Direct Adaptive Neurocontrol of Structures under Earth Vibration

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Abstract: A direct adaptive neurocontroller is proposed to reduce structure response to earth vibrations by actively creating an equal but opposite force to that of the first mode force of the structure. While earthquake forces are generally considered to be unpredictable, the short-term predictions by the proposed neurocontrol architecture significantly reduce structure vibrations. To demonstrate its general applicability and utility to future earthquakes, the proposed adaptation algorithm is also shown to be asymptotically convergent. The approach is validated by several simulations in which actual time series from the Hachino, Northridge, Kobe, and Bam earthquakes are applied against structures of various heights, three-, five-, and seven-story structures. The simulation results are then compared with those of a conventional linear quadratic regulator. Results indicate a significant and consistent improvement in minimal structure displacement.

DOI: 10.1061/(ASCE)0887-3801(2009)23:5(299)

CE Database subject headings: Structure control; Active control; Modal analysis; Neural networks; Earthquakes; Vibration.

Introduction

There are many different approaches for active structure control. These methods can be broadly classified into intelligent and conventional control methodologies. Among the intelligent control approaches, a popular technique of structural control is to use model-based adaptive control (Chen et al. 1995; Ghaboussi and Joghataie 1995; Nikzad et al. 1996; Ghaboussi and Bani-Hani 1997; Bani-Hani and Ghaboussi 1998; Hosuner et al. 1997). In these schemes, two neural networks are used. The first neural network, a neural-emulator network, predicts the structural response based on the structure displacement, earth acceleration, and control force in the last few time steps. The error function of this neural network is derived from the difference between actual outputs of the structure and predicted ones from the emulator network. The second neural network is a neurocontroller network that determines an appropriate control force based on the emulator's predicted structural response. The neurocontroller's output is the actual control force that is applied to the structure; and the error function of the neurocontroller is the difference between desired displacement (u^d) and structural output (u).

The above adaptative algorithm assumes knowledge of the rate of variations of the error function with respect to the control force. Since this is not known, it is instead approximated using a neural network that is trained to model the structure. The first person who used this algorithm for structure control was Chen in 1995 (Chen et al. 1995). He applied this control algorithm in an offline mode. First, by using structural algorithm, a neural-emulator network is trained. Then, by using the structural algorithm and emulator, the neural network controller is trained. Finally, the controller is placed in the control structure.

The above algorithm, while being effective in offline mode, is not desirable due to a lack of online training. Considering the unpredictability of the earthquakes and their patterns, it would be more appropriate if the two neural networks were trained during occurrence of the earthquake. But, this goal either requires fast convergence of the training algorithms or a complete revisioning of the control approach. The first approach that addresses the problem of convergence speed uses a momentum term in the training algorithm (Yu-Ao and Jianjun 1998). The second approach investigates small modifications in the structure of the neural network to increase the speed of training (Yu-Ao and Jianjun 1998). In the third procedure, connection weights of the neural network controller are updated after each pattern (online) presentation, in contrast to the batch (off-line) training mode, in which the training patterns are presented to the network in a batch for updating the connection weights (Madan 2006). In the fourth scheme, a neurocontroller network is trained to directly control the structure without use of the neural-emulator network. By eliminating the neural-emulator network, the time delay due to network training network is reduced and the inherent time delay of the system is deteriorated by neurocontroller network (Ghaboussi and Joghataie 1995). The other control structure is using a neural network emulator and one control law (Newton-Raphson minimization method). The neural network predicts structural response and the control law determine the appropriate control force in the next step by using the response of neural network and the rate of the first and second changes with respect to control force (Ratneshwar and Chengli 2002) In the sixth procedure, the control scheme uses two sets of neural nets: the first is

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Note. This manuscript was submitted on April 10, 2007; approved on November 25, 2008; published online on August 14, 2009. Discussion period open until February 1, 2010; separate discussions must be submitted for individual papers. This technical note is part of the ***Journal of Computing in Civil Engineering***, Vol. 23, No. 5, September 1, 2009. ©ASCE, ISSN 0887-3801/2009/5-299–307/$25.00.

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used to obtain the generalized acceleration from the actually measured acceleration of the structure, and the second provides the control force with input as the generalized acceleration of the structure and the ground acceleration (Rao and Datta 2006). The seventh method is the NEURO-FBG smart control system. This smart system is comprised of three parts: a structural condition surveillance system, three converters, and a controller. Surveillance system, fiber Bragg grating (FBG) sensors, can scrutinize structure, as well as forming the dendrites for both converters and the controller. The converter can convert local FBG sensor readings into global system indices. The controller, built with aid of the converter, can then control the structure in predictable ways (Lin et al. 2006).

In this paper, we consider the first mode to be the dominant mode of oscillation. The error function for the proposed neurocontroller is therefore defined simply to minimize the net force that is applied to the structure's first mode. Since structure is a passive system, small errors, from either predictions or excitation of higher oscillation modes, are damped naturally. The gained advantage is similicity in approach, i.e., only one neural network is used, reducing the computational time delay and hence enhancing controller's response to the rapid earth vibrations. This is in contrast to typical control system applications where the goal is to minimize displacement.

This paper is organized as follows. At first, the modal analysis of structure and the desired control force is described. Then, the proposed control algorithm is explained, and in continuing, the stability of the learning algorithm is proved. Finally, the proposed neurocontrol method is simulated against three testbed structures of various heights and two different earthquakes. It should be mentioned that the neurocontrollers here are being trained online and do not have any prior training.

Modal Analysis of Structures

Here, modal analysis is used for producing the desired control force. Structure balance equations for n degrees of freedom includes n differential unknowns in n equations. Modal analysis decouples this nth order differential equation into a system of n first order differential equations. In other words, all modes of structure displacements are decoupled. In the end, by adding structural modes, local displacement of structure can be found. Modal analysis of structure balance equations for n degrees of freedom are as follows:

$$[m]\{\ddot{u}\} + [c]\{\dot{u}\} + [k]\{u\} = -[m]\{\ddot{u}_g\} + \{f\} \tag{1}$$

$$\{u\} = [\Phi]\{y\} = \sum_{i=1}^{n} \{\Phi_i\} \,.\, y_i(t) \tag{2}$$

$$\ddot{y}_i + 2\xi_i\omega_i\dot{y}_i + \omega_i^2 y_i = \frac{\{\Phi_i\}^{\mathrm{T}}\{P(t)\}}{\{\Phi_i\}^{\mathrm{T}}[m]\{\Phi_i\}} + \frac{\{\Phi_i\}^{\mathrm{T}}\{f\}}{\{\Phi_i\}^{\mathrm{T}}[m]\{\Phi_i\}} \tag{3}$$

$$\{P(t)\} = [m]\{I\}\ddot{u}_g \tag{4}$$

where $\{f\}$=control force; u=structure displacement; $\{\Phi_i\}$=ith structural displacement mode; n=modes number; and ξ_i=ith damping rate.

If an actuator is placed on a structure story, only one of the vector components $\{f\}$ will be nonzero. The structure first mode has a great share in local displacement when the value of nonzero vector component $\{f\}$ is equal to the value on the right hand side of Eq. (4) such that the net force to the first mode is zero. Therefore, the local displacement of the first mode will also approach zero, and the greater part of structure local displacement is controlled. As a result, $\{f\}$ in control structure will be the desired control force $\{f^D\}$.

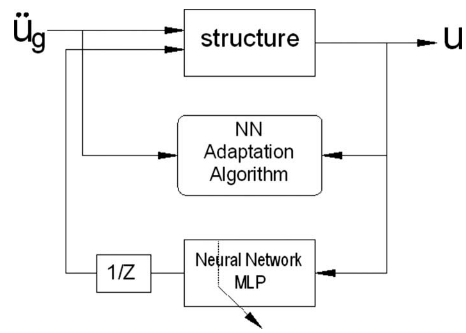

Fig. 1. Structural control algorithm with neural network

$$\{\Phi_1\}[m]\{I\}\ddot{u}_g - \{\Phi_1\}[m]\begin{Bmatrix} f^D \\ 0 \\ 0 \\ \vdots \\ 0 \end{Bmatrix} = 0 \tag{5}$$

where $\{\Phi_1\}$=structure first mode.

Proposed Neurocontroller

Error function of the neural network controller is achieved from control force error, which is derived from neural network and desired control force. This function is given as below

$$E_c = \frac{1}{2}[f^D - f^N]^2 \tag{6}$$

where f^N=control force, which is derived from neural network controller, and f^D=desired control force.

This control structure performs online and weights of the neural network are adapted continuously. Achieving the desired control force is very important in this method. There is not any desired control force in ith step. When the earth acceleration is determined in ith step, with any conventional or intelligent algorithm, it can determine the desired control force. Then, considering the desired control force and the produced force by controller, the controller neural network weights are adapted. Using this procedure, the neurocontroller becomes ready to produce control force in $(i+1)$th step.

Fig. 1 shows the control structure. The suggested neural network in this technique is a multilayer perceptron. The input of the neural network is the structure response in ith step. The output is the product of the control force in the $(i+1)$th step.

Stability of Learning Algorithm

If a three-layer neural network is used for controller, the equations are as follows:

$$I_i(t) = u_i(t) \tag{7}$$

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$$H_j(t) = f[\text{net}_j(t)], \quad \text{net}_j(t) = \sum_j w_{ij}^1 I_i(t), \ \ f(x) = \frac{1}{1 - e^{-x}} \tag{8}$$

$$f^N = \sum_j w_j^2 H_j(t) \tag{9}$$

where $\{f^N\}$=predicted control force and $u_i(t)$=displacement in the ith story. Considering the desired control force $\{f^D\}$, the error function is defined as

$$E_c = \frac{1}{2}[f^D - f^N]^2, \quad e(t) = f^D - f^N \tag{10}$$

Then, the rate of gradient of the error function with respect to output and input's weights are computed as follows:

$$\frac{\partial E_c}{\partial w_j^2} = -e(t) \cdot \frac{\partial f^N}{\partial w_j^2} = -e(t) \cdot H_j(t) \tag{11}$$

$$\frac{\partial E_c}{\partial w_{ij}^1} = -e(t) \cdot \frac{\partial f^N}{\partial w_{ij}^1} = -e(t) \cdot \frac{\partial f^N}{\partial H_j(t)} \cdot \frac{\partial H_j(t)}{\partial w_j^2} = -e(t) \cdot w_j^2 \beta_{ij}(t) \tag{12}$$

$$\beta_{ij}(t) = f'[\text{net}_j(t)] \cdot I_i(t) \tag{13}$$

The weights of the neural network are achieved as below

$$w(t+1) = w(t) + \eta(t) \cdot \left(-\frac{\partial E_c}{\partial w}\right) \tag{14}$$

For stabilizing the learning algorithm, the Lyapunov rule is applied. So, the Lyapunov function is used as follows:

$$L(t) = \frac{1}{2} e^2(t) \tag{15}$$

In order to guarantee stabilizing, the rate of Lyapunov function changes should be negative

$$\Delta L(t) = \frac{1}{2}[e^2(t+1) - e^2(t)] \tag{16}$$

$$e(t+1) \cong e(t) + \frac{\partial e(t)}{\partial w}\Delta w = e(t) + \frac{\partial f^N(t)}{\partial w}\Delta w \tag{17}$$

$$\Delta w = -\eta(t)\frac{\partial E_c}{\partial w} = -\eta(t)e(t)\frac{\partial e}{\partial w} = -\eta(t)e(t)\frac{\partial f^N}{\partial w} \tag{18}$$

$$\Delta L(t) \cong \frac{1}{2}\left\{\left[e(t) - \eta(t)e(t)\left(\frac{\partial f^N}{\partial w}\right)^2\right]^2 - e^2(t)\right\} \tag{19}$$

$$\Delta L(t) \cong \frac{1}{2}\left\{-2\eta(t)e(t)^2\left(\frac{\partial f^N}{\partial w}\right)^2 + \eta^2(t)e^2(t)\left(\frac{\partial f^N}{\partial w}\right)^4\right\} = -\lambda e^2(t) \tag{20}$$

$$\lambda = \frac{1}{2}\eta(t)\left(\frac{\partial f^N}{\partial w}\right)^2\left[2 - \eta(t)\left(\frac{\partial f^N}{\partial w}\right)^2\right] \tag{21}$$

If the value of λ is greater then zero, stabilization is guaranteed. To get the goal requires the following condition:

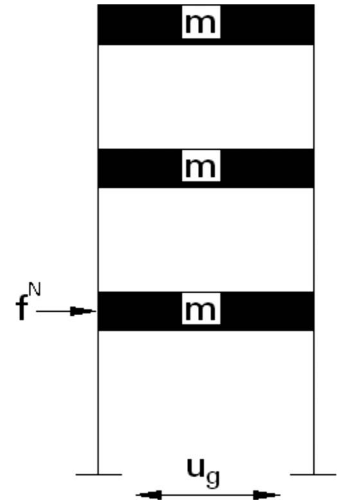

Fig. 2. Control force scheme for three-story structure

$$2 - \eta(t)\left(\frac{\partial f^N}{\partial w}\right)^2 > 0 \Rightarrow 0 < \eta(t) < \frac{2}{\left(\frac{\partial f^N}{\partial w}\right)^2} \tag{22}$$

First Example

The three-story structure in Fig. 2 shows the first numeral example. To compare the proposed method with a conventional one, the linear quadratic regulator (LQR) control scheme is used (Chung et al. 1989). The neural network in suggested technique is a three-layer perceptron neural network. Its hidden layer has five neurons with sigmoid function and output layer has one neuron with linear function. Control force is applied in the first story of structure. Figs. 3 and 4 show local displacement and local acceleration of the structure third story in three states of: 1-uncontrolled; 2-controlled with proposed method with the learning rate η=0.6; and 3-LQR control. Fig. 5 shows control

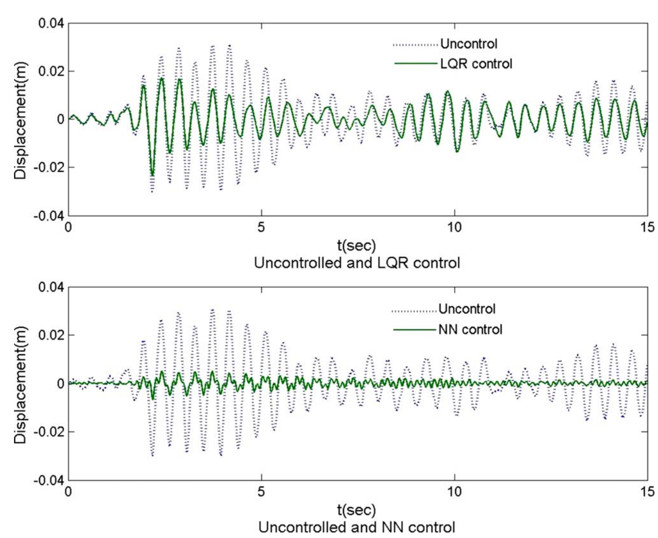

Fig. 3. Third story's local displacement subjected to Hachino earthquake record

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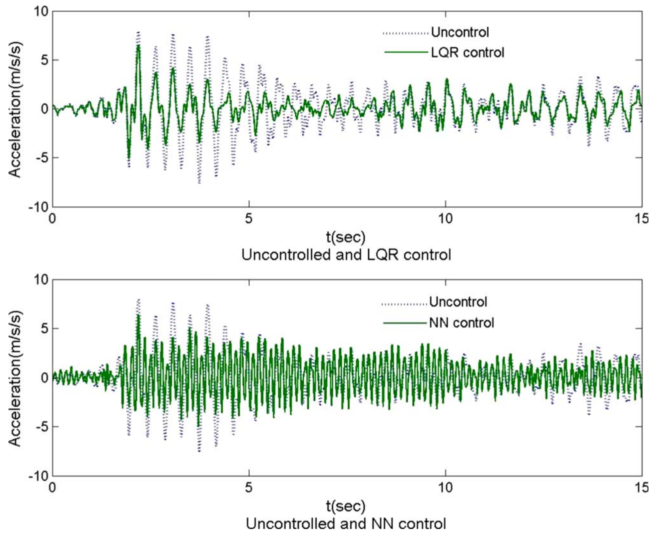

Fig. 4. Third story's local acceleration subjected to Hachino earthquake record

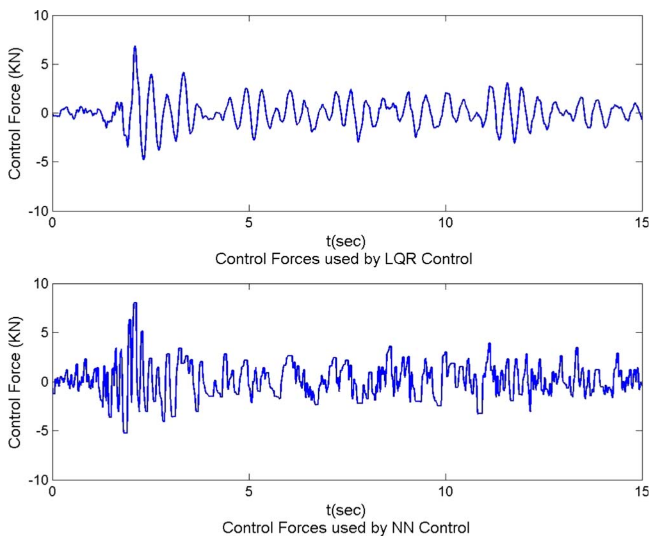

Fig. 5. Control forces used by LQR control and NN control

forces used by LQR control and neural network (NN) control. Table 1 shows the rate of minimum and maximum of the structural response in three states and control forces

$$[m]=\begin{bmatrix} 33.196 & 0 & 0 \\ 0 & 33.19 & 0 \\ 0 & 0 & 33.19 \end{bmatrix} \text{ kN s}^2/\text{m}$$

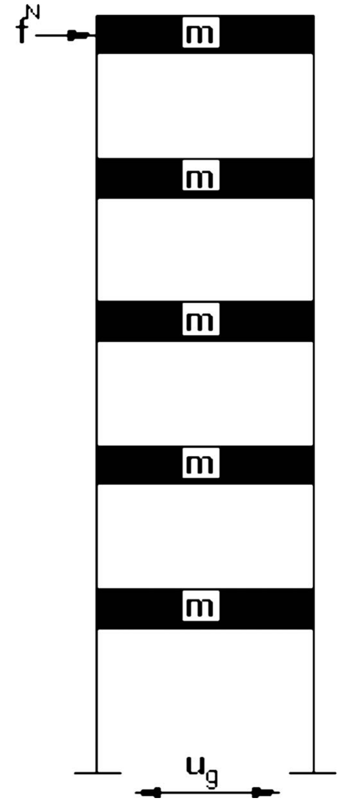

Fig. 6. Control force scheme for five-story structure

$$[k]=\begin{bmatrix} 78424.60 & -52346.40 & 11771.00 \\ -52346.40 & 96368.70 & -51810.10 \\ 11771.00 & -51810.10 & 42525.10 \end{bmatrix} \text{ kN/m}$$

$$[c]=\begin{bmatrix} 12.20 & -1.82 & 1.96 \\ -1.82 & 14.57 & -0.08 \\ 1.96 & -0.08 & 13.9 \end{bmatrix} \text{ kN s/m}$$

$$[\omega]=[2.24 \quad 6.83 \quad 11.53]^T \text{ rad/s}$$

$$[Q]=1{,}000^*[I]_{6^*6}, \quad [R]=[1]$$

From all figures and tables of the first numeral examples, it can be concluded that the proposed method has better result in minimizing the structural local displacement in comparison with the LQR procedure. On the other hand, this technique can reduce the acceleration and base shear not that much.

Table 1. Rate of Minimum and Maximum of Structure Response in Third Story and Control Force Subjected to Hachino Earthquake Record

Controlled methods	Displacement (cm)		Acceleration (cm/s/s)		Control force (kN)	
	Maximum	Minimum	Maximum	Minimum	Maximum	Minimum
Uncontrolled	3.10	−3.00	795.07	−764.57	—	—
LQR control	1.84	−2.43	644.11	−503.11	6.83	−4.79
NN control	0.83	−830	644.19	−501.91	8.03	−5.24

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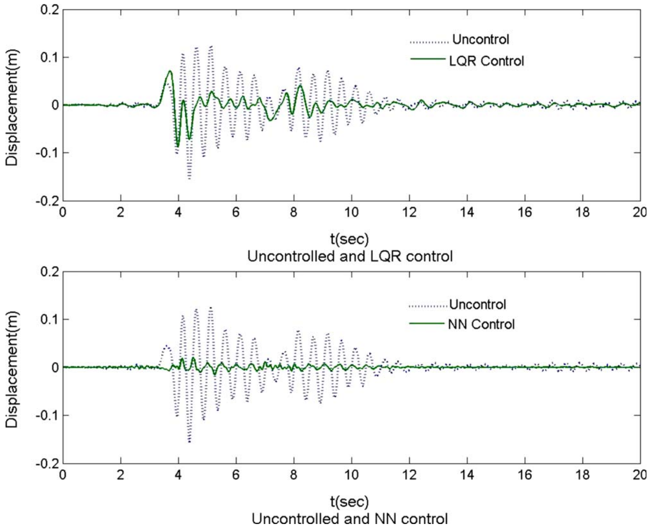

Fig. 7. Fifth story's local displacement subjected to Northridge earthquake record

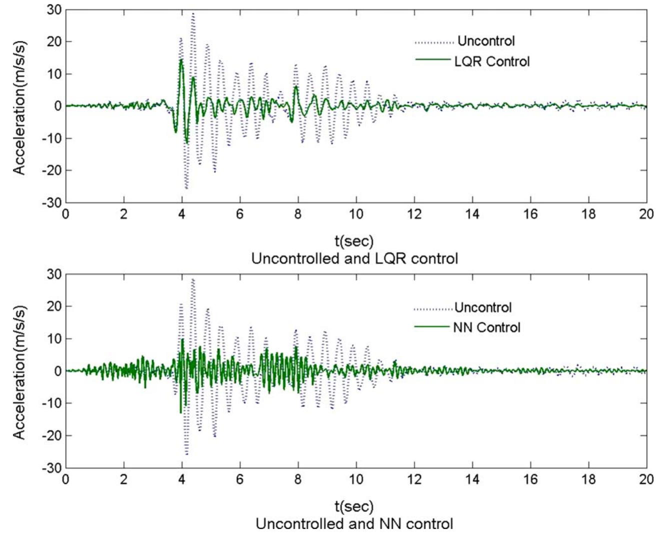

Fig. 8. Fifth story's local acceleration subjected to Northridge earthquake record

Second Example

This numeral example is the five-story structure in Fig. 6. the structural response by the suggested scheme is compared with LQR control method. The structure is under the effect of Northridge acceleration. The structure specifications are as follows:

$$[m]=\begin{bmatrix} 5.58 & 0 & 0 & 0 & 0 \\ 0 & 5.58 & 0 & 0 & 0 \\ 0 & 0 & 5.58 & 0 & 0 \\ 0 & 0 & 0 & 5.58 & 0 \\ 0 & 0 & 0 & 0 & 5.58 \end{bmatrix} \text{ kN s}^2\text{/m}$$

$$[k]=\begin{bmatrix} 21.7 & -10.8 & 0 & 0 & 0 \\ -10.8 & 21.7 & -10.8 & 0 & 0 \\ 0 & -10.8 & 21.7 & -10.8 & 0 \\ 0 & 0 & -10.8 & 21.7 & -10.8 \\ 0 & 0 & 0 & -10.8 & 10.8 \end{bmatrix} \times 10^3 \text{ kN/m}$$

$$[c]=\begin{bmatrix} 49.38 & -22.07 & 0 & 0 & 0 \\ -22.07 & 49.38 & -22.07 & 0 & 0 \\ 0 & -22.07 & 49.38 & -22.07 & 0 \\ 0 & 0 & -22.07 & 49.38 & -22.07 \\ 0 & 0 & 0 & -22.07 & 27.32 \end{bmatrix} \text{ kN s/m}$$

$$[\omega]=[12.77 \quad 36.69 \quad 57.83 \quad 74.28 \quad 84.72]^T \text{ rad/s}$$

$$[Q]=1{,}000^*[I]_{10^*10}, \quad [R]=[1]$$

The control force is applied in the fifth story. The structure is controlled by LQR and the suggested method. The neural network for the proposed approach is a three-layer perceptron neural network. Hidden layer of the neural network includes ten neurons with sigmoid function and output layer of the neural network includes one neuron with linear function. The results show that the structure is controlled better by given neural network. Figs. 7 and 8 respectively show local displacement and local acceleration of the fifth story of structure in uncontrolled state and controlled state by the suggested technique with the learning rate $\eta=0.4$ and LQR control method. Fig. 9 shows control forces used by LQR control and NN control. Table 2 shows the value of maximum, minimum of the structural response in these three states and control forces (Fig. 10).

Paying attention to the first and second examples, this conclusion is achieved that if actuator is placed in the upper story of the structure and the force is applied in this story, then, the suggested method gives better structural responses.

Third Example

This numeral procedure considers the control of a seven-story structure (Paz 1980). Like the past numeral examples, the structural response by the suggested scheme is compared with LQR control method. The structure is under the effect of Bam, Northridge, and Kobe accelerations. The structure specifications are as follows:

$$[m]=\begin{bmatrix} 5.92 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 5.92 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 5.92 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 5.92 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 5.92 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 5.92 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 5.92 \end{bmatrix} \text{ kN s}^2\text{/m}$$

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$$
[k]=\begin{bmatrix} 22,705 & -11,353 & 0 & 0 & 0 & 0 & 0 \\ -11,353 & 22,705 & -11,353 & 0 & 0 & 0 & 0 \\ 0 & -11,353 & 22,705 & -11,353 & 0 & 0 & 0 \\ 0 & 0 & -11,353 & 22,705 & -11,353 & 0 & 0 \\ 0 & 0 & 0 & -11,353 & 22,705 & -11,353 & 0 \\ 0 & 0 & 0 & 0 & -11,353 & 22,705 & -11,353 \\ 0 & 0 & 0 & 0 & 0 & -11,353 & 11,353 \end{bmatrix} \text{kN/m}
$$

$$
[c]=\begin{bmatrix} 66.74 & -31.34 & 0 & 0 & 0 & 0 & 0 \\ -31.34 & 66.74 & -31.34 & 0 & 0 & 0 & 0 \\ 0 & -31.34 & 66.74 & -31.34 & 0 & 0 & 0 \\ 0 & 0 & -31.34 & 66.74 & -31.34 & 0 & 0 \\ 0 & 0 & 0 & -31.34 & 66.74 & -31.34 & 0 \\ 0 & 0 & 0 & 0 & -31.34 & 66.74 & -31.34 \\ 0 & 0 & 0 & 0 & 0 & -31.34 & 35.36 \end{bmatrix} \text{kN s/m}
$$

$$
[\omega]=[9.155 \quad 26.89 \quad 43.79 \quad 58.60 \quad 70.85 \quad 80.01 \quad 85.66]^T \ \text{rad/s}
$$

$$
[Q]=1{,}000^{*}[I]_{14*14}, \quad [R]=[1]
$$

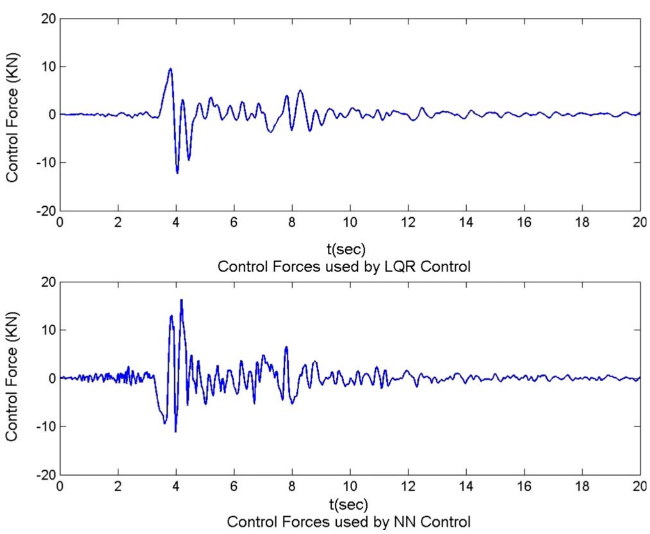

Fig. 9. Control forces used by LQR control and NN control

The neural network in the proposed method is constructed from three layers that is a five-node input layer, a 10-node hidden layer and a 1 output layer. The time delay is 0.05 s and the learning rate is 0.3. The control force is applied in seventh story. Figs. 11–13 show the comparison of the results for Bam acceleration and also Tables 3–5 show the comparison of the results for Bam, Northridge, and Kobe earthquake records.

With considering the above examples, the application of offered method in reduction of structure deflection is suitable. But in high structure, acceleration will increase. To decrease acceleration, the both control systems (LQR control and NN control) is combined and the control force will be achieved by averaging the two control forces. This force is applied to the seventh story of the last example. Fig. 14 and Table 6 show the results.

Conclusions

Using the neural network and modal analysis, online structure active control is achieved. The neurocontroller's learning objective is to contain the structure's first mode of oscillation due to earth movement. In the suggested scheme, only one actuator is

Table 2. Rate of Minimum and Maximum of Structure Response in Fifth Story and Control Force Subjected to Northridge Earthquake Record

Controlled methods	Displacement (cm)		Acceleration (cm/s/s)		Control force (kN)	
	Maximum	Minimum	Maximum	Minimum	Maximum	Minimum
Uncontrolled	12.38	−15.70	2,860.00	−2,570.00	—	—
LQR control	7.10	−8.82	1,450.00	−1,150.00	9.61	−12.32
NN control	2.02	−1.60	976.28	−1,300.00	16.31	−11.22

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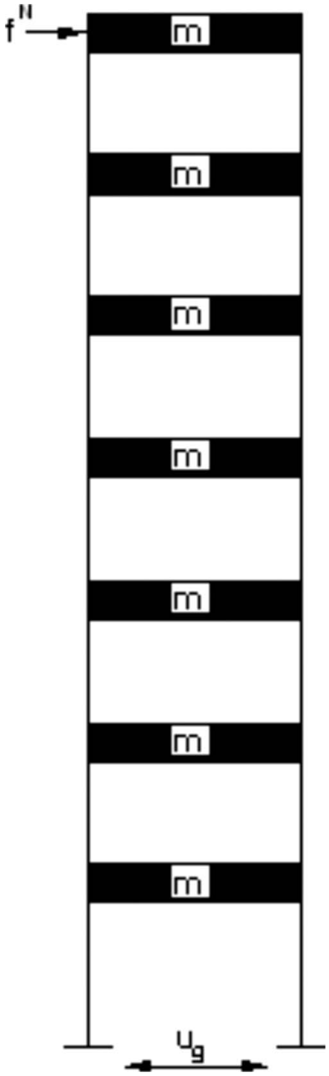

Fig. 10. Control force scheme for seven-story structure

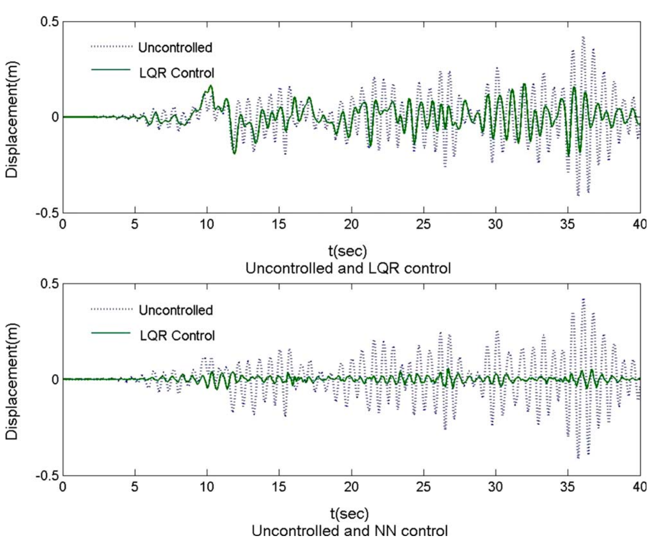

Fig. 11. Seventh story's local displacement subjected to Bam earthquake record

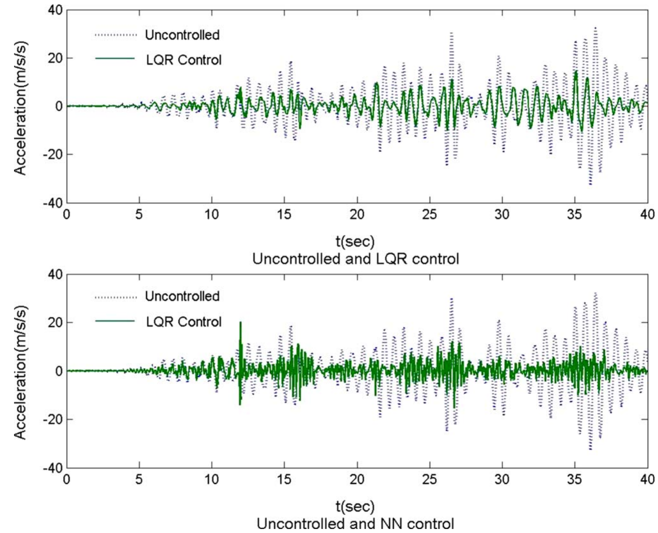

Fig. 12. Seventh story's local acceleration subjected to Bam earthquake record

needed that is placed on any desired story. Learning convergence is generally proved by Lyapunov analysis. Furthermore, the wide applicability of the algorithm is numerically tested on four different real earthquakes and three different structures. Comparing the result with those of a conventional LQR controller, the proposed method consistently and substantially produces improved responses in terms of minimal displacement. This is while there is no clear advantage to other algorithms in term of acceleration or base shear. Naturally by combining LQR control system with offered method, acceleration will be reduced to some extent but displacement will be increased. In conclusion, the choice of error function, i.e., predicting first modal force due to earth vibration, coupled with the simple neurocontrol architecture provides a fast and adaptive learning paradigm for effective vibration control of structures.

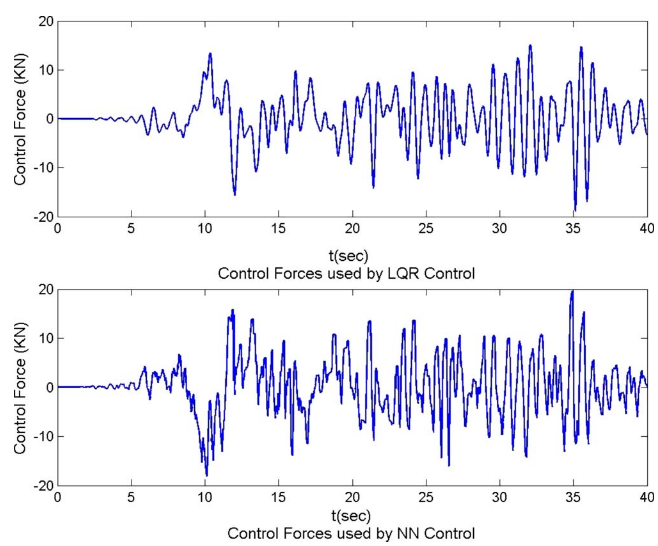

Fig. 13. Control forces used by LQR Control and NN Control

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Table 3. Rate of Minimum and Maximum of Structure Response in Seventh Story and Control Force Subjected to Bam Earthquake Record

Controlled methods	Displacement (cm)		Acceleration (cm/s/s)		Control force (kN)	
	Maximum	Minimum	Maximum	Minimum	Maximum	Minimum
Uncontrolled	42.31	−41.19	3,239.03	−3,300.94	—	—
LQR control	17.62	−20.26	1,459.14	−1,050.47	15.15	−18.91
NN control	5.82	−5.42	2,016.37	−1,546.06	19.57	−18.08

Table 4. Rate of Minimum and Maximum of Structure Response in Seventh Story and Control Force Subjected to Northridge Earthquake Record

Controlled methods	Displacement (cm)		Acceleration (cm/s/s)		Control force (kN)	
	Maximum	Minimum	Maximum	Minimum	Maximum	Minimum
Uncontrolled	10.40	−19.40	2,314.05	−1,528.96	—	—
LQR control	13.06	−11.25	1,364.46	−1,117.08	21.27	−16.91
NN control	4.19	−2.95	2,072.29	−1,502.73	38.88	−27.78

Table 5. Rate of Minimum and Maximum of Structure Response in Seventh Story and Control Force Subjected to Kobe Earthquake Record

Controlled methods	Displacement (cm)		Acceleration (cm/s/s)		Control force (kN)	
	Maximum	Minimum	Maximum	Minimum	Maximum	Minimum
Uncontrolled	28.38	−30.76	2,768.53	−2,349.28	—	—
LQR control	20.24	−13.64	1,108.62	−1,371.45	30.11	−21.47
NN control	4.86	−5.11	2,050.63	−1,412.28	37.71	−24.98

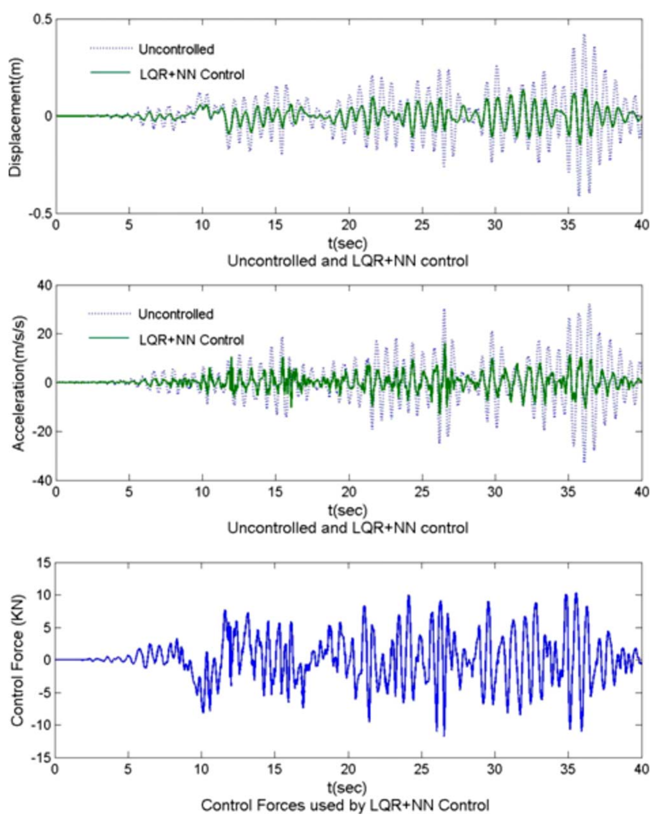

Fig. 14. Seventh story's local responses subjected to Bam earthquake record

Notation

The following symbols are used in this technical note:

c = structure damping;
$E_c, e(t)$ = error function;
f^D = desired control force;
f^N = controller output;
H = hidden layer output;
I = neural network input;
k = structure stiffness;
m = structure mass;
P = force;
Q, R = LQR coefficients;
t = time;
u = structure response;
u^d = desired displacement;
w = weight and bias;
η = learning rate;
ζ = damping rate;
Φ = displacement mode;
ω = natural frequency of structure; and
$1/z$ = time delay.

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Table 6. Rate of Minimum and Maximum of Structure Response in Seventh Story and Control Force Subjected to Bam Earthquake Record

Controlled methods	Displacement (cm)		Acceleration (cm/s/s)		Control force (kN)	
	Maximum	Minimum	Maximum	Minimum	Maximum	Minimum
LQR control+NN control	14.05	−14.67	16,091.11	−1,313.99	10.33	−11.72

References

Bani-Hani, K., and Ghaboussi, J. (1998). "Nonlinear structure control using neural network." *J. Eng. Mech.*, 124(3), 319–327.

Chen, H. M., Tsai, K. H., Qi, G. Z., and Yang, J. C. S. (1995). "Neural network for structural control." *J. Comput. Civ. Eng.*, 9(2), 168–176.

Chung, L. L., Lin, R. C., Soong, T. T., and Reinhorn, A. M. (1989). "Experimental study of active control for MDOF seismic structures." *J. Eng. Mech.*, 115(8), 1609–1627.

Ghaboussi, J., and Bani-Hani, K. (1997). "Neural network for structure control of a benchmark problem, active tendon system." *Earthquake Eng. Struct. Dyn.*, 27, 1225–1245.

Ghaboussi, J., and Joghataie, A. (1995). "Active control of structure using neural network." *J. Eng. Mech.*, 121(4), 555–567.

Hosuner, G. W., et al. (1997). "Structural control: Past, present, and future." *J. Eng. Mech.*, 123(9), 897–971.

Nikzad, K., Ghaboussi, J., Paul, L. S and (1996). "Actuator dynamics and delay compensation using neurocontrols." *J. Eng. Mech.*, 122(10), 966–975.

Lin, T.-K., Chang, K.-C., Chung, L.-L., and Lin, Y.-B. (2006). "Active control with optical fiber sensors and neural networks. I: Theoretical analysis." *J. Struct. Eng.*, 132(8), 1293–1303.

Madan, A. (2006). "General approach for training back-propagation neural networks in vibration control of multidegree-of-freedom structures." *J. Comput. Civ. Eng.*, 20(4), 247–260.

Paz, M. (1980). *Structural Dynamics*, Van Nostrand Reinhold, New York.

Rao, M. M., and Datta, T. K. (2006). "Modal seismic control of building frames by artificial neural network." *J. Comput. Civ. Eng.*, 20(1), 69–73.

Ratneshwar, J., and Chengli, H. (2002). *Neural network based adaptive prediction control for vibration suppression*, American Institute of Aeronautics and Astronautics (AIAA).

Yu-Ao, H., and Jianjun, W. (1998). "Control of structural selsmic response by self-recurrent neural network (SRNN)." *Earthquake Eng. Struct. Dyn.*, 27, 641–648.

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