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SEICMIC CAPACITY OF STRUCTURAL ELEMENTS USING NEURAL NETWORKS

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SUMMARY

This paper presents the applicability of neural networks trained on the compiled experimental database to predict the seismic capacity of reinforced concrete walls and columns. The best built network is used for prediction of the behavior of new elements.
Use of neural networks enables dependence analysis of observed behavior on different variables and simplifies behavior prediction of building elements under seismic loadings. It could be used for comparison with other methods for performance prediction of critical horizontal load carrying elements.
For the seismic capacity evaluation required input for walls and columns is: type of loading, dimension and type of cross section, material properties and reinforcement. They are fed to the neural network trained on the experimental database and as output variables we get prognosis of: shear strength, failure type, critical loads and displacements. The whole procedure, input data, optimized neural network model and output variables are implemented in one worksheet.

INTRODUCTION

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 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 column 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. This empirical

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approach is commonly used in Japan but its applicability to the walls and columns used in other part of the world is questionable.

The main goal of this paper is to make a contribution towards the quantitative determination of the performance capability of specific vertical structural elements, which have a very favorable lateral load resistance. Their performance, expressed in terms of shear strength and deformation capacity is of vital importance for the evaluation of the seismic performance of existing buildings as well as for the design of new earthquake resistant reinforced concrete buildings [3].

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. 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 walls subjected to horizontal loading. The neural network has been trained through learning on the example patterns.

Neural network architecture

Experimental data base 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 that can be 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.
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, backpropagation network architecture with multiple hidden slabs and different activation functions was chosen (Figure 1).

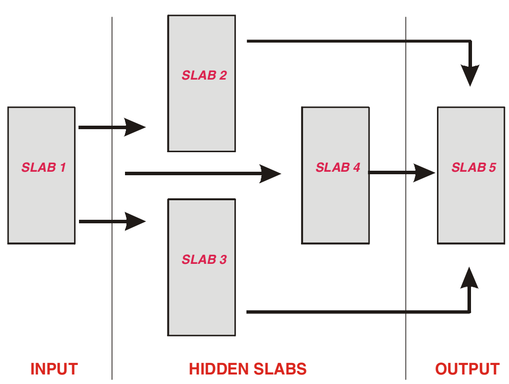

Figure 1. Neural network architecture scheme

PREDICTION OF WALL SEISMIC PERFORMANCE

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.

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.) rhos (ρ_s) - ratio of effective volume of confinement reinforcement in boundary element to the volume of the core,
4.) f_{ys} - yield stress of confinement reinforcement in boundary element,
5.) rhobe (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.) rhoh (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 - height of the walls.

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).

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 backpropagation network architecture, the results were better with only one output variable. So, for every and 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 1.

Table1. Neural network training models overview

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

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.

We used a regular three-layer backpropagation 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. 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 values in our data are 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.

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 2 and in Table 2.

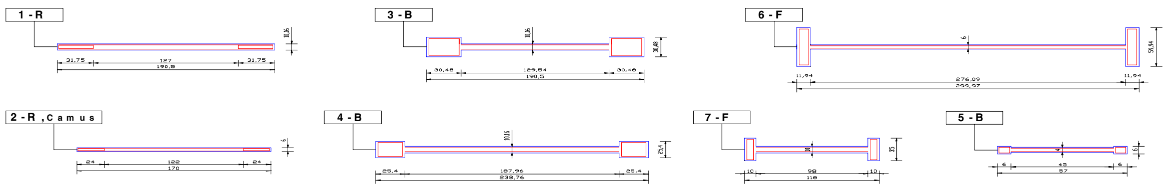

Figure 2. Cross-sections of the tested structural walls

Table 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

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.

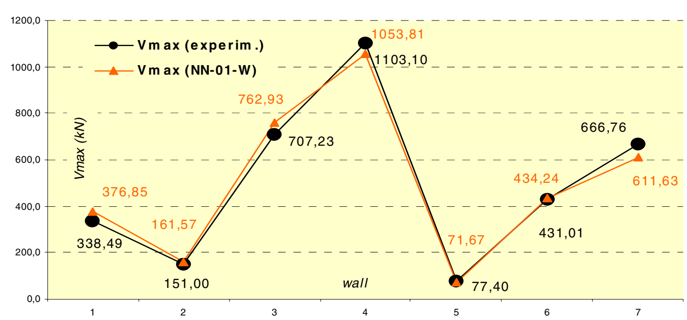

Figure 3. Comparison of experimental results and NN-01-W network's prediction for V_{max}

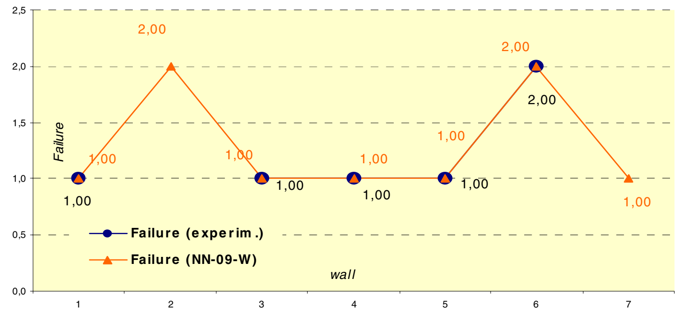

Figure 4. Comparison of experimental results and NN-09-W network's prediction for failure type

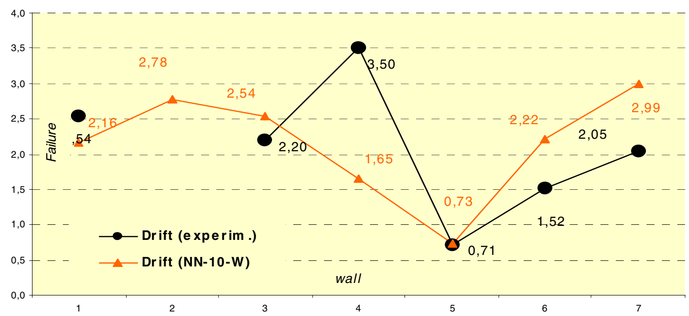

Figure 5. Comparison of experimental results and NN-10-W network's prediction for drift

PREDICTION OF COLUMN SEISMIC PERFORMANCE

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 [6].

Input variables

Based on theoretical background and available database, the following variables were chosen as input variables influencing structural columns behavior subjected to horizontal loading:
1.) f_c - characteristic compressive strength of concrete (MPa),
2.) P - axial load (kN),
3.) B - column width (mm)
4.) H - column Depth (mm)
5.) L - length of equivalent cantilever
6.) ϕ_L- diameter of longitudinal reinforcement bars (mm)
7.) n_L- number of longitudinal reinforcement bars
8.) a - clear cover
9.) rhol - longitudinal reinforcement ratio
10.) fyl - yield stress of longitudinal reinforcement(MPa)
11.) ϕ_T - bar diameter of transverse reinforcement (mm)
12.) rhot - transverse reinforcement ratio
13.) fyt - yield stress of transverse reinforcement

Output variables

The following variables were chosen as output variables describing structural columns behavior subjected to horizontal loading:

1.) Fy - yield shear force
2.) dy - yield displacement
3.) Fu - ultimate shear force
4.) du - ultimate displacement
5.) Failure type (F - flexure 1; S - shear 2; flexure - shear 3).

Neural networks training models

We used a regular three-layer backpropagation 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. All other neural network training parameters are the same as in the neural network used for the structural walls database.

Table 3. Neural network training models overview

Neural Networks	*Number of examples*	*Column type*	*Complete input variables*	*Number of inputs*	*Outputs*
NN-01-C	91	R	complete	13	Fy
NN-02-C	91	R	complete	13	dy
NN-03-C	91	R	complete	13	Fu
NN-04-C	91	R	complete	13	du
NN-05-C	91	R	complete	13	Failure type

Test examples

The selected test columns geometrical and material properties are shown in Table 4 and on Figure 6.

Table 4. Test columns geometrical and material properties (input variables)

Test Columns	***1 (RO)***	***2 (RJ)***	***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	160,00	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
rhol	0,0151	0,0157	0,0222	0,0380	0,0163	0,0179
fyl (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
rhot	0,0057	0,0255	0,0073	0,0161	0,0154	0,0350
fyt (Mpa)	255,00	333,00	559,00	328,40	363,00	294,00

Confinement Type **R** Confinement Type **RI** Confinement Type **RO**

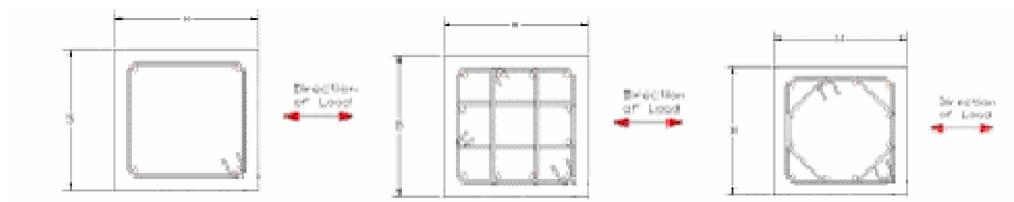

Figure 6. Test columns geometrical properties and confinement types

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 figure.

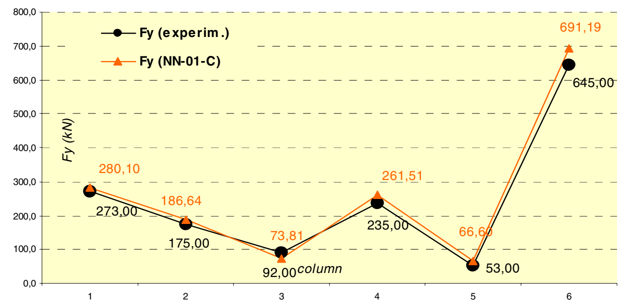

Figure 7. Comparison of experimental results and NN-01-C network's prediction for F_y

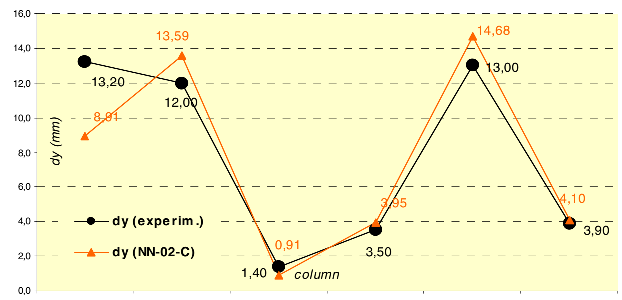

Figure 8. Comparison of experimental results and NN-02-C network's prediction for d_y

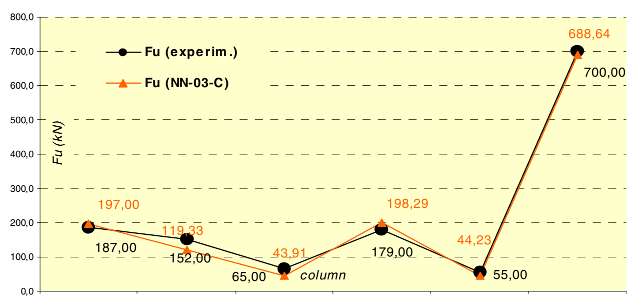

Figure 9. Comparison of experimental results and NN-03-C network's prediction for F_u

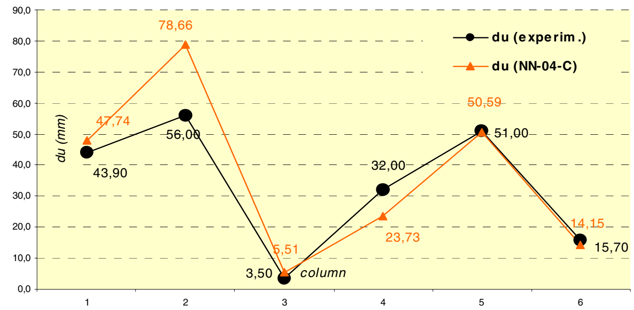

Figure 10. Comparison of experimental results and NN-04-C network's prediction for d_u

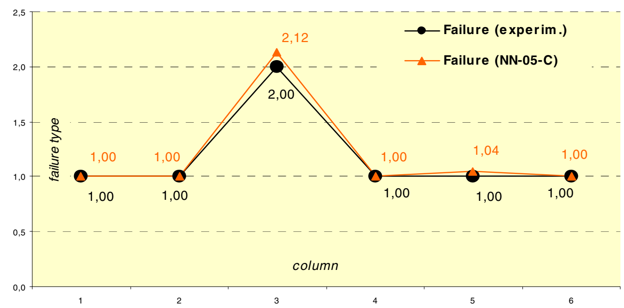

Figure. 11. Comparison of experimental results and NN-05-C network's prediction for failure type

The figures 12 –14 show the comparison between experimentally acquired force displacement histories for tested columns and the force displacement primary curve obtained using neural network.

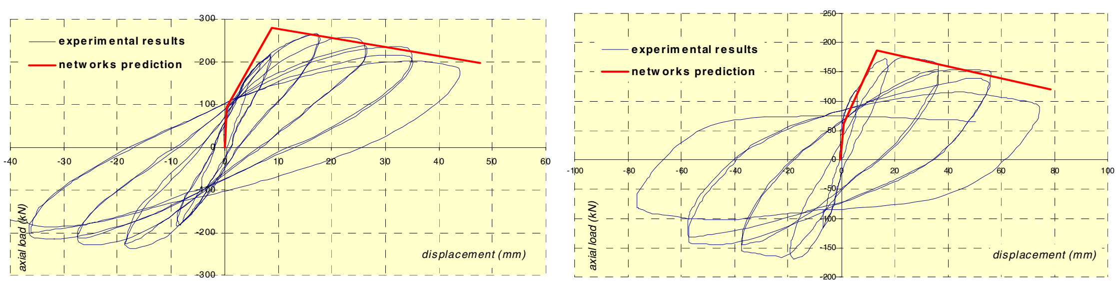

Figure. 12. Comparison of networks prediction and force-displacement history of column 1 and 2

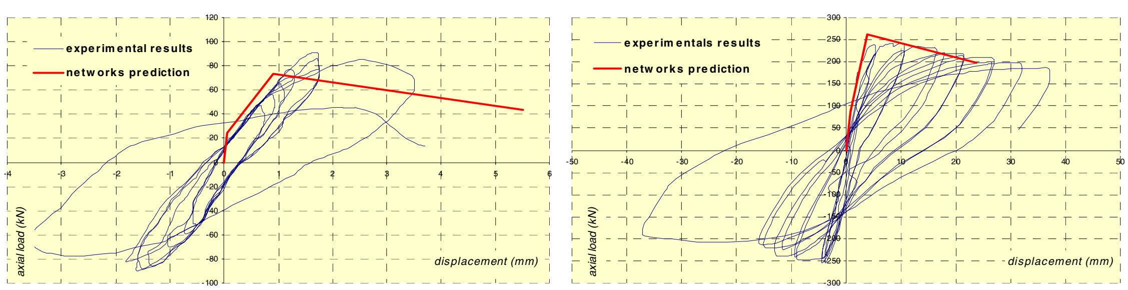

Figure. 13.Comparison of networks prediction and force-displacement history of column 3 and 4

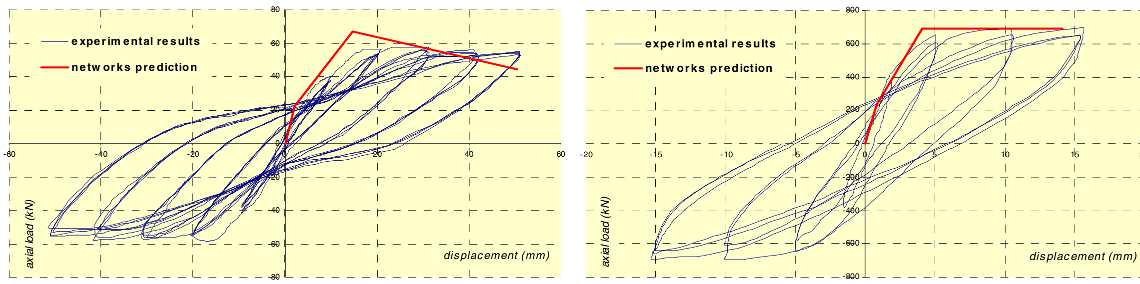

Figure. 14. Comparison of networks prediction and force-displacement history of column 5 and 6

CONCLUSION

Understanding of the true behavior of structural walls and columns is essential for any performance based design procedure. Evaluation of the structural wall and column performance can be achieved by:
(1) Stress-strain properties of materials. This represents quite a difficult task due to the inhomogeneous, anisotropic nature of materials and complex interaction processes involved;
(2) Empirical and semi-empirical methods. They are suitable tools for use in seismic assessment of buildings (Japan), and preliminary design (Rossetto) [4], etc.;
(3) Neural networks, calibrated on the sufficiently big empirical database that is proposed in this paper.

The advantages of neural network are that they are taught on the vast experimental database. Therefore, they constantly consider all variables influencing performance in real structures but are difficult to take numerically into account. Contribution of various variables can also be analyzed on how they influence the respective performance criteria. The results of performance predictions using 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 use of neural networks in seismic capacity evaluation of structural elements 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 work on the collected database, that can be further enriched, enables conclusion making about the overall experimental results, increase understanding of elements performance depending on various variables at various demand levels and could be used for optimization of their design.

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