Paper No. 425. (quote when citing this article)
Eleventh World Conference on Earthquake Engineering
ISBN: 0 08 042822 3

FUZZY OPTIMAL CONTROL SYSTEM OF BUILDINGS BY NEURAL NETWORK (SINGLE-DEGREE-OF-FREEDOM SYSTEM, SELECTION OF TRAINING DATA OF STRUCTURAL IDENTIFICATION BY GENETIC ALGORITHM)

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ABSTRACT

This paper describes an optimal adaptive and predictive control system and its digital simulations for a single-degree-of-freedom system subjected to earthquake loading. In this system, an active mass driver system and an equivalent variable mass system are employed as an active control method. Prediction of earthquake input and structural identification are performed by using feedback neural networks based on the error back-propagation method. To make proper training data of structural identification, the genetic algorithm is employed. Optimization is performed by means of maximizing decision. In maximizing decision, optimal target control variables are determined by using assumed membership functions of target responses. Results of digital simulations show the effectiveness of the proposed control system.

Keywords

Active Control, Fuzzy Optimal Control, Prediction of Earthquake Input, Prediction of Structural response, Neural Network, Genetic Algorithm

INTRODUCTION

Recently many researches on active control of structures are carried out (Chong et al., 1990 and Soong et al., 1991). To develop the dynamic control system of civil engineering and building structures, it is necessary to take account of their special features such as complexity, uncertainty and large scale (Yao, 1972 and Yao et al., 1987). Kawamura, one of the authors, and Yao (1990) already proposed a new idea of the application method of fuzzy logic (Zadeh, 1965) and fuzzy maximizing decision (Bellman et al., 1970) to civil engineering structures subjected to earthquake loading. According to this paradigm, the authors presented fuzzy optimal adaptive and predictive control systems and those digital simulations (Kawamura et al., 1990 and Tani et al., 1992). In these system, to realize an effective control system, it is also necessary to perform the prediction of earthquake inputs and structural identification accurately. So, the authors employ multi-layered neural networks based on error back-propagation method (Rumelhart et al., 1986) and also presented an active control method and its digital simulations (Tani et al., 1993 and 1994). Furthermore, to improve the accuracy of proposed control systems, a neural network, which has feedback loops from the output layer to the input layer at the training of it, is employed to predict the future earthquake inputs and structural identifications (Tani et al., 1994 and 1995b). This neural network was proposed by Jordan (1989) and Matsuba (1991) pointed out the effectiveness for the prediction of time series data.

In this paper, to improve the accuracy of proposed control systems, a selection method of the training data of neural network of structural identification by the operation of Genetic Algorithm (Holland, 1993) is also employed (Tani et al., 1995a). A fuzzy optimal active control system is proposed by neural networks which are trained the training data using the proposed method. Objective building is assumed to be one-degree-of-freedom system with an active mass driver system at the top of building. As active control methods, an equivalent variable mass method is employed. Digital simulations are carried out for the objective structure to verify the effectiveness of the proposed active control system against the earthquake loading.

OUTLINE OF CONTROL METHOD

Flow chart of Control System

Fig.1 shows a flow chart of fuzzy optimal control system (Kawamura et al., 1990) employed in this system. This control method has following special features:

1) Target responses and control variables are described with membership functions of fuzzy theory,
2) Real time prediction of earthquake input and structural identifications are performed,
3) Optimization is performed by using fuzzy maximizing decision (Bellman et al., 1970).

Fundamental Assumptions

Fig.2 shows a controlled structure employed in this paper. This structure is assumed to be single-degree-of-freedom system with an active mass driver at the top of it. It assumed that mass of structure (m_1, and m_d), spring constants (k_1 and k_d) and damping factor (c_1 and c_d) are constant and assumed values of them are also shown in Fig.2. As a control method, an equivalent variable mass method is employed. Equations of motions are as follows:

$$m_1\ddot{y}_1 + c_1\dot{y}_1 - c_d(\dot{y}_d - \dot{y}_1) + k_1 y_1 - k_d(y_d - y_1) + u_m = -m_1\ddot{x} \quad (1)$$
$$m_d\ddot{y}_d + c_d(\dot{y}_d - \dot{y}_1) + k_d(y_d - y_1) - u_m = -m_d\ddot{x} \quad (2)$$
$$u_m = -\alpha \cdot m_1(\ddot{y}_1 + \ddot{x}) \quad (3)$$

where y_1, $\dot{y}_1$, $\ddot{y}_1$:displacement, velocity and acceleration of the structure relative to the foundation at the first story, y_d, $\dot{y}_d$, $\ddot{y}_d$:those at the active mass driver, $\ddot{x}$:acceleration of earthquake, u:control force, α : reduction factor. Control force u is calculated by Eq.(3) and activate to the structure by Eq.(1). In this system, α is

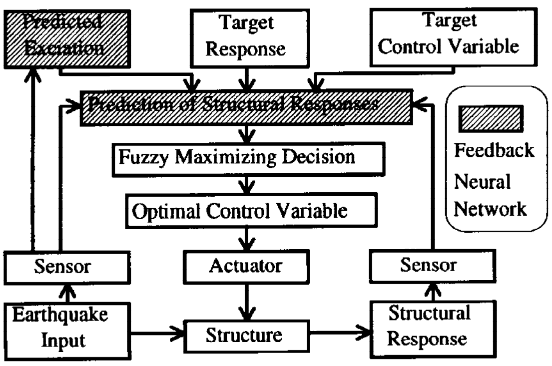


Fig.1 Flow chart of proposed control system (Kawamura et al., 1990)

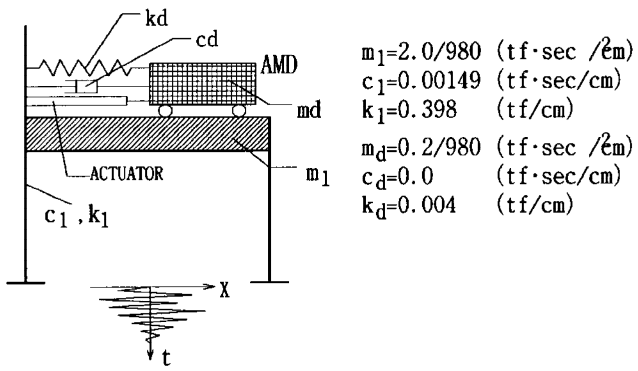


Fig.2 Objective structures

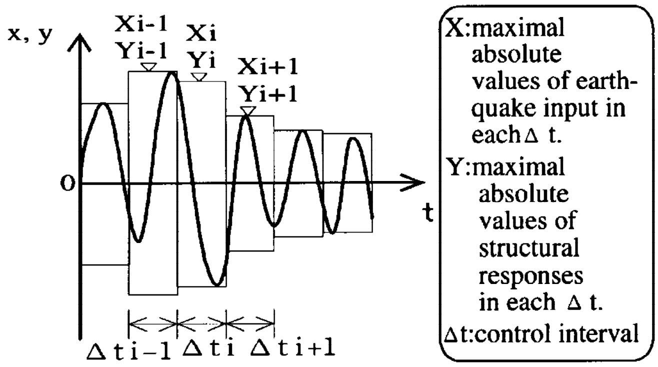


Fig.3 Assumption of earthquake inputs and structural responses (Kawamura et al., 1990)

employed as a control variable. In this system, a control interval time Δt is also introduced to make this control more practical (Kawamura et al., 1990). X_i and Y_i in Fig.3 are defined as the i-th maximal absolute values of x and y within i-th control interval Δt_i and optimal control variables are determined by the maximum absolute values of earthquake inputs and structural responses within each Δt. Here, the maximal absolute values X and Y are assumed to be that of earthquake input and those of response displacements of the structure, control forces and strokes of actuator, respectively. The i-th control variable α_i is assumed to be kept constant during Δt_i.

PREDICTION OF EARTHQUAKE INPUTS

Fig.4 shows a multi-layered neural network for the prediction of earthquake inputs. This network has 4 layers, i.e., an input layer with 6 units, two hidden layers with 12 units and an output layer with 3 units. Details of input and output layers are shown in Table 1. This network has feedback loops from the output layer to input layer and the differences $\Delta X_a=T_a-X_a$ are feedback to the 4th, 5th and 6th units of input layer at the training of neural network. Here, T_a is teaching data and X_a is prediction values by the neural network in each training stage. In the prediction of earthquake inputs, zero is input to those three units in the input layer. As the training data, three observed earthquakes, i.e., Nos.1, 3 and 4 in Table 2 are employed and maximal acceleration is normalized to 200 gal. Control interval Δt is assumed to be 0.6 sec.. At first, maximal acceleration data in each Δt are calculated and 200 sets of training data, i.e., the first 45 data in No.1 (EERL, 1976), the data between 35th and 109th in No.3 (AIJ, 1992) and the last 85 data in No.4 (AIJ, 1992), are employed. Input and output values are normalized between 0 and 1 by normalized function in Table 1. The training is terminated when the average values of error are less equal to 0.01 or the number of times of training reaches to 200,000. The training program of neural network with feedback loops is developed based on that by Yagi and Suzuki (1987).

PREDICTION OF STRUCTURAL RESPONSES (STRUCTURAL IDENTIFICATION)

Fig.5 shows multi-layered neural networks for the prediction of structural responses (structural identification). These neural networks has 4 layers, i.e., an input layer , two hidden layers and an output layer. Details of input and output layers are shown in Tables 3 and 4. This network also has feedback loops from the output layer to the input layer. As for the network as shown in Fig.5(a), the differences between teaching data (Y(T) and U(T)) and prediction values by neural network (Y(P) and U(P)) such as Y(T)-Y(P) and U(T)-U(P) for response displacements and control forces, respectively, are feedback to 4 units, i.e., 7th to 10th units, of the input layer at the training of neural network. In the prediction of structural responses, zero is input to those six units in the input layer.

In the preceding system (Tani et al., 1994 and 1995b), many earthquake response analysis are carried out to

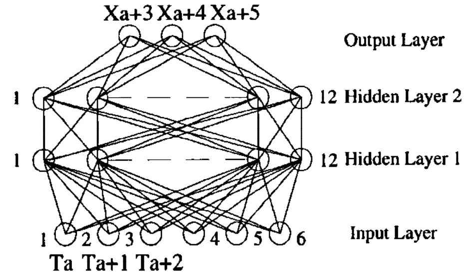


Fig.4 Feedback Neural Network for the Prediction of Earthquake Input

Table 1 Input and Output Units of Feedback Neural Network for the Prediction of Earthquake Input

Input Layer	Ta	The maximal eartqhauke input in the a-th control Interval
	Ta+1	The maximal eartqhauke input in the a+1-th control Interval
	Ta+2	The maximal eartqhauke input in the a+2-th control Interval
	Unit 4	in training:Δ Xa+3=Ta+3-Xa+3, in prediction: 0 T:Teaching Data
	Unit 5	in training:Δ Xa+3=Ta+3-Xa+3, in prediction: 0 X:Prediction
	Unit 6	in training:Δ Xa+3=Ta+3-Xa+3, in prediction: 0
Output Layer	Xa+3	Prediction Value in the a+3-th control interval
	Xa+4	Prediction Value in the a+4-th control interval
	Xa+5	Prediction Value in the a+5-th control interval
Normalizing Func.		X/Xmax (Xmax=200 gal)

Table 2 Observed Earthquake Waves

No.	Place of Observation	Date of Occurrence	Direct.	Duration (sec.)	Max. Acc. (gal)	Ref.
1	Taft	1952.06.21	N090E	54.38	175.90	EERL, 1976
2	El Centro	1940.05.18	N000E	53.78	341.70	EERL, 1976
3	Hachinohe	1968.05.16	N000E	35.99	225.00	The BC of Japan, 1986
4	Iwai-Minami(KT522)	1987.12.17	N090E	117.00	43.62	AIJ, 1992

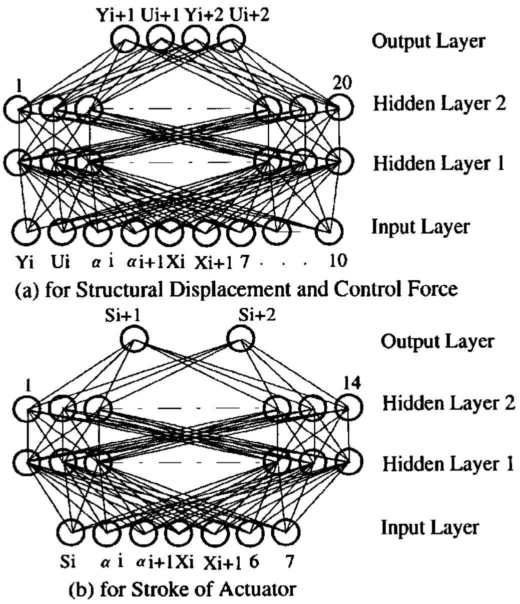


Fig.5 Feedback Neural Network for the Prediction of Structural Responses

Table 3 Input and Output of Feedback Neural Network for the Prediction of Structural Responses:(Y and U)

Input Layer	Yi	The maximal response displacement in the i-th control interval
	Ui	The maximal control force in the i-th control interval
	α i	The reduction factor in the i-th control interval
	α i+1	The reduction factor in the i+1-th control interval
	Xi	The maximal earthquake input in the i-th control interval
	Xi+1	The maximal earthquake input in the i+1-th control interval
	Unit 7	in training: Yi+1(T)-Yi+1(P), in prediction: 0; (T):Teaching Data
	Unit 8	in training: Ui+1(T)-Ui+1(P), in prediction: 0
	Unit 9	in training: Yi+2(T)-Yi+2(P), in prediction: 0
	Unit 10	in training: Ui+2(T)-Ui+2(P), in prediction: 0
Output Layer	Yi+1	The maximal response displacement in the i+1-th control interval
	Ui+1	The maximal control force in the i+1-th control interval
	Yi+2	The maximal response displacement in the i+2-th control interval
	Ui+2	The maximal control force in the i+2-th control interval
Normalizing Func.		Y/3.0, U/1.0, X/200

Table 4 Input and Output of Feedback Neural Network for the Prediction of Structural Responses:(S)

Input Layer	Si	The maximal control force in the i-th control interval
	α i	The reduction factor in the i-th control interval
	α i+1	The reduction factor in the i+1-th control interval
	Xi	The maximal earthquake input in the i-th control interval
	Xi+1	The maximal earthquake input in the i+1-th control interval
	Unit 6	in training: Yi+1(T)-Yi+1(P), in prediction: 0; (T):Teaching Data
	Unit 7	in training: Ui+1(T)-Ui+1(P), in prediction: 0
Output Layer	Si+1	The maximal stroke of actuator in the i+1-th control interval
	Si+2	The maximal stroke of actuator in the i+2-th control interval
Normalizing Func.		S/100, X/200

obtain the suitable training data of the neural network by using the assumed structural characteristics and the control variable which are changed randomly. Then, many times of try and error are necessary to obtain and set the training data. In this paper, a selection method of the training data of the structural identification is proposed by using Genetic Algorithm (Holland, 1993). At first, a chromosome is assumed as shown in Fig.6. Each 4 bits of it represents a control variable α of one control interval Δt. Each bit has a binary values such as 0 or 1. These control variables represented by binary values are decoded into decimal values by using Eq.(4). Here, maximal control variable α_{max} is assumed to be 0.6 and the variable Decode show a decoded control variable. Total control interval is assumed to be 30, then the total bit length of a chromosome is 120. The population is assumed to be 30. Initially, each chromosome is assumed randomly. Using these chromosomes, earthquake response analysis are carried out and maximal absolute values of structural responses, the strokes of the actuator and control forces are calculated. By using these results, the

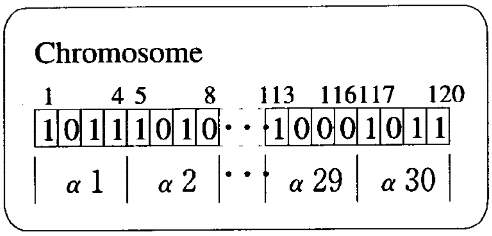


Fig.6 An Example of Chromosome

$$\alpha = \alpha_{max} \cdot \text{Decode} \ / 15.0 \quad (4)$$

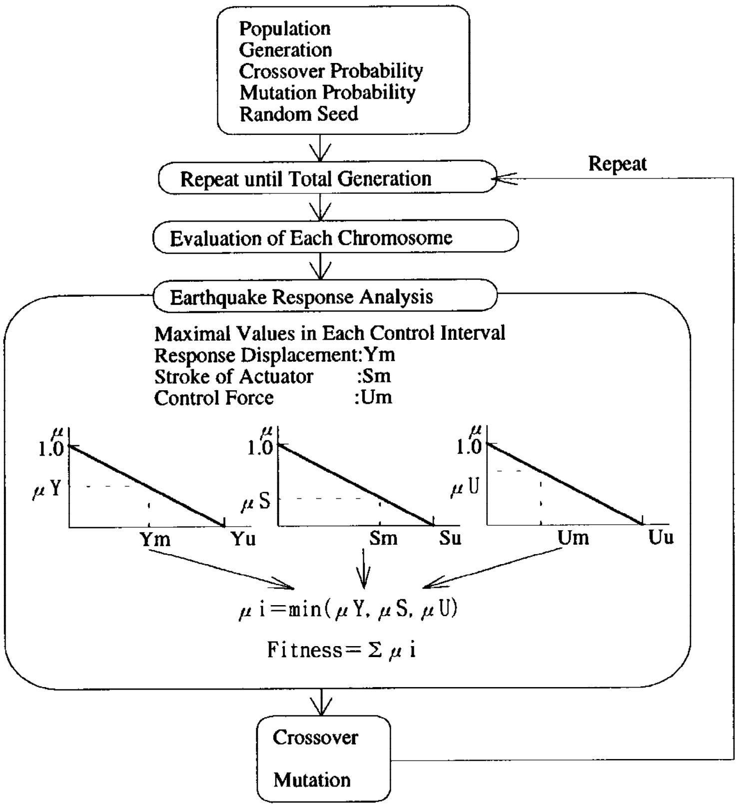


Fig.7 Flow Chart of Genetic Algorithm

Table 5 Initial Condition and Results of GA

	No.2(El Centro)		No.3(Hahinohe)	
	Type 1	Type 2	Type 1	Type 2
Population	30	30	30	30
Generation	100	100	100	100
Crossover Probability	6	6	6	6
Mutation Probability	0.03	0.03	0.03	0.03
Random Seed	0.5	0.5	0.5	0.5
Maximal Fitness	13.7	19.8	17.9	20.6

Table 6 Assumed Membership Function for GA

	Yu	Su	Uu
Type 1	4.0 cm	50 cm	0.30 tf
Type 2	2.5 cm	100 cm	0.75 tf

evaluation of each chromosome is performed. The evaluation method is assumed as shown in Fig.7.

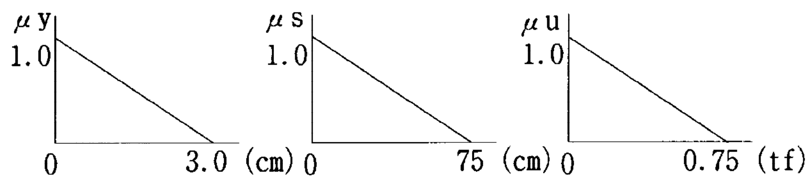
The evaluation of each chromosome is performed by using the assumed membership functions of the structural response Y, the stroke of the actuator S and the control force U as shown in Fig.7. By using the results of earthquake response analysis, the membership values of μ_y, μ_s, μ_u in the i-th control interval are obtained and the minimum value μ_i of these membership values is obtained. Summation of μ_i is assumed to be the fitness value of each chromosome. By using this fitness value, a roulette wheel parent selection method and one-point crossover method are employed as a crossover method and the crossover is performed in accordance with the fitness values of each chromosome. The operation of mutation is also employed. The total generation of GA operations are assumed to be 100 and the chromosome which has the maximal fitness value is selected as the most suitable training data of the neural network.

The flow chart of GA operations are shown in Fig.7. Here, two earthquake waves Nos.2 and 3 in Table 2 are employed and the maximal acceleration value is regulated into 200 gal. The control interval Δ t is assumed to be 1.2 sec. The initial conditions and the results of GA operations are shown in Table 5. Two types of membership functions are assumed as shown in Table 6. According to these operations, 4 training data are obtained. The program of GA operations is developed based on that by Gorldberg (1989).

Finally, input and output data of the neural network are normalized between 0 and 1 by normalized function as shown in Tables 3 and 4. Total number of training data is 144 sets. The training is terminated when the average values of error are less equal to 0.001 or the number of times of training reaches to 50,000 and/or the average of the training error is less equal to 0.0001. The same training program is used in case of the prediction of earthquake inputs.

OPTIMIZATION BY FUZZY MAXIMIZING DECISION

In this system, control interval Δt is introduced (Kawamura et al., 1990), and optimization is performed by fuzzy maximizing decision (Bellman et al., 1970) by using maximal absolute values of the response displacement Y, the control force U and the stroke of actuator S in each Δt. Here, membership functions are assumed for Y, U and S as shown in Fig.8, respectively, taken account of comfort, structural safety, the limitation of control devices and the cost of control and so on. In Fig.8, μ denotes the membership degrees of Y, U and S. By using the neural network of the prediction of earthquake input, the maximal absolute value of earthquake input X in the next control interval is predicted and by using those of structural responses, maximal absolute response values of Y, U and S in the next control interval are also predicted. In these predictions, the next control variable α is changed parametrically. Consequently, those values are transformed into the plane of membership degree μ and control variable α by using assumed membership functions as shown in Fig.9. The maximizing decision is performed for all α. In these results, the optimal control variable, which has the largest membership degree μ^*, is determined as optimal control variable α^* as shown in Fig.9.



(a) Response Displacement (b) Stroke of Actuator (c) Control Force

Fig.8 Assumed membership functions

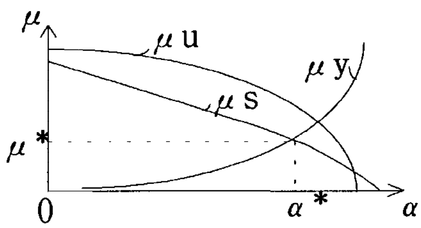
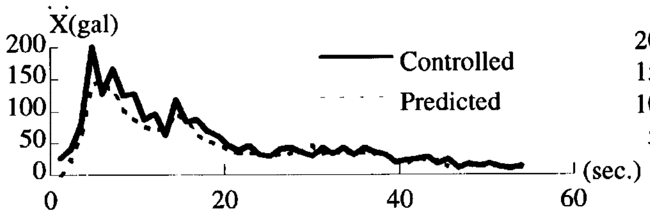


Fig.9 Maximizing Decision

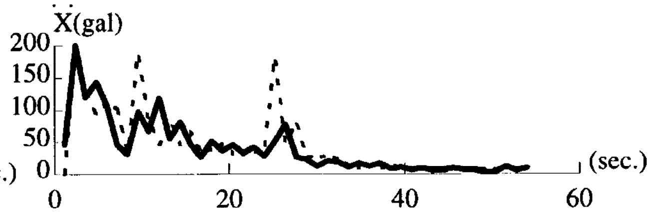
DIGITAL SIMULATION

Here, digital simulations on fuzzy optimal control are carried out by using trained neural networks and maximizing decision described in preceding chapters. Values of structural characteristics are employed as shown in Fig.2. The control interval is assumed to be 1.2 sec. (= Δt) for the prediction of structural responses and maximizing decision and 0.6 sec. (= $\Delta t/2$) for the prediction of earthquake inputs. Therefore, the prediction of earthquake inputs is performed twice in each Δt. So, the maximal value in the second prediction is employed as the prediction of earthquake inputs in that of structural responses. Furthermore, proposed method can not determine the optimal control variables at the first control interval. Then, the control variable α_1=0.3 is assumed as the initial values in the first Δt. The reduction factor α is assumed to be between 0 and 0.5 at intervals of 0.05. Membership functions are assumed as shown in Fig.8.

Fig.10 shows the comparison between observed and predicted earthquake waves in each Δt in case of earthquakes Nos.1 and 2 in Table 2. Fig.11 shows the results of active control in case of earthquake wave No.1 in Table 2. Fig.12 shows the comparison between the results of active control and the assumed membership function in case of earthquake wave No.1 in Table 2.

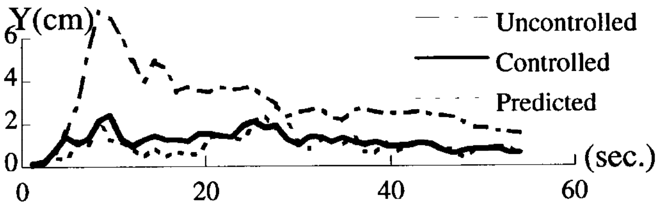


(a) No.1 in Table 2

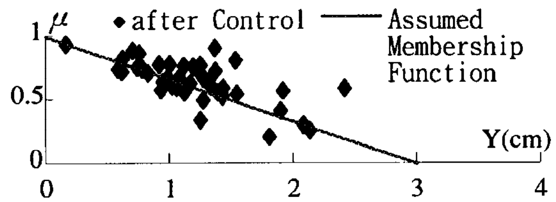


(b) No.2 in Table 2

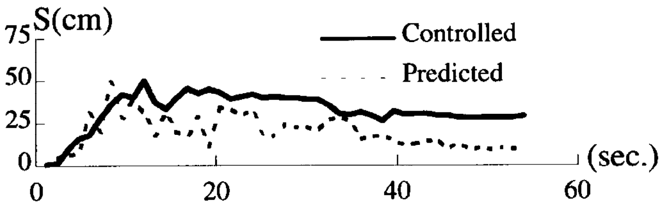
Fig.10 Comparison between Observed and Predicted Earthquake Inputs in each Control Interval (Δ t=1.2 sec.)



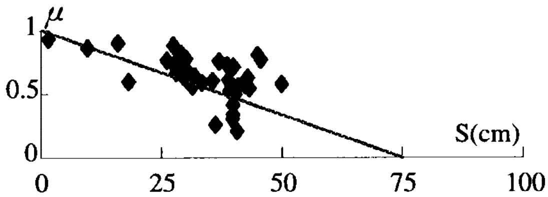
(a) Comparison between Uncontrolled and Controlled Response Displacements



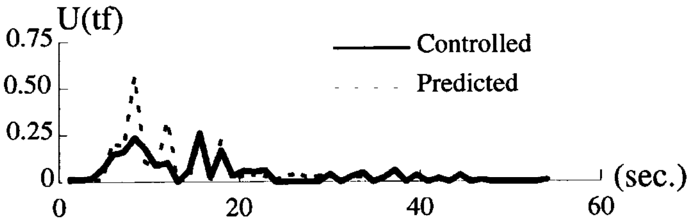
(a) Response Displacements



(b) Changes of Strokes of Actuator

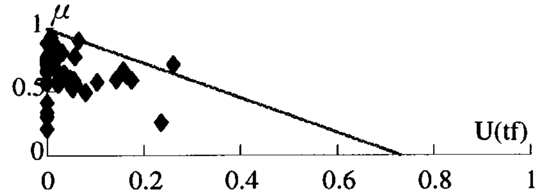


(b) Strokes of Actuator



(c) Changes of Control Forces

Fig.11 Optimal Control Results(No.1 in Table 2)



(c) Control Forces

Fig.12 Actual Membership Plane after Control(No.1 in Table 2)

CONCLUSION

In this paper, an fuzzy optimal control system of structures subjected to earthquake loading is proposed by using the neural network with the feedback loops at the training. The training data are selected by using the genetic algorithm. The objective structure is assumed to be single-degree-of-freedom system with active mass driver. Digital simulations are carried out and following conclusions are obtained:

(1) Proposed active control system can decrease the structural responses well in comparison with non-controlled responses. (Fig.11)
(2) As for the prediction of earthquake inputs, proposed neural network can predict the future maximal accelerations well in case of earthquake Nos.1 and 2 in Table 2. (Fig.10)
(3) As for the prediction of structural responses, proposed neural network can predict the quantitative characteristics of the future maximal structural responses in case of earthquake No.1 in Table 2. However, the accuracy of the prediction of strokes of actuator is rather worth than that of response displacements and control forces. (Fig.11)
(4) As for the results of active control, the proposed selection method of the training data by using genetic

algorithm is effective to set the suitable training data systematically and easily. (Fig.11)

(5) The comparison between the controlled results and the assumed membership functions shows that the controlled structural responses can be distributed around the assumed membership functions. Therefore, fuzzy maximizing decision is effective for multi-objective optimizing problem. (Fig.12)

(6) Above all, it is proved that the proposed control system is proved to be effective for the active control of buildings. Actually, it is necessary to perform further training by using another earthquake inputs and structural responses to realize more effective and practical control system.

ACKNOWLEDGMENT

This research is financially supported by the Grant-in-aid for Scientific Research (C), No.06650633.

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