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NEURO-HYBRID SUBSTRUCTURING ON-LINE TEST ON MOMENT RESISTANT FRAMES

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ABSTRACT

Substructuring on-line test is recognized as alternative technique for full scale tests. The expected damage portions of the structure are tested simultaneously with analytical modeling of the remaining part of the structural system. Therefore, the elements are classified into analysis modeling elements and test specimen elements. The degrees of freedom on the structure are split into mass associated and non-mass associated. The displacements of the structural system are computed through incremental dynamic analysis. On the dynamic modeling of middle or high rise buildings with concrete stiff slabs, the masses of the system are concentrated at the floor levels and the displacements on the elements are considered as a function of the mass associated lateral displacements. However, in the case of steel frames composed of flexible beam-columns and non-stiff diaphragm, unbalance forces appear in the non-mass associated degree of freedom, and the representation of deformations as function of the lateral displacements is not valid. In this research an on-line test on moment resistant frame is conducted to verify the effectiveness of the artificial neural network predictor in the removal of the unbalance moment which appears on the non-mass associated components. This scheme utilizes an artificial neural network as predictor of the incremental forces on the specimen to achieve the displacements of the system. A brief description of the applicability of the neural network computing in the problem is presented together with the configuration of the network system and input parameters. The transformations between the coordinate systems which are required in the execution of the algorithm, are briefly presented. A T-type structure is choose as structural system, where box shaped sections 100x100x6 are the structural members. The performance of the neural network predictor is compared with a full numerical analytical simulation. The test is carried out considering constant normal force in the specimen under the excitation of El Centro Earthquake.

KEYWORDS

Pseudo-dynamic Test; Neural Network; Substructure; Unbalance Moment; Moment Frame.

SUBSTRUCTURING ON-LINE HYBRID TEST

The on-line or pseudodynamic test (Takanashi ,1974) has been widely recognized as one of the most reliable testing methods for earthquake excitation on full-scale structures. Unfortunately, the performance of full-scale tests on high-rise or middle-rise buildings involves the use of large scale laboratories requiring substantial investment. An alternative is the execution of subassembly tests, using parts of the structure with full-size specimens, which in combination with adequate analytical models of the remaining parts of the structure, can reproduce the behavior of the whole structural system; this procedure is termed substructuring on-line hybrid technique. Different applications have been developed, mainly in Japan (Takanashi et al., 1980) and the United States (Mahin et al., 1985) with good results.

Unbalance Moment Removal Scheme

Flexible steel framed structures are widely represented by a discrete lumped mass system. The dynamic system is solved by the following equation of motion in case of no viscous damping:

$$[M]\{\ddot{X}\} + \{F_v\} = -[M]\{I\}\ddot{Y}_g \quad (1)$$

where [M] : mass matrix of the structural system; [Fv] : force vector associated with mass excitation;
{I} : vector where all the elements are 1; $\ddot{Y}_g$: earthquake ground acceleration.

Using the central difference method as integration scheme, the incremental solution for the equation of motion on the mass associated displacements {X} is given by:

$$\{\Delta X\}^{i->i+1} = \{\Delta X\}^{i-1->i} - \Delta t^2 \left\{ [M]^{-1}\{F_v\}^i + \{I\}\ddot{Y}_g \right\} \quad (2)$$

In the case of flexible framed structures with non-rigid slab, unbalance forces denoted by $\Delta\Omega^{i->i+1}$ appear on the non-mass associated displacements {Θ}, due to material and geometric non-linearity. These unbalance forces must be removed to avoid the contamination of the test results. To remove these unbalance forces the principle of Kannan (et.al.,1973) is adopted. Then, because the stiffness matrix of the specimen is unknown, its terms are separated from the incremental equilibrium equation . Therefore, to computed {Θ} the following scheme is applied:

$$\left\{\Delta\Theta^{i->i+1}\right\} = -\left[K^*_{mo}\right]^{-1}\left\{\left\{\Delta\Omega^{0->i}\right\} + \left\{\Delta\Omega_S^{i->i+1}\right\} + \left[K^*_{md}\right]\left\{\Delta X^{i->i+1}\right\}\right\} \quad (3)$$

where $\left[K^*_{mo}\right]$ and $\left[K^*_{md}\right]$ the stiffness matrix without contribution of the specimen and $\left\{\Delta\Omega_S^{i->i+1}\right\}$ the specimen resistance increment on non-mass associated DOF, the one shall be predicted. In this work a self-organizing parameter model, which can represent by itself the incremental response of the specimen, is proposed using an artificial neural network model.

ARTIFICIAL NEURAL NETWORK PREDICTOR

Artificial Neural Networks are systems with inputs (Xp) and outputs (Yj), integrated by a finite number of processing units (Fig.1). These units operate in parallel and are arranged in layers similar to the patterns found in the biological neural nets. The processing elements or units are connected to each other by adjustable weights (W_{jk}, W_{ji}, etc.). The artificial neural network needs the training or sampling presentation of the input data in order to learn from a set of desired outputs. If the weights change, the outputs of the network also change, therefore, the selection of optimum set of weights which produce the desired output become the goal in the solution. To achieve this goal, systematic process for adjusting the weights has been developed. This process is termed "training" or "learning" of the neural network.

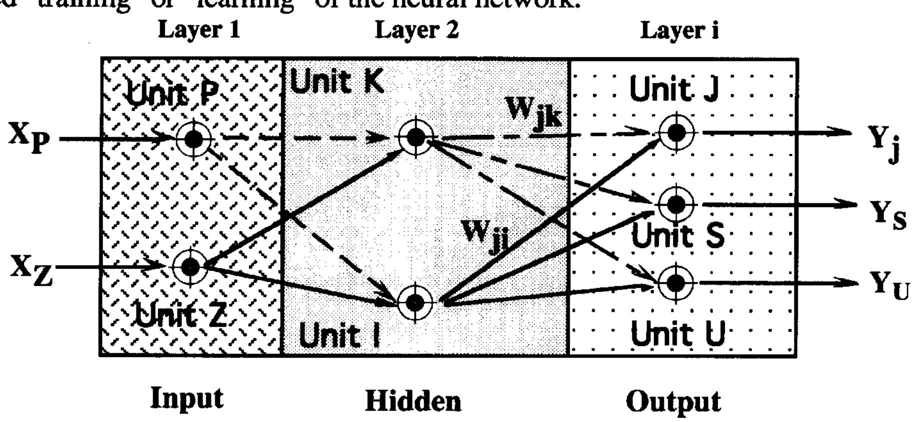

Fig.1 : Layered Artificial Neural Network

Processing Units

Every unit receive several output (Y_k,Y_i) from units on the previous layer which become inputs on the current unit "**j**" and produce only one output (Y_j). To process the inputs, the weighted sum of them is performed to generate the general input (X_j). Here an additional term named the bias or threshold (T_j) of the unit is used for the computation of the total input. The unit then passes the total input through a nonlinear function (usually Sigmoid or Hyperbolic type), which produces the output value of the unit. It must be mentioned that at the beginning of the process the values of the weights and thresholds are assumed to be random values. Then the threshold is assumed to be an additional output from a virtual unit with value $Y_O=1$ and weight $\omega_O=T_j$. Then the value of T_j is adjusted by the same algorithm as the rest of the weights on the net.

A typical unit pass the general input through one of the above non-linearities to produce the output of the unit, where the general input is defined by :

$$X_j = \sum_{i}^{i} Y_i \omega_{ji} - T_j \quad (4)$$

where X_j = General input in unit j ; Y_i = Output from the unit i on the previous layer.
ω_{ij} = weight connector between unit i and j ; T_j = Threshold of the unit j.

Then, the output of the unit is computed by the following function in the case of Sigmoid non-linearity :

$$Y_j = \alpha_{(X)} = \frac{1}{1+e^{-X}} \quad (5)$$

Topology of Neural Networks

According to Hrycej (1992), the computational power of the units taken alone is rather limited. If a system made of such processing units has to solve complex tasks, its sophistication must consist of something different from the processing units themselves, namely, their interactions. It is the topology of the nets that determines which interactions can take place. The conectivity and the direction of the input/output and its spread are crucial parts on the complex structure of the nets. The conectivity must consider the feed forward interaction between units and a structural order must be defined. For the reader who is interested in network topology and configuration the work of Lippman(1987) is an excellent reference.

Scaling or Normalization of Data

The input data and output data must be selected carefully, considering the existence of constraint into the non-linear processing function (e.g.. sigmoid). A non-scaling on the data can generate saturation on the functions or non-learning, giving unsuccessful results. The normalization of the data transforms each real value within particular range, conditioned by the transfer function. The more likely used ranges are: from -1 to 1, from -0.5 to 0.5, from 0 to 1. In this way the saturation of the processing unit is avoided. Once saturation occurs, the changes in the input value result in little or no change in the output. Because this, the intelligence is limit and knowledge can not be captured on the network. Therefore, saturation should be avoided.

Training of Neural Networks

The training of the network is a sampling presentation of the input-output patterns to the network. In each presentation, an input pattern is passed forward through each layer of the network. In each unit the output from the previous layer units and interconnection weights are used to generate the general input; later the general input is passed through the nonlinear processing function (e.g.. sigmoid) to produce the output of the unit. This output is used for the units of the next layer to generate other outputs. In this way each input vector is passed forward through the network, and an output vector is calculated. During the training, the network's output is compared to desired data (training data), and an error term is created.
Modifying the interconnection weights, this error could increase or decrease. Due to this fact, several training algorithms have been developed. The most popular training procedure for multi-layer feedfoward networks, is the back-propagation algorithm (Rumelhart et al.,1986), that is used on this research.

Model For Unknown Restoring Forces

The question is: why to choose an artificial neural network as restoring force model ? mainly the answer can be done with the properties of the neural nets :
- Neural networks can infer subtle, unknown relationships from data.
- Networks can generalize, it means, they can respond correctly to patterns that are only broadly similar to the original training patterns.

- They are highly non-linear, and the interaction between the units and the amount of hidden layers make possible to reproduce unknown non-linearities for non-training data.

A neural network simulator termed ZOT-BP has been implemented on a Sun Sparc-10 workstation coded in FORTRAN. The simulator was installed in order to achieve the training process with the supervision of the operator and to carry out the experimentation and improvement of the network's parameters.

The use of a neural network as predictor for the incremental vector $\{\Delta\Omega_S^{i->i+1}\}$, needs a set of real test data in order to execute a successful training. Using calibration responses as training data, a guarantee of a real non-linearity for the prediction is expected. For a set of 300 sets of data, which represent 3 sec. of excitation with varying moment capacity in both ends (ΔM_{AB} and ΔM_{BA}) and constant axial capacity (ΔN), ZOT performs the training of the network. An input layer of 21 units, a hidden layer with 42 units and an output layer with 3 units (ΔM_{AB}, ΔM_{BA}, ΔN) are adopted in this problem. For this case the learning rate (η) value for the modification of the gradient was equal to 0.000065 at the beginning of the process.

After 60000 sweeps of presentation of the data, the neural network reproduced the training data with enough accuracy. Fig.2 shows the output value of the neural network after the training process. A good agreement between the training data and the testing output of the neural network is found.

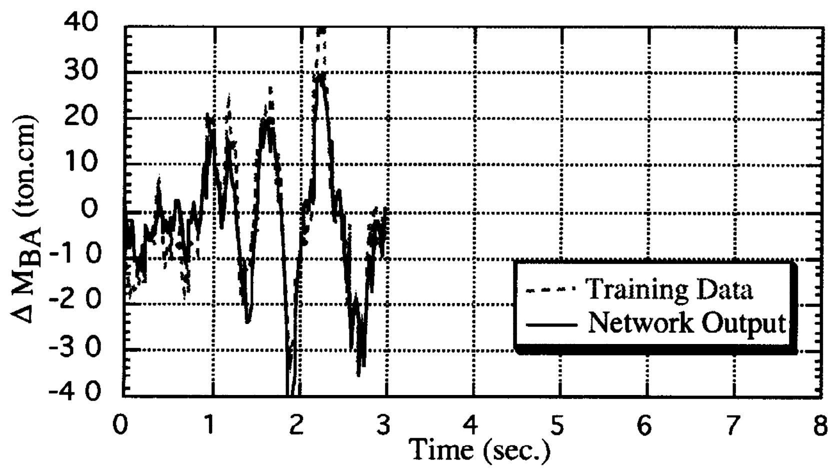

Fig.2 : Training data and Output data after the Learning of the ΔM_{BA} component.

<u>Interaction between the Analysis and the Test</u>

In the execution of an hybrid simulation, three coordinate systems must be used, to perform the analysis, reproduce the desired displacement configuration of the beam-column specimen and drive the actuator system to reach the target position where the restoring forces involved in the simulation shall be measured. A brief description of the used coordinate systems is presented as follow:

- Analysis Coordinate system : this system is defined by the nodal displacements ($\Delta X_A \Delta Y_A, \Delta\Psi_A$) and nodal forces ($Fx_A, Fy_A, M_A$), which are involved in the numerical solution of the system (Fig. 3).

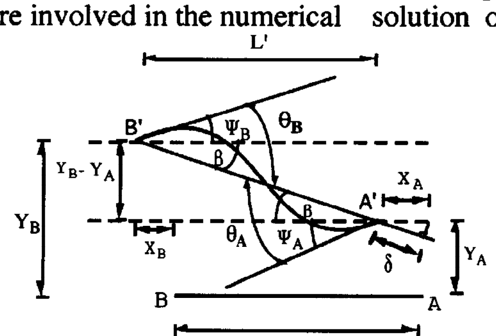

Fig.3 : Analysis and Condensed Coordinates

- Condensed Coordinate system : become a system available to reproduce large deformations(Fig. 3), where the components of the system are expressed in function of the rotation angles between the tangent to the deformed element in the node and the cord between the ends points of the element, and the normal deformation in the member ($\Delta\theta_A, \Delta\theta_B, \Delta\delta$). These displacements are related with the corresponding condensed forces ($\Delta M_A, \Delta M_B, \Delta N$). Using this system, a generalized representation of a beam-column element deformed is achieved. The relations between the analysis coordinate system and the condensed coordinate system is given by the transformation matrix [C] ; the relation between the forces on the analysis coordinate and the measuring forces expressed in condensed form is given by :

$$\{\Delta F\} = [C]\{\Delta G\} \quad \text{, that is,}$$

$$\begin{Bmatrix} \Delta Fx_A \\ \Delta Fy_A \\ \Delta M_A \\ \Delta Fx_B \\ \Delta Fy_B \\ \Delta M_B \end{Bmatrix} = \begin{bmatrix} 0 & 0 & -1 \\ -1/H & -1/H & 0 \\ 1 & 0 & 0 \\ 0 & 0 & 1 \\ 1/H & 1/H & 0 \\ 0 & 1 & 0 \end{bmatrix} \begin{Bmatrix} \Delta M_A \\ \Delta M_B \\ \Delta N \end{Bmatrix} \tag{6}$$

Using the transposed matrix $[C]^T$ it is possible to express the condensed displacements in terms of the compute analysis displacements, in order to drive the specimen to the deformed desired position:

$$\{\Delta\Theta\} = [C]^T\{\Delta X\} \quad \text{,that is,}$$

$$\begin{Bmatrix} \Delta\theta_A \\ \Delta\theta_B \\ \Delta\delta \end{Bmatrix} = \begin{bmatrix} 0 & -1/H & 1 & 0 & 1/H & 0 \\ 0 & -1/H & 0 & 0 & 1/H & 1 \\ -1 & 0 & 0 & 1 & 0 & 0 \end{bmatrix} \begin{Bmatrix} \Delta X_A \\ \Delta Y_A \\ \Delta\Psi_A \\ \Delta X_B \\ \Delta Y_B \\ \Delta\Psi_B \end{Bmatrix} \tag{7}$$

- Test Coordinate System : Using the above transformation the required condensed coordinate position is known, but its configuration depends only of the actuator coordinates or test coordinates, the ones must reach the condensed position by use of the transformation matrix [T] . This relates the condensed coordinate with the test coordinate system and the following equation gives the incremental value for the displacement control to drive the actuators (Fig. 5) :

$$\{\Delta Xe\} = [T]\{\Delta\Theta\} \qquad \begin{Bmatrix} \Delta Xex_1 \\ \Delta Xex_2 \\ \Delta Xex_3 \end{Bmatrix} = \begin{bmatrix} 0 & \dfrac{-(L_2L_3)}{(L_2+L_3)} & 0 \\ -L_1 & \dfrac{(L_1L_3)}{(L_2+L_3)} & 0 \\ 0 & 0 & \dfrac{(L_5+L_6)}{(L_5+L_6+L_7)} \end{bmatrix} \begin{Bmatrix} \Delta\theta_A \\ \Delta\theta_B \\ \Delta\delta \end{Bmatrix} \tag{8}$$

The measuring of the restoring forces is executed using the load cells built-up on the actuators, and condensed components are found through the transposed matrix $[T]^T$.This result is inserted in analysis coordinates on the restoring force vector to continue the analysis of the hybrid system.

$$\{G\} = [T]^T\{FF\}$$

$$\begin{Bmatrix} M_A \\ M_B \\ N \end{Bmatrix} = \begin{bmatrix} 0 & -L_1 & 0 \\ \frac{-(L_2 L_3)}{(L_2 + L_3)} & \frac{(L_1 L_3)}{(L_2 + L_3)} & 0 \\ 0 & 0 & \frac{(L_5 + L_6 + L_7)}{(L_5 + L_6)} \end{bmatrix} \begin{Bmatrix} FF_1 \\ FF_2 \\ FF_3 \end{Bmatrix} \tag{9}$$

THE PROTOTYPE TEST

The structural model is shown in Fig.4. Steel box-shaped sections, 100x100x6 are used as structural members . Here, the beams are considered analytically and the central column is tested. The system was subjected to the NS-component recorded at El Centro with duration of 8 seconds and peak acceleration of 250 gals.

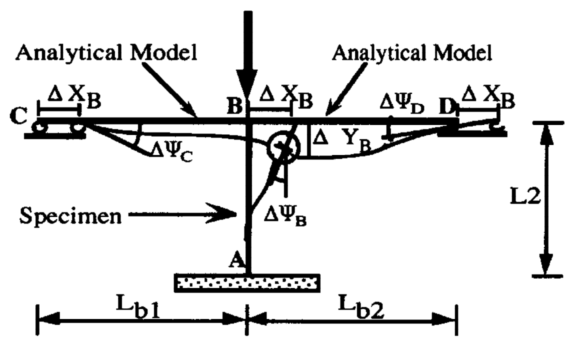

Fig.4 : Structural Model

For this test the mass was considered equal to 0.0311296 ton.sec^2/cm, under constant axial load of 33 ton. (around 40% of the axial capacity), using the test setup configuration shown in Fig. 5. Details of the general beam-column test apparatus used in the test are given by Zavala et. al 1994.

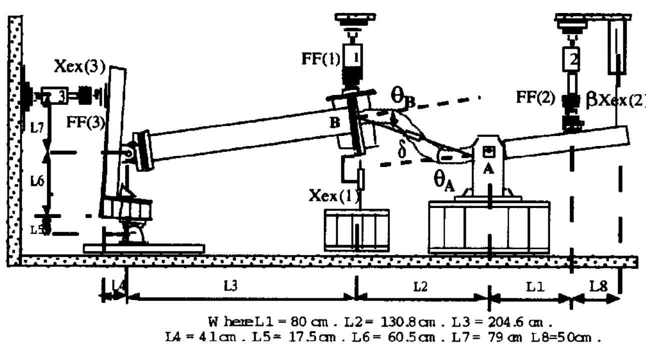

Fig.5 : Test Apparatus

The unbalance moment around node B is presented in Fig.6 with negligible value. The performance of the neural network predictor is presented in Fig.7 for the ΔM_{BA} component; Here the self-organization of the model is proved with the good agreement of the prediction and the measure signal.

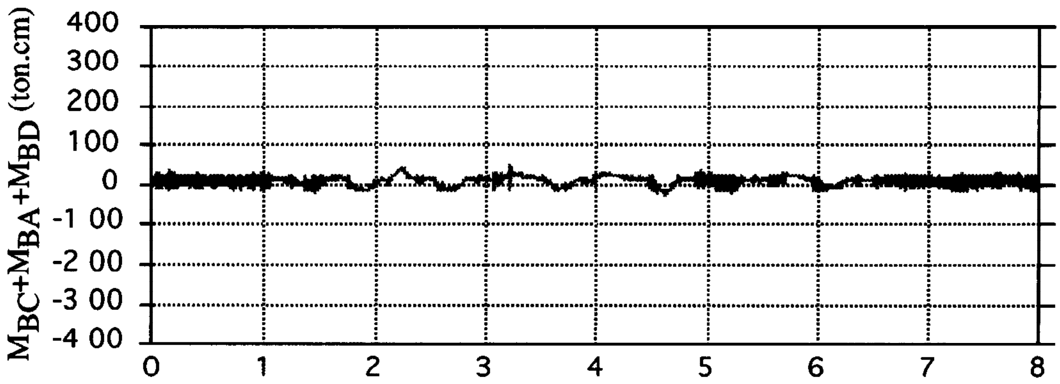

Fig.6 : Unbalance Moment on node B

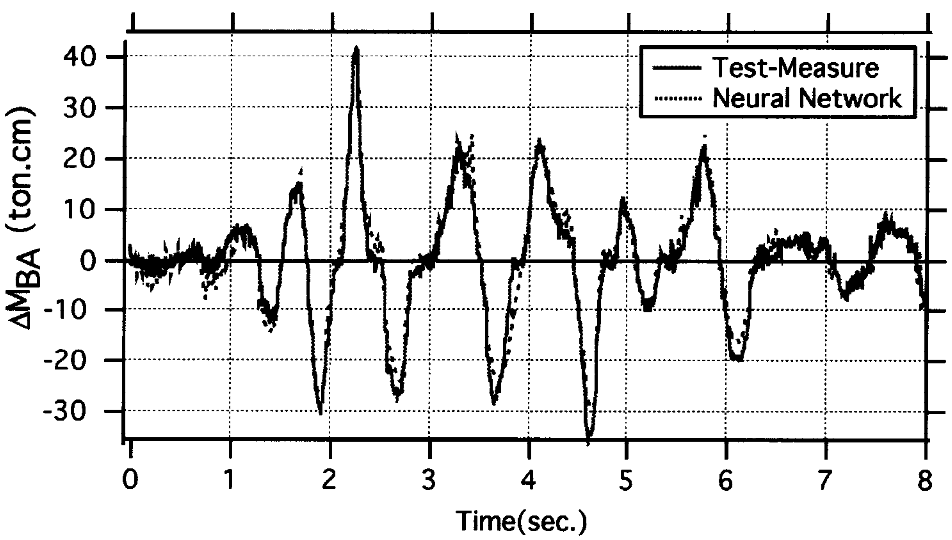

Fig.7 : Neural Network Performance during the Test

To accept the true hybrid response obtained by the simulation, a full numerical analysis using a Multi-Spring model (Ohi et al.,1986) is compared with the test results. Shear resistance vs. drift for test and analysis results are shown in Fig. 8 with very good agreement.

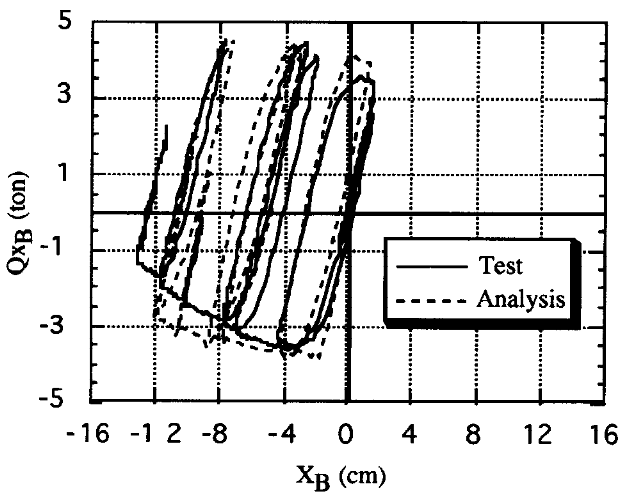

Fig.8 : Drift vs. Shear relations

CONCLUSIONS

- The neural network predictor is applied successfully in the removal scheme of the unbalance moment, which is reduced to a negligible level.
- The improvement of the prediction depends on the training of the artificial neural network. Selection of the proper topology, transfer function, and training data, provide a powerful tool for the simulation of earthquake excitation on flexible beam-column members.
- A well known multi-spring joint model is compared with the presented neural network predictor. From the results, the confidence on the technique is assured.

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