DYNAMIC RESPONSE OF CONICAL SHELL USING NEURAL-NETWORK-BASED VIBRATION CONTROL

Kiyotoshi HIRATSUKA[1] And Kiyoshi SHINGU[2]

SUMMARY

It was proposed by the authors that neural network algorithm was applied to vibration control of a shell structure. The control object is the shell comprised of dampers, which work in the vertical direction at the antinode of the first mode, and the damping ratio alternates between from 0.02 to 0.2. The purpose of control is reduction of stresses. In order to carry out it, relative displacements to the ground at the whole shell is reduced through adjusting damping ratio. Controlling the shell, the Elman type neural network is employed and network weights are updated by on-line back-propagation procedure. Miyagiken-oki and El Centro earthquakes are employed to input accelerations. The control effects are estimated by comparison with non-control results.

INTRODUCTION

A wide variety of researches on motion control using neural network algorithm has widely been made. For example, a control algorithm was proposed by means of control simulation [Jordan and Rumelhart]. An algorithm of motion control was estimated by means of artificial neural networks based on comparison of the analysis of the results of the physiological experiment with biological neural networks [Kawato and Gomi, 1995]. Both of these research groups pay special attention to flows of learning methods and information.

As the study for applications to the engineering of motion/vibration control by means of neural networks, for example, autonomous underwater vehicles [Fujii, Ura and Kuroda, 1990], vibration control of cantilevers [Morishita, Kuroda and Ura, 1992], vibration control of a particles system structure [Hiratsuka and Shingu, 1997; Hiratsuka and Shingu, 1997], and other such works can be referred to.

Shallow rotational shell structures are subjected to greater influence in the case of vertical motion than in the case of horizontal earthquake motion [Nishimura and Shingu, 1983]. Accordingly it is very important to lower the stresses by restricting vibration of the shells subjected to the vertical seismic forces [Shingu and Fukushima, 1994].

Application of neural-network-based vibration control to a conical shell subjected to vertical seismic forces was proposed by the authors [Hiratsuka and Shingu, 1997, Hiratsuka and Shingu, 1998]. This study has been modified. The control object is the conical shell that is comprised of dampers, which work in the vertical directions at the antinode of the first mode and which alternate between 0.02 and 0.2. The purpose of the control is reduction of stresses in the shell. To practice it, relative displacements to the ground at the whole shell are decreased through adjusting damping ratio. The neural network is the Elman type, which has three layers hierarchical re-current network. The network weights are updated by back-propagation procedure. In this paper, Miyagiken-oki and El Centro are employed to input acceleration waves whose maximum values are changed to $2 m/s^2$, respectively. The simulation of vibration control of the shell structure using the neural network subjected to Miyagiken-oki earthquake is carried out at first. Furthermore El Centro earthquake is used. Here, the initial states are the same. The ability of the neural network based vibration control is estimated by the results of these simulations. Then the control effects are estimated by comparison with the maximum values of displacements.

[1] *Shingu Laboratory, Nihon Univ., Funabashi 274-8501, Japan, kiyo@shinguu2.cs.cst.nihon-u.ac.jp*
[2] *Dept. of Oceanic Architecture and Eng, Nihon Univ., Funabashi, Japan, kshingu@shinguu2.cs.cst.nihon-u.ac.jp*

VIBRATION CONTROL OF SHELL

An outline of the control method using the neural network for the shell is described in the following.

Flow of vibration control

With vibration control of the shell, the control target, a settled value in connection with relative displacement complying with the ground, is zero. The displacement hereby referred to is the vertical displacement on a nodal point of the discrete shell structure. It is equivalent to the relative vertical displacement complying with the ground obtained by the measurement unit attached to the said nodal point in the case of the real structure. The control target is the settled value of zero, which stems from the reason why the stress becomes smaller as the relative displacement is made smaller to avoid collapse of the structure. Let it be understood that the input values to the controller are the vertical displacements of the time delay, the output data of the hidden layer in the neural network and acceleration of seismic wave. The control signals, which are fed to a damper attached to the shell, help change the viscosity of the damper and the vibration control of the shell is accomplished. The controller is the Elman type neural network, and the learning regulations will be in accordance with the back-propagation using the relative displacement as a consequence of the control. The flow of vibration control is shown in Fig.1.

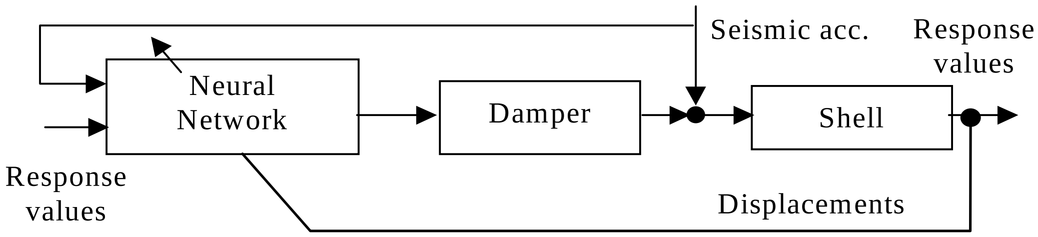


Fig.1 Flow of vibration control

Control Object

The control object is the conical shell that is comprised of dampers, which work in the vertical direction at the antinode of the first mode. The section of the controlled shell is shown in Fig. 2. A modified step-by-step integration method is used for the vibration analysis of the conical shell [Shingu, 1993]. This method is considered on the variable damping ratio. Then the lumped mass matrix is used. The vibration equation is expressed in Eq. (1). The geometrical and material constants of the shell are shown in Table 1.

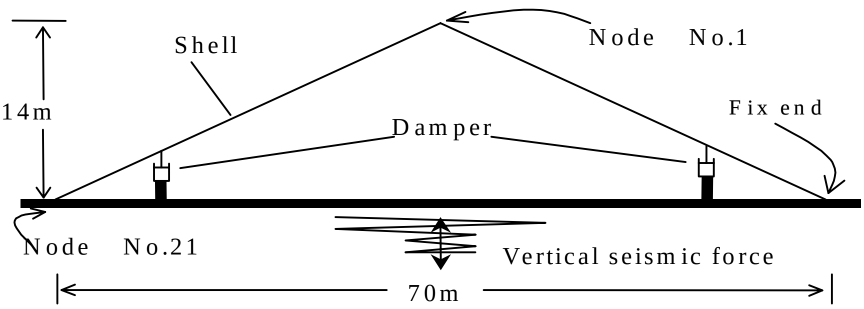


Fig. 2 Conical shell with dampers

Table 1 Geometrical and material constants of shell

Rise	$H = 14m$	Young's modulus	$E = 1.3524 \times 10^{-3}\text{N}/m^2$
Span	$l = 70m$	Poisson's ratio	$\nu = 0$
Thickness	$t = 1.0m$	Mass density	$\rho = 400\text{kg}/m$

$$[M]\{\ddot{d}\} + [C]\{\dot{c}\} + [K]\{d\} = -f\{m\} \tag{1}$$

where

$[M]$, $[K]$: Mass and stiffness matrix of shell

$\{\ddot{d}\} = \{\ddot{u}_1^*, \ddot{w}_1^*, \ddot{\chi}_1^*, \cdots, \ddot{u}_{20}^*, \ddot{w}_{20}^*, \ddot{\chi}_{20}^*\}^T$ **:** Acceleration vector

$\{\dot{d}\} = \{\dot{u}_1^*, \dot{w}_1^*, \dot{\chi}_1^*, \cdots, \dot{u}_{20}^*, \dot{w}_{20}^*, \dot{\chi}_{20}^*\}^T$ **:** Velocity vector

$\{d\} = \{u_1^*, w_1^*, \chi_1^*, \cdots, u_{20}^*, w_{20}^*, \chi_{20}^*\}^T$ **:** Displacement vector

$u_i^*, w_i^*, \chi_i^* \ (i = 1, \cdots, 20)$**:** Vertical and horizontal displacements, and angle of rotation

f **:** Acceleration of seismic force

$\{m\} = \{m_1, 0, 0, m_2, 0, 0, \cdots, m_{20}, 0, 0\}^T$ **:** Mass vector

$1, \cdots, 20$ **:** Node number without supported end

The total element and node numbers are 20 and 21, respectively. The node numbers are 1 at the apex, and 21 at the supported end. The damper is attached at node 14. The boundary condition is the fixed end.
Damping matrix and damping ratios are assumed as follows**:**

$$[C] = 2\omega_1 diag.(m_1\zeta_1, m_1\zeta_1, m_1\zeta_1, \cdots, m_{13}\zeta_{13}, m_{13}\zeta_{13}, m_{13}\zeta_{13}, m_{14}\zeta(t), m_{14}\zeta_{14}, m_{14}\zeta_{14}, \cdots$$
$$m_{15}\zeta_{15}, m_{15}\zeta_{15}, m_{15}\zeta_{15}, \cdots, m_{20}\zeta_{20}, m_{20}\zeta_{20}, m_{20}\zeta_{20})$$

$\zeta_i = 0.02 \quad (i = 1, \cdots, 20)$

$0.02 \le \zeta(t) \le 0.2$ **:** Damping ratio at the antinode of the first mode

ω_1 **:** First natural circular frequency

Neural network

The controller utilized here is the 3-layer hierarchical neural network as mentioned above (see Fig. 3). Each function at a unit in the hidden and the output layer is the sigmoid function. The sigmoid function is as follows.

$$s(x) = \frac{1}{1 + \exp(-x)} \tag{2}$$

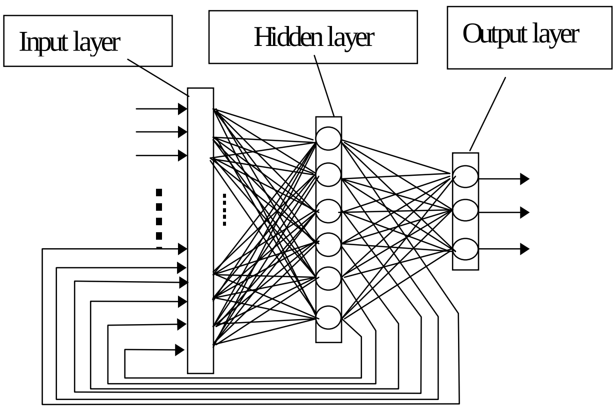


Fig. 3 Neural network

Flow of control simulation

The control simulation is repeated in the following procedures from (a) to (d). Dynamic analysis of the shell is carried out at 0.002 seconds interval, and the shell is controlled at 0.02 seconds interval.

(a) Input into the neural network

There are 63 units in the input layer, 42 units in the hidden layer and 3 units in the output layer. The functions of the units in the hidden and the output layer are sigmoid functions described above. The input data to the network at time $t + \tau + h$ are the displacement u^*, acceleration of seismic wave at time $t + \tau$ and $t + \tau - h$, the output data of the hidden layer in the neural network y at time $t + \tau$. Here t, h and τ are time, small time interval during the integration and time interval of the control, respectively. The output data are calculated by

Eqs. (3) and (4).

The value of the unit in the hidden layer is as follows.

$$y_j = s\left(\sum_{k=1}^{63} w_{jk}^{(1)} x_k + \vartheta_j\right) \qquad (j = 1, \cdots, 42) \tag{3}$$

where

$w_{jk}^{(1)}$ **:** Weights of connection between the hidden and the input layer,

ϑ_j **:** Thresholds of the units in the hidden layer

The value of the unit in the output layer is as follows.

$$o_i = s\left(\sum_{j=1}^{42} w_{ij}^{(2)} y_j + \varphi_i\right) \qquad (i = 1,2,3) \tag{4}$$

where

$w_{ij}^{(2)}$ **:** Weight of connection between the output layer

φ_i **:** Thresholds of the units in the output layer

The input data are shown in Eq.(5).

$$\{x_1, \cdots, x_{63}\} = \{u_{t+\tau-h,1}^{*}, \cdots, u_{t+\tau-h,20}^{*}, u_{t+\tau,1}^{*}, \cdots, u_{t+\tau,20}^{*}, y_{1,}, \cdots, y_{21}, f_{t+\tau-h}, f_{t+\tau}\} \tag{5}$$

where

u^* **:** Vertical displacements

y **:** Output of the hidden layer in the neural network

index h **:** Small time interval during integration $(= 0.002(\text{sec}))$

index τ **:** Time interval during control $(= 0.02(\text{sec}))$

index $1, \cdots, 20$ **:** Node numbers

(b) Calculation of damping ratio

The damping ratio is computed at time $t + \tau + h$ from the output of the neural network by Eqs. (6) and (7).

$$z_i = 0.02 + 0.18 \cdot o_i \qquad (i = 1,2,3) \tag{6}$$

$$\zeta(t + \tau + h) = (z_1 - z_2 + 1) \cdot z_3 + 0.09 \cdot z_3 + 0.02 \tag{7}$$

where if $\zeta(t + \tau + h) \geq 0.2$ then $\zeta(t + \tau + h) = 0.2$

(c) Dynamic response analysis

The dynamic response of the shell is computed by the modified step-by-step integration method [Shingu and Fukushima, 1993].

(d) Learning

During the control, the neural network makes learning sequentially. The learning regulation is a renovation method of the weight of the network. The learning means renovating the weight of the network using the input data and control results in accordance with the learning regulations. The learning regulations will renovate the weight in a method in accordance with back-propagation. Changing the weight of the network using the displacement in the case of time $t + \tau + h$ makes the learning. Change of the weight is calculated in accordance with the equation shown in the following. The value of weights and thresholds are evaluated by Eqs. (8)-(12) and those are renovated by Eqs. (13)-(14). η is equal to 0.0021.

$$\Delta E = \eta D \tag{8}$$

where $D = b_{i_0}$

$$\{b\} \equiv \{u^*_{t+\tau+h,1}, w^*_{t+\tau+h,1}, \chi^*_{t+\tau+h,1}, \cdots, u^*_{t+\tau+h,20}, w^*_{t+\tau+h,20}, \chi^*_{t+\tau+h,20}\}$$
$$\equiv \{b_1, \cdots, b_{60}\}$$
$$|A| = \max_{1 \le i \le 60} |b_i| \qquad i_0 = \max\{i \mid |b_i| = |A|, i = 1, \cdots, 60\}$$
$$\Delta w^{(2)}_{ij} = \Delta E \cdot o_i \cdot (1 - o_i) \cdot y_j \tag{9}$$
$$\Delta \varphi_i = \Delta E \cdot o_i \cdot (1 - o_i) \tag{10}$$
$$\Delta w^{(1)}_{jk} = \sum_{i=1}^{3} \Delta E \cdot o_i \cdot (1 - o_i) \cdot w^{(2)}_{ij} \cdot y_j \cdot (1 - y_j) \cdot x_k \tag{11}$$
$$\Delta \vartheta_j = \Delta E \cdot o_i \cdot (1 - o_i) \cdot w^{(2)}_{ij} \cdot y_j \cdot (1 - y_j) \tag{12}$$
$$w^{(2)}_{ij} \leftarrow w^{(2)}_{ij} + \Delta w^{(2)}_{ij} \quad , \qquad \varphi_i \leftarrow \varphi_i + \Delta \varphi_i \tag{13}$$
$$w^{(1)}_{jk} \leftarrow w^{(1)}_{jk} + \Delta w^{(1)}_{jk} \quad , \qquad \vartheta_j \leftarrow \vartheta_j + \Delta \vartheta_j \tag{14}$$
$$(i = 1,2,3), \ (j = 1, \cdots, 42), \ (k = 1, \cdots, 63)$$

SIMULATION RESULTS

Figs. 4 and 5 show Miyagiken-oki and El Centro earthquakes used for input acceleration, whose maximum accelerations are changed to $2\, m/\sec^2$. The control effects are estimated by comparison with non-control results. These results are shown in Figs. 6-17. The meanings of symbols, NON, CONT, $\boxed{\text{M}}$ and $\boxed{\text{E}}$ are as follows**:**

NON**:** Non-control (damping ratio is 0.02)   CONT**:** Control
$\boxed{\text{M}}$: Miyagiken-oki earthquake $\boxed{\text{E}}$: El Centro earthquake

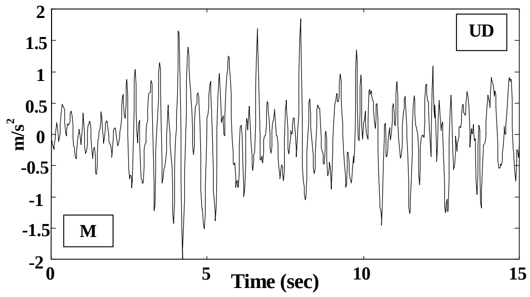


Fig. 4 Miyagiken-oki earthquake

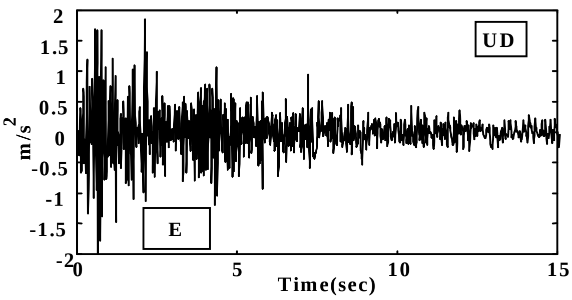


Fig. 5 El Centro earthquake

Maximum displacements (Input acc. : Miyagiken-oki earthquake)

Figs. 6 and 7 show the maximum displacements in the vertical and horizontal directions, respectively.

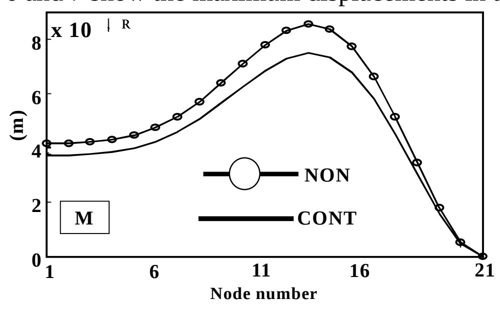


Fig. 6 Vertical displacements u^*

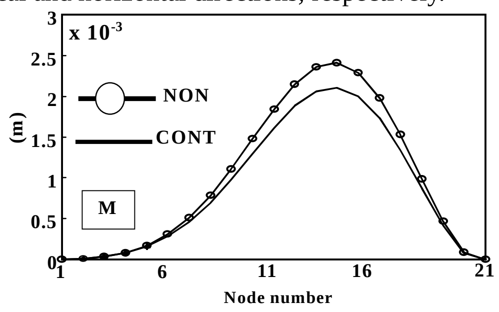
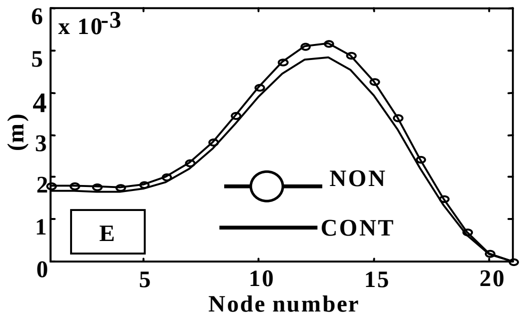


Fig. 7 Horizontal displacements w^*

Maximum displacements (Input acc. : El Centro earthquake)

Figs. 8 and 9 show the maximum displacements in the vertical and horizontal directions, respectively.



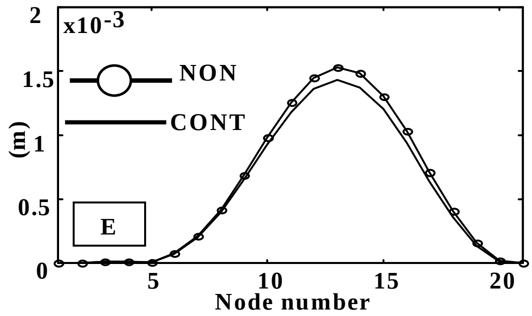
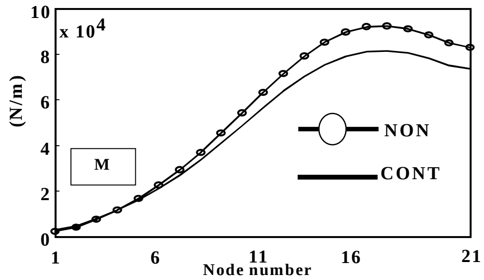


Fig. 8 Vertical displacements u^*

Fig. 9 Horizontal displacements w^*

Maximum stresses

Figs. 10-13 show the maximum stresses N_S, N_θ, M_S and M_θ in the case of Miyagiken-oki earthquake, respectively.



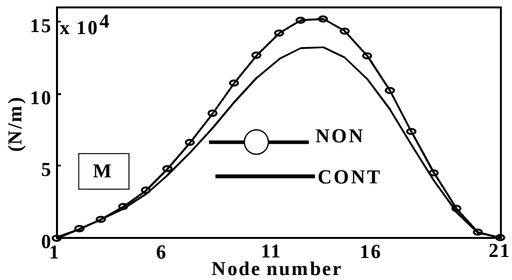
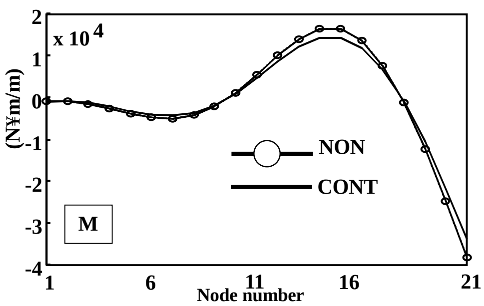


Fig. 10 Axial force N_S

Fig. 11 Axial forces N_θ



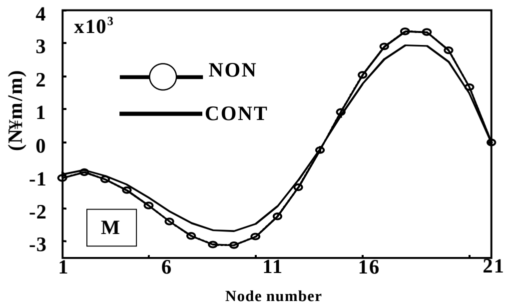
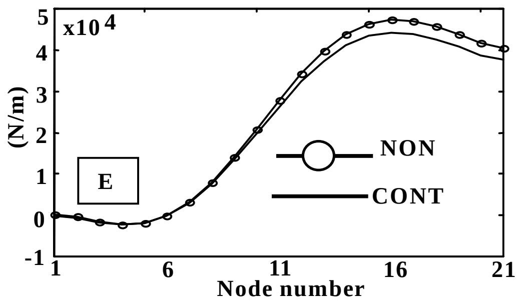


Fig. 12 Bending moments M_S

Fig. 13 Bending moments M_θ

Figs. 14-17 show the maximum stresses N_S, N_θ, M_S and M_θ in the case of El Centro earthquake, respectively.



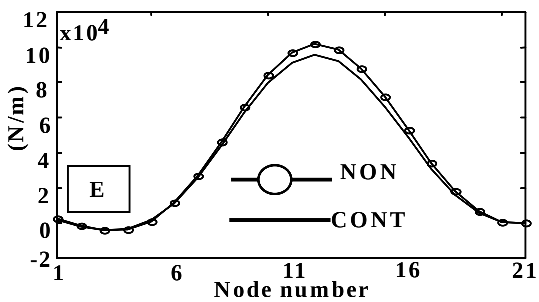


Fig. 14 Axial force N_S

Fig. 15 Axial forces N_θ

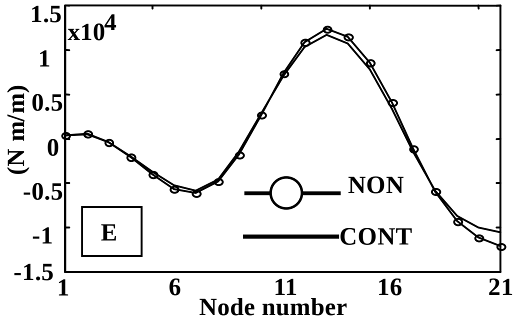


Fig. 16 Bending moments M_S

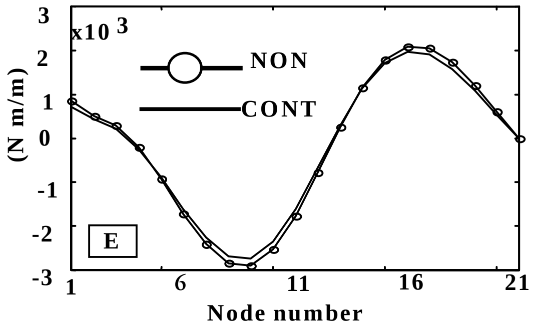


Fig. 17 Bending moments M_θ

Time history and damping ratio

The time histories of the damping ratios are shown in Figs. 18 and 19.

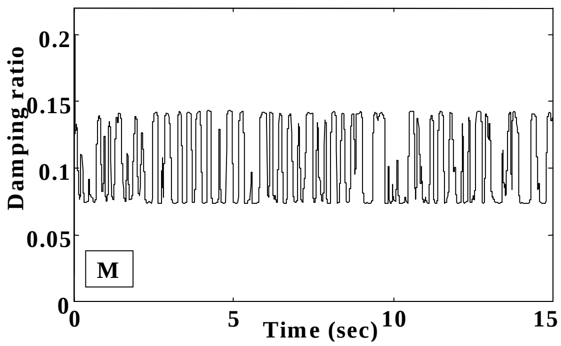


Fig. 18 Time history of damping ratio

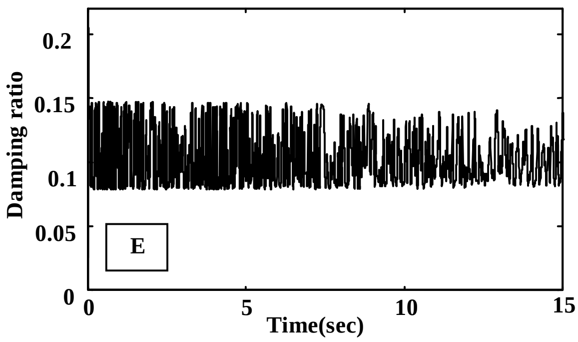


Fig. 19 Time history of damping ratio

Averages of controlled damping ratios are shown in the following.

Table 2 Averages of damping ratios

Non-controlled	0.020
Miyagiken-oki (controlled)	0.102
El Centro (controlled)	0.096

OBSERVATION

The following analytical results are obtained from the research.

1) With respect to the maximum response displacement in the vertical and horizontal directions, the controlled (CONT) results are reduced by 12% (Miyagiken-oki), 6% (El Centro) of the non-controlled (NON) ones.

2) With respect to the maximum stresses of N_S, N_θ, M_S and M_θ, the CONT results are reduced by 12% (Miyagiken-oki), 7-12% (El Centro) of the NON ones.

CONCLUSIONS

The displacements and stresses in the shell under the CONT are smaller than those of the NON. The vibration control in the shell with neural network restricts the displacements and stresses in the shell.

ACKNOWLEDGEMENT

This study was supported in part by the Nihon University Joint Research Grant for 1999 (Representative: K. Shingu).

REFERENCE

Fujii, Ura and Kuroda, 1990, “Development of Self-Organizing Neural-Net-Controller System and Its Application to Underwater Vehicles”, *Journal of The Society of Naval Architects of Japan,* Vol. 168, pp 275-281 (in Japanese)

Hiratsuka and Shingu, 1997, “A Study on Vibration Control of Multi-Degree-of-Freedom System Structure Using Neural Network Algorithm”, *Proceeding of the Conference on Computational Engineering and Science,* Vol. 2, No. 2, pp 677-680 (in Japanese)

Hiratsuka and Shingu, 1997, “Vibration Control with Neural Network Algorithm of Conical Shell Subjected to Seismic Forces in Vertical Direction”, *Proceeding of Prevention Research Institute*, Kyoto University, pp 167-171, (in Japanese)

Hiratsuka and Shingu, 1998, “Application of Neural Network Algorithm for Vibration Control of Shell Structures Subjected to Vertical Seismic Forces”, *PVP-Vol. 379, SEISMIC, SHOCK, AND VIBRATION ISOLATION*, The American Society of Mechanical Engineers, pp 177-184

Jordan and Rumelhart, “Forward Models, Supervised Learning with a Distal Teacher”, *MIT Center for Cognitive Science*, Occasional Paper #40

Kawato and Gomi, 1995, *Kinematics Model of The Human Brain, From Brain to Mind*, Iwanami Shoten, pp 235-244 (in Japanese)

Morishita, Kuroda and Ura, 1992, “Adaptive Vibration Control System with Controllable Dynamic Damper”, *Transaction of Japan Society of Mechanical Engineering*, Vol. 58, No. 550, pp 1748-1754 (in Japanese)

Nishimura and Shingu, 1983, “Study on Dynamic Response of Rotational Shells with Edge Beams Subjected to Seismic Forces in the Vertical and Horizontal Directions”, *Transaction of the Architectural Institute of Japan,* Vol. 326, pp 47-59 (in Japanese)

Shingu and Fukushima, 1993, “Study on Fuzzy Control of Shells Subjected to Seismic Forces”, *Journal of Japan Society for Fuzzy Theory and Systems,* Vol. 5, No. 3 , pp 650-662 (in Japanese)

Shingu and Fukushima, 1994, “Seismic Isolation and Fuzzy Vibration Control of Shell Structure Subjected to Vertical Seismic Forces”, *Transaction of the Japan Society of Mechanical Engineers (C)*, Vol. 60, No. 577, pp 2999-3005 (in Japanese)