A COMPARATIVE STUDY OF LEARNING METHODS AND MATHEMATICAL ALGORITHMS IN STRUCTURAL CONTROL

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ABSTRACT

A neuro controller, a neuro–fuzzy controller and a predictive optimal controller have been trained and used for the control of a three storey frame structure subjected to earthquakes. Their performance is assessed for different earthquakes and results are compared. Sensitivity of their performance to changes in structural properties is investigated. It is concluded that while the results are similar, the predictive optimal controller shows less sensitivity to the changes in structural parameters. On the other hand the neuro controller and the neuro–fuzzy controller are more optimal and show more capability of reducing the structural response by applying smaller control forces. However the three controllers have been capable of controlling the structure significantly regardless of the amount of damage.

KEYWORDS

Structural control, active control, neural networks, fuzzy logic, neuro control, fuzzy control, neuro–fuzzy control, optimal control, predictive control, learning control.

INTRODUCTION

Active control methods such as optimal control, pulse control and predictive optimal control methods, where control force vector is found from an explicit mathematical function of structural response vector, may be called 'Mathematical Control Methods'. On the other hand active structural control methods which are based on the use of the so called adaptive, learning and smart systems such as neural networks and fuzzy logic, where the adaptive and learning system learns or extracts the knowledge of controlling the structure implicitly, may be called 'learning control methods'. A large number of papers have been published on both the mathematical and learning control of structures recently, where a useful collection of the most recent papers can be found in the proceedings of the First World Conference on Structural Control (1WCSC 1994). One of the main advantages counted for the learning controllers versus the mathematical conventional controllers is that it is not required for the design of the learning controllers the

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provision of a mathematical model of the structure, actuators, sources of delay and any other parameters of the control system since learning controllers are supposed to learn and extract from rough data of the structure's response the necessary knowledge for controlling the structure. This lets the learning controllers be capable of controlling complicated structural systems for which a parameter identification is hard or not possible to achieve. Even if the controlled structure is identified with appropriate precision it may be a nonlinear system, as is in most of the real cases. While it is necessary to prepare an approximate linear model for the controlled structure in order to design a conventional mathematical controller for it, a more precise nonlinear model can be prepared and a learning controller may be designed based on the data about the response of the structure, obtained through a numerical or an experimental simulation. Results of a series of numerical studies by the authors for the use of neural networks and fuzzy logic in structural control have been reported in their previous publications and they have proposed algorithms for the training of neuro controllers and construction of fuzzy controllers for structural control, and have tested their methodology in the control of a three storey frame structure (Joghataie and Ghaboussi 1994, Joghataie 1994, Ghaboussi and Joghataie 1995). These studies have shown the capabilities of learning systems in structural control. Joghataie and Ghaboussi (1995) have designed a predictive optimal controller and tested it in the control of the same three story frame structure and have compared the results of the learning and optimal control methods. This paper contains the concise results of the previous studies as well as a comparative study on the generalization capabilities of the learning and mathematical control methods and sensitivity of their performance to changes in the structural properties.

CONTROLLED STRUCTURE AND THE CONROL SYSTEM

Information about the controlled three storey frame structure, actuators and their mechanical properties are put in Fig. 1. A sampling period of 0.02 sec. has been used and one delay of 0.02 sec. due to the time required for the conversion of digital to analogue control signal and other sources of delay has been assigned to the controlled system.

NEURO, NEURO—FUZZY AND PREDICTIVE OPTIMAL CONTROLLERS

Details about neuro and neuro—fuzzy controllers and their training scheme and construction, as proposed by the authors, can be found in the previous publications by the authors (Joghataie 1994, and Joghataie and Ghaboussi 1994). Also details for the construction of predictive optimal controllers can be obtained from Rodellar, Martin—Sanchez and their co—workers (1987, 1989) and also Joghataie and Ghaboussi (1995). The two following paragraphs contain brief explanations regarding construction of these controllers.

Neuro and Neuro—Fuzzy controllers

First a neural network, called the emulator neural network, is trained to learn to predict the future response of the structure from information collected about its previous response and control forces. The emulator is then used in a preliminary control of structure. Results of the preliminary control is used in the training of the neuro—controller which extracts from its training data, the general knowledge required for a smooth control. A fuzzy controller is designed and put in series after the neuro—controller which acts as a secondary controller to make corrections to the neuro—controller signals.

Predictive Optimal Controller

Actuator Properties :
A = area of ram = 5.06 cmsup2
V = chamber volume = 151.80 cmsup3
C = leakage coefficient = 0.10 cmsup5/(NT.sec.)
β = compressibility = 2.1 MN/cmsup2/(NT.sec.)
τ = time constant = 0.2 sec.
q_{max} = max. valve flow = 616 cmsup3/sec.
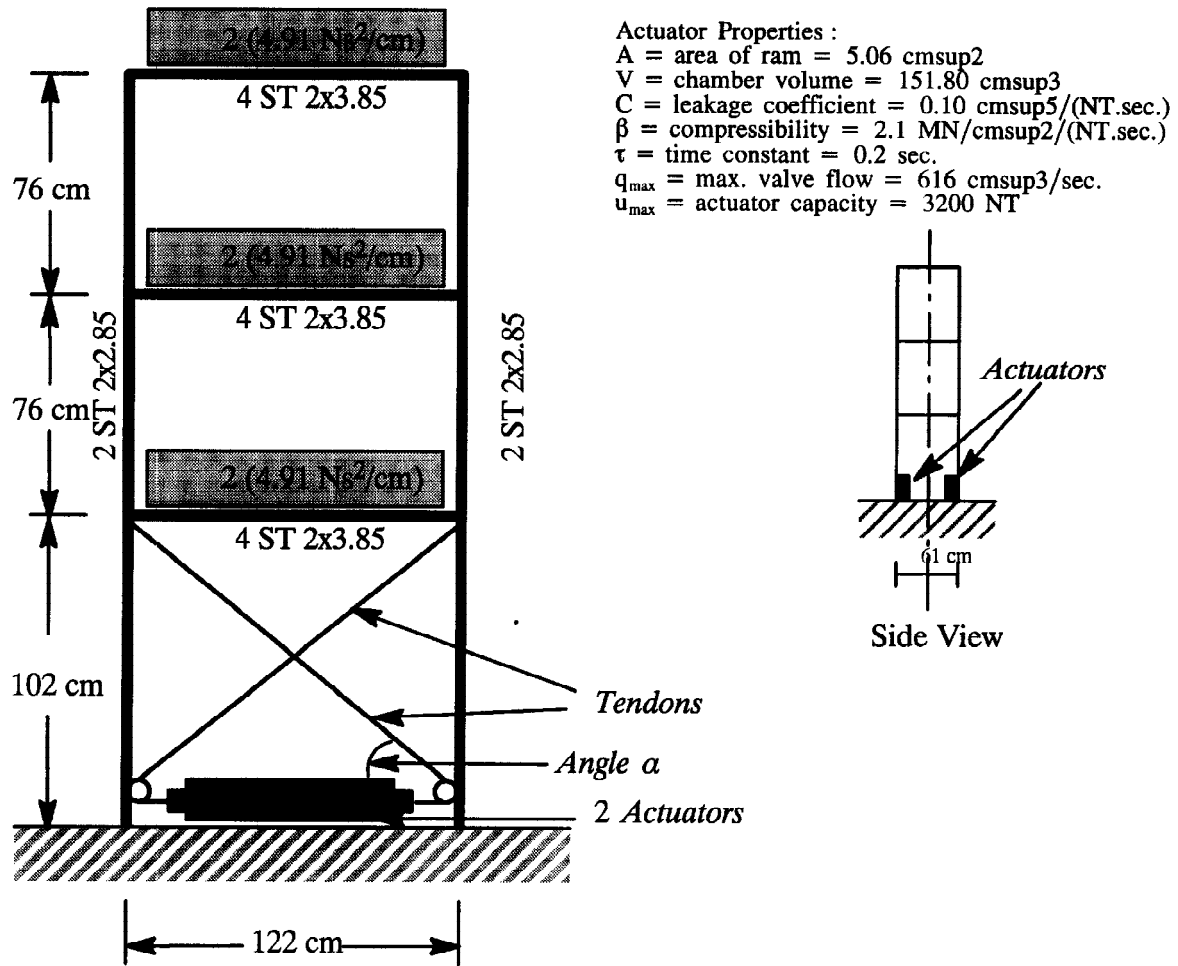u_{max} = actuator capacity = 3200 NT

Side View

Figure 1. The structure and the schematics of the tendon control system with the actuator.

First structural properties are identified and a mathematical model describing the motion of structure is developed. An objective function, called the performance index, representing cost of control and penalty for response is defined. The objective function is then optimized and control rules are obtained. Cost of control and penalty for response are shown by weighting matrices R and Q respectively. For the controlled structure of this study the cost matrix reduces to a scalar r and the response weighting matrix is a 6 dimensional vector. The authors have studied the controller performance as a function of r and have found the best control results by selecting $r = 3 \times 10^{-9}$. Also since the structure has been considered as a three degrees of freedom system, with emphasize on the reduction of its relative displacements, $Q = diag.$ [1.0 1.0 1.0 0.0 0.0 0.0] has been used. More information can be obtained from Joghataie and Ghaboussi (1995).

EVALUATION OF THE CONTROLLERS

The neuro and the neuro—fuzzy controllers have been designed based on data obtained from the response of the structure to the 25% El Centro earthquake to evaluate the performance of the three controllers, the structure was subjected to the same earthquake and controlled by the three controllers. Then, to assess the generalization capabilities of the controllers, the structure was subjected to the 100% Taft earthquake and controlled by the three controllers. Sensitivity of the structure was then studied by subjecting the structure to the 25% El Centro earthquake while the resisting moment of inertia of the right hand side columns

were reduced from 100% to 60% equivalent to a damage from 0% to 40%. Results have been compared for these three cases as explained in the following sections.

25% El Centro Earthquake

Results of this case are shown in Figs. 2 and 3 and Table 1. The three controllers have shown similar performance however the neuro−fuzzy controller has been the most successful in reducing the relative displacements, while the predictive optimal controller has been able to reduce the accelerations more. Also it is obvious that the neuro and the neuro−fuzzy controllers use smaller forces to and absorb more energy from the structure which can be considered as points of advantage over the predictive optimal controller. The three controllers have been able to reduce the response of the structure significantly.

100% Taft Earthquake

Results of this case can be found in Figs. 4 and 5. Again, similar performance can be seen as in the 25% El Centro case, and once again, the three controllers have been able to control the structure successfully. Specially for the neuro and the neuro−fuzzy controllers which their training has been based on the 25% El Centro earthquake, this study shows that they have learned the general features of controlling the structure subjected to any earthquake of similar intensity.

Sensitivity of the Controllers to Damage

The strength of the right hand side columns of the structure were reduced as a source of damage gradually and effect of damage on the performance of the controllers was studied while the structure was subjected to the 25% El Centro earthquake. Figure 6 contains the detailed results of this case. Damage was increased from 0% to 5% to 10% to 20% to 40%. In Figs. 6a through 6f the horizontal axis represents the damage percentage d and the vertical axis represent the maximum observed response, the maximum required control force and the absorbed energy during 20 seconds of controlling the structure. As can be

Table 1. Comparison of results for uncontrolled, neuro−controlled and neuro−fuzzy controlled structure, subjected to 25% El Centro earthquake.

|	uncont.	neuro cont.	neuro − fuzzy cont.	predictive opt. cont.
max. relative displacement x_{max}. (cm.)	0.95	0.43	0.30	0.36
$(x_{max.})_{cont.}$ / $(x_{max.})_{uncont.}$	—	0.45	0.32	0.38
max. relative velocity $\dot{x}_{max}$. (cm/sec.)	11.98	5.38	5.30	6.18
$(\dot{x}_{max.})_{cont.}$ / $(\dot{x}_{max.})_{uncont.}$	—	0.45	0.44	0.52
max. absolute acceleration $\ddot{x}_{max.}$(cm/sec²)	260	124	152	145
$(\ddot{x}_{max.})_{cont.}$ / $(\ddot{x}_{max.})_{uncont.}$	—	0.48	0.58	0.56
max. control force (Nt.)	—	855	1050	2135
control energy (Nt. cm.)	—	6391	5591	1574
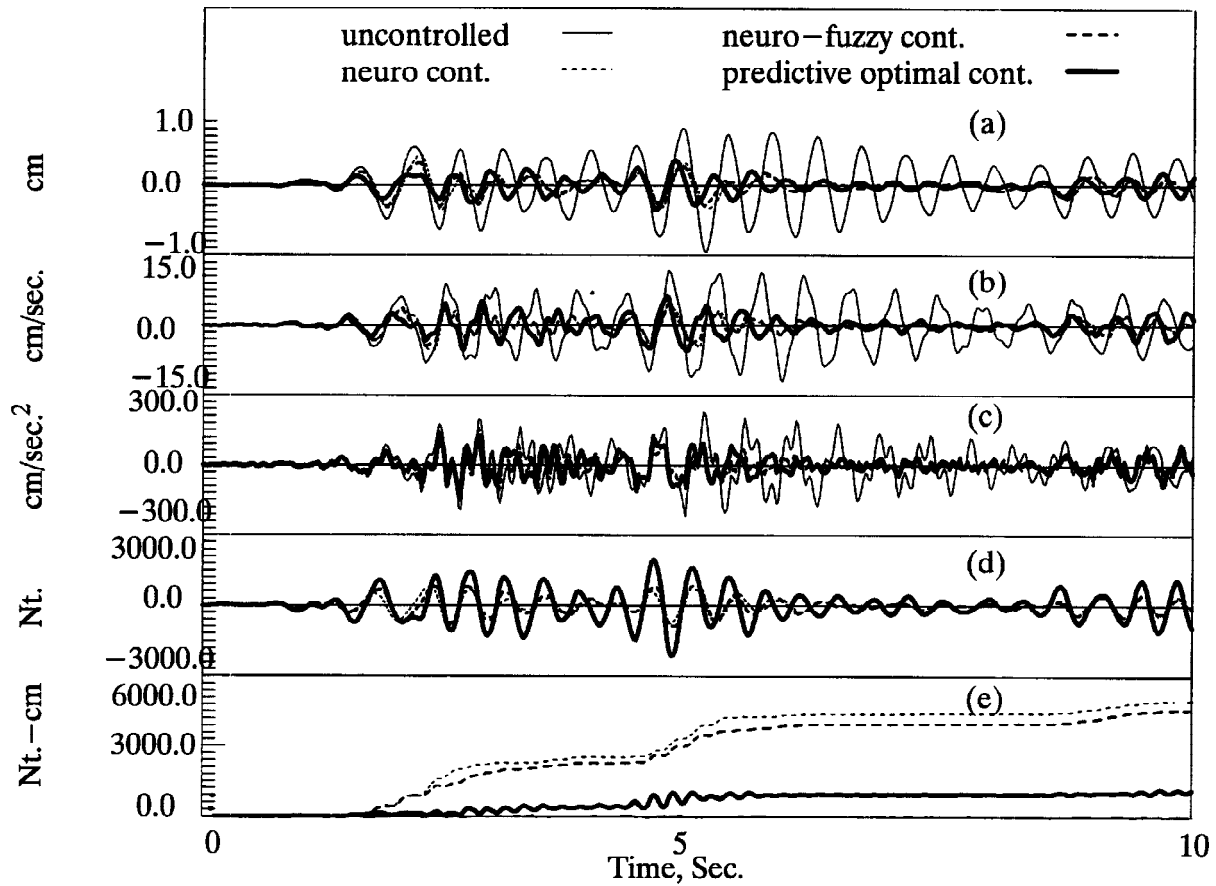
Figure 2. Results of controlling the structure subjected to 25% El Centro Earthquake. (a) Relative displacement of the first floor (b) Relative velocity of the first floor, (c) Absolute acceleration of the first floor, (d) Control force, and (e) Absorbed energy by the controllers.
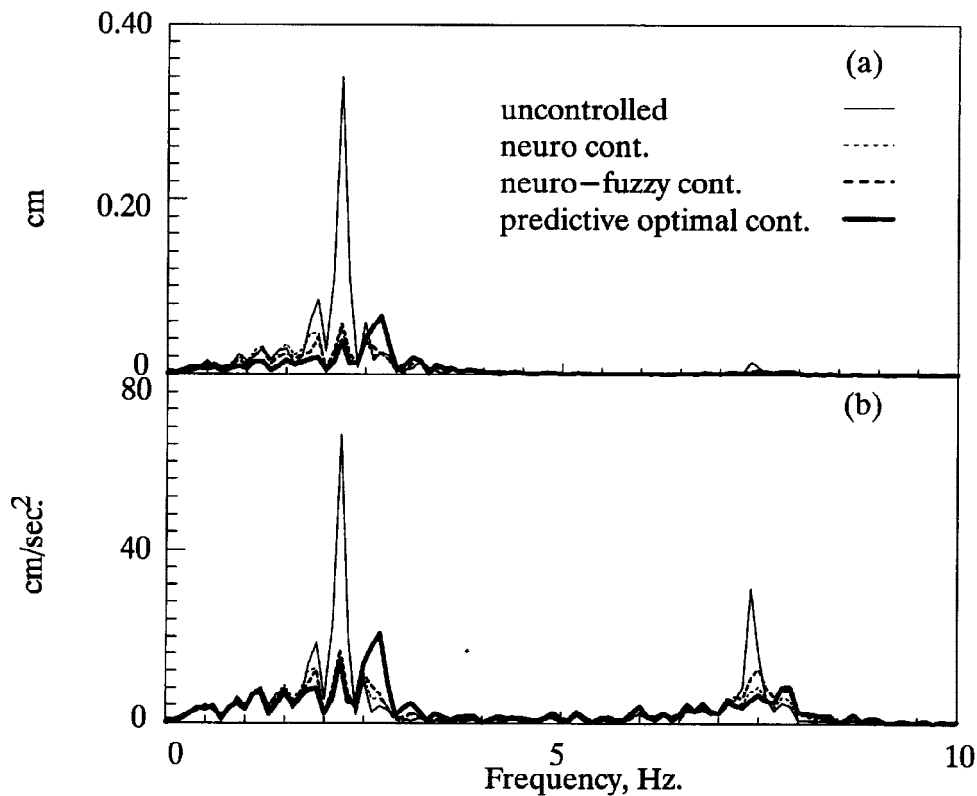

Figure 3. Results of controlling the structure subjected to 25% El Centro Earthquake. Fourier spectra for (a) Relative displacement of the first floor (b) Absolute acceleration of the first floor.
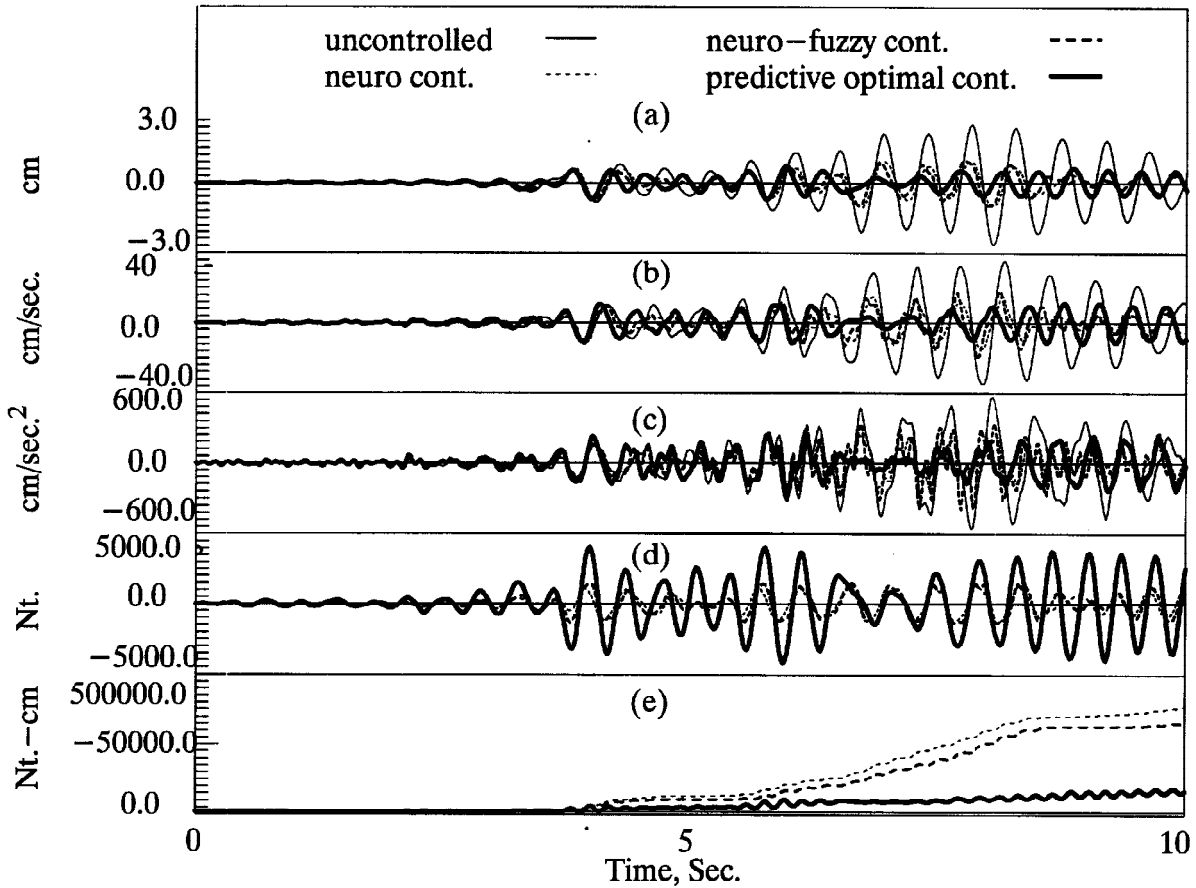
Figure 4. Results of controlling the structure subjected to 100% Taft Earthquake. (a) Relative displacement of the first floor (b) Relative velocity of the first floor, (c) Absolute acceleration of the first floor, (d) Control force, and (e) Absorbed energy by the controllers.
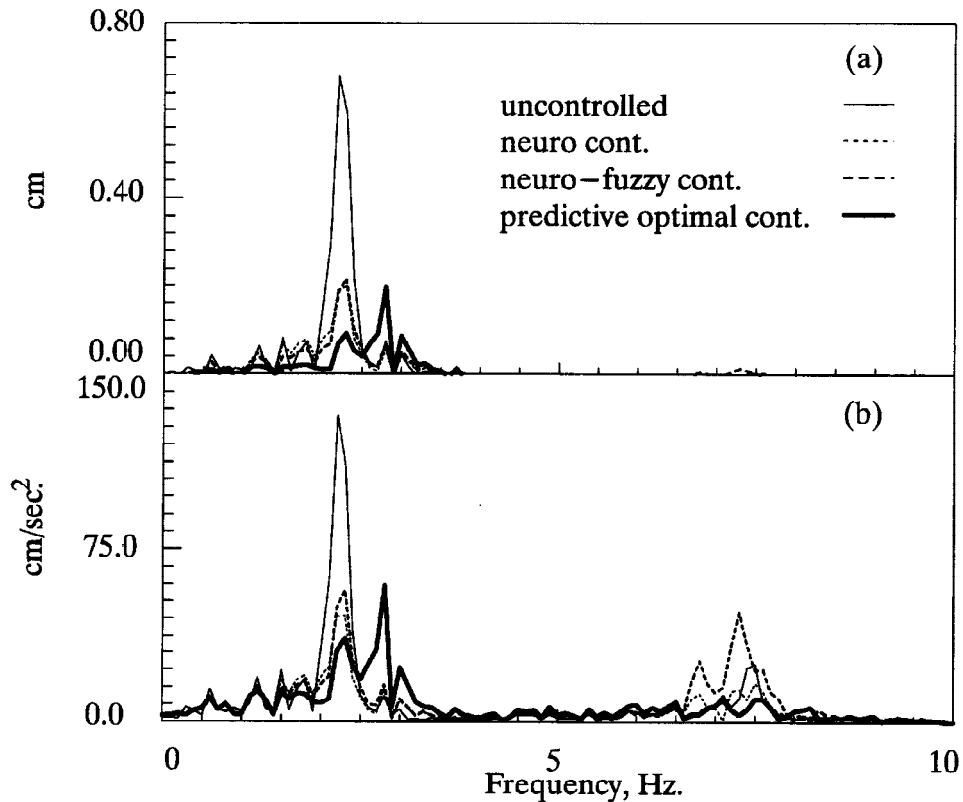

Figure 5. Results of controlling the structure subjected to 100% Taft Earthquake. Fourier spectra for (a) Relative displacement of the first floor (b) Absolute acceleration of the first floor.

seen the three controllers show no significant sensitivity to a minor damage up to 10%, although their performance deteriorates as a direct function of the amount of damage. The neuro–fuzzy controller still shows the best performance in the control of displacement and velocity. As the damage increases beyond 10%, performance of the neuro–fuzzy controller declines rapidly. The neuro controller shows more stability however its performance declines rapidly too. The predictive optimal controller shows stability and no matter what the amount of damage, it issues approximately the same control force, absorbs the same amount of energy and reduces the response to the same percentage. Although more detailed studies are necessary, it may be concluded from these results that the predictive optimal controller tries to fix the relative position of the floor masses regardless of the strength of the structure. On the other hand, the neuro and the neuro–fuzzy controllers try to use the strength of the structure and apply smaller control forces and due to the fact that they have been trained for the control of the undamaged structure, they fail to respond appropriately when structural properties change significantly.

CONCLUDING REMARKS

The most significant result of this study is that the neuro–fuzzy and the predictive optimal controllers are all capable of reducing the response of the structure even when there is significant damage to the structure, and show similar performance with minor differences. The issue of sensitivity of the learning controllers to structural damage has been addressed here. The neuro controller is weaker than the neuro–fuzzy controller, although when structural damage is significant it shows more stability. The predictive optimal controller is less sensitive to structural damage than the neuro and the neuro–fuzzy controllers but the neuro–fuzzy controller is more successful in reducing the structural response for the undamaged and slightly damaged structure. One significant advantage of the neuro–fuzzy controller over the predictive optimal controller seems to be that it uses much smaller control forces to obtain similar results and hence it seems more optimal.

REFERENCES

Proceeding of the First World Conference on Structural Control, 1WCSC (1994). 3–5 August 1994, Los Angeles, California, USA.

Joghataie, A. (1994). *Neural Networks And Fuzzy Logic For Structural Control*. Ph.D. Thesis, University of Illinois at Urbana–Champaign, Illinois, USA

Joghataie, A. and J. Ghaboussi (1994). Neural Networks And Fuzzy Logic In Structural Control. *Proceedings, First World Conference on Structural Control*, 3–5 Aug. 1994, Los Angeles, California.

Ghaboussi, J. and A. Joghataie (1994). Active Control Of Structures Using Neural Networks. *Journal of Engineering. Mechanics Division, ASCE*, April 1995, v. 121, n. 4, pp. 555–567.

Joghataie, A. and J. Ghaboussi (1995). Active Structural Control Using Neural Networks And Fuzzy Logic. Submitted for publication in *Computers and Structures*.

Rodellar, J., A. H. Barbat and J. Martin–Sanchez (1987). Predictive Control of Structures *Journal of Engineering Mechanics Division,. ASCE*, v.113, pp 797–812.

Rodellar, J., L. L. Chung, T. T. Soong and A. M. Reinhorn (1989). Experimental Digital Control Of Structures. *Journal of Engineering Mechanics Division, ASCE*, v.115, pp 1245–61.
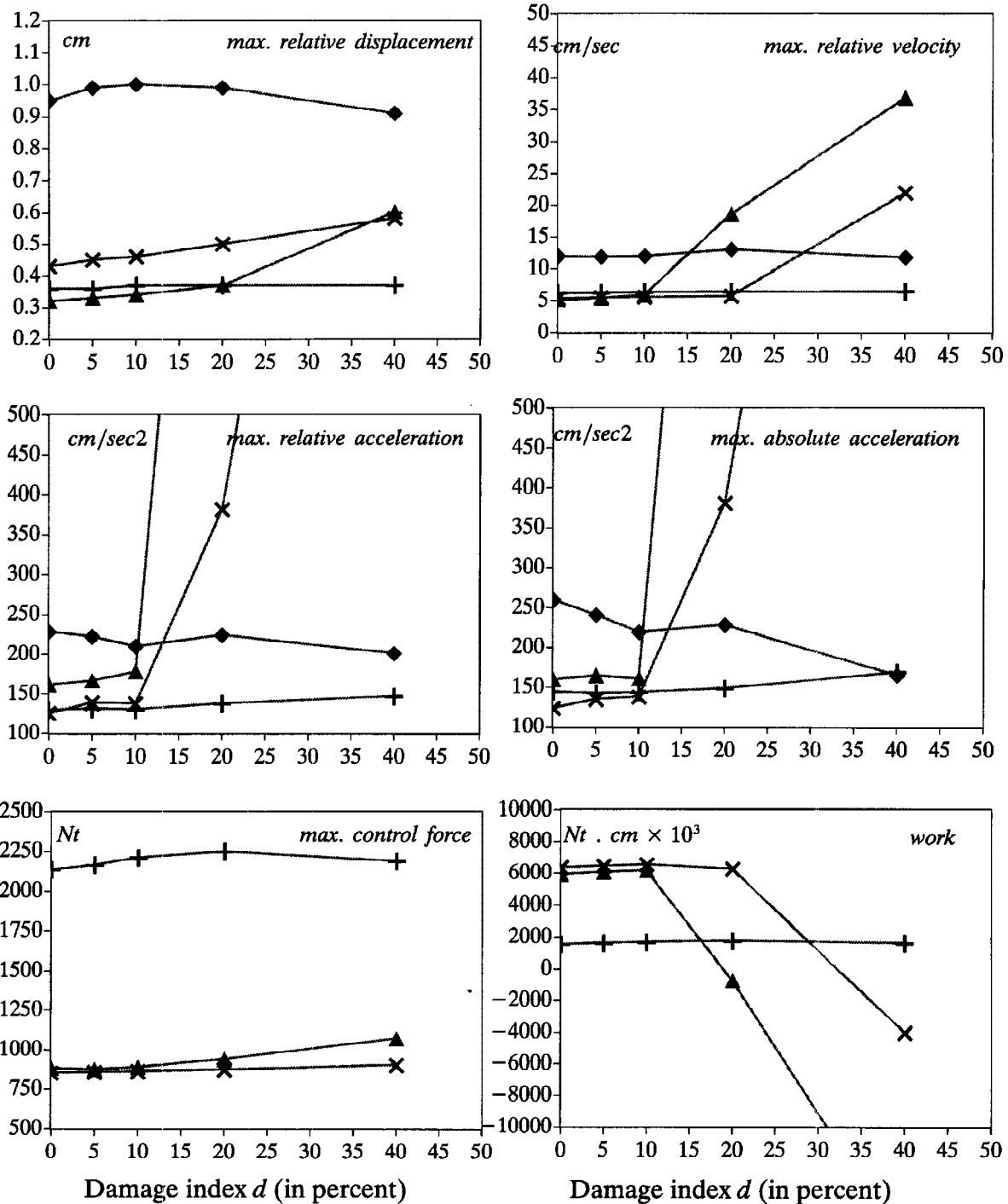
Figure 6. Effect of damage index d on several performance measure of the three control algorithms.