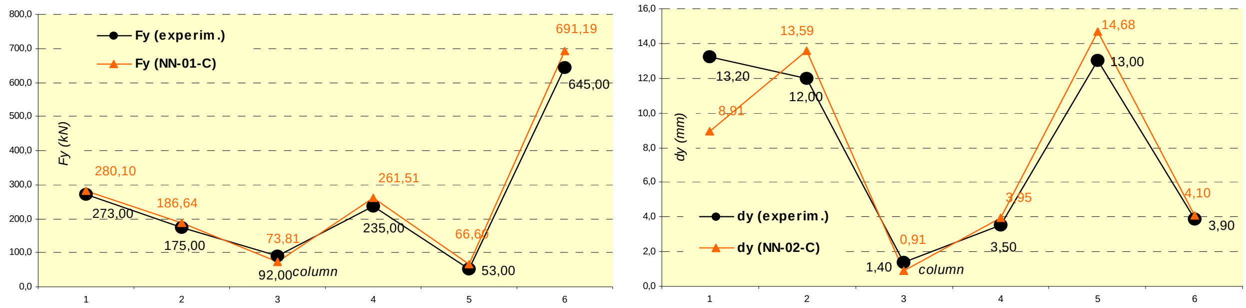

Figure 3.2 Comparison of experimental results and network's prediction for F_y and d_y

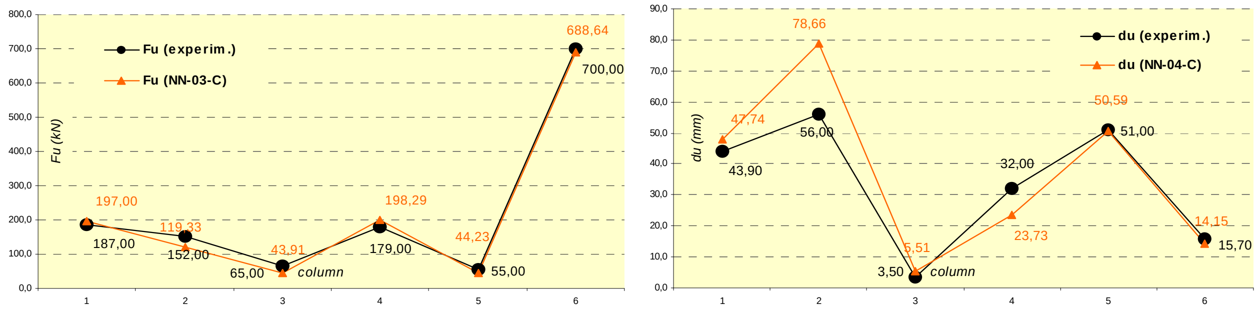

Figure 3.3 Comparison of experimental results and network's prediction for F_u and d_u

The figure 3.4 shows the comparison between experimentally acquired force displacement histories for tested columns and the force displacement primary curve obtained using neural network.

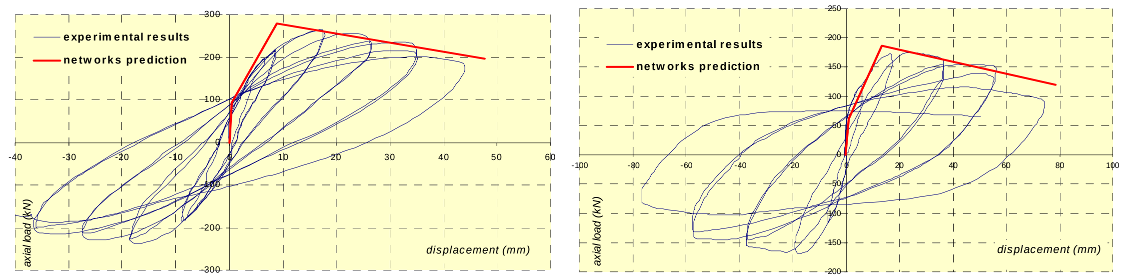

Figure 3.4 Comparison of networks prediction and force-displacement history of column 1 and 2

4. APPLICATION OF NEURAL NETWORK TO RC WALLS

4.1. The experimental database

The database used in this study includes data from laboratory tests carried out on 285 reinforced concrete walls. All test specimens were isolated walls fixed at the base. Test walls with rectangular (R), barbell (B) and flanged cross-sections (F) were subjected to either monotonic or various cyclic horizontal loading regimes. The measured response variables are maximum shear force (V_{max}), drift index (ratio of maximum top displacement to the height of the wall) and failure type (S-shear and F-flexural failure). It should be pointed out that for a number of tests the available data were incomplete – so, the original database had to be reduced and rearranged in form suitable for the neural network.

4.1.1. Input variables

Based on theoretical background and available database, the following variables were chosen as input variables influencing structural wall behavior subjected to horizontal loading:
1.) L-type of loading: A (1) - alternating, R (2) - repeated: specimen is loaded in one direction, unloaded, and reloaded in the same direction, M (3) - monotonic: specimen is loaded in one direction to failure, C (4) - cyclic: alternating or repeated; 2.) S-cross section type: R(1) – rectangular, B (2) – barbell, F (3) – flanged; 3.)(ρ_s) - ratio of confinement reinforcement effective volume in boundary element to the volume of the core; 4.) f_{ys} - yield stress of confinement reinforcement in boundary element; 5.)(ρ_b) – ratio of longitudinal reinforcement in boundary element; 6.) f_{ybe} - yield stress of longitudinal reinforcement in boundary element; 7.) rhov (ρ_v) - ratio of distributed vertical web reinforcement in wall; 8.) f_{yv} - yield stress of distributed vertical web reinforcement; 9.)(ρ_h) - ratio of distributed horizontal web reinforcement in wall; 10. f_{yh} - yield stress of distributed horizontal web reinforcement; 11.) b_e - thickness of the wall web; 12.) b_f - width of boundary element; 13.) h_f - length of boundary element; 14.) L_w - length of the wall; 15.) f_c - concrete cylinder compressive strength; 16.) I - moment of inertia; 17.) P/A - axial stress in the wall.
Particular input variables having some kind of functional interdependence have been left out in order to increase the effectiveness of neural networks to be trained: *A_{be} - cross-section area of boundary element, A_{web} - cross-section area of wall web, A_{cw} - cross-section area of wall, and steel areas A_{sbe} i A_{swv} , h_w – wall height.*

4.1.2. Output variables

The following variables were chosen as output variables describing structural walls behavior subjected to horizontal loading:
1.) V_{max} (maximum shear force); 2.) u_{max} / h_w (drift index); 3.) Failure type (F – flexure 1; S - shear 2).

4.2. Neural networks training models

First, test walls with too many missing input variables were left out, reducing the database to 197 examples. Secondly, we have reduced the number of input variables to 17 by leaving out the variables showing no significant influence on output results as well as variables having functional interdependence. Thus, number of input variables was reduced to 17. Using back propagation network architecture, the results were better with only one output variable. So, for each output variable, we created one neural network. Overview of the created networks regarding wall types, number of examples and data completeness is given in Table 4.1.

Finally, there were 17 input variables describing particular wall geometrical and material properties while the output variable in neural networks NN-1 to NN-8 was maximum shear force V_{max}, in NN-9 output was failure type and in NN-10 – drift index.

Table 4.1 Neural network training models overview

Neural Network	*Number of examples*	*Wall type*	*Complete input variables*	*Number of inputs*	*Outputs*
NN-01-W	197	R, B, F	incomplete	17	V max
NN-02-W	86	R, B, F	complete	17	V max
NN-03-W	27	R	incomplete	17	V max
NN-04-W	11	R	complete	17	V max
NN-05-W	135	B	incomplete	17	V max
NN-06-W	54	B	complete	17	V max
NN-07-W	35	F	incomplete	17	V max
NN-08-W	20	F	complete	17	V max
NN-09-W	178	R, B, F	incomplete	17	Failure type
NN-10-W	142	R, B, F	incomplete	17	Drift

We used a regular three-layer back propagation network with two slabs in the hidden layer. Input variables are in slab 1 with 17 neurons. Hidden slabs 2, 3 and 4, had 7 neurons each. Output variables are in element 5. Thus, each of the 17 input variables is connected, through 21 neurons in both hidden slabs, to the output variables. Different activation functions were applied to hidden layer slabs in order to detect different features in a pattern processed through a network: *Gaussian function* on elements 2 and 4, *tanh* on element 3 and finally, on output layer it is a *logistic function*. All other neural network-training parameters are the same as in the neural network used for the structural columns database.

4.3. Test examples

Once the network is trained, it could be used for prediction of wall seismic performance. Network quality is checked against the independent data network has never seen before. The selected test walls geometrical and material properties are shown on Figure 4.1 and in Table 4.2.

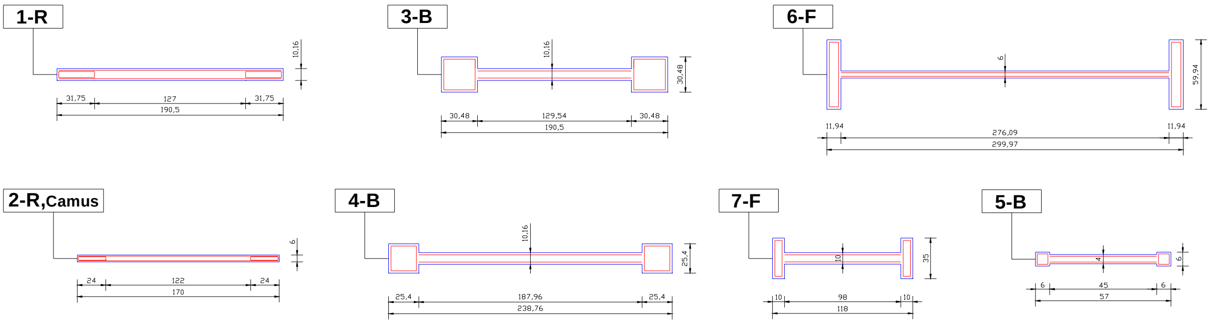

Figure 4.1 Cross-sections of the tested structural walls

Table 4.2 Test walls geometrical and material properties (input variables)

Wall type	***1 (R)***	***2 (R) Camus***	***3 (B)***	***4 (B)***	***5 (B)***	***6 (F)***	***7 (F)***
Shape	1	1	2	2	2	3	3
Loading	1	1	1	1	3	1	3
rhos (%)	0,68	0,32	1,35	1,70	0,51	0,84	1,18
fys (kN/m2)	472997	547333	464034	570906	293727	275800	574354
rhobe (%)	2,40	2,01	1,97	3,52	4,70	0,82	1,13
fybe (kN/m2)	476445	547333	442659	501267	293038	370951	574354
rhov (%)	0,28	0,22	0,29	0,83	0,92	0,45	1,13
fyv (kN/m2)	472997	563000	464034	506093	294417	276490	574354
rhoh (%)	0,42	0,32	0,63	0,83	0,92	0,45	0,57
fyh (kN/m2)	472997	563000	464034	506093	294417	275800	537121
f'c (kN/m2)	23305	39600	45645	34475	42563	23691	35626
P/A (kN/m2)	233,05	1779,90	3925,32	2723,53	8,96	2129,87	2493,92
I (cm4)	5853938	2456500	13880482	20378627	77878	40220618	2830788

4.4. Test results

By comparing the experimental wall result with the estimations for maximum shear force V_{max} given by the neural networks NN-01 to NN-08, the best match was achieved with the prediction of NN-01. The NN-01 is the network with incomplete input data for particular walls and uses all three (R, B, F) wall cross-sectional shapes. However, the networks NN-02 to NN-08 gave good predictions too, but only for particular wall cross-section on which the training was carried out. Therefore, the NN-01 neural network was used to estimate the failure type (NN-09) and drift index (NN-10) and good results were obtained.

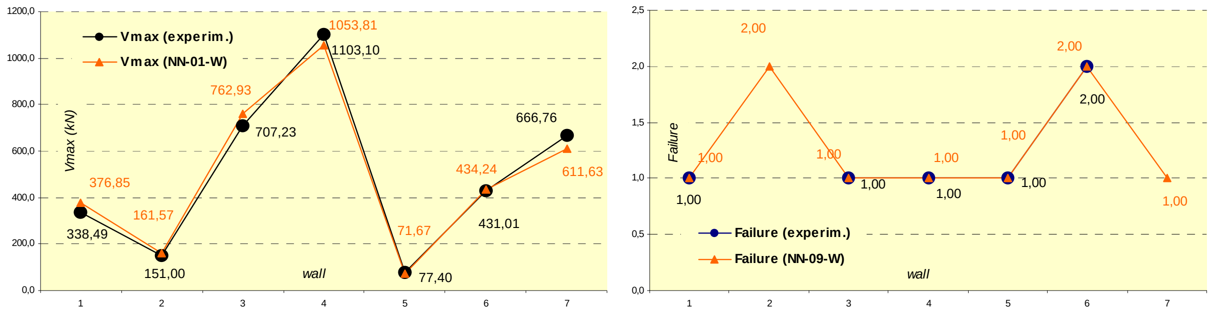

Figure 4.2 Comparison of experimental results and network's prediction for V_{max} and Failure type

5. CONCLUSION

Understanding of the true behavior of structural elements is essential for any performance based design procedure. This study has demonstrated the application of neural network techniques to predict the complicated behavior of RC columns and walls, basing its entire process on a set of examples presented to the network. The use of neural networks in structural elements behavior evaluation under in-plane horizontal loadings can be two-folded:

1. For evaluation of the element capacity when its geometry and material data are known and performance behavior is required;
2. Performance ideal is set and geometry and strength of the elements is required.

The advantages of neural network are in their ability to learn on the vast experimental database. Therefore, they constantly consider all variables influencing performance in real structures but are difficult to take numerically into account. In addition, contribution of various variables can be analyzed and how they influence the respective performance criteria. The results of performance predictions achieved by the neural networks are compared with independent experimental results. They showed good accuracy of the obtained predictions implying a reliable applicability of neural networks. The quality of the prediction depends mainly on the quality of the database. In principle, any number of input parameters (which are contained in the database) can be used. By increasing the size of the databases and by introducing new input parameters, new trends may be revealed, studied and incorporated in the mathematical models.

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