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HYBRID CONTROL SYSTEM WITH OPTIMAL FUZZY LOGIC AND GENETIC ALGORITHM FOR HIGH-RISE BUILDINGS

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SUMMARY

Structural vibrations are primarily caused by earthquakes and wind. These vibrations affect the daily life of many people. Vibrations induced by an earthquake need to be measured to assure building safety in Japan, which experiences numerous earthquakes, and those by wind to assure comfort for people in high-rise buildings. Countermeasures against structural vibration are therefore required.

A countermeasure against vibration is structural control, which can be categorized into passive and active controls. Although passive control is currently used widely because it does not require external energy, it is effective only for the particular earthquakes for which it was designed. Active control has attracted the attention of engineers as it is effective for various winds and earthquakes. Most active control systems are based on linear quadratic control by a linear system and are effective only against small earthquakes and daily wind. Therefore, active control systems are needed that are effective against vibrations induced by large earthquakes and strong winds and that include nonlinearity and uncertainty.

The main objective of this study was to construct an active structural control system as a smart structure system. The effectiveness of a hybrid control system composed of optimal fuzzy control (OFC) and genetic algorithm (GA) was evaluated. In this OFC/GA hybrid control system, the OFC has three fuzzy rules: prediction of an earthquake, determination of the feedback gain, and determination of the suitable rate of feedforward and feedback gain. This hybrid control system has functions of a smart system similar to a human being (e.g., evolution, learning and immunization), can update the fuzzy rules, and can search for optimal solutions derived from GA. Experimental results validated the feasibility of OFC. Numerical simulations showed that OFC responds to a disturbance system (e.g., an earthquake) that has nonlinearity and input saturation, and that OFC is robust for various earthquakes.

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INTRODUCTION

Rapid urban redevelopment and construction of high-rise buildings are recently evident throughout Asia. Such buildings require countermeasures against vibrations caused by earthquakes and wind. A structural control system is one solution to the vibration problem. Such systems are classified as passive control, which requires external power, and active control, which requires only internal power. Examples of passive control devices include viscoelastic dampers and rubber bearings. Although passive structure control systems are used widely, they are effective only for particular vibrations induced by a specific type earthquake for which the control system was designed. Active structural control systems have attracted the attention of engineers because of the response of such systems to various types of vibrations.

Most active control systems used as a countermeasure against vibrations of a structure use linear quadratic (LQ) control as its linear control. However, the response of a high-rise building induced by large earthquakes and winds has nonlinearity and uncertainty. Therefore, an intelligent control system is needed. An example of such a system is fuzzy control (Kawamura [1], Casciati [2], Ahalawat [3], Yamada [4], [5]) and neural network control. These systems can control disturbance systems that have nonlinearity and uncertainty. Intelligent control systems, however, require more intelligent functions, like a human being.

Smart structures are structures that have functions similar to those of human beings, such as evolution, learning and immunization. The field of smart structures is currently an active area of research.

The main objective of this study was to evaluate the advantages of an active vibration control method that involves a hybrid control system composed of optimal fuzzy logic (OFC) and a genetic algorithm (GA) for use in high-rise buildings subjected to strong earthquakes. First, this OFC/GA hybrid control system was shown. Then, experiment and numerical analysis were done for evaluating OFC/GA hybrid control system.

MODEL

Figure 1 shows the experimental structure. This structure was a 2-m-high scaled model of a 500-m-high high-rise building under constant gravitation, with length dimension scaled down to $1/250$ and time dimension scaled down to $1/\sqrt{250}$. An Active Mass Damper (AMD) for reducing the vibrations was located on the top story of the structure. The mass of the AMD was about 5% of the structure. The 1st and 2nd natural frequencies were 3.1 and 13.9 Hz, respectively. The equation of motion for this structure-AMD system was

$$\mathbf{M}\ddot{\mathbf{Q}} + \mathbf{C}\dot{\mathbf{Q}} + \mathbf{K}\mathbf{Q} = \mathbf{M_0}\mathbf{D}\ddot{x}_0 + \mathbf{B}v_a \tag{1}$$

where $\mathbf{M}$, $\mathbf{C}$ and $\mathbf{K}$ are mass, damping, and stiffness matrices; $\ddot{\mathbf{Q}}$, $\dot{\mathbf{Q}}$ and $\mathbf{Q}$ are relative acceleration, velocity, and displacement vectors of the structure; $\ddot{x}_0$ is acceleration of the earthquake; v_a is the input voltage; and $\mathbf{M_0}\mathbf{D}$ and $\mathbf{B}$ are external force vectors for disturbance and control input.

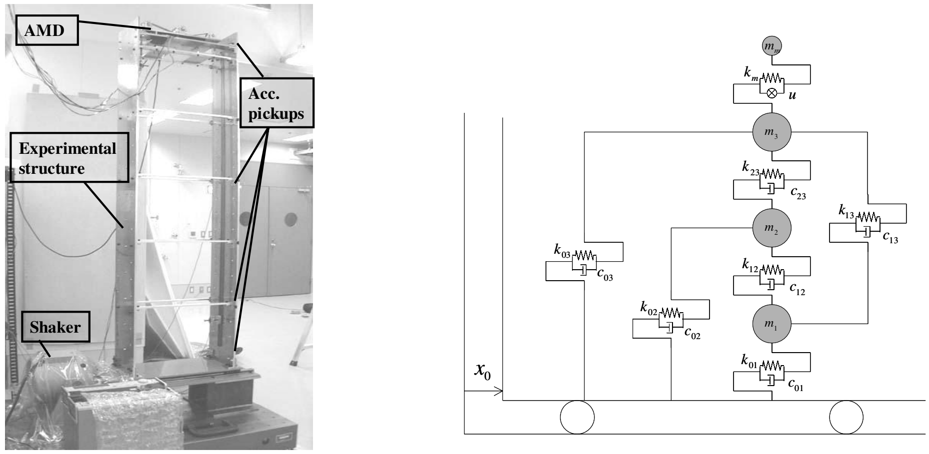

Fig. 1 Experimental set-up and schematic of controlled system

HYBRID CONTROL SYSTEM

Figure 2 shows the OFC/GA hybrid control system. The OFC has three fuzzy rules. Fuzzy rule 1 is earthquake prediction, rule 2 is determination of feedback gain, and rule 3 is determination of optimal feedforward and feedback rate. After an earthquake movement and the associated response of a structure are finished, these fuzzy rules in the OFC are updated and optimized by the GA. These updating and optimizing operations mean adding OFC to a smart function, similar to what human beings do when they grow up.

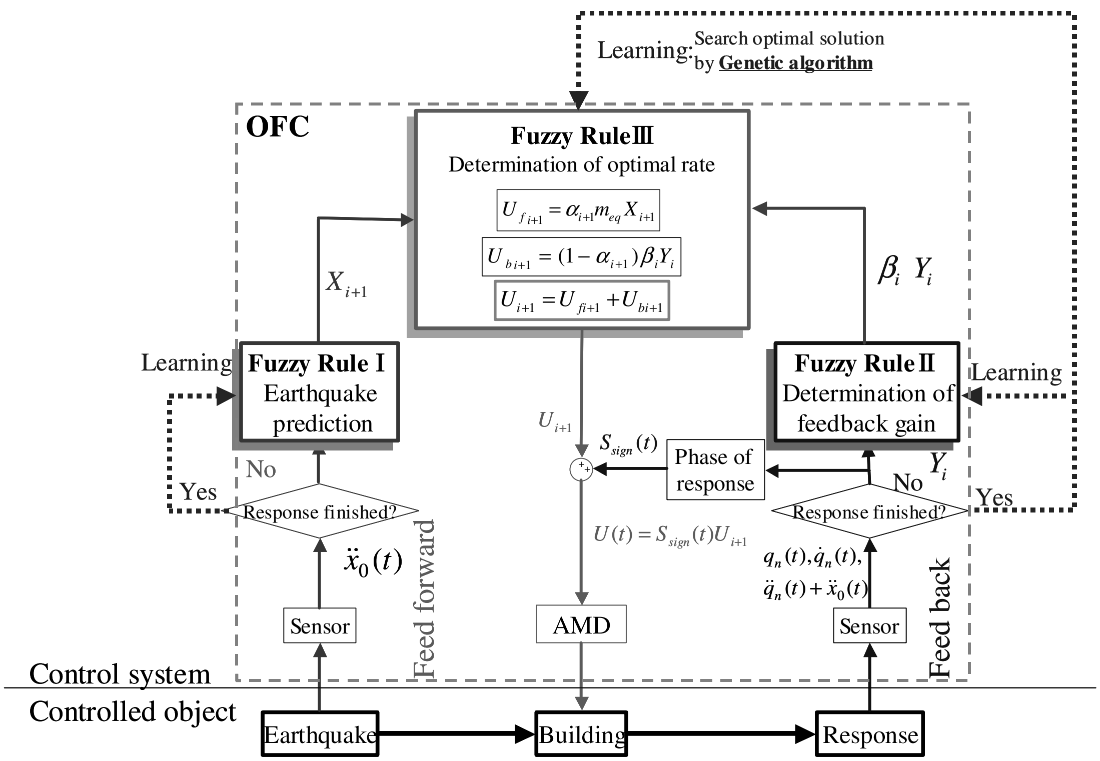

Fig. 2 Flowchart of a hybrid control system

Optimal fuzzy controller (OFC)

In the OFC, parameter X is the absolute maximum earthquake acceleration and Y is the structure's velocity during the control interval Δt as shown in Fig. 3. X_i and Y_i express these values for the ith X and Y.

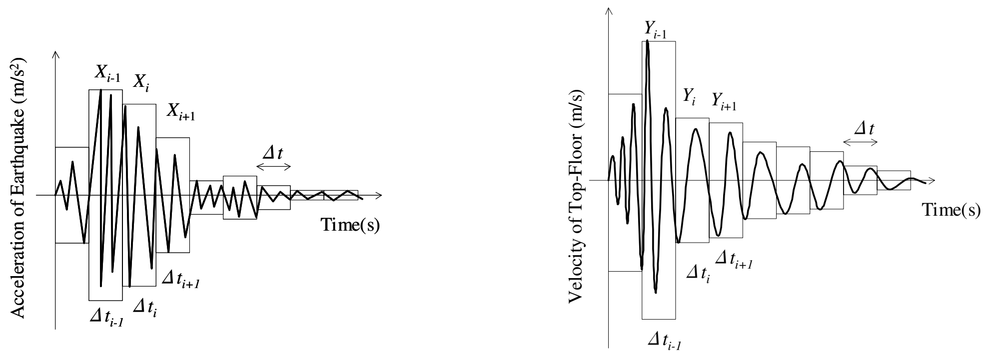

Fig. 3 Parameters in OFC

The control force is composed of a feedforward control, a feedback control, and phase of the control force. A feedforward control force $U_{f_{i+1}}$ is expressed by Eq. (2), feedback control force $U_{b_{i+1}}$ by Eq. (3), control force $U(t)$ is derived from Eqs. (4) and (5), and the phase of control force S_{sign} is shown in Table 1.

$$U_{f_{i+1}} = \alpha_{i+1} m_{eq} X_{i+1} \tag{2}$$

$$U_{b_{i+1}} = (1-\alpha_{i+1})\beta_i Y_i \tag{3}$$

$$U_{i+1} = U_{f_{i+1}} + U_{b_{i+1}} \tag{4}$$

$$U(t) = S_{sign}(t) \cdot U_{i+1} \tag{5}$$

where α_{i+1} is the optimal rate of feedforward and feedback input derived from the maximizing decision; m_{eq} is the 1st equivalent mass; X_{i+1} is the predicted earthquake acceleration; β_i is the feedback gain; and Y_i is the response of the top story of the structure.

Table 1 Phase of control force, S_{sign}

Phase of top-floor displacement	+	+	-	-
Phase of top-floor velocity	+	-	-	+
Phase of control force S_{sign}(t)	-	0	0	+

Fuzzy rule 1 is composed of membership functions as shown in Fig. 4, where the horizontal axis is ΔX_i derived from Eq. (6), and the vertical axis is $\Delta^2 X_i$ described by Eq. (7). Each membership function (left schematic in Fig. 4) is ΔX_{i+1} of the distribution frequency. The goal of learning by the OFC is to set up Eqs. (6), and (7) using earthquake data, and then to add these data to fuzzy rule 1. The prediction of an earthquake involves setting up Eqs. (6) and (7) interval of control time respectively, to set up ΔX_{i+1} from defuzzification, and then to obtain X_{i+1} from Eq. (8).

$$\Delta X_i = X_i - X_{i-1} \tag{6}$$

$$\Delta^2 X_i = X_i - 2X_{i-1} + X_{i-2} \tag{7}$$

$$X_{i+1} = X_i + \Delta X_{i+1} \tag{8}$$

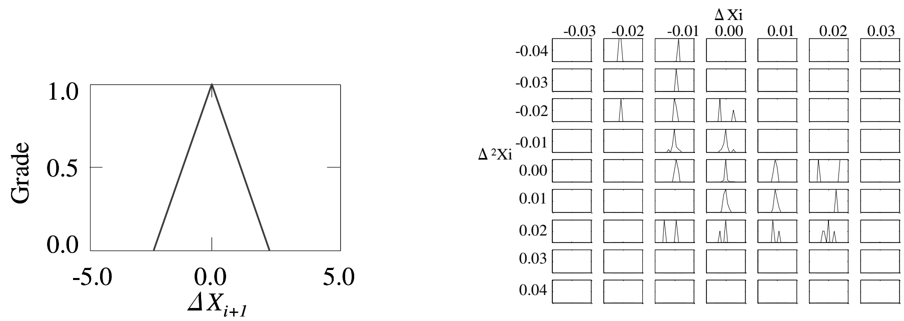

Fig. 4 Fuzzy rule 1. Left is a detailed schematic of representative component, or membership function, of fuzzy rule 1 shown at right.

Fuzzy rule 2 (Fig. 5) is used to determine the feedback gain β_i expressed as

$$\beta_i = 2 \cdot h_B \sqrt{m_{eq} k_{eq}} \tag{9}$$

where k_{eq} is 1st equivalent stiffness. y_1, y_2 and y_{sign} are the parameters of fuzzy rule 2. When the velocity of the top floor of the structure Y_i is less than y_1, h_B is set at 0, and when it is more than y_2, h_B is set at 100%. When the velocity Y_i is between y_1 and y_2, h_B is proportional to the membership function. y_{sign} is determined shape (+, - or 0) of membership function.

Fuzzy rule 3 (Fig. 6) is used to determine the rate of feedforwad and feedback control forces. u_1, u_2 and u_{sing} are the parameters of fuzzy rule 3. α_{i+1} is obtained by the maximizing decision derived from Eqs. (2), (3).

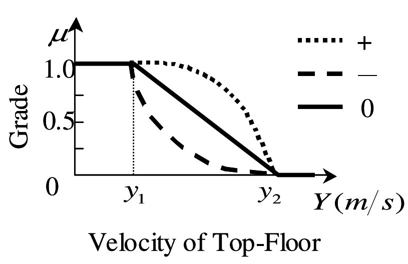

Fig. 5 Fuzzy rule 2

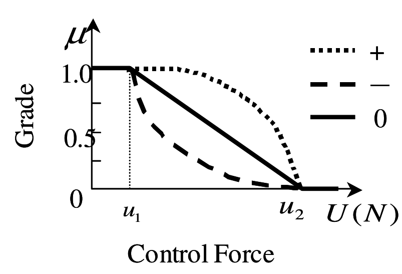

Fig.6 Fuzzy rule 3

Genetic algorithm (GA)

Optimal parameters of fuzzy rules 2 and 3 are decided by GA whose 23-bit–long chromosome consists of y_1, y_2, y_{sign}, u_1, u_2, and u_{sign}. The target of the GA is a maximum fitness function F. F shown in Eq. (10) is obtained by combining, $F_{d\text{-}max}$, $F_{d\text{-}rms}$, $F_{v\text{-}max}$ and $F_{v\text{-}rms}$ shown in Figs.7 and 8, where D is the displacement of the top floor of the structure under control, D_{max} is the maximum D without control, D_{rms} is the R.M.S. D without control, and U is the control force. $F_{d\text{-}max}$ derived from D_{max} is the fitness function of max-displacement of top-floor. $F_{d\text{-}rms}$ derived from D_{rms} is the fitness function of R.M.S-displacement of top-floor. $F_{v\text{-}max}$ is the fitness function of max-control-force. $F_{v\text{-}rms}$ is the fitness function of R.M.S-control-force. Learning by GA involves 20 initial populations chosen at random, a roulette selection and an elitist-preserving selection used as a reproduction, and 5-point crossover and mutation are used.

$$F = F_{d-\max} \cdot F_{d-rms} \cdot F_{v-\max} \cdot F_{v-rms} \tag{10}$$

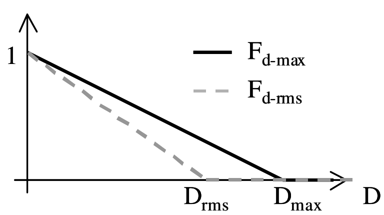

Fig.7 Fitness functions $F_{d\text{-}max}$ and $F_{d\text{-}rms}$

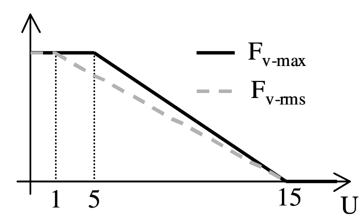

Fig.8 Fitness functions $F_{v\text{-}max}$ and $F_{v\text{-}rms}$

EXPERIMENTS FOR STRUCTURE CONTROL

Experimental method

Fuzzy rule 1 was trained by using the motions of seven earthquakes as input, and then y_1=0.00, y_2=0.03, y_{sign}=0, u_1=0, and u_2=0.35. AMD had a total stroke of less than ± 0.023 m, and the peak control voltage was less than 20 and the input sine was 3.1 Hz.

Experimental results and discussion

Figures 9 and 10 show the time histories and Fourier amplitude spectrums, respectively, of acceleration and displacement of the top floor of the experimental structure with and without control. The structure with control showed a lower maximum and R.M.S. acceleration response by 128% and 77.8%, respectively, a lower maximum and R.M.S. displacement response by 96.2% and 60.2% respectively, and a lower maximum Fourier amplitude spectrum by 58.4%. The structure with control also showed response in high frequency due to the moving AMD. These results show that OFC can effectively reduce the 1st natural mode response.

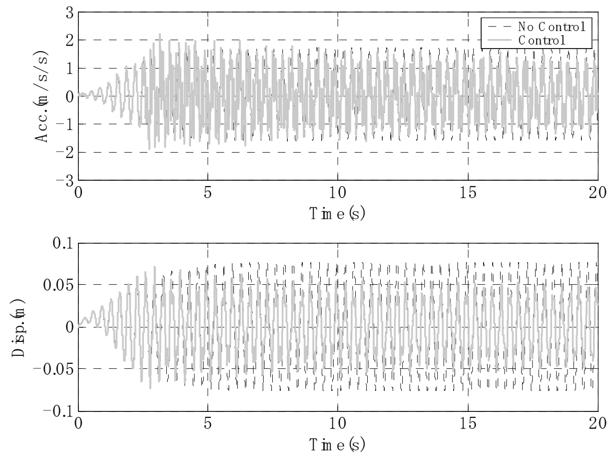

Fig.9 Time history of acceleration and displacement of top floor

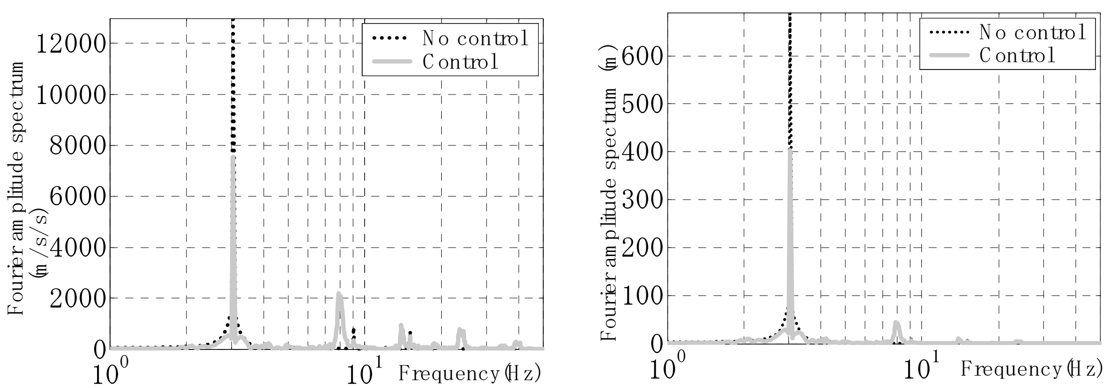

Fig.10 Fourier amplitude spectrum of acceleration and displacement of top floor

NUMERICAL SIMULATIONS

Comparison between control by LQ and by OFC

For evaluate OFC, the numerical simulation comparison between control by LQ and by OFC was done. The verifying model system used a 1 degree-of- freedom as a restoring force, and used a bi-linear model to apply a yield force that was 0.2 times the mass weight. The stiffness after yielding was 0.1 times the stiffness before yielding. The AMD allowed a maximum control force of ±3N.

Controller gains

The OFC gains were y_1=0.001, y_2=0.015, y_{sign}=0, u_1=1.00, u2=3.00, and u_{sign}=0. The LQ control input was derived from Eq. (11), where $\mathbf{F_{LQ}}$ is LQ control gain. For $\mathbf{Q_{LQ}}$=diag(1,1) and r=10^{-5}, $\mathbf{F_{LQ}}$ was determined by minimizing the criterion function expressed in Eq. (12).

$$u = -\mathbf{F}_{LQ}\left(\mathbf{Q} \quad \dot{\mathbf{Q}}\right)^T \tag{11}$$

$$J = \int_0^\infty \left[\begin{pmatrix} \mathbf{Q} & \dot{\mathbf{Q}} \end{pmatrix} \mathbf{Q}_{LQ} \begin{pmatrix} \mathbf{Q} & \dot{\mathbf{Q}} \end{pmatrix}^T + ru^2 \right] dt \tag{12}$$

Numerical simulation results and discussion

The resulting time histories of structure-displacement of the top story, AMD stroke, control force, and displacement-restoring force for the OFC-controlled structure (Fig. 11) and LQ-controlled structure (Fig. 12) showed that OFC control is more robust than LQ control at the point of counterbility of nonlinear and saturation.

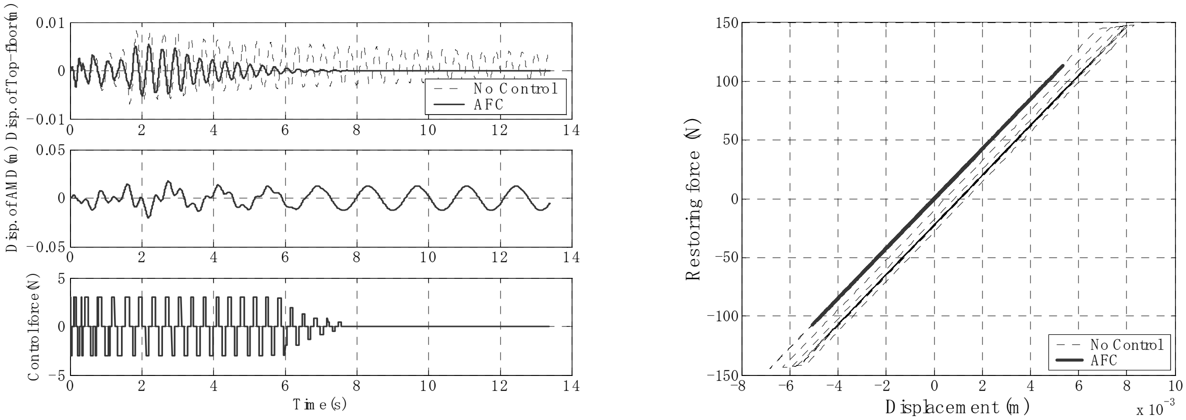

Fig.11 Time histories of structure-displacement of the top story, AMD stroke, control force, displacement-restoring force under OFC control and no control

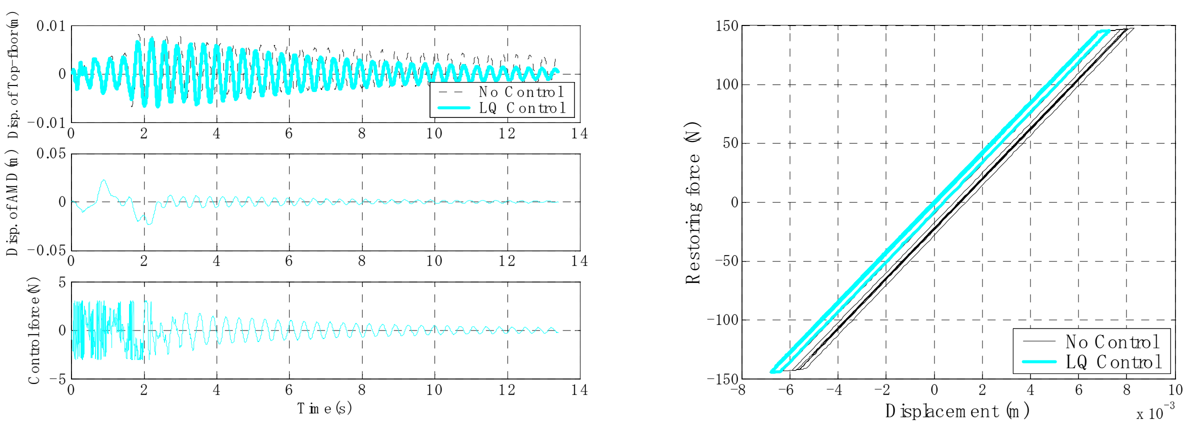

Fig.12 Time histories of structure-displacement, AMD stroke, control force, displacement-restoring force under LQ control and no control

Smart function of hybrid control

GA determines the optimal OFC parameters. Earthquakes (Table 2) are classified Group A used training fuzzy rule 2 and 3 and Group B used verifying. Fuzzy rules 2 and 3 were trained by using specific earthquake input (1) A1-A4, (2) A5 and A6[6], or (3) A1-A6. The model shown in Fig.1 is subjected to the earthquake motions in all groups A and B.

Table 2 Earthquakes input into numerical simulation of smart function of hybrid control

	Earthquake	Scaled	Max. Acc. (m/s^2)
Group A	A1: El Centro 1940 NS	Scaled max. vel. of 0.5 m/s	5.11
	A2: Taft 1952 NS	Scaled max. vel. of 0.5 m/s	4.86
	A3: Tohoku 1978 NS	Scaled max. vel. of 0.5 m/s	3.57
	A4: Hachinohe 1968 NS	Scaled max. vel. of 0.5 m/s	3.33
	A5: Shinjyuku 1998.8.29	10 fold	8.92
	A6: Shinjyuku 2000.4.10	10 fold	3.91
Group B	B1: El Centro 1940 EW	Scaled max. vel. of 0.5 m/s	2.85
	B2: Taft 1952 EW	Scaled max. vel. of 0.5 m/s	4.97
	B3: Tohoku 1978 EW	Scaled max. vel. of 0.5 m/s	3.69
	B4: Hachinohe 1968 EW	Scaled max. vel. of 0.5 m/s	2.39
	B5: Shinjyuku 1998.11.8	10 fold	4.05
	B6: Random		3.58

Numerical simulation results and discussion

Table 3 shows the parameters of fuzzy rules determined from numerical simulation. In fuzzy rule 3, the parameters for group (3) training motions are coupling (1) and (2). Figure 13 shows that the use of specific earthquake motions to train the controller reduced the structure responses subjected to those specific motions; for example, the use of motions A1-A4 to train the controller reduced the structure responses to motions A1-A4 (group 1 in Table 3), and similarly for A5 and A6 (group 2), and for A1-A6 (group 3). In addition, the use of motions A1-A6 (group 3) also reduced the structure response subjected to motions B1-B6, which are motions that the OFC did not learn. These results reveal the smart function of this hybrid control, namely, that the hybrid control system exhibits immunization corresponding to the same earthquake motion used in the learning process, and exhibits leaning and evolution corresponding to other earthquakes.

Table 3 Parameters of fuzzy rules 2 and 3 determined by smart function

Training earthquake	Fuzzy rule 2			Fuzzy rule 3		
	y_1	y_2	y_{sign}	u_1	u_2	u_{sign}
(1) A1-A4	0.0084	0.0102	0	11	11	0
(2) A5 and A6	0.0080	0.0098	+	0	2	0
(3) A1-A6	0.0010	0.0112	0	0	11	+

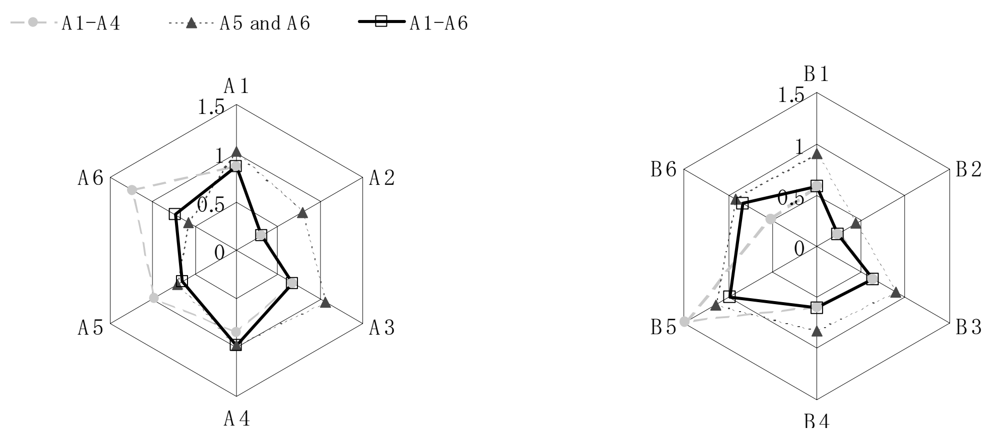

Fig.13 Ratio of control and no-control response

CONCLUSION

An active control method that uses optimal fuzzy logic (OFC) and a genetic algorithm (GA) as a smart structure was developed. Evaluation experiments validated the use of OFC. Numerical simulations showed that a hybrid controller has smart functions, such as immunization, learning, and evolution.

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