Decentralized Control of a Cable-stayed Bridge Using Multi-layer Neural Networks

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The structural identification and dynamic control of a cable-stayed bridge are considered to be difficult due to the structural complicacy and system uncertainties. In this paper, based on the concept of decentralized information structures, a decentralized non-parametric identification and control method is proposed with neural networks for the purpose of suppressing the vibration of a well-studied and documented two-cable-stayed bridge induced by earthquake excitations. The control strategy proposed here uses the stay cables as active tendons to provide control forces through appropriate actuators. Each individual actuator is controlled by a decentralized neuro-controller that only uses local velocity and relative displacement information. The feature of decentralized control simplifies the implementation of the control algorithms and makes decentralized control easy to practice and cost effective. The effectiveness of the decentralized identification and control algorithm is evaluated through numerical simulations. The performance of the decentralized control is compared with that of the linear decentralized control method. And the adaptability of the decentralized neuro-controllers for different kinds of earthquake excitations is demonstrated via simulations.

Key Words: artificial neural networks, decentralized identification, decentralized control, active control, cable-stayed bridge

1. INTRODUCTION

With increasing research activities in the field of structural control in recent years, tremendous progress has been made over the last two decades toward making active structural control a viable technology for enhancing structural functionality and safety against natural hazards such as strong earthquakes and high winds. Since the initial conceptual study by Yao⁹, a number of structural control methods and devices have been proposed. Some of the widely used structural control methods are explained by Leipholtz et al⁵ and Soong⁸. Most of these control algorithms require the analysis and identification of the system in explicit mathematical forms. However, there are many factors such as structural uncertainties, non-linearities, and measurement noises which are so difficult to be identified and incorporated in control loop as to result in poor mathematical models and less-effective control algorithms. Although significant strides have been made in recent years towards the development and application of active control schemes for vibration control of civil structures in seismic zones, its application to large-scale structures, such as cable-stayed bridges, under earthquake loading has not been addressed extensively.

The vibration control of cable-stayed bridge structures has been the subject of research in the control community for the past several years, which represents a new, difficult, and unique problem with many complexities in modeling, control design and implementation, such as nonlinear behavior and the participation of highly coupled, high order vibration modes in the overall dynamic response(Meirovitch and Baruh, 1983; Chait et al., 1988; Matsumoto et al., 1994; Ohsumi and Sawada, 1993⁴). Recently, some researchers have attempted to use decentralized control techniques to distributed parameter systems. Using a continuous system model to represent a bridge with four cable-stays, Yang et al. performed some of the earliest work in this area, where they studied the application of active control to cable-stayed bridges under the excitation of strong wind gusts⁸. Warnitchai et al. experimentally and analytically studied the control of cable-stayed bridges subject to vertical
sinusoidal force utilizing a simple cable-supported cantilever as a model\(^{(18)}\). Hutton used active control to control vertical deflections of a cable-stayed guideway under a moving constant load\(^{(11)}\). Several active tendon control schemes have been proposed to reduce the transversal vibration of the bridge deck, among which the centralized linear active control and decentralized nonlinear active control have received more and more attention. Using a simply supported, lumped mass beam supported by two cables, Volz et al. employed a decentralized active controller to reduce the bridge’s vertical deflections and Magana et al. examined robust nonlinear decentralized active control to attenuate displacements under adverse conditions\(^{(12-13)}\). Achkire et al. experimentally and analytically examined active vibration control of cables and systems using a signal active tendon\(^{(14)}\).

As a parallel distributed processing methodology, neural network has been regarded as a potential method for large-scale and complex dynamic systems with adaptability. Neural-network-based control algorithms have attributes that make them potentially effective in dealing with most of these problems. Modeling the dynamic systems by using neural networks has been increasingly recognized as one of the system identification paradigms. At present, several neural networks with different structures have been proposed to solve the identification and control problems. The most widely used neural network is the feed forward multi-layer neural network, which is trained by the back-propagation algorithm.

Numerous engineering applications of neural networks have been reported in the literature of recent years. The applications of neural networks in the field of civil engineering were reviewed by Ghaboussi et al.\(^{(15)}\), Chen et al.\(^{(16)}\), and Xu et al.\(^{(17-19)}\).

Research in decentralized control has been motivated by the inadequacy of contemporary control theory to deal with certain issues in large-scale systems. A key concept in modern control theory is that of state feedback. However, it is often impossible to instrument a system to the extent required for full state feedback. A key characteristic of the techniques ranging from linear-quadratic-Gaussian (LQG) control to observer-based control is that every sensor output affects every actuator input. We term this situation “centralized control”. Of course, in many systems, but particularly large-scale system, it is impossible to incorporate so many feedback loops into the design. Because of the high dimensionality of the full finite element model, multiple inputs and outputs, and complex performance criteria, it is difficult to design a control strategy to achieve desired stability, robustness and so on for large-scale structures. There seems to be a need for additional research in order to develop more robust and more effective identification and control algorithm for large-scale or complex structures. To solve this problem, in the study of Hannsen et al.\(^{(17)}\) and Xu et al.\(^{(18-19)}\), the concept of localized vibration control was proposed to construct a control strategy for a large-scale or complex structure. On the other hand, decentralized control strategy can be also considered as a useful method in response to this difficulty\(^{(21-24)}\).

The basic characteristics of decentralized control are that there are some restrictions on information transfer between certain groups of sensors or actuators.\(^{(12-13,21-23)}\)

In this paper, based on the concept of decentralized information structures for large-scale structure, a decentralized non-parametric identification and control method is proposed for the purpose of suppressing the vibration of a well-studied and documented two-cable-stayed bridge structure induced by earthquake excitations. The control strategy proposed here uses the stay cables as active tendons to provide control forces through appropriate actuators. Each individual actuator is controlled by a decentralized neuro-controller that only uses local velocity and relative displacement information. The feature of decentralized control simplifies the implementation of the control algorithms and makes decentralized control easy to practice. The design methodology of decentralized control is simple and the implementation of the decentralized controller is very cost effective because only local information is used to generate control signals for each of the actuators. The effectiveness of the decentralized identification and control algorithm is evaluated through numerical simulations. It is shown that the decentralized emulator neural networks are able to identify dynamics of the cable-stayed bridge structure. Based on each of the trained decentralized emulator neural networks, a neuro-controller is trained to implement the control objective of reducing the amplitude of the deflections of its deck down to a desired level automatically. And the adaptability of the decentralized neuro-controllers for different kinds of earthquake excitations is demonstrated via simulations.

2. EQUATIONS OF MOTION OF A CABLE-STAYED BRIDGE WITH CONTROL

Let the two-cable-stayed structure have the configuration shown in Fig.1. The model considered in this paper could be construed as a first approximation of a segment of a cable-stayed bridge (Warnitchai et al., 1993; Yang and Giannopoulos, 1979; Garevski and Severn, 1993).\(^{(6-10,24)}\)

The two-cable-stayed bridge structure is built on a hard rock foundation at its right end and supported at its left end. The tower, where the stay cables are attached to, is assumed to be rigid. The \(i\)th stay cable is anchored at the location \(d_i(=1,2)\) from the fixed right end of the bridge deck and sensors are put at the same points of anchor to measure the relative displacement and velocity of the bridge deck, respectively. The
control forces are generated through the actuators installed at the end of the cables by the method of increasing or decreasing the effective length of the stay cables in the presence of seismic excitations. The actuator displacements are constrained to the axial directions of the cables and are assumed to be smaller than the static cable elongation. The torsional motion associated with the horizontal deflections of the beam is neglected. Also, other nonlinear effects of the structure such as those due to cable sag are neglected.

The finite element modeling technique using concentrated masses is adopted to derive the dynamic mathematical model of the cable-stayed bridge structure.

The following assumptions are made,
(a) The deck segment is approximated as a uniform beam of constant mass;
(b) The mass of the stay cable that affects degree of freedom \(i\) is small compared to the \(i\)th concentrated mass of such a degree of freedom;
(c) The stay cables are used as active tendons and operate in the linear elastic range. The sags are minimal and therefore neglected;
(d) The structural damping is very small and can be neglected.

Let the dynamic behavior of the beam be described by the five-lumped-mass model shown in Fig.2, where \(m_i\) is one sixth of the mass of the beam, and \(f_i(t)\), \((i=1,2)\) are the vertical components of the cable stay forces described by

\[
f_{i1}(t) = \frac{E_i A_i}{l_i} y_2 \sin \Theta_i - u_2 \sin \Theta_i \tag{1}
\]

\[
f_{i2}(t) = \frac{E_i A_i}{l_i} y_4 \sin \Theta_i - u_4 \sin \Theta_i \tag{2}
\]

where \(E_i, A_i, l_i\), \((i=1,2)\), are the modulus of elasticity, the cross-sectional area, and the lengths of the cables, respectively; and \(u_i(t), i=2,4\), are the displacements of the control actuators.

Let \(\{y\}=[y_1 y_2 y_3 y_4 y_5]^T\) be the deflections in the vertical direction of the five lumped-masses and \(\{z\}=[y_1-y_5, y_5, y_5 y_5 y_5]^T\) be the static displacement vector which is decided by the weight of the structure and the prestresses of the cables. \(\{y, z\}\) can be described by

\[
\begin{align*}
\{y\} &= \left[K\right]^{-1}
\{m_i g \begin{bmatrix} 1 & 1 & 1 & 1 & 1 \end{bmatrix} + \begin{bmatrix} 0 & p_2 & 0 & p_4 & 0 \end{bmatrix}\} \\
\{z\} &= \begin{bmatrix} 1 & 0 & 0 & 0 & 0 \end{bmatrix} \{y\}
\end{align*}
\tag{3}
\]

where \(p_2\) and \(p_4\) is the prestress in the cable 1 and 2, respectively.

Then the behavior of the beam can be approximated by

\[
\left[M\right] \ddot{\{z\}} + \left[K\right] \{z\} = \{f_i\} - \left[M\right] \ddot{\{y\}} \tag{4}
\]

where \([M]=m_i[I]\) is the mass matrix, \([I]\) is a 5*5 identify matrix, \([K]\) is the stiffness matrix that include the effect of the stay cables. And \(\{f_i\}=[0 1, 0 1, 0 1, 0 1]\) is the vector of the control forces due to the actuators placed at the end of the cables, where \(l_i=(E_i A_i/l_i) \sin \Theta_i\).

The two-cable-stayed bridge structure used in the simulation is a 3-meter long steel beam with the following properties:

Beam (material: steel)

\[
I = 6.7 \times 10^{-8} \text{m}^4.
\]

\[
A = 0.1m \times 0.02m = 2 \times 10^{-3} \text{m}^2
\]

\[
E = 2.06 \times 10^{11} \text{N/m}^2, \quad \rho = 7860 \text{kg/m}^3.
\]

Cable (stainless steel wires, SUS304JIS)

\[
A_{i2} = 2.1 \times 10^{-7} \text{m}^2, \quad E_{i2} = 1.076 \times 10^{11} \text{N/m}^2.
\]

\[
l_1 = 3.58m, \quad l_2 = 3.16m.
\]

\[
\Theta_1 = 56.81^\circ, \quad \Theta_2 = 71.57^\circ
\]

The mass matrix of the cable-stayed bridge structure is as follow,

\[
[M] = \begin{bmatrix}
7.86 & 0 & 0 & 0 & 0 \\
0 & 7.86 & 0 & 0 & 0 \\
0 & 0 & 7.86 & 0 & 0 \\
0 & 0 & 0 & 7.86 & 0 \\
0 & 0 & 0 & 0 & 7.86
\end{bmatrix} \text{ (kg)}
\]
By the finite element method, the stiffness matrix of the cable-stayed bridge structure including the effect of stay cable can be decided, the stiffness matrix is as follow,

$$\begin{bmatrix}
109 & -105 & 457 & -1.24 & 0.355 \\
-105 & 1.54 & -117 & 4.93 & -1.41 \\
457 & -117 & 159 & -1.19 & 5.28 \\
-1.24 & 4.93 & -119 & 161 & -131 \\
0.355 & -1.41 & 5.28 & -131 & 207
\end{bmatrix} \times 10^7 \text{ (N/m)}$$

The vertical disturbances used in the simulations are the earthquake records of the magnified El-Centro earthquake and the Taft earthquake in order to demonstrate the power of the control approach. It is assumed in the simulations that the vertical disturbances are applied at the concentrated masses.

### 3. Neural-networks-based Decentralized Identification and Control Algorithm for a Cable-stayed Bridge

#### 3.1 Concept of Decentralized Identification and Control by Neural Networks

All of the modern state space methods rest on the common presupposition of centrality. All the information available about the system, and the calculations based upon this information are centralized. When considering large-scale systems the presupposition of centrality fails to hold due either to the lack of centralized information or the lack of centralized computing.

Usually, it is difficult to control the vibration of the entire large-scale or complex structures, moreover the full finite element model is not suitable for controller design because the high-order modes may be inaccurate and the computations for the controller become too time-consuming and inefficient. In the case of decentralized vibration control, the structural system is divided into several subsystems, and sensors and actuators are usually located within the subsystems (control areas), which comprise only a small portion of the full structure. A subsystem is controlled by one controller(control station). The information submitted to each control station is obtained from each subsystem, the control commands act in each subsystem and there are no information transfer between subsystems.

The basic concept of completed decentralized control is demonstrated in Fig.3.

In this study, a neural networks based decentralized control algorithm has been proposed for a two-cable-stayed bridge structure. The control strategy proposed here uses a subset of the stay cables as active tendons to provide control forces through appropriate actuators. Each individual actuator is controlled by a decentralized controller, which uses local velocity and local relative displacement information only. The design methodology is simple and the implementation of the local controllers is very cost effective because only local information is used to generate control signals for each of the actuators.

#### 3.2 Architecture of Decentralized Control With Multi-layer Neural Networks

In the case of decentralized control, a number of control stations associated with the same number of subsystems will be used to carry out control function. In each control station, two typical three-layer back-propagation neural networks are adopted as emulator (neural-emulator network) and neuro-controller (neural-action network) respectively.

The architecture of decentralized control with neural networks is illustrated in Fig.4. It includes two stages: decentralized identification and neuro-controller training for each subsystem of structure.

In the first stage, the dynamical characteristics of each subsystem is identified by training the neural-emulator network. In the second stage, based on the trained neural-emulator network, neuro-controller is trained in order to generate control commands for each subsystem. The control criterion includes the desired limits that the response of each subsystem is required to be reduced to, and the limits of the maximum capability (maximum stroke) of the actuator.

In this paper, the first 8-second record of El-Centro earthquake with the amplitude of $10.0 \text{ m/s}^2$ is used to train the neuro-controller. In order to study the adaptability and robustness of the trained neuro-controller, the effectiveness of the trained neuro-controller for El-Centro earthquake record with the amplitude of $20.0 \text{ m/s}^2$ and the first 8 seconds Taft earthquake with the amplitude of $20.0 \text{ m/s}^2$ and $30.0 \text{ m/s}^2$ are shown. The actuator signals are generated by neuro-controller at the beginning of each sampling period and are kept constant within each sampling period.

### 4. Decentralized Identification

#### 4.1 Decentralized Emulator neural networks

Responding to the two stay cables, two subsystems were studied. The two

![Fig. 3 Concept of decentralized control](image-url)
subsystems are shown in Fig. 5. And two emulator networks were established to identify the two subsystems.

Most of the current modern-state-space based active structural control strategies for earthquake protection have been based either on full-state feedback (i.e. all structural displacements and velocities) or on velocity feedback. In this study, the displacement and velocity response of each of the two subsystems are used to train the emulator neural networks. The architecture of the decentralized emulator neural network is shown in Fig. 6. The number of neurons in hidden layer is set to be two times of those in input layer. The neurons in output layer represent the forecast relative displacement response at the end of current sampling period. The number of input, hidden and output layer includes 4, 8 and 1 neurons.

4.2 Training of Decentralized Emulator Neural Networks

The training process of emulator neural network is to establish the appropriate connection weights between neurons of each layer by a form of supervised learning with the help of training cases which are composed of a number of patterns of inputs and desired outputs of structure system.

Based on the error back-propagation algorithm, emulator neural network is off-line trained at first to achieve a desired accuracy for modeling the dynamic behavior of the cable-stayed bridge structure system.

The training cases for the purpose of training emulator neural network are constructed from the numerical integration analysis results while the cable-stayed bridge structure is subjected to random control signals and earthquake excitation. The numerical integration analysis is carried out with integration time step of 0.004 second. The training cases are performed with the data taken at the intervals of the sampling period of 0.02 second.

In this study, five kinds of load cases, which are the combination of different kinds of earthquakes and random signals, are used to investigate the performance of the decentralized emulator neural networks.
(1) Case 1: El-Centro earthquake with the amplitude of 10.0 m/s² and random signal with a upper and a lower limit of 0.05 m and −0.05 m;
(2) Case 2: El-Centro earthquake with the amplitude of 10.0 m/s²;
(3) Case 3: El-Centro earthquake with the amplitude of 10.0 m/s² and random signal with a upper and a lower limit of 0.10 m and −0.10 m;
(4) Case 4: Taft earthquake with the amplitude of 10.0 m/s² and random signal with a upper and a lower limit of 0.05 m and −0.05 m;
(5) Case 5: Taft earthquake with the amplitude of 10.0 m/s² and random signal with a upper and a lower limit of 0.10 m and −0.10 m;

Emulator neural network is trained with the results when the cable-stayed bridge structure system is subjected to the load Case 1. The data sets, used for training the emulator neural networks are the 400 patterns of input and output data taken from the 8 seconds of displacement and velocity response records. The whole off-line training process takes 30000 cycles.

The training cases performed above are used to train each emulator neural network in order to model the dynamics of the subsystem and to generate the dynamic responses of each subsystem.

Evaluation of the prediction capabilities of the trained emulator network is presented in time domain. Fig. 7 gives the result of the comparison between the displacement response at the control point determined from the numerical integration analysis and those forecast by the trained emulator neural network in Case 1, Case 2, Case 3, Case 4, and Case 5, respectively.

The RMS (Root Mean Square) Error and RRMS (Relative Root Mean Square) Error are used as evaluation indexes for evaluating the performance of the decentralized identification. The RRMS error of each substructure can be defined as follow,

\[
e_i = \sqrt{\frac{1}{n-1} \sum_{i=1}^{n} (d_n - d_r)^2} = \frac{\sqrt{\frac{1}{n} \sum_{i=1}^{n} d^2_r}}{n} \quad (i = 1, s)
\]

(3.2)

where \( n \) is the number of sampling data, in this study, \( n=400 \). \( d_n \) is the forcast displacement of subsystem \( i \) by the trained decentralized neural networks, \( d_r \) is the displacement of the corresponding subsystem calculated by numerical simulation under earthquake excitations, and \( s \) is the number of the substructures. Table 1 gives the error between the displacement response at the control point determined from the
Fig. 7 Comparison between the displacement response at the control point determined from the numerical integration analysis by FEM and those forecast by the trained decentralized emulator neural network.

<table>
<thead>
<tr>
<th>Subsystems</th>
<th>RMS Error (m)</th>
<th>RRMS Error(%)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>2</td>
<td>4</td>
</tr>
<tr>
<td>Case 1</td>
<td>0.0003</td>
<td>0.0003</td>
</tr>
<tr>
<td>Case 2</td>
<td>0.0001</td>
<td>0.0001</td>
</tr>
<tr>
<td>Case 3</td>
<td>0.0007</td>
<td>0.0005</td>
</tr>
<tr>
<td>Case 4</td>
<td>0.0003</td>
<td>0.0003</td>
</tr>
<tr>
<td>Case 5</td>
<td>0.0007</td>
<td>0.0005</td>
</tr>
</tbody>
</table>

Numerical integration analysis and those forecast by the trained decentralized emulator neural networks. Clearly, the decentralized emulator network trained with the data in case 1 is able to reproduce the structural response under different seismic excitations very accurately. This makes the emulator network independent of the training cases and a generalized model for the structure system. On the other hand, the input variables for emulator networks are suitable and enough to carry out non-parametric identification for the cable-stayed bridge system.

5. Neural-networks-based Vibration Control for a Cable-stayed Bridge

5.1 Architecture of Neuro-controller The neuro-controller replaces the feedback control algorithm in a conventional
control method. The neuro-controller receives the feedback information as its inputs to the input layer and issues an appropriate signal to the control system from its output layer.

The neural-action network is trained based on the above offline pre-trained neural-emulator network. The trained emulator network learns the transfer function between the control signals and the output of sensor measuring the response of the structure. The emulator neural network is used to provide a path for back-propagation of the errors in training of the neuro-controller. At first, the error of signals can be decided by back-propagating the error between the forecast response and the control criterion through the trained neural-emulator network without changing the weights. After that, the error of signal is back-propagated to adjust the weights of the neuro-controller network. This training process is repeated until the structural responses reach the desired responses within the specified tolerance. The neuro-controller training method used in this study is the generalized delta rule method described above.

The architecture of neuro-controller is indicated in Fig.8. Thus, the measurements that are directly available for control force determination are the displacement and velocity measurements. In the numerical simulation of the control problem, the sensor data is received at discrete time intervals, referred to as the sampling period. The output of the neuro-controller is also sent to the control system at the same discrete sampling period.

5.2 Cases Study In this study, control criteria is to reduce the displacement response to a small value of 0.005m. And the actuators have a maximum stroke of 0.03m, which is supposed to be smaller than the static cable elongation of the cable caused by the weight of the beam and the prestresses in the cables, so compressive stresses are not occurred during the course of control. A neuro-controller was trained with this control criterion and was applied to control the structure response subjected to earthquake excitations. In this section we present the results of four case studies in which the structure is subjected to four different earthquake ground accelerations.

In the first case study the structure is subjected to the El-Centro earthquake record with the amplitude of 10.0m/s² which is used to produce the training data for training emulator neural network.

The numerical results are summarized in Fig.9 and 10, it is indicate that the neuro-controller was successfully in mitigating and reducing the system vibrations effectively. Clearly the displacement response of each subsystem has been reduced. Fig.11 shows the control signal of each actuator. The control signal means the stroke of the actuators with the order of length.

It is evident that the displacement at the mid-span of the beam of the two-cable-stayed bridge in vertical direction has been reduced to less than 0.0016m, which has been reduced to 13% of it without control. The reduction ratio of the controlled response to the uncontrolled response by neural networks is less than the reduction ratio of about 16.7% by linear decentralized control method and higher than the reduction ratio of about 9.0% by nonlinear decentralized control method proposed by M.E. Magana. (12) The neural-networks-based decentralized control method is a nonlinear control method, which can deal with control problem to some extent.

In the previous case study, the structure is subjected to the same earthquake record as that used in the training of the neuro-controller. The performance of the neuro-controller, when the structure is excited by other earthquake records and controlled by the neuro-controller that has been trained with the El-Centro earthquake record with the amplitude of 10.0m/s², is demonstrated in the following case studies by numerical simulation.

5.3 Discussion of Adaptability In the second case studies, the structure is subjected the El-Centro earthquake record with the amplitude of 20.0m/s². Fig.12 gives the results of displacement response of each subsystem when structure is excited by the El-Centro earthquake record with the amplitude of 20.0m/s² and controlled by the trained neuro-controller above. Fig.13 and Fig.14 give the results when structure is excited the Taft earthquake record with the amplitude of 20.0m/s² and 30.0m/s² and controlled by the trained neuro-controller.

This demonstrates that the neuro-controller learns to control the motion of the structure in each case. In summary, for different earthquake records, similar observations have been made. This demonstrates that the fact that the neuro-controller learns to control the motion of the structure, regardless of the source of excitation. The adaptability of the neuro-controller was investigated and verified.

6. Summary

A multi-layer neural-networks-based decentralized active tendon control system for a two-cable-stayed bridge system was proposed. In this proposed control method, decentralized neuro-
Fig. 9 Comparison of displacement response of each subsystem subjected to El-Centro earthquake with amplitude of 10.0m/s² and controlled with neuro-controller.

Fig. 10 Comparison of displacement response of at the mid-span of the bridge subjected to El-Centro earthquake with amplitude of 10.0m/s² and controlled with neuro-controller.

Fig. 11 Control Signal of each subsystem Subjected to El-Centro earthquake with amplitude of 10.0m/s² and controlled with neuro-controller.
controllers are used to replace the control algorithm of the conventional control. From the present study, the following conclusions can be drawn:

(1) Based on the generalized delta rule training method, decentralized emulator neural networks can be trained to predict the future response of the responding subsystem according to displacement and velocity, control signal from each subsystem and the earthquake record. The decentralized emulator neural network is trained to learn the mapping between the control signal and the response of the structure. In other words, the decentralized identification can be carried out successfully by the multi-layer neural networks for two-cable-stayed bridge system.

(2) During the vibration control of two-cable-stayed bridge system under earthquake excitations, based on the trained emulator neural network, a decentralized neuro-controller can also be trained to decide the necessary control signal for each subsystem. The dynamic response can be controlled successfully by the decentralized neuro-controller when actuators with enough ability are available.

(3) The method of vibration control using multi-layer neural network is adaptable for the cases that the structure is subjected to different earthquakes from it used for training the neuro-controller.

(4) A reduction of the controlled response to the uncontrolled
one, which is less than the it of a linear decentralized control method, can be get by the neural-networks-based decentralized control.

In the case of decentralized control, each of the two controllers utilizes local information from the corresponding subsystem only, this feature is of practical importance because it simplifies the implementation of the control algorithm and makes this control technique is very cost effective.

REFERENCES