DESIGNING A GENERAL NEUROCONTROLLER FOR WATER TOWERS

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ABSTRACT: This study deals with the capabilities of artificial neural networks in learning to control water towers of different structural properties that are subjected to earthquakes. To this end, water towers were considered as single-degree-of-freedom systems. First, a number of water towers of different structural properties were controlled by the predictive optimal control method, and then the data collected through this control were used in the training of a general neural network controller, called the general neurocontroller. Capabilities of the general neurocontroller were tested in the control of a number of water towers with structural parameters different from, but in the range of, those used in its training. One of the aims of this study was the introduction of general neurocontrollers as ready-to-use devices that may be used in the design of actively controlled structures, in this case, water towers. Results of this numerical study were promising.

INTRODUCTION

In the conventional design of structures, the aim is to design structural members so that the structure can withstand both normal and exceptional loads of high intensity during its useful life span. In most cases, this results in structural members of large dimensions. It has been proposed to use passive and active methods of structural control for the design of a structure for normal service loads and then to equip it with adequate devices that can help the structure withstand the exceptional loads of high intensity earthquakes, hurricanes, etc. Whereas passive control strategies and devices have been well studied and used in a number of structures such as high-rise buildings, the area of active control is still in its childhood. However, in the last two decades special attention has been paid to the subject, and considerable literature has been produced by many authors [e.g., Rodellar et al. (1987, 1989) and Soong (1990)]. The First World Conference on Structural Control, which was held in 1994 with the purpose of promoting communication among the interested persons in the field, was the first international conference on the subject and can be considered as a milestone in the development of passive, active, and hybrid control of structures theory and application (*Proc.* 1994). With the advent of the theory and application of neural networks in engineering, including civil engineering, attention of researchers has been attracted toward the use of neural networks in all areas of structural engineering including active control of structures, where strategies and mechanisms have been proposed for this purpose (Nikzad and Ghaboussi 1991; Chassiacos and Masri 1996). Among the many contributions to the field, Joghataie and his coworkers designed a control scheme based on the use of a neural network emulator that can learn to predict the response of a structure from its previous response. The predictions are then used by a neural network that gradually learns, through adaptation, to control the structure by sending control signals to the actuators. The writers and other researchers also have numerically studied the proposed control scheme in the control of a three-story frame structure by an active tendon mechanism (Joghataie and Ghaboussi 1994; Ghaboussi and Joghataie 1995). Although such algorithms may prove applicable to many types of structures, it seems too complicated for some of the structures, such as the simple model of the water towers of this study that can be simulated as single-degree-of-freedom (SDOF) systems. Conventional active control methods such as the predictive optimal control method may be applied easily to such structures.

In this paper, use was made of both the simplicity of the predictive optimal control method and the learning, filtering, and generalization capabilities of neural networks in the control of water towers. First, a number of water towers of different structural properties (i.e., mass and stiffness), which were designed for their dead loads only, were controlled by the predictive optimal control method. Then a neural network called the general neurocontroller was trained based on the data obtained through this control. The general neurocontroller contains the filtered and general information required for the control of not only the water towers, for which their controlled response has been used in obtaining the training data, but also a wide range of other water towers in the space of the general neurocontroller generalization and prediction capability. The following sections explain the strategy and the corresponding results in more details.

WATER TOWERS

The type of water tower used in this study is shown in Fig. 1. The tower is composed of four straight tubular columns that support a water tank. The connections of the tank to the ground and columns were considered fixed. Columns were tied together by using horizontal and cross bracings and were designed so that they could transfer the dead load of the tank to the ground. However, they were not designed for the earthquake loading.

It was assumed appropriate to use an active tendon control mechanism for the water tower in Fig. 1 so that it also could withstand earthquakes. When the water tower is considered as an SDOF system with a lumped mass on the top of its columns, its dynamic response could be expressed completely by its mass, damping, stiffness, and also external excitations. Ef-

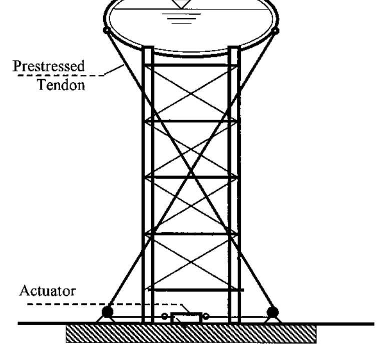

FIG. 1. General Shape of Water Towers and Active Tendon Control Mechanism Used in Study

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fects such as water sloshing, tendon elasticity, and actuator dynamics, although important, were not considered in this first study of the subject.

PREDICTIVE OPTIMAL CONTROL OF WATER TOWERS

The predictive optimal control method proposed by Rodellar et al. (1987, 1989) has been used in the digital control of frame structures both numerically and experimentally. One of the advantages of this method over the other optimal control methods is its capability to control the structures that are subjected to inherent delays and nonlinearities. For an n-degrees-of-freedom controlled structure, with a control time delay of d times the sampling time interval ΔT and a prediction horizon of λ time steps, based on the response at any sampling time step k, motion of the structure is predicted for the next $\lambda + d$ time steps from the following equation:

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

$$j = 1, 2, \ldots, \lambda + d \tag{1}$$

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

To find the control rule, a performance index J is defined for each time step k

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

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

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

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

The above formulation was used to construct a linear control algorithm for the SDOF structures of water towers in this study. Here, for the SDOF system of a water tower, $\mathbf{x}(k) = [q(k), \dot{q}(k)]^T$, where $q(k)$ = relative displacement; and $\dot{q}(k)$ = relative velocity at time step k. Also, the control signal is a scalar quantity, $\mathbf{u}(k) = u(k)$, which is taken equal to the horizontal component of the control force applied by the prestressed tendons, as shown in Fig. 1. The following weighting matrices were used in this study:

$$\mathbf{Q} = \begin{bmatrix} 1 & 0 \\ 0 & 0 \end{bmatrix}; \quad \mathbf{R} = [R] \tag{4}$$

where the appropriate R value is found based on trial and error. Also defining $\mathbf{F}$, $\mathbf{G}$, and $\mathbf{P}$

$$\mathbf{F} = \begin{bmatrix} 0 & 1 \\ -\omega_0^2 & -2\xi\omega_0 \end{bmatrix}; \quad \mathbf{G} = \begin{bmatrix} 1 \\ -1/m \end{bmatrix}; \quad \mathbf{P} = \int_0^{\Delta T} \exp(s\mathbf{F})\, ds \tag{5}$$

where ω_0, ξ, and m = undamped natural frequency, damping, and mass of the water tower, respectively. The discrete time state and control matrices can be found from

$$\mathbf{A} = \exp(\Delta T\mathbf{F}); \quad \mathbf{B}_u = \mathbf{P}\mathbf{G} \tag{6}$$

A 30-m^3 water tower of 20-m height was controlled by the predictive optimal control method. The stiffness of the structure and its natural period were 549,040 N/m and 1.51 s, respectively. A 5% damping was considered for the water tower. Also the following values were used: numerical integration time step and sampling period = ΔT = 0.02 s; time delay = d = 1; and prediction horizon indicator = λ = 8.

The water tower was subjected to the El Centro (N00W) 1940 earthquake and the effect of R on the response and control force was studied, as shown in Fig. 2. Generally, increasing R has reduced the maximum control force and also the maximum absolute acceleration, while the maximum relative displacement and velocity increased. Because $R = 5 \times 10^{-8}$ produced suitable results, it was decided to use this value of R in the rest of this study. The uncontrolled as well as the controlled response of the structure for $R = 5 \times 10^{-8}$ are

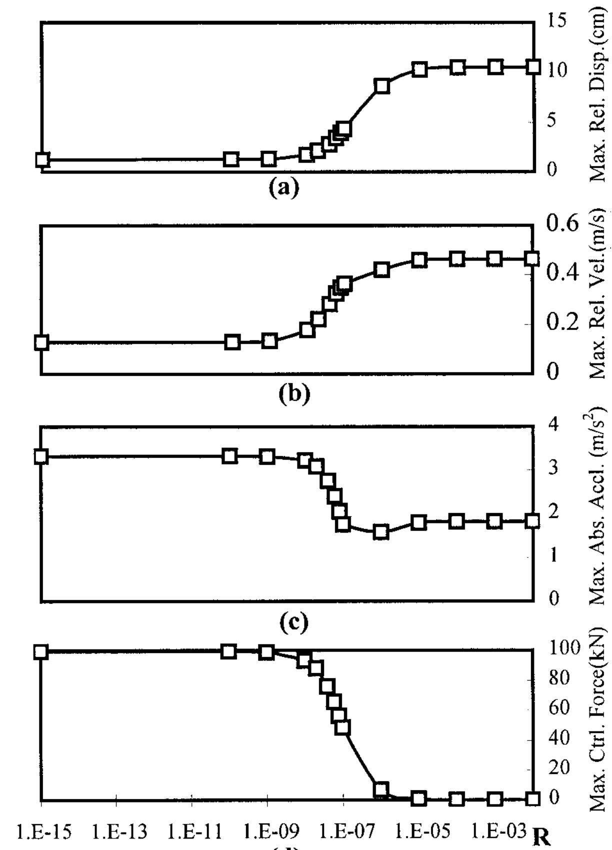

FIG. 2. Effect of *R* on Response and Control Force in Predictive Optimal Control of Water Tower, Showing Maximum of: (a) Relative Displacement; (b) Relative Velocity; (c) Absolute Acceleration; (d) Control Force

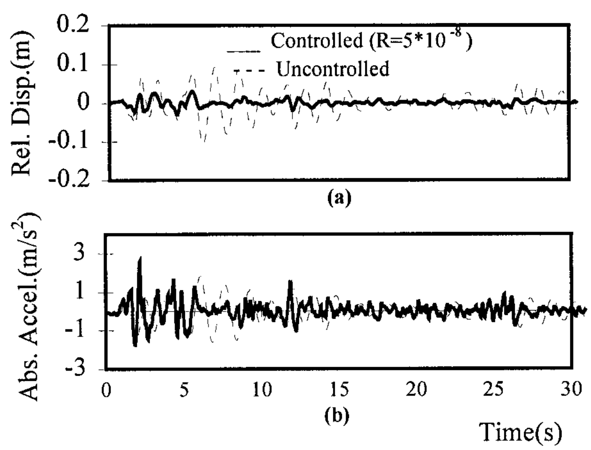

FIG. 3. Time History of Controlled Response by Predictive Optimal Control Method Compared to Uncontrolled Response for $R = 5 \times 10^{-8}$: (a) Relative Displacement; (b) Absolute Acceleration

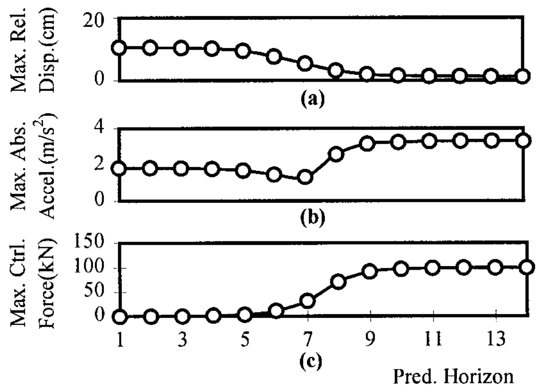

FIG. 4. Effect of λ, Prediction Horizon, on Peak Response and Control Force for $R = 5 \times 10^{-8}$: (a) Relative Displacement; (b) Absolute Acceleration; (c) Control Force

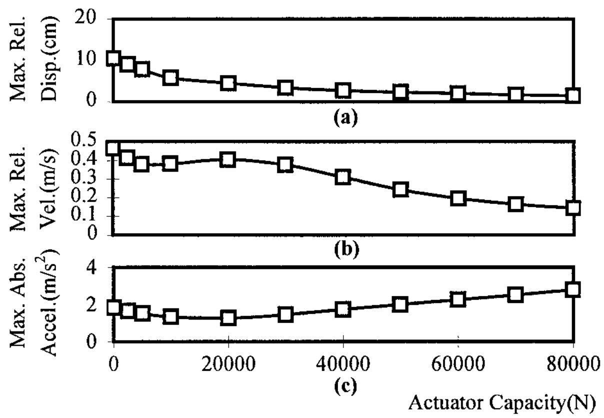

FIG. 5. Effect of Actuator Capacity on Peak Response for $R = 5 \times 10^{-8}$: (a) Relative Displacement; (b) Relative Velocity; (c) Absolute Acceleration

shown in Fig. 3. For this control, a maximum control force of about 100 kN was required.

The effect of the prediction horizon indicator λ on control results also was studied, as shown in Fig. 4. In this case, the weight of the control cost was held fixed to $R = 5 \times 10^{-8}$. A larger λ had a significant effect on reducing the relative displacement. However, it had an adverse effect on both the absolute acceleration and control force. Noting Fig. 4, it seemed appropriate to select $\lambda = 8$ for the rest of this study.

Next, the effect of actuator capacity on the controlled response of the water tower was investigated where the control force was taken equal to minimum (actuator capacity, calculated control force assuming infinite actuator capacity). Results are shown in Fig. 5 for $R = 5 \times 10^{-8}$. The relative displacement and velocity of the controlled structure was reduced with the increase in the actuator capacity. However, this reduction is not significant for capacities larger than 40,000 Nt. On the other hand, it has an adverse effect on the absolute acceleration and increases it. Hence, it was concluded that a 40,000 Nt actuator is appropriate for the control of this water tower.

CONSTRUCTION OF NEURAL NETWORK CONTROLLER

Neural networks are adaptive systems that can learn, from a set of input-output pairs of data collected from a phenomenon, about the cause-effect relationship governing that specific phenomenon. Multilayer feedforward neural networks, also called perceptrons, with back-propagation of error learning rule have been proven to be universal approximators, i.e., they can learn any mapping problem, with any desired accuracy, based on a set of appropriate data pairs collected for mapping (Hornik 1991). The theory of neural networks is well developed and issues such as representation of knowledge, learning algorithms, and architecture determination have been discussed by many authors including Mezard and Nadal (1989), Reed (1993), and Joghataie et al. (1995), and it seems that there is now available a strong foundation, a common knowledge, and a number of accepted algorithms for constructing appropriate neural networks for any application problem. So, in the following sections, discussion is limited only to the explanation of the main points about the neural networks used in this study.

Neural networks have been applied recently to many civil engineering problems. The interested reader may refer to Ghaboussi (1993) for more information. Neural networks have also been used in many structural control engineering problems, both as emulators and controllers (Conte et al. 1994; Joghataie and Ghaboussi 1994; Ghaboussi and Joghataie 1995). In this part of the study perceptrons were used to learn to control the water tower under study, based on the results obtained in the previous section.

Perceptron Used in Study

A three-layer perceptron with 4 input, 10 hidden, and 1 output units, as shown in Fig. 6(a), was found suitable for this application after a number of trials and errors. The four input units represent the input vector $\mathbf{I} = [q(k), \dot{q}(k), u(k-1), u(k-2)]^T$, where $q(k)$, $\dot{q}(k)$, $u(k-1)$, and $u(k-2)$ are the relative displacement at time step k, the relative velocity at time step k, and the control signals sent to the actuator at time steps $k-1$ and $k-2$, respectively. The output of the neural network $O = u(k)$ is the control signal that should be sent to the actuator.

The shifted sigmoidal activation function, as shown in Fig. 6(c), was used for all the units. Also the input and output values were scaled so that input and output units fell in the range of $[-1, 1]$. Weights were generated randomly in the range of $[-0.1, 0.1]$ and the generalized delta rule of learning was used for updating of the weights. Teaching samples were collected from the records obtained, through the application of the predictive optimal control to the water tower, as explained in the previous section, and then the neural network was trained offline based on the collected training samples. During the training procedure, cases were selected randomly from the pool of the collected training data. Also, when one training case was fed to the neural network it was not used for training again until all the remaining training cases in the pool were fed to the neural network. Defining a training cycle as one feeding of all the training cases in the pool to the neural network, it was observed that it took about 10 cycles for the

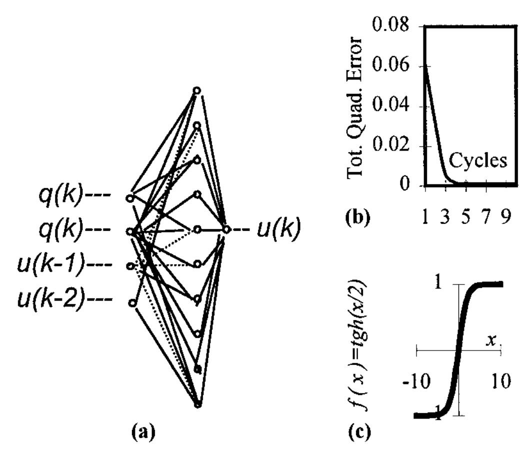

FIG. 6. Preceptron Used in First Part of Study: (a) Architecture; (b) Total Quadratic Error versus Training Cycle; (c) Shifted Sigmoidal Activation Function Used

neural network to learn the problem and fall into a minimum with a negligibly small total quadratic error, as shown in Fig. 6(b). However, for more reduction of errors, training continued for 130 more cycles. This random selection of training cases strategy has been found effective in faster convergence of neural networks in the previous studies by Joghataie et al. (1996).

Testing of Neurocontroller

The neurocontroller was then tested in the control of the same water tower, subjected to the El Centro (N00W) 1940 earthquake with a peak ground acceleration of 0.348*g*. However, to check the generalization capability of the neurocontroller and how well it performs during other earthquakes, it was also tested in the control of the same water tower when subjected to the Parkfield (N25W) 1966, San Fernando (N21E) 1971, and Tabas, Iran (N16W) 1978 earthquakes with peak ground accelerations of 0.347*g*, 0.315*g*, and 0.94*g*, respectively. The Tabas earthquake is much stronger than the three other earthquakes and has, in fact, been used for testing the extrapolation capabilities of the neurocontroller.

It was found that the neurocontroller could control the structure appropriately for the El Centro earthquake, and results are comparable to those of the predictive optimal controller, as shown in Fig. 7. However as can be seen in Fig. 7(d), the neurocontroller used slightly smaller control forces.

Results of predictive optimal and neurocontrolling of the water tower for the above earthquakes are summarized and compared in Table 1. Also Figs. 8(a and b) represent the control force time history used for controlling the structure by the predictive optimal and neurocontrollers under the effect of the Parkfield 1966 and Tabas 1978 earthquakes, respectively. Figs. 8(a and b) indicate that the neurocontroller has learned, with great precision, from the predictive optimal controller how to apply appropriate control forces. Referring to Table 1, it can be seen that for four different earthquakes, including the high intensity Tabas earthquake, the neurocontroller reduced the peak displacement and velocity considerably, although it was not able to reduce, in any of the cases except for the Tabas earthquake, the absolute acceleration and increased it as expected but not as desired. This is due to high frequency noise induced into the response by the actuator forces. In these cases, the neurocontroller also performed very similarly to its supervisor, the predictive optimal controller.

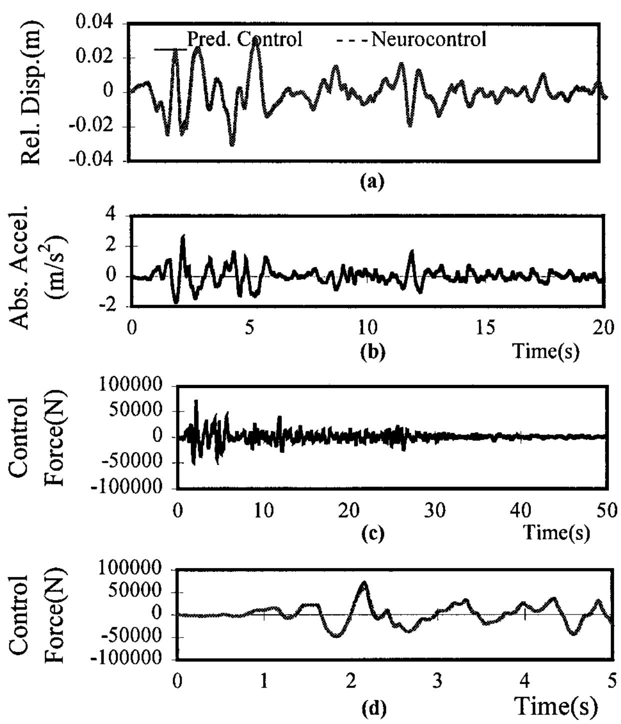

FIG. 7. Comparison between Controlled Response of Water Tower by Predictive Optimal and Neurocontrollers for El Centro Earthquake, Where Results are Similar: (a) Relative Displacement; (b) Absolute Acceleration; (c) 20 s of Control Force; (d) Initial 5 s of Control Force

TABLE 1. Comparison between Control Results from Predictive Optimal and Neurocontrolling

Response (1)	Maximum relative displacement (cm) (2)	Maximum relative velocity (cm/s) (3)	Maximum absolute acceleration (cm/s^2) (4)	Maximum control force (N) (5)
(a) El Centro (N00W) 1940				
Predictive	3.12	0.3044	2.5782	70,635
Neuro	3.08	0.3238	2.1762	57,586
No control	10.54	0.4638	1.8306	0
(b) Tabas, Iran (N16W) 1978				
Predictive	8.35	0.5304	3.6178	121,176
Neuro	10.08	0.6092	3.3691	69,982
No control	25.49	1.0981	4.4203	0
(c) Parkfield (N25W) 1966				
Predictive	1.65	0.1844	1.6481	43,480
Neuro	1.69	0.1855	1.5836	41,259
No control	3.48	0.2764	0.5686	0
(d) San Fernando (N21E) 1971				
Predictive	1.64	0.1416	1.2372	33,180
Neuro	1.58	0.1401	1.2316	32,809
No control	4.32	0.2181	0.7595	0

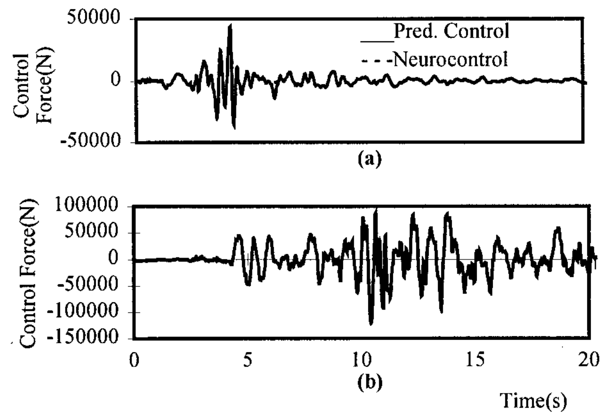

FIG. 8. Control Force Applied by Predictive Optimal Controller and Neurocontroller for 20 s during: (a) Parkfield 1966 Earthquake; (b) Tabas 1971 Earthquake (Neurocontroller Has Applied Similar, But Slightly Smaller, Forces)

DESIGNING A GENERAL NEUROCONTROLLER

It was desired to design a general neurocontroller by the same algorithm used in the design of the neurocontroller for the water tower of the previous sections, so that it could be used in the control of water towers with properties different from, but close to, those of the water towers studied before.

To this end, 16 water towers, with structural properties including mass, height, and period of vibration shown in Table 2, were controlled under the El Centro earthquake by the predictive optimal control method. To account for the effect of water level in the reservoirs, three cases of full, half-full, and empty situations were considered for each reservoir, resulting in a total of $16 \times 3 = 48$ controlled cases. Again, as in the previous sections, the mass of the water tower was assumed lumped and rigid at the top of the columns. To provide the neural network with enough data, covering the space of water towers to be controlled, the time history of the controlled response and control force for each of these 48 cases were recorded for 20 s. With a sampling period of 0.02 s, this resulted in 48,000 input-output pairs. The neurocontroller was then trained based on the random selection of training cases from the pool of these 48,000 input-output pairs. For this part of the study too, a perceptron with 4 input, 10 hidden, and 1 output units was used as in the preceding sections. However, to include the required information about the structural properties of the water towers, the input vector and the output of the neurocontroller were defined as $\mathbf{I} = [q(k), \dot{q}(k), u(k-1)/m, T]^T$ and $O = u(k)/m$, where m and T represent the mass and vibration period of the water tower, respectively, as explained before.

TESTING GENERAL NEUROCONTROLLER

The neurocontroller was tested in the control of a number of water towers that included the cases where controlled responses were used in the training of the general neurocontroller and other cases. Results have shown that for all the training cases, the general neurocontroller was able to perform similarly to the predictive optimal controller and reduce the response considerably but while using smaller and smoother control forces. To show the generalization and interpolation capabilities of the general neurocontroller, it was then tested in the control of a water tower that was in the range of the training cases but had not been used in the training of the neurocontroller. This 27-m-high, 25,000-kg capacity water tower was subjected to the El Centro 1940 and Parkfield 1966 earthquakes and was controlled for the cases when it was full and half-full of water. Table 3 contains information about its uncontrolled response and the results of its control by the general neurocontroller when the water tower was full of water. Table 4 shows the results for the half-full water tower. As can be seen, the general neurocontroller was able to control the structure and reduce the maximum relative displacement and velocity by more than 50%, although high frequency noise was introduced into the system and hence the maximum absolute acceleration increased in most cases.

To study the extrapolation capability and precision of the general neurocontroller to control structures out of the range of its training cases, a 10-m-high, 70,000-kg capacity water

TABLE 2. Periods of Vibration (s) for 16 Water Towers Used in Training

Capacity (m^3) (1)	Mass (kg) (2)	Height (m) 15 (3)	20 (4)	25 (5)	30 (6)
20	m_1 = 21,440	0.92	1.41	1.97	2.59
	m_2 = 15,000	0.77	1.18	1.65	2.17
	m_3 = 10,000	0.63	0.96	1.35	1.77
30	m_1 = 31,740	0.98	1.51	2.11	2.78
	m_2 = 20,000	0.78	1.20	1.68	2.20
	m_3 = 15,000	0.68	1.04	1.45	1.91
40	m_1 = 42,050	1.00	1.53	2.14	2.82
	m_2 = 30,000	0.84	1.29	1.81	2.38
	m_3 = 20,000	0.69	1.06	1.48	1.94
50	m_1 = 52,350	1.00	1.54	2.15	2.83
	m_2 = 40,000	0.87	1.35	1.88	2.47
	m_3 = 25,000	0.69	1.06	1.49	1.95

Note: m_1 = full; m_2 = half-full; and m_3 = empty.

TABLE 3. Interpolation Capabilities of General Neurocontroller in Control of 27-m-High Water Tower Subjected to Earthquakes When Water Tower Was Full of Water (*m* = 25,000 kg)

Response (1)	Maximum relative displacement (cm) (2)	Maximum relative velocity (cm/s) (3)	Maximum absolute acceleration (cm/s^2) (4)	Maximum control force (N) (5)
(a) El Centro 1940				
Predictive	2.70	0.2486	2.7195	63,777
Neuro	2.63	0.2656	2.4208	56,109
No control	25.86	0.6581	1.5977	0
(b) Parkfield 1966				
Predictive	1.45	0.1588	1.7547	40,972
Neuro	—	0.1646	1.7825	41,829
No control	4.65	0.1954	0.3174	0

TABLE 4. Interpolation Capabilities of General Neurocontroller in Control of 27-m-High Water Tower Subjected to Earthquakes When Water Tower Was Half-Full of Water (*m* = 12,500 kg)

Response (1)	Maximum relative displacement (cm) (2)	Maximum relative velocity (cm/s) (3)	Maximum absolute acceleration (cm/s^2) (4)	Maximum control force (N) (5)
(a) El Centro 1940				
Predictive	3.07	0.2902	2.5828	28,578
Neuro	3.06	0.2979	2.4246	26,706
No control	12.66	0.519	1.7775	0
(b) Parkfield 1966				
Predictive	1.58	0.1794	1.6558	17,889
Neuro	1.4	0.1708	1.8031	19,988
No control	2.99	0.2434	0.3975	0

TABLE 5. Extrapolation Capabilities of General Neurocontroller in Control of 10-m-High Water Tower Subjected to Earthquakes When Water Tower Was Full of Water (*m* = 70,000 kg)

Response (1)	Maximum relative displacement (cm) (2)	Maximum relative velocity (cm/s) (3)	Maximum absolute acceleration (cm/s^2) (4)	Maximum control force (N) (5)
(a) El Centro 1940				
Predictive	3.13	0.3462	5.124	118,794
Neuro	3.02	0.3499	4.8795	96,268
No control	5.81	0.6943	8.016	0
(b) Parkfield 1966				
Predictive	1.81	0.2927	3.3106	101,871
Neuro	1.80	0.3068	3.4265	85,241
No control	2.56	0.3464	3.5636	0

TABLE 6. Extrapolation Capabilities of General Neurocontroller in Control of 10-m-High Water Tower Subjected to Earthquakes When Water Tower Was Half-Full of Water (*m* = 35,000 kg)

Response (1)	Maximum relative displacement (cm) (2)	Maximum relative velocity (cm/s) (3)	Maximum absolute acceleration (cm/s^2) (4)	Maximum control force (N) (5)
(a) El Centro 1940				
Predictive	1.34	0.2405	3.9723	51,100
Neuro	1.31	0.2511	3.8966	41,471
No control	1.85	0.3203	5.0133	0
(b) Parkfield 1966				
Predictive	1.83	0.3122	4.5089	48,051
Neuro	1.83	0.2971	4.6827	47,906
No control	3.28	0.5439	8.295	0

tower, with structural properties out of the training range but not far from it, was controlled by the general neurocontroller, and results are reported in Table 5. Also Table 6 represents the results of the neurocontrolling of the same water tower when it was half-full of water. Again, the general neurocontroller was able to control the relative displacement and velocity and reduce them significantly for both cases. Also it reduced the accelerations.

CONCLUDING REMARKS

In this paper neural networks were used in the control of water towers of different structural properties—including mass, height, and weight—numerically simulated as SDOF structures. After controlling a number of water towers, which were subjected to the El Centro earthquake, by the predictive optimal control method, their time history of controlled response and control force were used in the training of a neural network, here called the general neurocontroller. The designed general neurocontroller is a three layer perceptron consisting of 4 input, 10 hidden, and 1 output units and was trained by the generalized delta rule for back-propagation of error. Such a trained general neurocontroller was found capable of controlling, not only the water towers that were used for preparing the training cases, but also other water towers with slightly different structural properties under the effect of different earthquakes. In all of the tests, the general neurocontroller was able to reduce the peak relative displacement and velocity by more than 50%, whereas in almost all cases the peak absolute acceleration was increased compared to the uncontrolled response.

One of the objectives of this study was to bring the idea of neurocontrolling of structural systems, in this case the water towers, closer to the real world of structural engineering design. Once such a general neurocontroller is designed for a specific type of structure, covering a wide range of structural properties, a designer can use it directly as a black box for the active control of other structures of similar type without the need to go through the design of a specific controller for it. However, there is still much left to be done to bring such ideas of active control and neurocontrol of structures to the real world of structural engineering design and practice. It is hoped that this study will serve as another step toward this objective.

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APPENDIX. REFERENCES

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