*Scientia Iranica*, Vol. 8, No. 1, pp 62–70


SCIENTIA
IRANICA

# Comparing Neuro-Fuzzy and Predictive Control of Structures

A. Joghataie* and J. Ghaboussi[1]

In this paper, a comparison is made between the predictive control method and a neuro-fuzzy control algorithm, which has been proposed recently by the authors, for controlling a benchmark three-story frame structure subjected to earthquakes. Through numerical simulations, it is demonstrated that the proposed neuro-fuzzy control algorithm can provide comparable and, in some cases, superior results.

## INTRODUCTION

In the last decade, special attention has been paid to the theory and application of active structural control [e.g., 1-3]. Different methods of using neural-networks and fuzzy logic for structural control have been proposed recently. One of these methods, proposed by the authors [4,5], has been tested in the control of a benchmark three-story frame structure subjected to earthquake loading, for which the results have been encouraging. On the other hand, the formulated control methods, such as the instantaneous optimal control, pulse control and predictive control methods have been found effective in the control of many structural test problems. In this paper, a comparison is made between the neuro-fuzzy control algorithm and the predictive control method in order to provide a better understanding of their strong and weak points. First, a neuro-fuzzy controller has been designed for the control of the three-story frame of Figure 1 and then a predictive controller has been designed for the control of the same structure. Results of their control of the frame subjected to different earthquakes are compared and conclusions are drawn in this regard.

## NEURO-FUZZY CONTROL OF STRUCTURES

The main idea behind using neural networks and fuzzy logic, in the proposed algorithm [4,5] has been to take advantage of the learning capability of neural networks as well as the flexibility and modifiability associated with fuzzy rules.

### Neural Networks

Neural networks are versatile computational tools that have attracted the attention of researchers in different fields of science and technology since the mid 80's. They can be considered as regression or mapping tools, used for classification purposes. Many types of neural networks have been proposed by researchers and used in a variety of application problems. The most widely used type of neural network is the Multi-Layer Feed-Forward back-propagation Neural Network (MLFFNN) which has also been used in this study. Figure 2 shows a typical MLFFNN which comprises a number of processing units, arranged in layers. The first and last layers are the input and output layers, respectively. Neural networks in general and, specifically, the MLFFNN are well-known mapping tools to the engineering community and complete information regarding their theory and application can be found in many references such as [6].

### Fuzzy Logic

Application of fuzzy logic and fuzzy set theory to the control of engineering processes is not a new concept. However, the possibility of its application to structural control has been recently mentioned by some researchers in the field [7]. A number of fuzzy "if-then" statements should be constructed for the control of the specific structure under study. These "if-then" rules are qualitative linguistic rules which could be specified by experts in structural control. The linguistic rules are then transferred into quantitative functions by using

*. *Corresponding Author, Department of Civil Engineering, Sharif University of Technology, Tehran, I.R. Iran.*

1. *Newmark Civil Engineering Laboratory, University of Illinois at Urbana-Champaign, USA.*

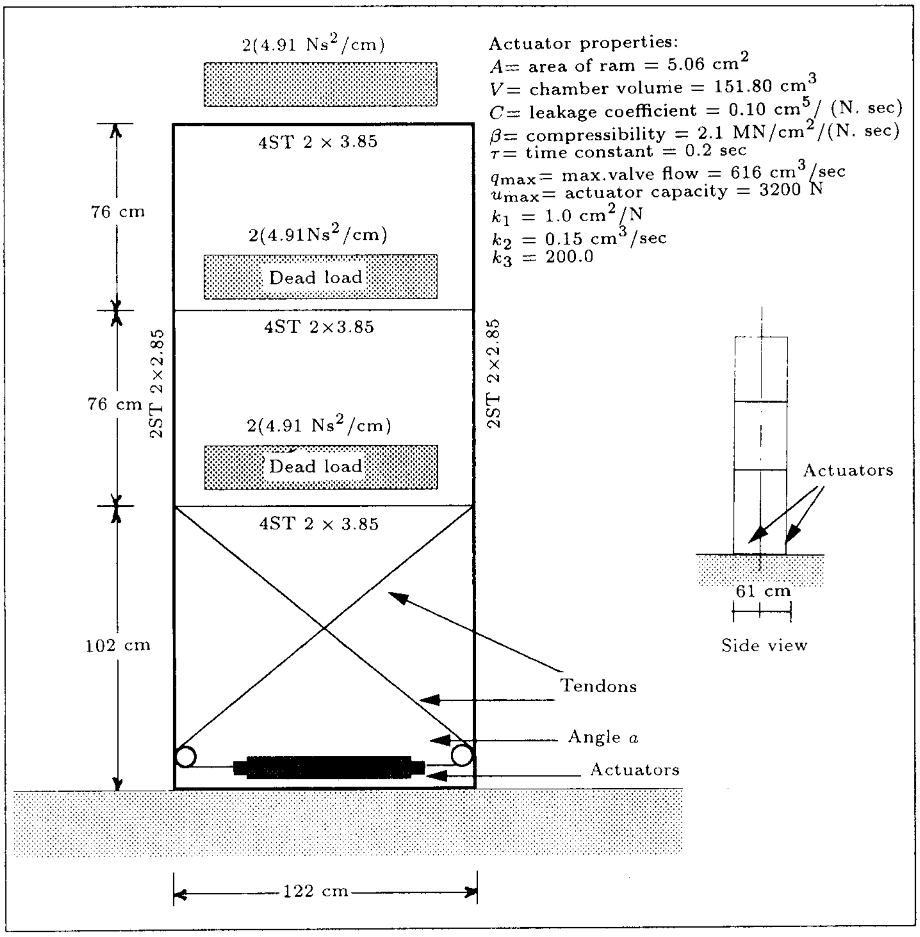


**Figure 1.** The structure, actuator and tendons.

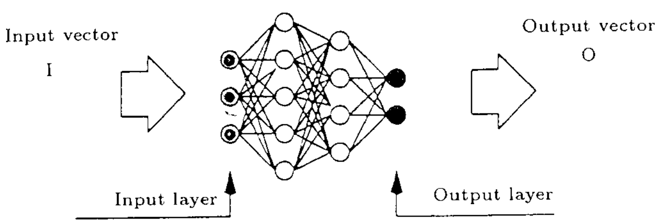


**Figure 2.** A typical multi-layer feed-forward neural network.

some implication and inference rules. Vast literature is available on the theory and application of fuzzy sets and fuzzy controllers such as [8-10].

## Methodology of the Neuro-Fuzzy Control

The neuro-fuzzy controller is comprised of a neuro-controller as the main controller and also a fuzzy controller which is placed in series with the neuro-controller and acts as a complementary controller for the adjustment and correction of the control signal issued by the neuro-controller. The arrangement of the neuro-controller and complementary fuzzy controller is illustrated in Figure 3.

### *Construction of Neuro-Controllers*

The following steps have been employed for the construction of an appropriate neuro-controller:

1. Training of an emulator neural network which is capable of predicting the response of the frame from the immediate history of response and control force.
2. Using the emulator to alleviate the undesired deformations of the structure according to an appropriate control criterion.
3. Forming training cases based on the response, as the cause, on one hand and the dictated control force, as the effect, on the other and construction of a neuro-controller for learning this case-effect relationship.
4. Using the neuro-controller and the emulator neural network together to provide better control results to be used in the training of a new neuro-controller.
5. Training a new neuro-controller from the results of the fourth step.

Steps four and five may be omitted or repeated several times, depending on the desired accuracy.

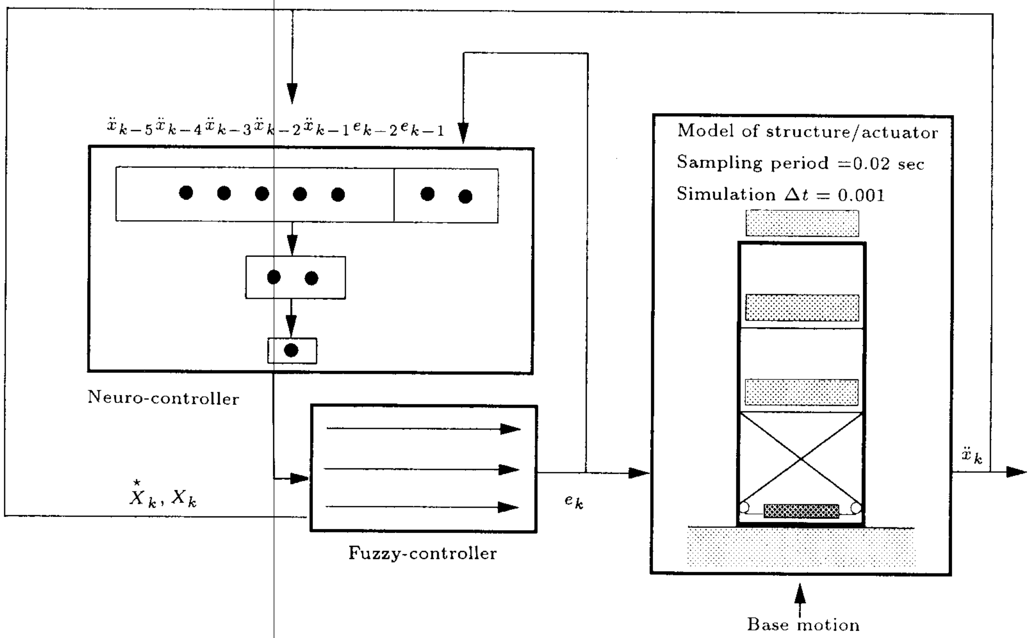


**Figure 3.** Control by the neuro-fuzzy controller.

**Table 1.** Parameters of the shear building model of the structure presented in Figure 1.

| | |
|---|---|
| **Mass Matrix M(N − s²/cm)** | $\begin{bmatrix} 9.82 & 0 & 0 \\ 0 & 9.82 & 0 \\ 0 & 0 & 9.82 \end{bmatrix}$ |
| **Stiff Matrix K(N/cm)** | $\begin{bmatrix} 40654 & -28758 & 0 \\ -28758 & 57516 & -28758 \\ 0 & -28758 & 28758 \end{bmatrix}$ |
| **Eigenvalue Matrix (rad²/s²)** | $\begin{bmatrix} 321.0281 & 0 & 0 \\ 0 & 3582.7859 & 0 \\ 0 & 0 & 9022.1860 \end{bmatrix}$ |
| **Eigenvectors Matrix (cm)** | $\begin{bmatrix} 0.4543 & 0.7532 & 0.4756 \\ 0.5924 & 0.1433 & -0.7928 \\ 0.6654 & -0.6419 & 0.3811 \end{bmatrix}$ |
| **Modal Frequencies (Hz)** | $\begin{bmatrix} 2.85 & 9.53 & 15.12 \end{bmatrix}$ |

### *Construction of the Fuzzy Controllers*

The neuro-controllers are capable of performing a smooth control. However, there are unusual situations where sharp changes in the control forces are required for mitigation of the response of the structure induced by an unexpected external excitation. Such situations, for example, occur at the onset of a strong earthquake. A fuzzy controller is a good candidate for helping the neuro-controller in these cases. The fuzzy controller acts on the control signal proposed by the neuro-controller, improves it and sends it to the actuators. In this study, the fuzzy controller developed by the authors [5] has been used. Briefly a table has been prepared to be used for determination of the correction to the control signal issued by the neuro-controller. The input to the table is the state vector of the frame where the relative displacement and velocity of the third floor of the frame have been used as the components of a two-dimensional input vector to the fuzzy complementary controller. For each of the components, seven membership functions representing the Large

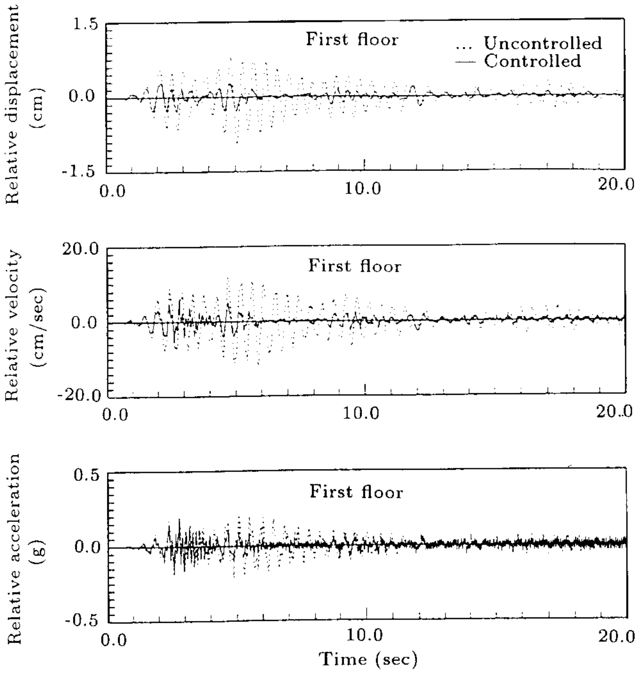


**Figure 4.** Control by neuro-fuzzy controller. First floor response is shown for 20 seconds. The structure has been subjected to 25% El Centro earthquake and control forces.

Negative, Medium Negative, Small Negative, Small, Small Positive, Medium Positive and Large Positive values have been defined, resulting in 49 fuzzy rules. For each rule, a control force has been considered. Upon receiving an input vector, the membership of the input to each of the rules can be determined. Using these membership functions as weights and the control forces defined for the rules, a weighted average of the control forces can now be found and considered as the final control force.

### Results of Neuro-Fuzzy Controlling

The frame shown in Figure 1 has been subjected to the 25% El Centro earthquake, controlled by the neuro-fuzzy controller and designed according to the steps set forth in the previous sections (shown in Figures 4 to 6). A delay of 0.02 second has been introduced in the controlled structure. In this study, only the relative acceleration of the first floor has been used in the construction of both the emulator and neuro-controller. After integrating acceleration, relative velocity and displacement have been calculated to be used by the fuzzy controller. In Figure 4, the response of the first floor, both uncontrolled and neuro-fuzzy controlled, is shown. In Figure 5, the Fourier spectra of the displacement and absolute acceleration of the three floors, both uncontrolled and neuro-fuzzy controlled, are demonstrated. Figure 6 demonstrates the history of control force as well as the work done on the structure by the control mechanism, where negative work means that energy has been absorbed from the structure by the control mechanism.

## PREDICTIVE OPTIMAL CONTROL METHOD

Predictive optimal control method has been proposed by Rodellar and his co-workers [11,12], for use in the

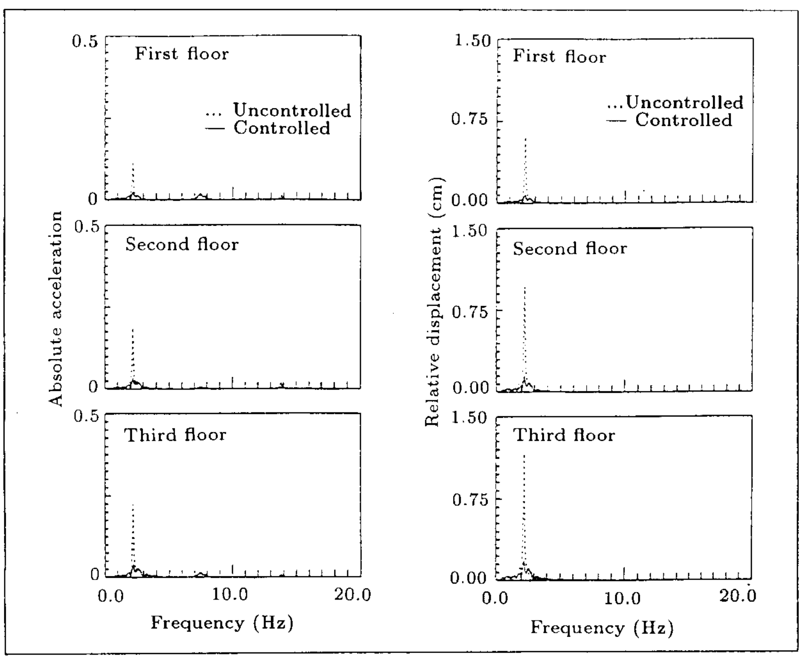


**Figure 5.** Control by neuro-fuzzy controller. Fourier spectrum of the relative displacements of the three floors are shown. The structure has been subjected to 25% El Centro earthquake and control forces.

digital control of frame structural systems both numerically and experimentally. A significant advantage of this method over the other formulated control methods is its ability to control structures in the presence of inherent time delays and nonlinearities. Considering an $n$-DOF controlled structure, with a time delay of $d$ times the sampling time interval $\Delta T$ and a prediction horizon of $\lambda$ time steps, using the measured response of the structure at any sampling time step $k$, the response of the structure can be predicted for the next $\lambda+d$ time steps according to the following prediction equation:

$$\mathbf{y}(k+j) = \mathbf{A}\mathbf{y}(k+j-1) + \mathbf{B}_u\mathbf{u}(k+j-1-d)$$
$$j = 1, 2, ...., \lambda + d, \quad (1)$$

where $\mathbf{y}(l)$ represents the predicted state vector at time step $l$, $\mathbf{A}$ and $\mathbf{B}_u$ stand for the discrete time state and control matrices, respectively, and $\mathbf{u}(l)$ is the control force at time step $l$.

The control rule is found after introducing a performance index $J$ which is defined for any time step $k$ as:

$$J = 1/2\mathbf{y}^T(k+\lambda+d)\mathbf{Q}\mathbf{y}(k+\lambda+d) + 1/2\mathbf{u}^T(k)\mathbf{R}\mathbf{u}(k), \quad (2)$$

where $\mathbf{Q}$ and $\mathbf{R}$ represent some weighting matrices which are positive semi-definite and positive definite, respectively. Then, the linear control rule is found from $\partial J/\partial \mathbf{u}(k) = 0$ as:

$$\mathbf{u}(k) = \mathbf{D}\mathbf{x}(k) + \sum_{i=1}^{d} \mathbf{H}_i \mathbf{u}(k-i), \quad (3)$$

where $\mathbf{x}(k)$ and $\mathbf{u}(k)$ represent the current state and control signal, respectively, $\mathbf{D}$ and $\mathbf{H}_i$, $i = 1, 2, ...d$ are constant matrices which contain information about both the controlled structure and control objective and are calculated based on $\mathbf{A}, \mathbf{B}_u$, $\mathbf{Q}$ and $\mathbf{R}$ matrices.

## Control of Three Story Frame

The state vector for the three story frame structure of this study, which has been simulated by a three degree of freedom shear frame, is $\mathbf{x}(k) = [\mathbf{q}(k), \dot{\mathbf{q}}(k)]^T$, where $\mathbf{q}(k)$ and $\dot{\mathbf{q}}(k)$ represent the relative displacement and velocity at time step $k$, respectively, and the control signal is a scalar quantity, $\mathbf{u}(k) = u(k)$, which is equal to the horizontal component of the force applied by the tendons on the first floor of the frame as shown in Figure 1. In this study, the following diagonal weighting matrices have been used:

$$\mathbf{Q} = diag.[1,\ 1,\ 1,\ 0,\ 0,\ 0], \ \mathbf{R} = [r], \quad (4)$$

where an appropriate $r$ value is found by trial and error. Also, the corresponding $\mathbf{A}$ and $\mathbf{B}_u$ matrices have been

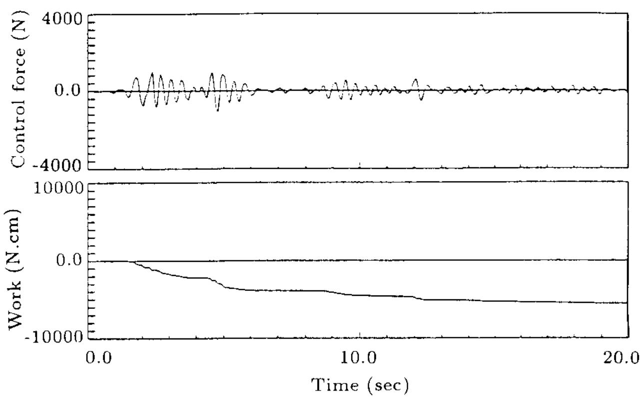


**Figure 6.** Control by neuro-fuzzy controller. Control force applied by each of the actuators and total work done by the actuators on the structure are shown for 20 seconds. The structure has been subjected to the 25% El Centro earthquake and control forces.

found based on the characteristics of the frame, which can be obtained from [13,4] as well as [14]. Tables 1 and 2 contain some information about structural properties of the frame.

Table 3 presents the summary of the results of this part of the study where the maximum relative displacement, velocity and acceleration of the first floor of the structure and, also, the control force and the work done by the actuators in 20 seconds are reported as functions of the $r$ value. Also, results of the neuro-fuzzy controlling of the frame, obtained previously by the authors [4,5], are reported. Increasing $r$ means increasing the control cost. Hence, as $r$ increases, the control force decreases and the response of the controlled structure increases. Figure 7 is a graphical representation of the results reported in Table 3.

For the case of $r = 1 \times 10^{-9}$, the actuators have become saturated, violating the optimality of the control method. To avoid saturation, the capacity of the actuators has been increased slightly and hence response of the structure has been reduced considerably, however, the control forces have been large and the controller has introduced energy to the structure.

For the case of $r = 3 \times 10^{-9}$, the best results have been obtained. It can be seen that the control forces are still large but the actuators are not saturated. Figures 8 to 10 illustrate the time history of the response of the first floor, Fourier transform of the response of the three floors, control forces and the work done by the actuators on the structure. These results seem similar to those obtained by the use of the neuro-fuzzy controller. However, except for the accelerations, the maximum value of the relative displacements, velocities and control forces are larger and the actuators have absorbed much less energy from the structure in comparison to the neuro-fuzzy case.

Results obtained for larger values of $r$ are not

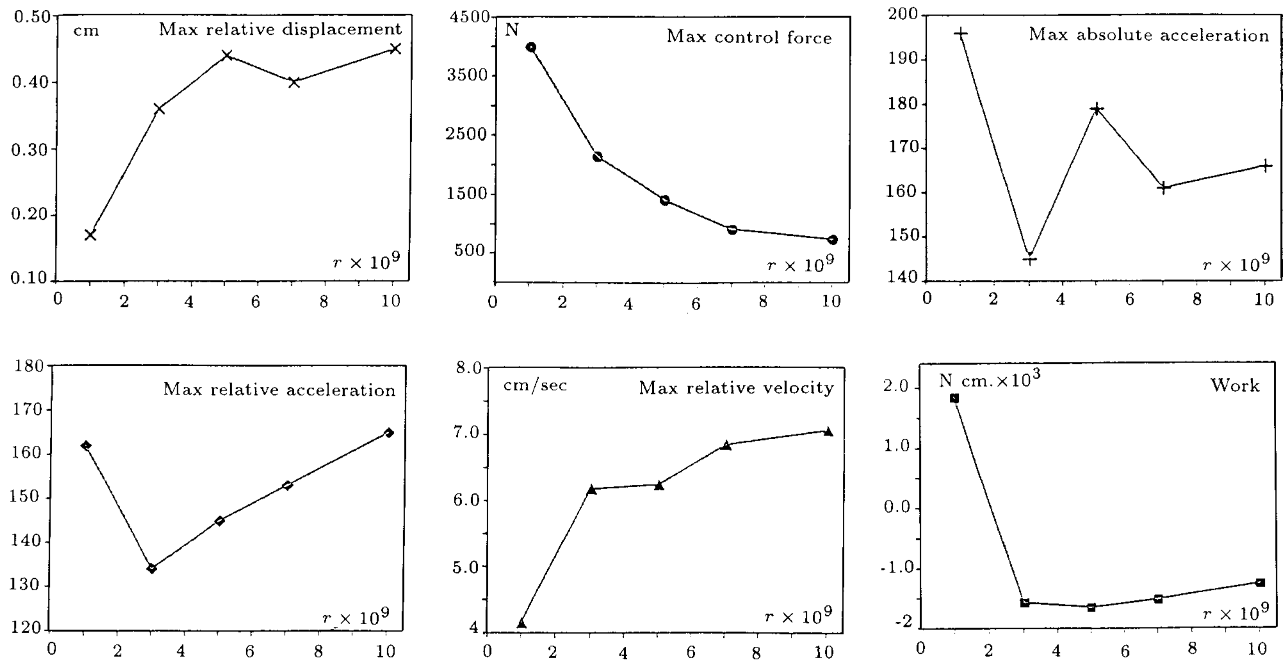


**Figure 7.** Effect of cost factor $r$ on the performance of the predictive optimal controller.

**Table 2.** Parameters of the shear building model of the structure presented in Figure 1.

| | |
|---|---|
| **Matrix A** | $\begin{bmatrix} 0 & I \\ -M^{-1}K & 0 \end{bmatrix}$ |
| **Eigenvalue Matrix of** $A$ | $\begin{bmatrix} 17.9173i & & & & & \\ & 59.8564i & & & & \\ & & 94.9852i & & & \\ & & & -17.9173i & & \\ & & & & -59.8564i & \\ & & & & & -94.9852i \end{bmatrix}$ |
| **Right Eigenvectors of A** | $\begin{bmatrix} -0.01268i & -0.00629i & -0.00250i & 0.01268i & 0.00629i & 0.00250i \\ -0.01653i & -0.00120i & 0.00417i & 0.01653i & 0.00120i & -0.00417i \\ -0.01857i & 0.00536i & -0.00201i & 0.01857i & -0.00536i & 0.00201i \\ 0.22717 & 0.37661 & 0.23782 & 0.22717 & 0.37661 & 0.23782 \\ 0.29620 & 0.07165 & -0.39640 & 0.29620 & 0.07165 & -0.39640 \\ 0.33266 & -0.32098 & 0.19055 & 0.33266 & -0.32098 & 0.19055 \end{bmatrix}$ |
| **Left Eigenvectors of A** | $\begin{bmatrix} 8.14056i & 45.08532i & 45.17789i & -8.14056i & -45.08532i & -45.17789i \\ 10.61406i & 8.57704i & -75.30460i & -10.61406i & -8.57704i & 75.30460i \\ 11.92060i & -38.42570i & 36.19892i & -11.92060i & 38.42570i & -36.19892i \\ 0.45434 & 0.75322 & 0.47563 & 0.45434 & 0.75322 & 0.47563 \\ 0.59239 & 0.14329 & -0.79280 & 0.59239 & 0.14329 & -0.79280 \\ 0.66531 & -0.64196 & 0.38110 & 0.66531 & -0.64196 & 0.38110 \end{bmatrix}$ |

**Table 3.** Effect of different cost weights $r$ on the predictive optimal control results and comparison to the results of the neuro-fuzzy controlled and uncontrolled structure.

| r | \|x\| max (cm) | $|\dot{x}|$max (cm/s) | $|\ddot{x}|$rel max (cm/s) | $|\ddot{x}|$abs max (cm/s$^2$) | \|Force\|max (N) | Work (N.cm) |
|---|---|---|---|---|---|---|
| $1 \times 10^{-9}$ | 0.17 | 4.15 | 162 | 196 | 3990 | +1841 |
| $3 \times 10^{-9}$ | 0.36 | 6.18 | 134 | 145 | 2135 | -1574 |
| $5 \times 10^{-9}$ | 0.44 | 6.24 | 146 | 179 | 1409 | -1653 |
| $7 \times 10^{-9}$ | 0.40 | 6.84 | 153 | 161 | 908 | -1516 |
| $10 \times 10^{-9}$ | 0.45 | 7.06 | 165 | 166 | 735 | -1250 |
| Neuro-Fuzzy | · 0.31 | 5.99 | 192 | 193 | 1083 | -5583 |
| Uncontrolled | 0.95 | 11.98 | 228 | 260 | – | – |

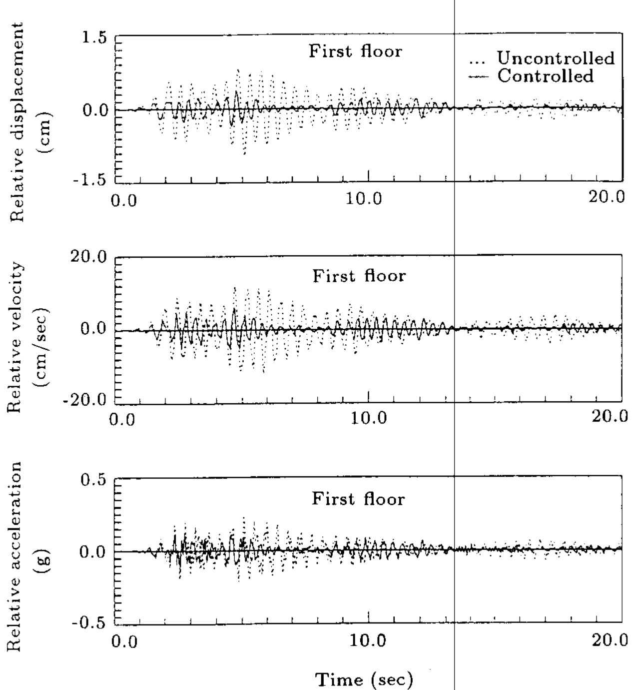


**Figure 8.** Control by predictive optimal control algorithm. First floor response is shown for 20 seconds. The structure has been subjected to the 25% El Centro earthquake and control forces. $r = 3 \times 10^{-9}$.

comparable to those of neuro-fuzzy control, where larger responses have been observed. As expected, the control force is reduced when $r$ is increased. As a result, the acceleration has been reduced also.

For better comparison between the predictive and the neuro-fuzzy control methods, several important points should be noted:

1. While the whole response of the structure has been fed back and used in the calculation of the above predictive control forces, the feedback to the neuro-fuzzy controller has only been the relative acceleration of the first floor.
2. The structure has been simulated as a linear system with only one source of time delay in the control loop. The only source of non-linearity has been the actuator dynamics which has not changed the linearity of the system considerably. Also, only one identified time delay has been considered in the control loop. However, these are not the real situations in the control of real structures. Structures are, generally, many degrees of freedom systems which cannot be simulated by such reduced models precisely. Also, there might be further sources of delay and non-linearity in the system. Due to these facts, neuro-fuzzy control systems are expected to deal with such problems better than predictive optimal controllers, considering their learning capability and adaptivity.

## CONCLUDING REMARKS

In this paper, the performance of a neuro-fuzzy controller and a predictive optimal controller, developed for the control of a three-story frame structure, were compared. It was demonstrated that the results of controlling are very similar. Although both systems work based on the prediction of the response of the frame, their means of prediction is different. The predictive controller is formulated, but the neuro-fuzzy controller uses an emulator directly or indirectly, which learns to predict the response of the structure. Hence, the neuro-fuzzy controller seems more powerful in dealing with situations where an appropriate formulation for the prediction of the response is not available or hard to develop (such as in the cases of high non-linearity) due to the constituting material of the structure or existence of an unidentified time delay in the control loop.

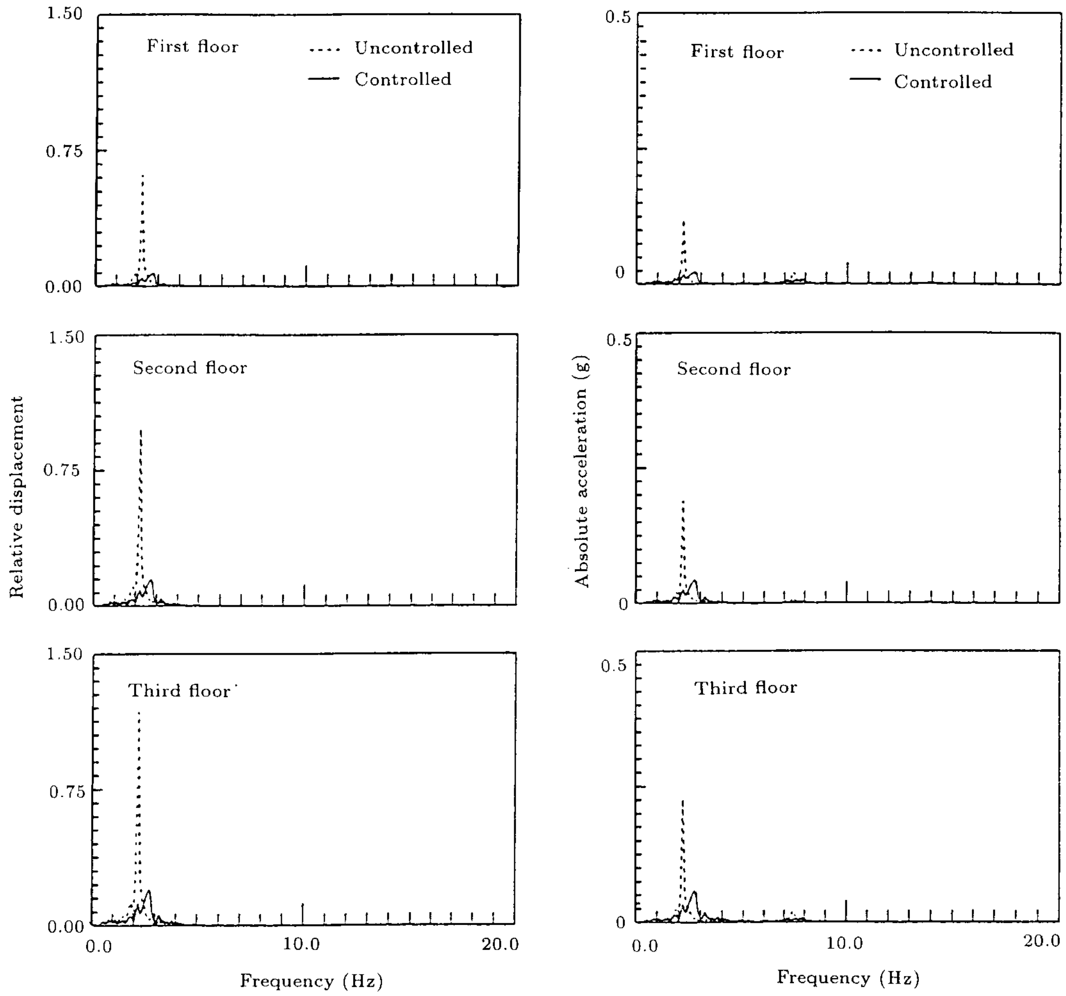


**Figure 9.** Control by predictive optimal control algorithm. Fourier transform of the relative displacement and absolute accelerations of the three floors are shown. The structure has been subjected to the 25% El Centro earthquake and control forces. $r = 3 \times 10^{-9}$.

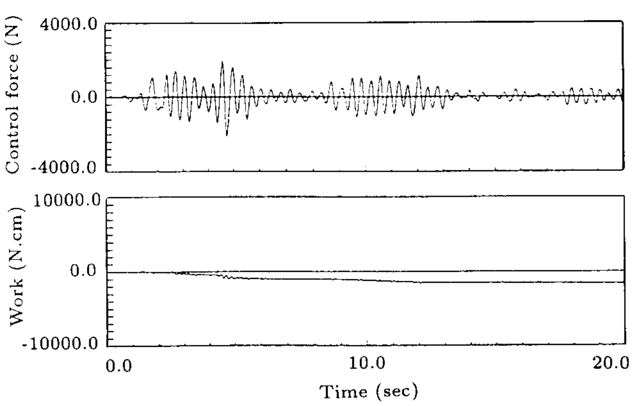


**Figure 10.** Control by predictive optimal control algorithm. Control forces applied by the tendons on the structure and the work done by both of the actuators on the structure are shown for 20 seconds. The structure has been subjected to the 25% El Centro earthquake and control forces. $r = 3 \times 10^{-9}$.

## ACKNOWLEDGMENT

This paper is prepared in relation to a research partially supported by the National Science Foundation Grant BCS-9201437. This support is gratefully acknowledged. Moreover, the first author would like to acknowledge the cooperation of the civil engineering department of the Sharif University of Technology, Tehran, Iran.

## REFERENCES

1. Soong, T.T. "Experimental simulation of degrading structures through active control", *Earthquake Engineering and Structural Dynamics*, **27**(2), pp 143-154 (1998).
2. Johnson, E.A., Voulgaris, P.G. and Bergman, L.A., "Multiobjective optimal structural control of the Notre Dame building model benchmark", *Earthquake Engi-*

*neering and Structural Dynamics*, **27**(11), pp 1165-1188 (1998).

3. Ribakov, Y. and Gluck, J. "Active control of MDOF structures with supplemental electrorheological fluid dampers", *Earthquake Engineering and Structural Dynamics*, **28**(2), pp 143-156 (1999).
4. Joghataie, A. "Neural networks and fuzzy logic for structural control", Ph.D. Thesis, University of Illinois at Urbana-Champaign, Illinois, USA (1994).
5. Joghataie, A. and Ghaboussi, J. "Neural networks and fuzzy logic in structural control", *Proc. First World Conference on Structural Control*, Los Angeles, California, pp WP1-21-30 (Aug 3-5, 1994).
6. Haykin, S., *Neural Networks: A Comprehensive Foundation*, Prentice Hall International Editions (1994).
7. Yao, J.T.P. "Uncertainties in structural control", *Vibration Control and Active Vibration Suppression*, Inman, D.J. and Simonis, J.C., Eds., the 1987 ASME Design Technology Conference.
8. White, D.A. and Sofge, D.A., *Handbook of Intelligent Control*, Multiscience Press Inc (1992).
9. Terano, T., Asai, K. and Sugeno, M., *Fuzzy System Theory and its Applications*, (1987) Translated from Japanese to English, published by Academic Press (1992).
10. Sugeno, M., Ed., *Industrial Applications of Fuzzy Control*, North Holland (1985).
11. Rodellar, J., Barbat, A.H. and Martin-Sanches, J. "Predictive control of structures", *ASCE J. of Engineering Mechanics*, **113**, pp 797-812 (1987).
12. Rodellar, J., Chung, L.L., Soong, T.T. and Reinhorn, A.M. "Experimental digital control of structures", *ASCE J. Engrg. Mech.*, **115**, pp 1245-61 (1989).
13. Ghaboussi, J. and Joghataie, A. "Active control of structures using neural networks", *ASCE J. Engrg. Mech.*, **121**(4), pp 555-567 (Apr. 1995).
14. Soong, T.T., *Active Structural Control: Theory and Practice*, Longman Scientific and Technical (1990).