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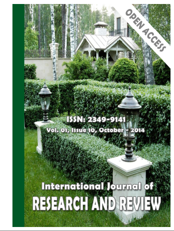

Full Length Review Article

DEVELOPMENT OF MIMO ANFIS CONTROL SYSTEM FOR SEISMIC RESPONSE REDUCTION USING MULTI-OBJECTIVE GENETIC ALGORITHM

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ABSTRACT

A multi-input multi-output adaptive neuro fuzzy inference system (MIMO-ANFIS) was proposed in this study to reduce dynamic responses of a seismically excited building. A multi-objective genetic algorithm (MOGA) was used to optimize the MIMO-ANFIS controller. Two MR dampers were used as multiple control devices and a scaled five-story building model was selected as an example structure. A MIMO fuzzy control algorithm was compared with the proposed MIMO-ANFIS controller. A multi-input multi output adaptive neuro-fuzzy inference system (MIMO-ANFIS) with several outputs was proposed. In case study, after numerical simulation, it has been verified that the MIMO ANFIS control algorithm can present better control performance compared to the MIMO fuzzy control algorithm in reducing both displacement and acceleration responses.

INTRODUCTION

Although significant studies have been conducted in recent years toward development and application of semi-active control schemes for vibration control of building structures in seismic zones, the application of intelligent controllers, including ANFIS controllers, has not been addressed extensively. As an alternative to classical control theory, ANFIS controller allows the resolution of imprecise or uncertain information. Because of the inherent robustness and ability to handle nonlinearities and uncertainties, ANFIS controller is used in this study to make a multi-input multi-output (MIMO) control algorithm for operating multiple MR dampers thus called MIMO ANFIS. Although ANFIS controller has been used to control a number of structural systems, selection of acceptable fuzzy membership functions have been subjective and time-consuming. To overcome this difficulty, a multi-objective genetic algorithm (MOGA) was used to optimize fuzzy rules and membership functions of ANFIS controller.

In order to compare the control efficiency of the proposed MOGA-optimized ANFIS controller, a MIMO fuzzy control algorithm was considered as the baseline in this study. A neuro-fuzzy system is based on an inference system formed by a training algorithm derived from the neural theory. There exists several approaches to integrate artificial neuron systems and the fuzzy logic, and very often the choice depends on the application. Jang and Sun introduced the adaptive network-based fuzzy inference system ANFIS.

ANFIS was later extended to generalize ANFIS for the modeling of a multivariable system. In this work we present a new type of multi inputs, multi-outputs Adaptive neuro-fuzzy system (MIMO ANFIS) which have multi outputs, and characterized by his method of correction of local parameters. The proposed MIMO ANFIS is used to obtain peak or maximum responce of three functions i.e. displacement, drift and acceleration but our study is concentrated to only two parameters i.e displacement and acceleration.

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MIMO ANFIS Controller

Adaptive Neuro-fuzzy Inference System for several outputs

Adaptive neuro-fuzzy system makes use of a hybrid-learning rule to optimize the fuzzy system parameters of a first order Sugeno system. The proposed MIMO-ANFIS for three outputs (displacement, drift and acceleration) proposed possesses a similar architecture to a classic ANFIS system, except a difference in the fourth layer. Architecture of the MIMO-ANFIS system for three outputs for a one-input first-order Sugeno fuzzy model is shown by Fig 1. Output of the nodes in each respective layer is represented by *Oi*, where i is the i th node of layer l. The following is a layer-by-layer description of a one input one rule first-order Sugeno system (Koltsakis *et al.* 1997).

Layer 1. Generate the membership grades:

$$O_i^1 = g(x) \tag{1}$$

g: the membership function of the MIMO-ANFIS system. In our case, the chosen membership function is the trapezoidal function.

Layer 2. Generate the firing strengths.

$$O_i^2 = w_i = \prod_{j=1}^{m} g(x) \tag{2}$$

Layer 3. Normalize the firing strengths.

$$O_i^3 = \bar{w}_i = \frac{w_i}{w_1 + w_2 + w_3} \tag{3}$$

Layer 4. Calculate rule outputs based on the consequent parameters.

$$O_i^4 = y_i = \bar{w}_i . f_i = \bar{w}_i . (p_i . x + q_i . x + r_i) \tag{4}$$

$$O_i'^4 = y'_i = \bar{w}_i . f_i' = \bar{w}_i . (p_i' . x + q_i' . x + r_i') \tag{5}$$

$$O_i''^4 = y''_i = \bar{w}_i . f_i'' = \bar{w}_i . (p_i'' . x + q_i'' . x + r_i'') \tag{6}$$

Layer 5. Sum all the inputs from layer 4.

$$O_1^5 = y_a = \sum_i y_i = \sum_i \bar{w}_i . f_i = \sum_i \bar{w}_i . (p_i . x + q_i . x + r_i) \tag{7}$$

$$O_2^5 = y_b = \sum_i y_i' = \sum_i \bar{w}_i . f_i' = \sum_i \bar{w}_i . (p_i' . x + q_i' . x + r_i') \tag{8}$$

$$O_3^5 = y_c = \sum_i y_i'' = \sum_i \bar{w}_i . f_i'' = \sum_i \bar{w}_i . (p_i'' . x + q_i'' . x + r_i'') \tag{9}$$

In this last layer the consequent parameters can be solved by using the algorithm of least squares. Let us rearrange this last equation into a more usable form:

$$y_a = \begin{pmatrix} w_1 x_1 & w_1 x_2 & w_1 & w_2 x_1 & w_2 x_2 & w_2 \end{pmatrix} \begin{bmatrix} p_1 \\ q_1 \\ r_1 \\ p_2 \\ q_2 \\ r_2 \end{bmatrix} \tag{10}$$

$$y_b = \begin{pmatrix} w_1 x_1 & w_1 x_2 & w_1 & w_2 x_1 & w_2 x_2 & w_2 \end{pmatrix} \begin{bmatrix} p_1' \\ q_1' \\ r_1' \\ p_2' \\ q_2' \\ r_2' \end{bmatrix} \tag{11}$$

$$y_b = \begin{pmatrix} w_1 x_1 & w_1 x_2 & w_1 & w_2 x_1 & w_2 x_2 & w_2 \end{pmatrix} \begin{bmatrix} p_1'' \\ q_1'' \\ r_1'' \\ p_2'' \\ q_2'' \\ r_2'' \end{bmatrix} \tag{12}$$

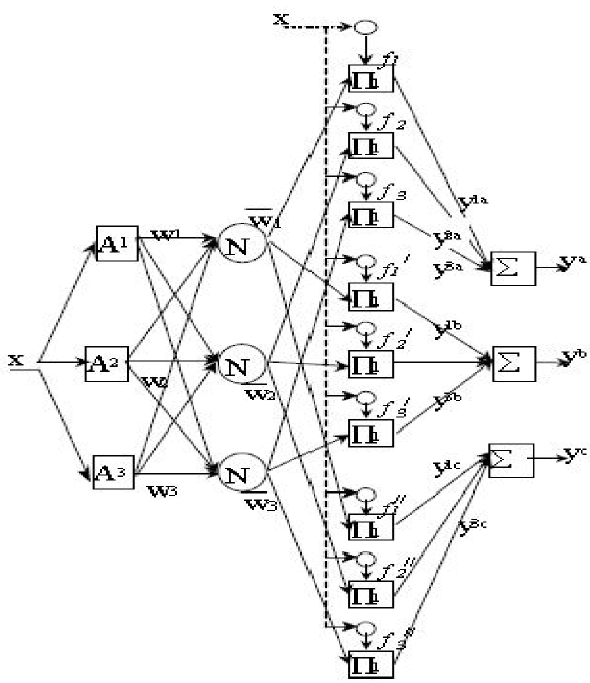

Figure 1. MIMO-ANFIS for one-input first-order Sugeno model with three rules - architecture with three outputs

The MIMO-ANFIS for three outputs comprises an alone input, so, there are no rules of inference for this system, but there exists a opérations of fuzzification and a défuzzification similar to that of ANFIS of one output (Heck *et al*., 2000).

Operation of training

The MIMO-ANFIS training paradigm uses a gradient descent algorithm to optimize the antecedent parameters, and a least squares algorithm to solve for the consequent parameters. The consequent parameters are updated first using a least squares algorithm, and the antecedent parameters are then updated by back-propagating the errors that still exist.

The back-propagation of the gradient

In the stage of back-propagation, the signal of error is back propagated and local parameters are updated by the method of gradient descent. For the neuro-fuzzy system to an alone output *y*, we have:

$$a_{ij}(t+1) = a_{ij}(t) - \frac{h}{p}.\frac{\partial E}{\partial a_{ij}} \tag{13}$$

h: the training rate for a_{ij} a ,
p : number of data of x (or yd),

The following rule is used to calculate partial derivatives, employed to update of the parameters of membership function *g*. (Zhenming *et al*. 2001).

$$\frac{\partial E}{\partial a_i} = \frac{\partial E}{\partial y}.\frac{\partial y}{\partial y_i}.\frac{\partial y_i}{\partial w_i}.\frac{\partial w_i}{\partial g}.\frac{\partial g}{\partial a_i} \tag{14}$$

$$E = \frac{1}{2}(y - y_d)$$

E: the quadratic cost function,

MIMO-ANFIS system for three outputs as shown by Fig.1, possesses similar entry weights to these of ANFIS system for an alone output (therefore similar local parameters (a_i, b_i, c_i, d_i). The difference resides in consequent parameters. For MIMO-ANFIS of three outputs, each output possesses these clean consequent parameters (p_i, q_i, r_i for y_a , p_i' , q_i' , r'_i for y_b and p_i'' , q_i'' , r''_i for y_c). To make the local parameter correction, MIMO-ANFIS of three outputs uses the sum of the gradient of the two errors of the two outputs:

$e_1 = y_a - y_{d1}$, $e_2 = y_b - y_{d2}$, $e_3 = y_c - y_{d3}$.

Such that

$$a_{ij}(t+1) = a_{ij}(t+1) - \frac{h}{p}\left(\frac{\partial E_1}{\partial a_{ij}} + \frac{\partial E_2}{\partial a_{ij}} + \frac{\partial E_3}{\partial a_{ij}}\right) \tag{15}$$

Where:

$$\frac{\partial E_1}{\partial a_{ij}} = f(e_1) \cdot \frac{\partial E_2}{\partial a_{ij}} = f(e_2) \cdot \frac{\partial E_3}{\partial a_{ij}} = f(e_3)$$

Application of MIMO-ANFIS systems for three outputs

To show the efficiency of the proposed MIMO-ANFIS, we consider the approximation of the three following functions:

$$y_{a1} = .2*sin(.3*x) \tag{16}$$

$$y_{a2} = .2*sin(-.3*x); \tag{17}$$

$$y_{a3} = .2*cos(.3*x); \tag{18}$$

The precision of MIMO-ANFIS increases with the number of weight of inputs. For MIMO-ANFIS of three outputs, it concerns three errors of estimation (for y_{d1}, y_{d2} and y_{d3}). To make the approximation of these three functions, we have used a MIMO-ANFIS of three weights in the input (in first layer). Then, and so as to have best results of approximation, we have used a MIMO-ANFIS with six weights in the input. Then we have made the comparison of the results of the approximation for the two MIMO-ANFIS systems. Local parameters are initialed to small values that we have chosen to accelerate the convergence. The type of membership function of MIMO-ANFIS that we have used is the trapezoidal function.

Scaled Building Model

In order to develop an MIMO semi-active ANFIS for effective control of multiple MR dampers, a 5-story example building structure shown in Fig. 2 is employed. This example structure is developed based on a scaled 3-story shear building model used in the literature. As shown in this figure 2, two MR dampers are rigidly connected to the first floor and the second floor of the structure, respectively.

The first five natural frequencies of the example structure model are 4.12, 11.27, 17.14, 23.02 and 26.31 Hz, respectively. In this study, the modified Bouc-Wen model is used to describe how the damping force is related to the velocity and applied command voltage. The mechanical model for the MR damper based on the Bouc-Wen hysteresis model is shown in Fig. 2. The detailed description and the parameter values of the MR damper model are presented in Dyke *et al.*'s work. This MR damper model has a maximum generated force of about 1600 N depending on the relative velocity across the MR damper with a saturation voltage of 2.52 V. In numerical analysis, the model of the example structure is subjected to the SE component of the 1997 Gadha Jabalpur India earthquake. Because the system under consideration is a scaled model, the earthquake has been reproduced at five times the recoded rate.

Multi Objective Genetic Algorithm for MIMO-ANFIS Optimizing Tuning

Here an internal loop for control of the output actuator force has been considered, with a MOGA optimized MIMO-ANFIS control algorithm, with parameters obtained by means of multi objective genetic algorithms (figure 3). The fitness function minimizes the error between the desired control force (fed into the loop as a set point) and the output control force of the damper. The performance index is to be minimized, and the algorithm returns the best set of ANFIS tuning parameters with the lowest performance index at the moment the stop condition for the algorithm is met.

Case Study

A numerical model of the 5-story example building structure with two MR dampers is implemented in SIMULINK and MATLAB. Using this numerical model, time history analyses of 15 seconds with a time step of 0.005 sec are performed in order to investigate the control performance of MR dampers controlled by the MOGA optimized MIMO ANFIS. The MOGA based optimization is performed with the population size of 100 individuals.

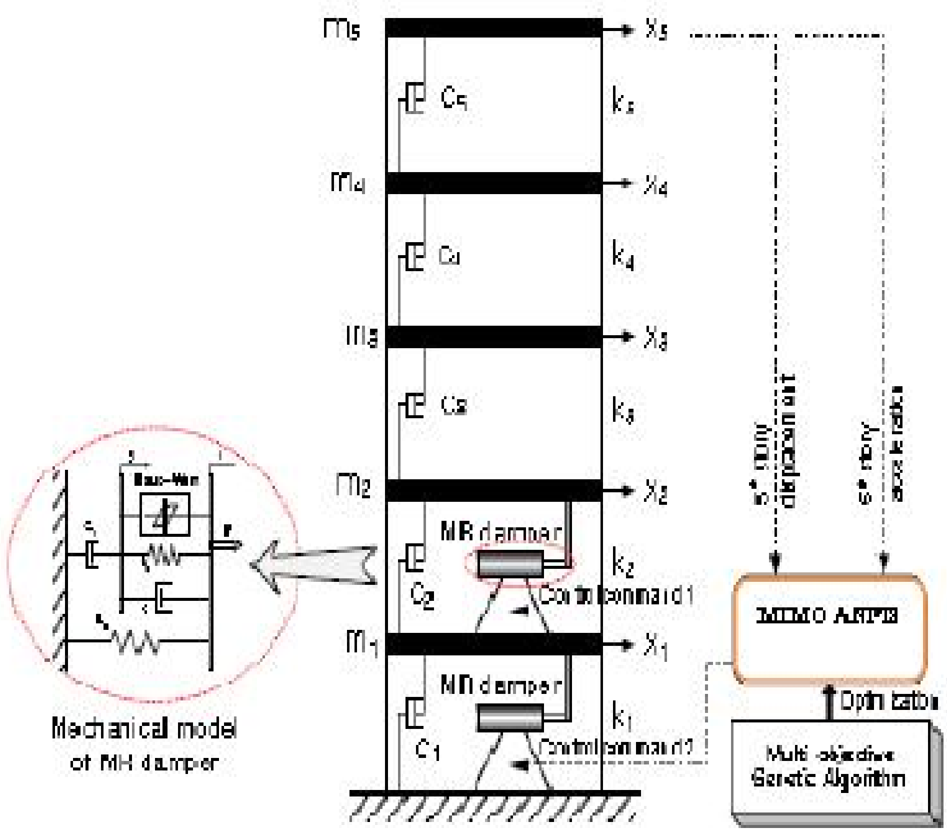

Figure 2. 5-story example building model

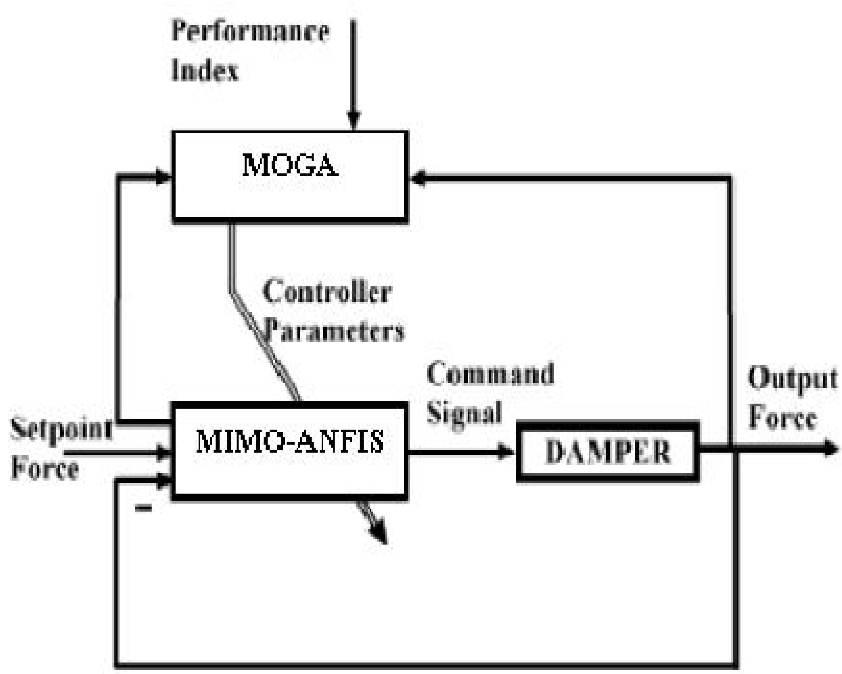

Figure 3. Multi Objective Genetic Algorithm (MOGA) optimizing of MIMO-ANFIS controller for damper

An upper limit on the number of generations is specified to be 1000. As the number of generations increases, the control performance of the elite (i.e. non-dominated) individuals is improved. After optimization run, a set of optimal solutions is obtained. Optimization results show that two objective function values of every solution in optimal record are less than 1. It means that the MOGA optimized MIMO-ANFISs can provide better control performance in reducing both displacement and acceleration responses compared to the MIMO fuzzy controller.
Consequently, one controller, that can appropriately control both displacement and acceleration responses, has been selected among the optimal ANFISs. The values of two objectives of the selected ANFIS are both 0.75 and it means that the selected MIMO ANFIS can reduce both the peak 5th floor displacement and acceleration responses by 25%, compared to the MIMO fuzzy controller. The peak responses of the MIMO ANFIS, MIMO FLC controller, and uncontrolled case for the five floors of the seismic-excited example building structure are compared in Table 1. The peak displacement of the 5th floor of the uncontrolled case is 0.970 cm. On the other hand, the peak displacement of the 5th floor of the MIMO ANFIS is 0.288 cm, which is only 29 % of the uncontrolled case. The peak acceleration of the 5th floor of the MIMO ANFIS is reduced by 71 % compared to the uncontrolled case.

In the elastoplastic analysis of the structure with MR dampers, the frame structure is simulated by the trilinear stiffness degeneration model. The stiffness of each floor changes in the fold line path during the earthquake. The model structure parameters are the mass vector

m = [3.25 3.04 2.88 2.78 2.66] × 104 kg, the initial stiffness vector
k = [1.82 2.50 2.50 2.50 2.50] × 107 N m−1, the story height
h = [4 3.5 3.5 3.5 3.5] m, the inter-story cracking drifts
Δ*c* = [6.3 4.9 4.2 3.87 3.75] mm, the inter-story yielding drifts
Δ*y* = [21.8 18.9 17.2 14.5 11.8] mm.

In this example, the model of the structure is subjected to the south east component of the 1997 Gadha Jabalpur India earthquake with 355 gal acceleration amplitude, and the sampling time is 0.025 s, i.e. the delay time. We developed a MATLAB program for the MOGA optimized MIMO-ANFIS control and elastoplastic analysis of the structure with MR dampers. The top-floor displacement and acceleration responses of the structure with the MR damper are compared with those of the structure without the MR damper, as shown in figure 4. Both the displacement and the acceleration responses of the controlled structure with the MR damper are reduced effectively.

Table 1. Comparison of peak story responses

Story	Displacement (cm)			Acceleration (cm/sec^2)		
	Uncontrolled	MIMO fuzzy	MIMO-ANFIS	Uncontrolled	MIMO fuzzy	MIMO-ANFIS
1	0.340	0.101	0.115	620.6	570.3	294.8
2	0.601	0.198	0.181	712.1	387.5	338.9
3	0.754	0.273	0.250	512..3	401.2	251.6
4	0.901	0.345	0.272	588.8	342.6	271.8
5	0.970	0.376	0.288	904.7	398.7	298.5

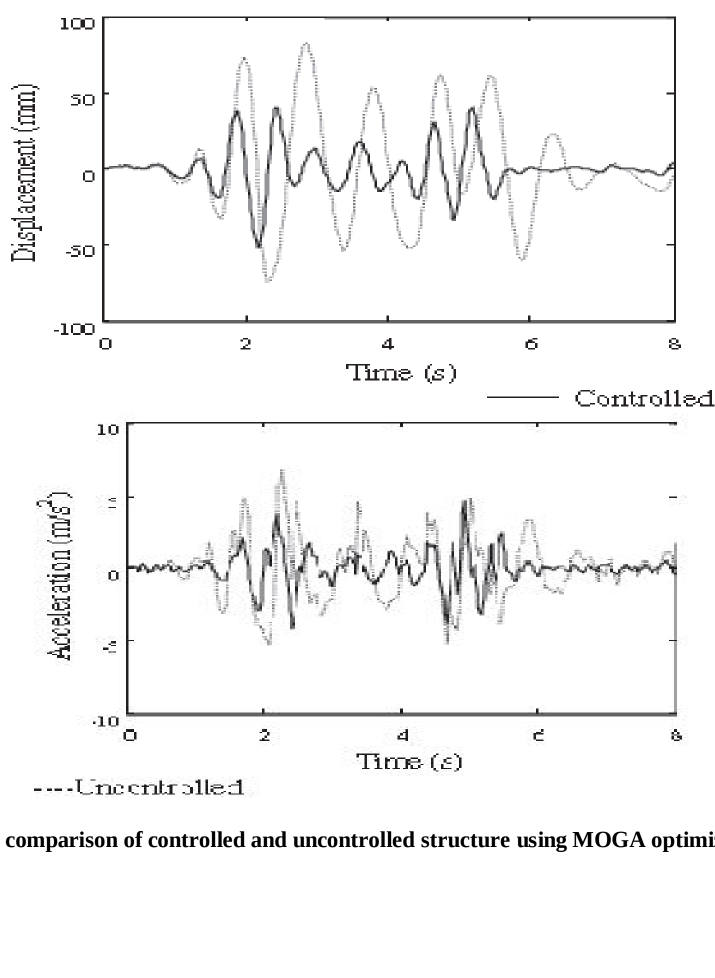

Figure 4. Response comparison of controlled and uncontrolled structure using MOGA optimized MIMO ANFIS

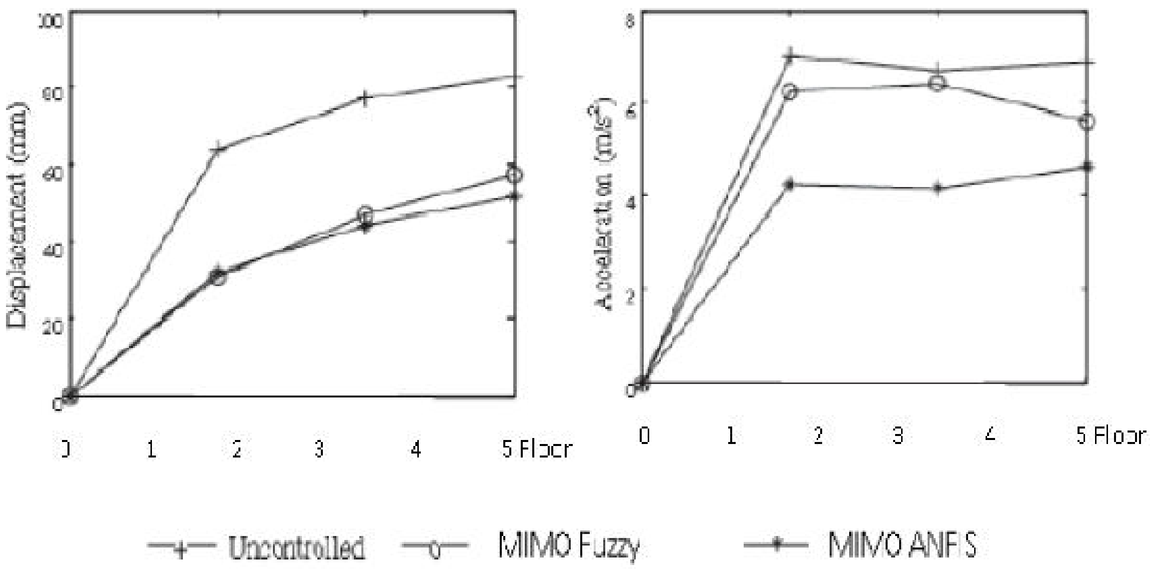

Figure 5. The maximum responses comparison of each floor

The maximum displacement of the uncontrolled structure is 0.970 cm, while the maximum displacement of the MIMO fuzzy controlled structure is 0.376 cm and of proposed MIMO-ANFIS controlled structure is 0.288 cm for fifth storey. The displacement response is reduced by 29%. The maximum acceleration of the uncontrolled structure is 6.86 m s^{-2}, while the maximum acceleration of the controlled structure is 904.7 cm s^{-2} for fifth storey. The peak acceleration of the 5th floor of the MIMO ANFIS is reduced by 71 % compared to the uncontrolled case. It can also be shown that the displacement responses are reduced more effectively than the acceleration responses. This is due to the fact that control forces produced by MR dampers are equivalent to increasing stiffness and damping of structures: both are beneficial to decreasing displacement responses, while increasing of stiffness will possibly increase acceleration responses. Figure 5 compares maximum displacement and maximum acceleration for the uncontrolled structure, the MIMO fuzzy controlled structure and the MIMO-ANFIS controlled structure. Both the displacement and the acceleration responses are reduced effectively when MR dampers are used. At the same time, it can be clearly seen that the MIMO-ANFIS method can reduce the dynamic responses of the structure more effectively than the uncontrolled structure, especially for the acceleration responses. Increasing the control forces blindly is equal to increasing the stiffness and the damping of the structure blindly, which will lead to increase of the dynamic responses, especially for acceleration responses.

Conclusions

This study investigates the control performance of the MIMO ANFIS optimized by an MOGA for control of a 5-story building subjected to earthquake. For comparison purpose, a MIMO fuzzy control algorithm is considered as the baseline. Based on numerical simulations, it can be seen that the MOGA-optimized MIMO ANFIS can effectively reduce both displacement and acceleration responses of the building structure by 25% compared to the MIMO fuzzy control algorithm. After single optimization run using MATLAB Software, an engineer can simply select another ANFIS that satisfies the desired performance requirements from among a number of optimal solutions. It would be important characteristics of the MOGA based optimization compared to other optimization methods. In a numerical example, a five-storey smart structure with a MR damper in the first floor is analyzed. Some conclusions can be drawn from the analysis.

(1) The MR damper is a kind of smart damper, and it can reduce the responses of structures effectively.
(2) The MOGA-optimized MIMO ANFIS real-time control method solves the problem of time delay. The responses of the structure with MR dampers by proposed method are smaller than those by the MIMO fuzzy method, especially for the acceleration responses.

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