Neural Network Active Control of Structures with Earthquake Excitation

Hyun Cheol Cho, M. Sami Fadali, M. Saiid Saiidi, and Kwon Soon Lee

Abstract: This paper presents a new neural network control for nonlinear bridge systems with earthquake excitation. We design multi-layer neural network controllers with a single hidden layer. The selection of an optimal number of neurons in the hidden layer is an important design step for control performance. To select an optimal number of hidden neurons, we progressively add one hidden neuron and observe the change in a performance measure given by the weighted sum of the system error and the control force. The number of hidden neurons which minimizes the performance measure is selected for implementation. A neural network was trained for mitigating vibrations of bridge systems caused by El Centro earthquake. We applied the proposed control approach to a single-degree-of-freedom (SDOF) and a two-degree-of-freedom (TDOF) bridge system. We assessed the robustness of the control system using randomly generated earthquake excitations which were not used in training the neural network. Our results show that the neural network controller drastically mitigates the effect of the disturbance.

Keywords: Neural networks, optimal neuron number, bridge control, earthquake engineering.

1. INTRODUCTION

Active control of structures subject to environmental loads, such as strong winds or earthquake excitations, is an important control application in civil engineering. The literature on vibration controls to reduce effects of earthquakes or strong winds includes a variety of control approaches [1]. The main control techniques are H_∞ [2], variable structure control [3], intelligent control based on fuzzy logic [4], neural networks [5], and genetic algorithms [6]. Neural networks offer significant advantages that are particularly suited to the active control of structure systems. They provide excellent control performance for nonlinear or uncertain systems.

The design of a neural network controller often requires extensive simulations to select optimal design parameters such as the learning rate, the initial weights and biases, the number of input patterns, and the number of hidden layer neurons for a multi-layer neural network [7]. All these parameters affect the performance of a neural network and its ability to reach a satisfactory design solution.

In control applications, the number of hidden neurons significantly affects performance. For example, neural networks with a large number of hidden neurons often result in expensive computation and memory requirements, and in an excessive learning time. On the other hand, an insufficient neuron number yields neural networks that may not be powerful enough for a given learning task. Therefore, the selection of the number of hidden neurons is an important step in the design of neural network control systems.

Kung and Sietsma devised pruning algorithms that use a penalty function for choosing hidden neuron number [8,9]. Their neural networks are started with a large number of neurons and successively decreased until a specified performance measure reaches an unacceptable level. Alternatively, they start with a small number of neurons and add new neurons until networks are achieved to a required performance. Lippmann reported that neural networks having eight hidden neurons yield the best results among two-input-two-output networks [10]. From his experience, he deduced the specific formula $H = log_2 T$ where T is number of input training patterns and H is number of neurons in a hidden layer. The results using his

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formula were compared to earlier research by Mirchandani and Cao [11]. Mehan, Mehrotra, and Ranka pointed out that the selection of a hidden neuron number depends on the number of input training patterns for classification problems in T-dimensional input space [12]. Even though there are considerable results available and ongoing research, the number of hidden neurons is typically chosen by trial and error through several numerical analyses, especially in control applications.

In this paper, we select an optimal number of neurons in the hidden layer of a neural network controller based on a measure of the network performance. The performance measure is formed by a weighed sum of the system error and the control input force for a given training time. We progressively increase the number of hidden neurons and observe the performance measure. The neural network is iteratively trained with a fixed number of hidden neurons under the same simulation conditions and the performance measure is calculated. Based on the results, we determine the neuron number with the minimum function for implementation of a neural controller.

The neural network controller was used to reduce vibrations in nonlinear bridge systems due to earthquake excitation. Two neural controllers were designed and trained against El Centro earthquakes: one for a single-degree-of-freedom (SDOF) and the other for a two-degree-of-freedom (TDOF) system. The seismic behavior of the majority of bridge population can be captured using two-degree-of-freedom models. To evaluate controller robustness, we tested the proposed control approach through computer simulations using randomly generated earthquake excitations, other than that used in network training.

The outline of this paper is as follows. Section 2 discusses a neural control design for bridge systems. Section 3 presents numerical examples for bridge control systems. Robustness of controllers is evaluated in Section 4. Finally, conclusions are given in Section 5.

2. NEURAL NETWORK CONTROLLER DESIGN

In this Section, we design a multi-layer neural network controller for bridge systems and develop a learning algorithm based on an optimization approach for minimizing an appropriate performance measure. Fig. 1 shows the neural control for structure systems subject to environmental disturbances such as wind forces or earthquakes. In Fig. 1, x is the system output, u is the active control force, and e is the system error expressed as $-x$ for zero reference input. The neural controller is a system whose external input is the error signal and that yields the control force applied to the structure.

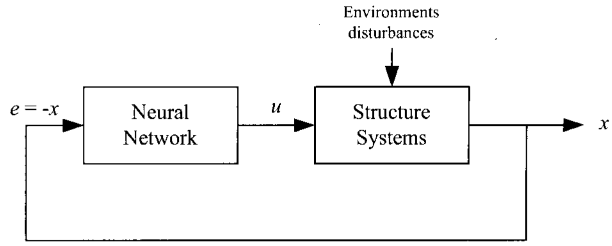


Fig. 1. A neural network control for structure systems.

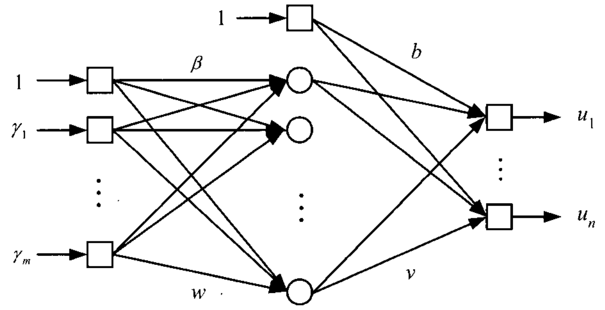


Fig. 2. A structure of a neural network controller.

We use a three-layer network structure with m input neurons, h hidden neurons, and n output neurons for each layer as illustrated in Fig. 2. The network output or control input is expressed as

$$u_i = \alpha\left(\sum_{j=1}^{h}(v_{ij}\varsigma_j) + b_i\right), \tag{1}$$

where $i = 1, \ldots, n$, α is a constant, v_{ij} and b_i are, respectively, the weight and bias between the second and the third layer. ς_j is the output signal of the hidden layer and is expressed as

$$\varsigma_j = \phi_j\left(\sum_{k=1}^{m}(w_{jk}\gamma_k) + \beta_j\right), \tag{2}$$

where $j = 1, \ldots, h$, w_{jk} and β_j are the weight and bias between the first and the second layer. ϕ_j denotes an activation function, and γ_k is the input signal. In this paper, the input signals are the error and the error change.

2.1. Learning algorithm for bridge systems

Structural control systems usually need a large control input force to reduce displacement due to environmental disturbances. In practice, the control force available is limited by actuator constraints [13]. Thus, we should consider means of reducing the control force amplitude in our controller design. To this end, we minimize a performance measure formed by the sum of the squares of the system errors and the control input forces. The performance measure is given by

$$J = \frac{1}{2}\sum_{i=1}^{n}\left(q_i e_i^2 + r_i u_i^2\right), \tag{3}$$

where q_i and r_i are nonnegative weights. The goal of network training is to minimize the objective function by selecting suitable network weights and biases w, v, β, and b in Fig. 2 using an optimization approach. We use a steepest gradient descent optimization method [7] and their adjustment rules are respectively given by

$$w_{jk}(t_k+1) = w_{jk}(t_k) - \eta\frac{\partial J}{\partial w_{jk}}, \tag{4}$$

$$v_{ij}(t_k+1) = v_{ij}(t_k) - \eta\frac{\partial J}{\partial v_{ij}}, \tag{5}$$

$$\beta_j(t_k+1) = \beta_j(t_k) - \eta\frac{\partial J}{\partial \beta_j}, \tag{6}$$

$$b_i(t_k+1) = b_i(t_k) - \eta\frac{\partial J}{\partial b_i}, \tag{7}$$

where $i = 1, \ldots, n, j = 1, \ldots, h, k = 1, \ldots, m$, t_k denotes discrete time, and η is a learning rate. To solve the partial differential equations (4)-(7), we use the chain rule to obtain the following expressions

$$\frac{\partial J}{\partial w_{jk}} = \frac{1}{2}\sum_{i=1}^{n}\left(q_i\frac{\partial e_i^2}{\partial e_i}\frac{\partial e_i}{\partial x_i}\frac{\partial x_i}{\partial u_i}\frac{\partial u_i}{\partial \varsigma_j}\frac{\partial \varsigma_j}{\partial w_{jk}} + r_i\frac{\partial u_i^2}{\partial u_i}\frac{\partial u_i}{\partial \varsigma_j}\frac{\partial \varsigma_j}{\partial w_{jk}}\right), \tag{8}$$

$$\frac{\partial J}{\partial v_{ij}} = \frac{1}{2}\left(q_i\frac{\partial e_i^2}{\partial e_i}\frac{\partial e_i}{\partial x_i}\frac{\partial x_i}{\partial u_i}\frac{\partial u_i}{\partial v_{ij}} + r_i\frac{\partial u_i^2}{\partial u_i}\frac{\partial u_i}{\partial v_{ij}}\right), \tag{9}$$

$$\frac{\partial J}{\partial \beta_j} = \frac{1}{2}\sum_{i=1}^{n}\left(q_i\frac{\partial e_i^2}{\partial e_i}\frac{\partial e_i}{\partial x_i}\frac{\partial x_i}{\partial u_i}\frac{\partial u_i}{\partial \varsigma_j}\frac{\partial \varsigma_j}{\partial \beta_j} + r_i\frac{\partial u_i^2}{\partial u_i}\frac{\partial u_i}{\partial \varsigma_j}\frac{\partial \varsigma_j}{\partial \beta_j}\right), \tag{10}$$

$$\frac{\partial J}{\partial b_i} = \frac{1}{2}\left(q_i\frac{\partial e_i^2}{\partial e_i}\frac{\partial e_i}{\partial x_i}\frac{\partial x_i}{\partial u_i}\frac{\partial u_i}{\partial b_i} + r_i\frac{\partial u_i^2}{\partial u_i}\frac{\partial u_i}{\partial b_i}\right). \tag{11}$$

Substituting (8)-(11) in (4)-(7), respectively, we finally obtain the adjustment rules

$$w_{jk}(t_k+1) = w_{jk}(t_k) + \eta\sum_{i=1}^{n}\left(\delta_i v_{ij}\right)\phi_j'\gamma_k, \tag{12}$$

$$v_{ij}(t_k+1) = v_{ij}(t_k) + \eta\delta_i\varsigma_j, \tag{13}$$

$$\beta_j(t_k+1) = \beta_j(t_k) + \eta\sum_{i=1}^{n}\left(\delta_i v_{ij}\right)\phi_j', \tag{14}$$

$$b_i(t_k+1) = b_i(t_k) + \eta\delta_i, \tag{15}$$

where ϕ_j' denotes the derivative of the activation function and

$$\delta_i = \alpha\left(q_i e_i\, sign\left(\frac{\partial x_i}{\partial u_i}\right) - r_i u_i\right). \tag{16}$$

We also adapt the simplification of [14] where $sign\left(\frac{\partial x_i}{\partial u_i}\right)$ is replaced by $\frac{\partial x_i}{\partial u_i}$.

2.2. Optimal hidden neuron number

Several important parameters must be properly determined in neural network design: the learning rate, the neuron number in each layer, the initial conditions of the weights and biases, etc. Unfortunately, there is no general result for their optimal selection. These numbers are typically iteratively determined using simulations or experiments under varying simulation scenarios prior to implementation. In this paper, we focus on the determination of an optimal number of neurons in the hidden layer assuming a fixed learning rate and random initial weights and biases. We run N iterative training cycles for the neural network with a fixed hidden neuron number which it progressively increased. We observe the average performance measure defined in (17) for each hidden neuron number during the control time interval [0, T] and select the optimal number which minimizes the performance measure

$$J_h = \frac{1}{N}\sum_{i=1}^{N}\sum_{t_k=0}^{T}\left\{qe_h^{\,2}(t_k) + ru_h^{\,2}(t_k)\right\}. \tag{17}$$

3. DESIGN EXAMPLE

To evaluate the proposed control approach, we applied it to the control of a nonlinear SDOF and a nonlinear TDOF bridge system. We designed two neural network controllers for each bridge system and carried out computer simulations, from which the time-histories of their displacements were plotted.

3.1. SDOF bridge control

We first consider a typical nonlinear SDOF bridge whose motion equation is

$$m_b\ddot{x} + c\dot{x} + f_k(x) = u - m_b f_e, \tag{18}$$

where m_b is a mass element, c is a damping constant, f_e is the earthquake excitation, x is the bridge displacement, u is the active control input force from a neural controller, and f_k is an inelastic restoring force. We model the restoring force as the Q-hysteresis nonlinearity [15] shown in Fig. 3. Earthquake excitation is an acceleration history of ground motion. Fig. 4 shows the time series of the well known El Centro earthquake.

We select the system parameters in (18) as m_b = 2.07 metric tons and c = 1.44 kN·sec/cm. For the neural network we selected a learning rate of 0.01, the initial weight and bias values as uniformly distributed in the interval [−0.5, 0.5], and a bipolar sigmoid activation function. The neural network has two input signals: the error e and the error change $\Delta e = x(t_k\text{-}1) - x(t_k)$.

To select an optimal hidden neuron number, we progressively increased the number of hidden neurons from 1 to 50, training the network for 500 iterations and evaluating it for each value. After each training period, we calculated the performance measure for a control time interval [0, 10] s with a 0.01 s sampling period. We selected an error weight $q = 1$ and a much smaller control input weight $r = 10^{-7}$, because the magnitude is much larger than the system error. Fig. 5 is a plot of the normalized cost versus the number of hidden neurons for the SDOF system.

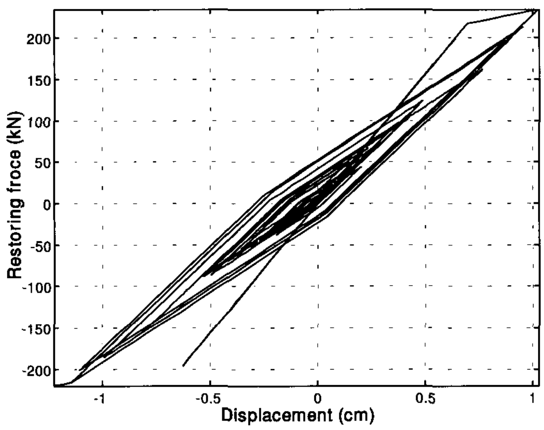


Fig. 3. Q-hysteretic nonlinearity model.

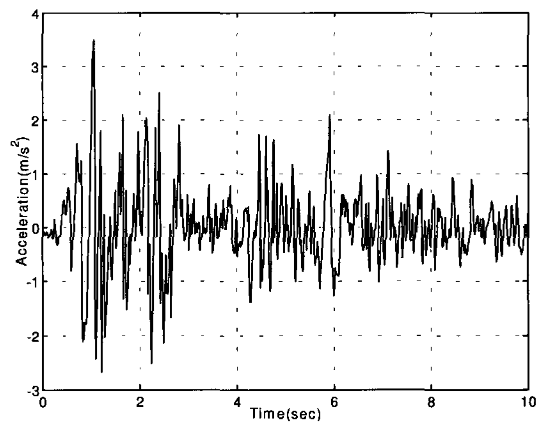


Fig. 4. Acceleration history of El Centro earthquake.

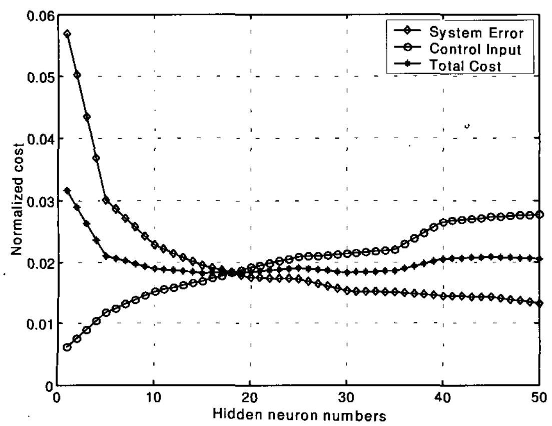


Fig. 5. Normalized cost for the SDOF system.

Fig. 5 reveals a gradual error reduction and a gradual increase in the control force as the hidden neuron number is increased. In other words, a neural network composed of a large number of hidden neurons provides a superior performance in terms of error reduction, but requires a greater control force. The overall optimum performance as given by (17) is achieved with 15 hidden neurons where the total cost is the lowest. We constructed a neural network with 15 hidden neurons as a controller for the SDOF bridge system. First, we simulated the system without control and plotted the trajectories of dynamic bridge displacements in Fig. 6. In Fig. 6, the total error which is calculated by summing absolute errors in the time interval [0, 10] sec, is about 354.83 cm with a maximum absolute displacement of about 2.17 cm.

Fig. 7 shows the trajectories of system responses and control input forces applying a neural control. In Fig. 7, the total error is about 90.22 cm, which is about a 74.57 % improvement over the uncontrolled case, and a maximum absolute displacement of less than 1 cm, which is less than half that of the free response.

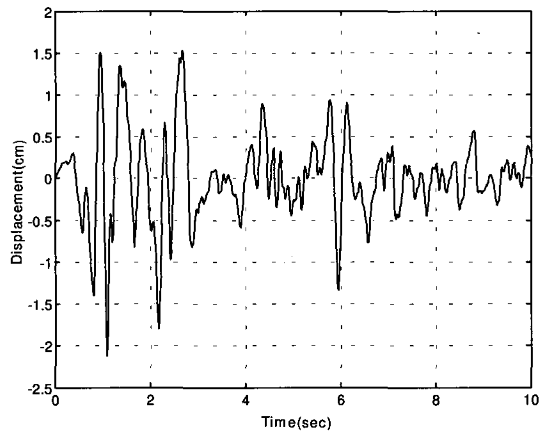


Fig. 6. Free system response of the SDOF system.

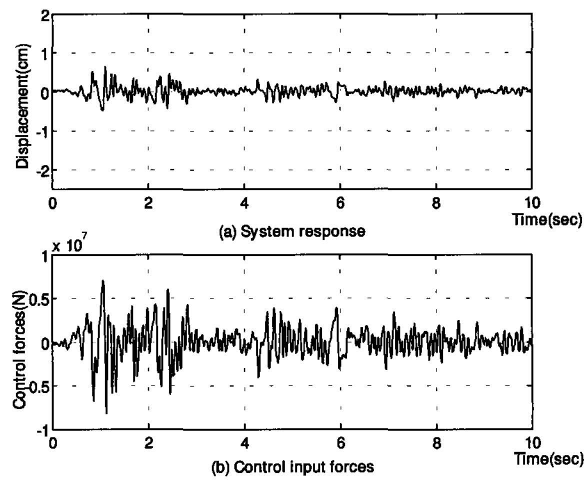


Fig. 7. System responses and control inputs of the SDOF system with neural control.

3.2. TDOF bridge control systems

We consider a TDOF system model of the Aptos Creek bridge, located on California Highway 1 in the USA. A more detailed description of this bridge is provided in [16]. The motion equations are

$$m_1\ddot{x}_1 + c_1 x_1 + (k_1 + k_4)x_1 + f_c(x_1, x_2) = u_1 - f_e, \quad (19)$$

$$m_2\ddot{x}_2 + c_2 x_2 + (k_2 + k_5)x_2 - f_c(x_1, x_2) = u_2 - f_e, \quad (20)$$

where m_1 and m_2 are bridge girder masses, k_1, k_2, k_4, and k_5 are stiffness coefficients, c_1 and c_2 are damping coefficients, x_1 and x_2 are relative displacements with respect to m_1 and m_2, u_1 and u_2 are active control input forces applied to m_1 and m_2, and f_c is a nonlinear spring force between two masses. The mathematical expression of f_c and the values of the bridge system parameters in (19) and (20) are given in [16]. We design a neural network controller composed of four input signals: e_1=-$x_1(t_k)$, Δe_1= $x_1(t_k$–1)-$x_1(t_k)$, e_2=-$x_2(t_k)$, and Δe_2=$x_2(t_k$–1)-$x_2(t_k)$, and with the two control inputs u_1 and u_2 as output signals. We use the same neural network parameters as in the SDOF controller. As in the SDOF case, we compute the performance measure (17) to find the optimal number of hidden neurons. Fig. 8 provides plots of normalized cost functions versus hidden neurons. Based on the minimum cost from Fig. 8, we construct a neural network with 20 hidden neurons. Fig. 9 illustrates trajectories of the bridge displacements x_1 and x_2 with no active control. From Fig. 9, the total errors are about 218.51 cm and 69.58 cm for x_1 and x_2 with maximum absolute displacements of about 1.22 cm and 0.58 cm, respectively.

The two system displacements and neural control input forces are plotted in Fig. 10. We observe from Fig. 10, that the total errors are about 82.95 cm and 30.05 cm for x_1 and x_2, with maximum absolute displacements are about 0.61 cm and 0.22 cm, respectively. This indicates that neural control provides an error reduction of 62.04 % and 56.81 % when compared with the uncontrolled system.

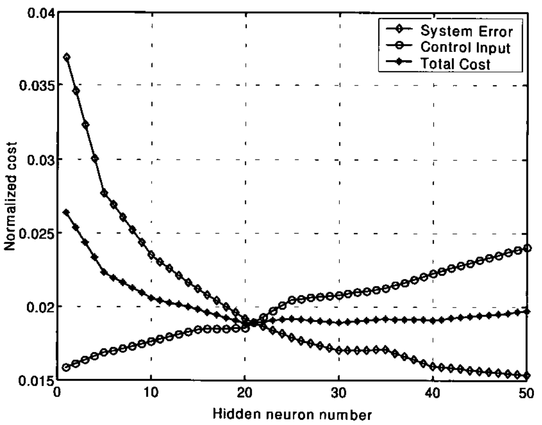


Fig. 8. Normalized cost for the TDOF system.

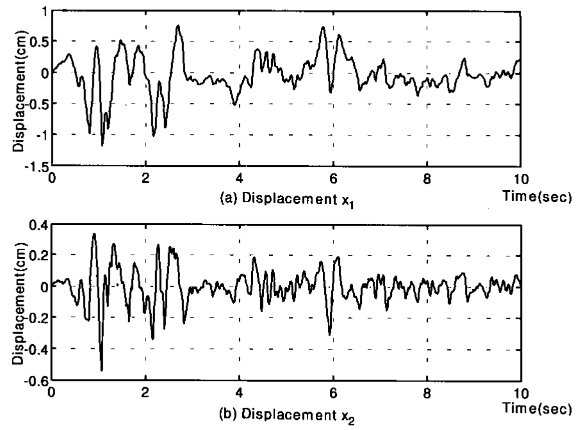
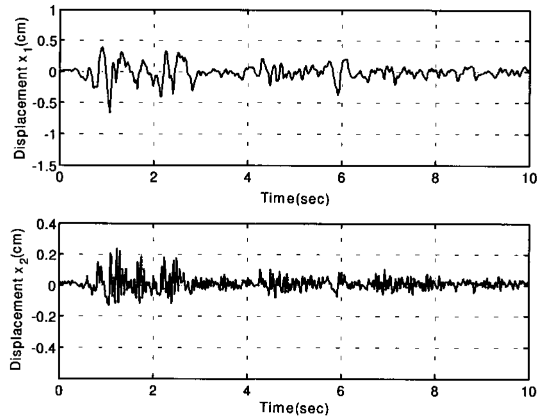
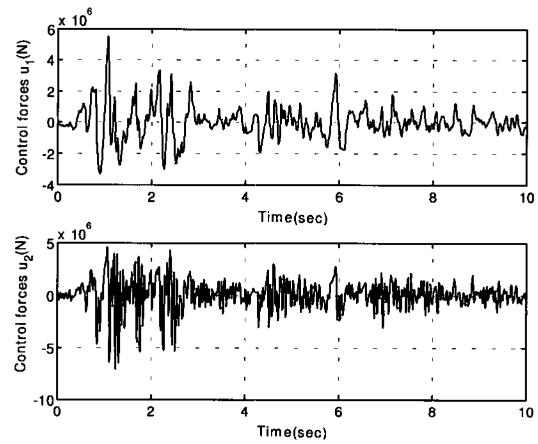


Fig. 9. Uncontrolled system responses of the TDOF system.



(a) Bridge displacement.



(b) Control input force.

Fig. 10. System responses and control inputs of the TDOF system with neural control.

4. ROBUSTNESS OF NEURAL CONTROLLERS

In this section, we consider the robustness of the neural controllers applied to active bridge control in Section 3 and simulated with the El Centro earthquake. For robustness evaluation, we generated a large number of earthquake excitations none of which was used in controller training or evaluation in Section 3. We then examined the behavior of the bridge active control systems of Section 3 when subjected to these excitations.

Case I: In this example, earthquakes with higher frequencies than El Centro, were applied to the bridge control system. The time-histories of the earthquake waveforms are shown in Fig. 11.

The displacement trajectories of the SDOF system without a control and with a neural control are plotted in Figs. 12 and 13, respectively. From Figs. 12 and 13, the total absolute error for an uncontrolled system is about 352.96 cm and the maximum absolute displacement is about 2.25 cm. For a neural control, the total absolute error is about 131.04 cm and a maximum absolute error of about 1 cm. A neural control shows about 62.87 % improvement in total error over the free response.

We also simulated the TDOF system with the same earthquake excitation. The displacement trajectories of the TDOF system without a control are illustrated in Fig. 14.

From these plots, we observe maximum absolute displacements for x_1 and x_2 of 1.59 cm and 0.58 cm, respectively, and total system errors of about 278.35 cm and 74.45 cm. Fig. 15 shows the trajectories of the system using a neural control. We realize that this result is obviously improved in a control performances viewpoint. The total errors are 64.90 cm and 39.91 cm for x_1 and x_2 respectively with maximum absolute displacements of about 1.52 cm and 0.58 cm. Hence, we have a 76.68 % and 46.39 % improvement over the free response by using active neural control.

Case II: We simulated the bridge system subject to earthquake waveforms with larger amplitudes than case I and with higher frequencies than El-Centro. The earthquake signals are created by multiplying Gaussian random signal with zero mean and unit variance to El Centro signals. Fig. 16 illustrates time-histories of the earthquakes.

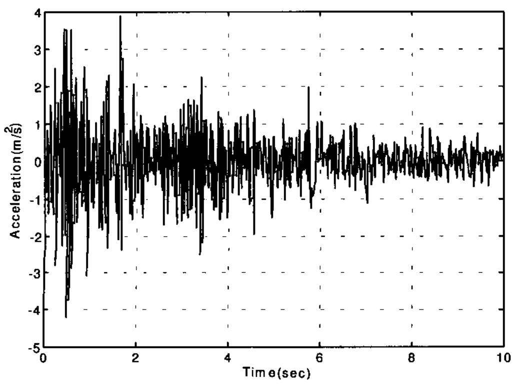


Fig. 11. Acceleration history of ground motion in Case I.

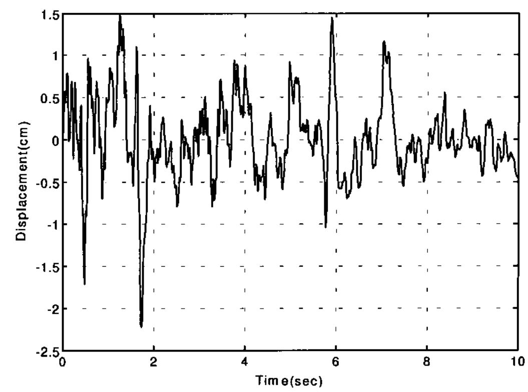


Fig. 12. Uncontrolled system responses of the SDOF system in Case I.

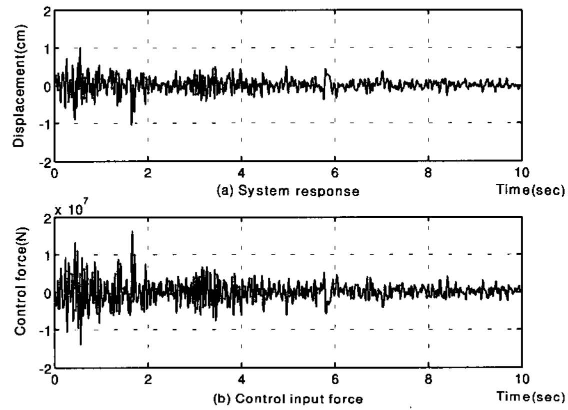


Fig. 13. System responses and control inputs of the SDOF system by a neural control in Case I.

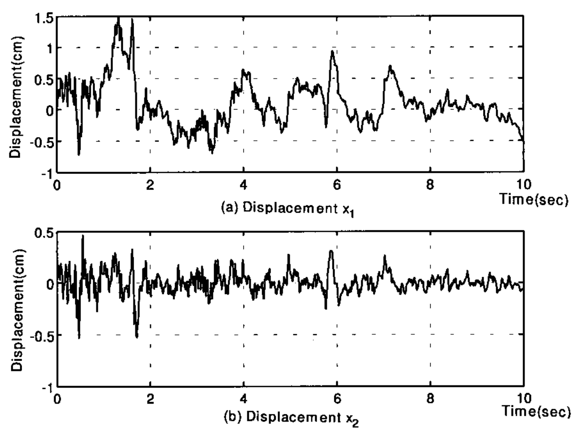
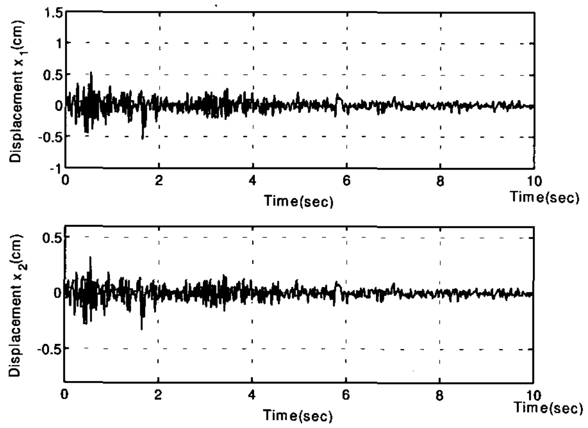


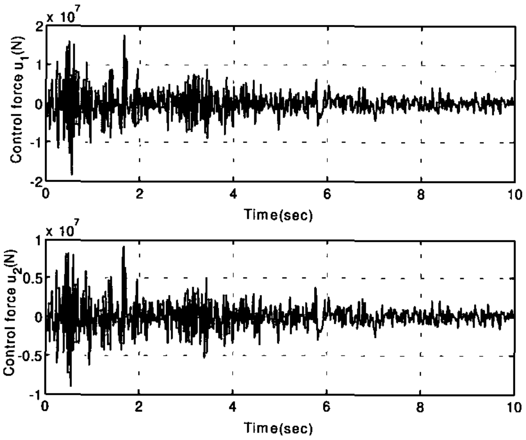
Fig. 14. Uncontrolled system responses of the TDOF system in Case I.

We simulated the SDOF bridge system with same simulation conditions as *Case* I. Plots of system trajectories for uncontrolled and neural control systems are provided in Figs. 17 and 18.

For the uncontrolled system, the maximum absolute displacement is about 5.01 cm and the total absolute error is about 687.00 cm. For neural control, the maximum absolute displacement is about 1.82 cm and the total absolute error is about 182.74 cm. We thus have a 73.40% reduction in total error and a 63.67 reduction in absolute value using neural control. The simulation results for the TDOF system with no active control are shown in Fig. 19. The results for uncontrolled systems show total errors of about 630.61 cm and 130.62 cm, and maximum displacements of about 1.97 cm and 1.38 cm for x_1 and x_2, respectively.



(a) Bridge displacement.



(b) Control input force.

Fig. 15. System responses and control inputs of the TDOF system by a neural control in Case I.

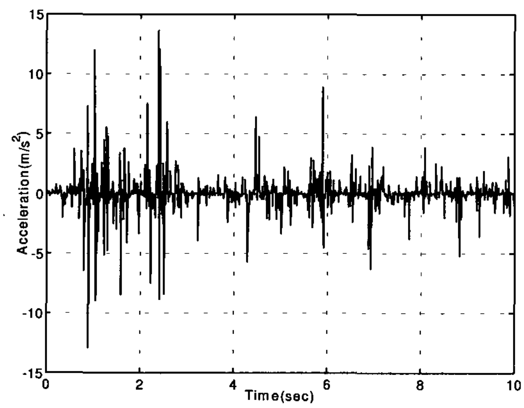


Fig. 16. Acceleration history of ground motion in *Case* II.

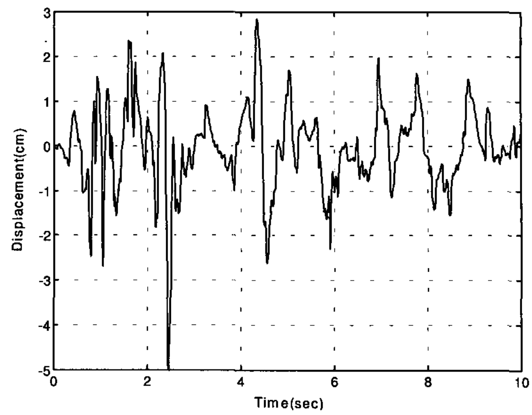


Fig. 17. Uncontrolled system responses of the SDOF system in *Case* II.

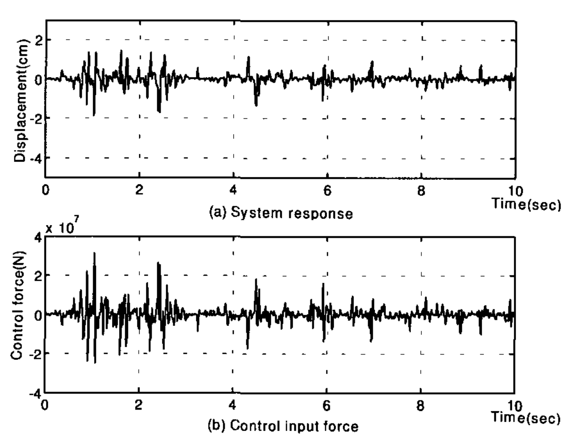


Fig. 18. System responses and control inputs of the SDOF system with neural control in *Case* II.

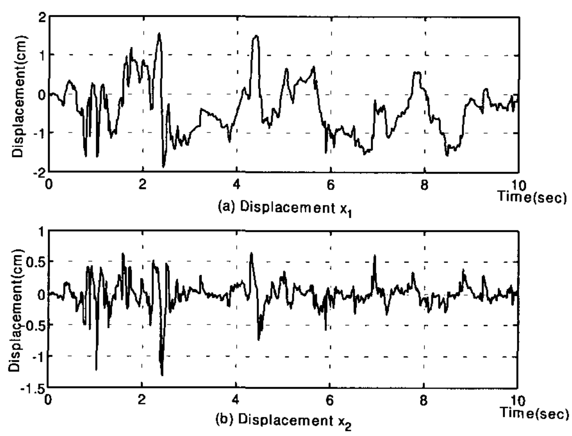
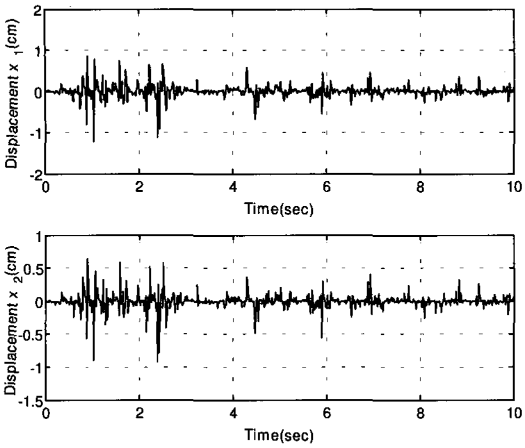
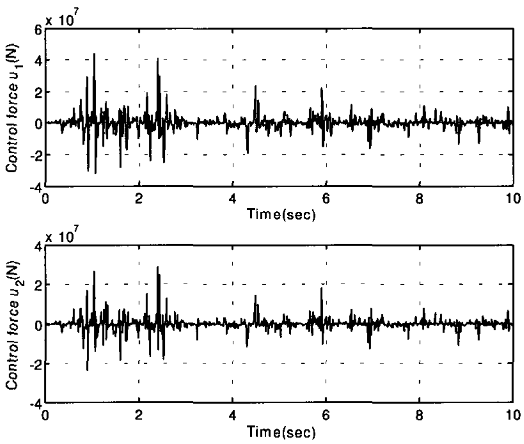


Fig. 19. Uncontrolled system responses of the TDOF system in *Case* II.

The trajectories of bridge displacements and control inputs using neural control are illustrated in Fig. 20. From Fig. 20, we observe maximum absolute displacements of about 1.22 cm and 0.93 cm for the system states x_1 and x_2, respectively, and total absolute displacements of about 82.09 cm and 52.53 cm. The improvement in absolute error is about 86.98 % for x_1 and 59.78 % for x_2.



(a) Bridge displacement.



(b) Control input force.

Fig. 20. System responses and control inputs of the TDOF system with neural control in *Case* II.

5. CONCLUSION

This paper presents a new neural controller design particularly suited to the active control of structures. We selected an optimal number of hidden layer neurons based on a performance measure that provides a compromise between system error and control input. We applied the neural control to nonlinear SDOF and TDOF bridge systems subject to El Centro earthquake. We showed that active neural control could drastically reduce the maximum absolute error and the total error from the high levels of the free system. We also investigated the robustness of the control systems by applying two different earthquake excitations to the bridge systems with same simulation scenarios. The simulations verified the robustness of the controller performance under a variety of earthquake excitations. Future work includes the design of more complicated neural controllers and their application to nonlinear structures with uncertain or randomly varying parameters.

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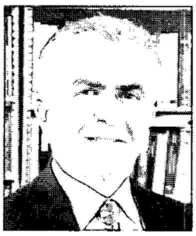

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