Damage Control of Structures Using Neuro-Genetic Algorithm

A. Karamodin¹* S. Khajekaramodin²

Structural engineering researchers have always been searching for new methods to control and limit structural and nonstructural damages due to earthquakes. Structural control concept has been considered as a new method of protection of structures from sixty years ago. Many researchers have been attracted to this concept and very research studies have been conducted in this field in recent decades. At early years, classical control methods have been used as an algorithm for control of structures. Introducing intelligent systems such as neural networks, fuzzy logic and genetic algorithms has led to more efficient control algorithms. These control systems are more efficient for structural control research due to several of their capabilities such as no need for mathematical modeling, plus ability to conduct nonlinearity and uncertainties. Many researchers have dealt with intelligent control systems in recent years.

In many neural network control systems two networks have been used. One network is used as the controller and the other one is used as an emulator for training the control network. This method is time consuming. So, many researchers such as Kim et al. have eliminated the emulator network and introduced a sensitivity algorithm and a cost function for training the controller network.

In this paper, a semi-active nonlinear neuro control system has been used to control a 3 story benchmark building (as shown in Figure 1). Magnetorehological fluid (MR) dampers have been selected as semi-active control devices in each story. The neuro controller has been trained by a genetic algorithm. The genetic algorithm defines the optimum values of the connection weights between layers. The Pak & Ang damage index of the structure, has been used as a fitness function for the genetic algorithm.

1. Control System

The control system is shown in Figure 3. The earthquake acceleration is loaded to the nonlinear structural model. The structural responses are measured by sensors and together with the forces of control devices at the previous step are input to the neuro controller at each time step. The controller is

- ^{1*} Corresponding Author: Assistant Professor, Department of Civil Engineering, Ferdowsi University of Mashhad. Email: akaramodin@yahoo.com
- ² M. S. Department of Civil Engineering, Ferdowsi University of Mashhad.

trained to predict the MR input voltage needed that can produce control forces that can minimize the damage index of the structure. The input voltages and story relative velocities are input to the MR dampers and the optimum control forces of the dampers are loaded to the structure. The structure is modeled as two dimensional beam and column frame elements. The nonlinear behavior of the structure is considered as plastic hinges at the end of the beam and columns. This model is proposed by Ohtori et al. for nonlinear benchmark buildings.



Fig. 1. 3story benchmark Building

2. MR model

The mechanical model of the MR damper is shown in Figure 2.



Fig. 2 MR model

The governing equations for this model are as follows:

 $f = C_0 \dot{q} + \alpha z \tag{1}$

$$\dot{Z} = \gamma |\dot{q}| \ z \ |z|^{n-1} - \beta \ \dot{q} \ |z|^n + A\dot{q}$$

$$\tag{2}$$

$$\alpha = \alpha(u) = \alpha_a + \alpha_b \, u \tag{3}$$

$$C_0 = C_0(u) = C_{0a} + C_{0b} u \tag{4}$$

$$\dot{u} = -\eta(u-v) \tag{5}$$



Fig. 3. Control System

In these equations q is the displacement of the device and z is an evolutionary variable that accounts for the history dependence of the response. By adjusting the parameters of the model α , β , n, and A, one can control the linearity in the unloading and the smoothness of the transition from the pre yield to the post yield region. The functional dependence of the device parameters on the effective voltage u is modeled by eqs. 3 and 4. The parameters of the MR damper were selected so that the device has a capacity of 1,000 kN.

3. Neuro-GA controller

A neuro-GA controller is a neuro controller that is trained by a genetic algorithm. In this study, the structure of the neural network is selected by trial and error and the connection weights of the layers are defined by the GA. The connection weights are so defined that the Park & Ang damage index of the structures can be minimized. Two scales of the El Centro Earthquake have been used to train the controller. The fitness function is the ratio of the controlled damage index to the uncontrolled damage index. The best fitness function after 50 populations is gained to be 0.517. This means that the damage index of the controlled structure is reduced by %48.3.

4. Evaluation and results

To evaluate the efficiency of the controller 11 evaluation criteria are defined. The first criterion, J1, is the ratio of maximum story drifts of the controlled to the uncontrolled structure. The second, J2, is the ratio of maximum story acceleration of the controlled to the uncontrolled structure. The third criterion, J3, is defined as ratio of the maximum base shear of the controlled to the uncontrolled structure. The next three criteria, J4, J5 and J6 are the ratio of mean root square of story drifts, accelerations and base shear of the controlled to the uncontrolled building. J7 is the ratio of the largest ductility of members in the

controlled to the uncontrolled structure. J8 is defined as the ratio of dissipated energy in the controlled to the uncontrolled structure. The ninth criterion, J9, is the ratio of plastic hinges of the controlled to the uncontrolled building. J10 is defined as the ratio of mean root square of ductility of members in the controlled to the uncontrolled structure. Finally J11 is the ratio of damage index of the controlled to the uncontrolled building.

These criteria are evaluated for four earthquakes with different intensities. These are 0.5, 1.0 and 1.5 scales of Hachinohe and El Centro earthquakes with 0.5 and 1.0 scales of Northridge and Kobe earthquakes.

The results show that the average value of J11 for different earthquakes is 0.238. This means that the damage to the controlled structure is reduced by %76.2. The average values of other criteria are shown in Table 1.

Table. 1. The average values of evaluation criteria

Criteria	J1	J2	J3	J4	J5
Average	0.516	1.265	0.436	0.803	7.437
Criteria	J6	J7	J8	J9	J10
Average	1.304	0.442	0.007	0.289	0.498

5. Conclusions

- 1- The results show that Neuro-Ga controller has reduced the damage to the structure %76.2.
- 2- The controller has performed well in reduction of story drifts (J1, %48.4), base shear (J3, %56.4), ductility (J7, %55.8), dissipated energy (J8, %99.9) and number of plastic hinges (J9, %71.1). However the performance of the controller in the reduction of maximum and root mean square of accelerations is not favorable.