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Integrated fuzzy logic and genetic algorithms for multi-objective control of structures using MR dampers

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Abstract

This study presents a design strategy based on genetic algorithms (GA) for semi-active fuzzy control of structures that have magnetorheological (MR) dampers installed to prevent damage from severe dynamic loads such as earthquakes. The control objective is to minimize both the maximum displacement and acceleration responses of the structure. Interactive relationships between structural responses and input voltages of MR dampers are established by using a fuzzy controller. GA is employed as an adaptive method for design of the fuzzy controller, which is here known as a genetic adaptive fuzzy (GAF) controller. The multi-objectives are first converted to a fitness function that is used in standard genetic operations, i.e. selection, crossover, and mutation. The proposed approach generates an effective and reliable fuzzy logic control system by powerful searching and self-learning adaptive capabilities of GA. Numerical simulations for single and multiple damper cases are given to show the effectiveness and efficiency of the proposed intelligent control strategy.

1. Introduction

In structural engineering, the mitigation of damage induced by severe dynamic loads, such as earthquake and strong wind, is of paramount interest. Finding an effective means to protect structures and their contents is one of the major challenges that civil engineers face today. Over the past two decades, researchers have investigated the possibility of using active, hybrid, and semi-active control methods to improve upon passive approaches to reduce structural responses [1]. In recent years, due to their reliability and adaptability, considerable attention has been directed to research and development of semi-active control devices. One such innovative device is the magnetorheological (MR) damper, which employs MR fluids to provide control capability. An MR damper offers a highly reliable mechanism for response reduction at a modest cost, and is fail-safe because the damper becomes passive if the control hardware malfunction [2]. From this point of view, structural vibration control using MR dampers is one of the most promising fields in civil engineering, and a wide range of theoretical and experimental studies have been performed to assess the efficacy of MR dampers [2–7]. Recent tests of a 20-ton MR damper at the University of Notre Dame have demonstrated that these devices can provide forces of the magnitude required for full-scale structural control applications [8].

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However, development of an effective control algorithm using traditional control theory is reliant on having an accurate model of the system to be controlled including both the plant and the actuator. An MR damper is a semi-active control device with highly nonlinear dynamics. Although the phenomenological model developed by Spencer et al. [4] can predict the damper force quite accurately, it is difficult to calculate the command voltage to send to an MR damper in order to achieve the desired control force. Civil infrastructures are also replete with nonlinearities and uncertainties; thus, it is a challenging task to develop effective control strategies that are implementable and can fully utilize the capabilities of MR dampers.

To date, several semi-active control algorithms for MR dampers have been proposed based on the following strategy: first, the ideal target force is calculated using selected structural responses based on a conventional optimal control algorithm such as LQR/LQG [2]; then, through an active to semi-active converter (ASAC) unit, the desired control force produced by the target controller which is regarded as an active control force is converted to a desired control force from an MR damper [9]. To effectively command voltage to an MR damper to generate a damping force that is close to the desired control force in the ASAC unit, several algorithms have also been developed. Dyke et al. [2] proposed a clipped-optimal control algorithm, and Chang and Zhou [10,11] used neural networks to emulate inverse dynamics of the MR damper, showing that the MR damper can be commanded to closely follow the desired control force. The problem, as mentioned above, is the difficulty of establishing an accurate mathematical model of a real structure in order to calculate the optimal control force under severe dynamic loads. Furthermore, the question of how to handle the nonlinear dynamics of an MR damper is another difficult problem and the ASAC unit may also introduce increased complexity into the control system.

An approach adopted to combat (or limit the effect of) these modeling difficulties is fuzzy logic control (FLC), which can offer a simple and robust framework for specification of nonlinear control laws that can accommodate uncertainty and imprecision [12,13]. Because of its inherent robustness and its ability to handle nonlinearities and uncertainties, structural vibration control using FLC theory has attracted the attention of researchers and engineers during the last few years [14–17]. However, there are drawbacks in these FLC systems. The fuzzy sets and rules that require a full understanding of the system dynamics must be correctly pre-determined for the system to function properly. Furthermore, to effectively reduce the responses of a seismically excited civil engineering structure, multiple MR dampers distributed throughout the structure should be used. But the fuzzy mapping from multi-input variables to multi-output variables is always involved in design of such a multi-input–multi-output (MIMO) fuzzy controller. Wang [18] described an adaptive fuzzy control strategy that Zhou et al. [19] successfully applied for control of linear and nonlinear structures. They show that the adaptive feature of a fuzzy controller has multiple advantages in controlling a building that has an MR damper system.

Another trend in the development of a FLC system is to combine the powerful searching capability of genetic algorithms (GA) in the design of a fuzzy controller. In structural control applications, GA can be utilized as a multi-objective optimization technique to pursue the goal of simultaneously reducing both the displacement response that determines the structural safety and the acceleration response that reflects the comfort level of occupants. Kim and Ghaboussi [20] applied GA to design an optimal controller for wind-excited vibration reduction of a 76story tall building in a widely used second-generation benchmark problem. Ahlawat and Ramaswamy [21] used the newly developed two-branch tournament GA to optimize the parameters of a fuzzy controller for a structure with an active tuned damper (AMD), showing that GA is an effective approach for multi-objective optimal design of fuzzy controllers.

In this study, GA is employed as an adaptive method for design of a FLC system for protecting buildings under dynamic hazards using MR dampers. The design process uses the excitation of the NS component of the 1940 El Centro ground acceleration record. Minimizations of the peak displacement and acceleration responses, nondimensionalized by the uncontrolled peak displacement and acceleration responses, respectively, are the two objectives. GA is used to derive proper rules that establish the fuzzy correlation between the inputs (structural responses) and the outputs (command voltages) of the controller, while it automatically adapts and optimizes the fuzzy controller according to the fitness function that reflects the multiple objectives. Numerical results considering both single and multiple damper cases are examined and compared with several nonlinear control algorithms.

2. Control strategy

Assume that a flexible building under earthquake ground excitation is to be controlled using MR dampers. Fig. 1 illustrates the proposed control strategy that integrates fuzzy logic and GA. Selected structural responses are used as the inputs of a fuzzy controller, and the fuzzy controller outputs command voltages to control MR dampers in order to generate damping forces that mitigate the structural responses. Since the correlation between the structural responses and the command voltages is difficult to determine in a conventional design approach, especially for a MIMO system, GA is introduced as an effective method to optimally design the fuzzy controller. As mentioned previously, the control objective is to minimize both the peak displacement and acceleration responses of the structure to ensure the security of the building and maintain an acceptable level of comfort for the occupants.

In an ordinary design approach, the membership functions and control rules of a fuzzy controller are usually determined by trial and error which is a tedious and time consuming task. For efficiency, an optimal design of fuzzy control rules and membership functions of the fuzzy controller is desired. In this study, for simplicity, GA is only employed as an adaptive method for selection of fuzzy rules of the FLC system, and other parameters of the fuzzy controller such as the shape and the distribution of the membership functions are unchanged once defined. First, the input and output space of the system to be controlled is divided into fuzzy regions and the membership functions are defined as for design of an ordinary fuzzy controller. The integrated GA-FLC architecture uses GA to derive proper rules from the initial rules (however, the initial rules are not necessarily needed in this study). By changing, adding and deleting rules, the GA automatically adapts and optimizes the fuzzy control system. Because accelerometers can readily provide reliable and inexpensive measurement of accelerations at arbitrary points on the structure [2], the absolute accelerations are selected as the fuzzy controller inputs. For simplicity and clarity of illustration, accelerations of the highest two floors are considered in this study, however, responses of other floors or more floors may be adopted in the same way as presented in following parts. It is expected that by using a GA, it can produce an effective fuzzy rulebase that establishes a suitable correlation between selected acceleration responses and command voltages. Generally, such a correlation is not easy to determine before a full understanding of the nonlinear dynamics of the building–MR damper system under earthquake is achieved.

3. Genetic algorithms

As a powerful computational search and optimization tool, GA is based on the mechanism of natural selection. It makes the analogy that survival of the fittest individual to its environment is akin to an optimal design [22,23]. GA uses operations of selection (reproduction), crossover, and mutation on a population of strings to perform evolution to obtain improved solutions.

In GA, a set (population) of possible solutions (individuals) can be represented by chromosomes, which are generally binary strings of 1 s and 0 s that represent design parameter values for each individual. New strings are produced every generation by repetition of a two-step cycle [24]. First, each individual string is decoded

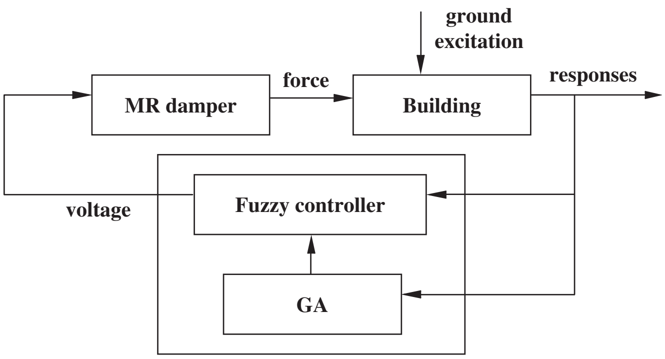

Fig. 1. Control strategy for integrated fuzzy logic and genetic algorithms.

and its ability to solve the problem is assessed. Each string is assigned a fitness value depending on how well it performs. Second, the fittest strings are preferentially chosen for recombination to form the next generation. Recombination involves selection of two strings, choice of a crossover point in the string, and switching of the segments to the right of this point between the two strings (the crossover operation). Meanwhile, mutation is used to maintain genetic diversity within a small population of strings. There is a small probability that any bit in a string will be flipped from its present value to its opposite (for example, 0 to 1).

GA uses a fitness value for the genetic operators, and this fitness value reflects the performance of the solution, namely the desired objectives. Because GA only uses fitness values to search the optimal solution in the genetic space and does not require derivatives, or even continuity of the function, it is has been shown to be a robust optimization method. Another feature of GA is that the genetic operators, i.e. selection, crossover and mutation, are performed on the whole population in parallel, namely on a set of individuals rather than for a single point; therefore, GA can be adopted for multi-objective optimization. In this study, this attractive characteristic of GA is utilized for multi-objective optimal design of a fuzzy controller for reduction of both the maximum displacement and acceleration responses of structure under earthquake excitation.

4. Design of genetic adaptive fuzzy controller

In this study, GA is employed as an adaptive method for selection of fuzzy rules of the FLC system. This is always a complicated task especially in a MIMO system. GA optimally establishes a reasonable fuzzy correlation between the selected structural responses, i.e. the absolute accelerations of the highest two floors in this study, and the corresponding command voltages for MR dampers. This correlation is the foundation for determination of the command voltages according to the structural acceleration responses during an extreme event. For simplicity, the parameters of the fuzzy controller such as the shape and the distribution of the membership functions are unchanged once they are defined. Design of the genetic adaptive fuzzy (GAF) controller proposed here consists of the following steps.

4.1. Fuzzify input and output region

The design of the fuzzy controller begins with dividing the input and output space of the system to be controlled into fuzzy regions and defining the membership functions just as in the design process of an ordinary fuzzy controller. Here, the fuzzy controller has been designed using five membership functions for each of the inputs and four membership functions for each of the outputs. The definition of the fuzzy input membership function abbreviations are as follows: NL = Negative Large, NS = Negative Small, ZO = Zero, PS = Positive Small, and PL = Positive Large. For convenience in defining the membership functions, values of inputs are normalized before entering the fuzzy controller. A reasonable range for each input must be selected since, if the range is too large, the outermost membership functions are rarely utilized and thus limits the variability of the control system. Conversely, if the range is too small, the outermost membership functions are essentially utilized at all the times, which again limits variability of the control system [15]. In our study, a reasonable range for each input is selected as 70~80% of the maximum uncontrolled acceleration responses of the corresponding floors. And the absolute values of the maximum of this range are adopted as denominators to normalize the corresponding acceleration inputs. The definition of the fuzzy output membership function abbreviations are as follows: ZO = Zero, S = Small, M = Medium, and L = Large. The range of the output corresponds to the operational voltage range of the MR damper used, however, without considering specific type of MR damper, a normalized voltage range of 0 to 1.0 is defined here. A generalized bell-shaped membership function is used because it can approximate almost all other types of membership functions based on its parameters in Eq. (1) [21]. The shape of the generalized bell shape membership function can be defined by parameters a, b and c [25].

$$\mu = \frac{1}{1 + \left|\frac{x-c}{a}\right|^{2b}}. \tag{1}$$

Membership functions for the input and output variables are shown in Fig. 2.

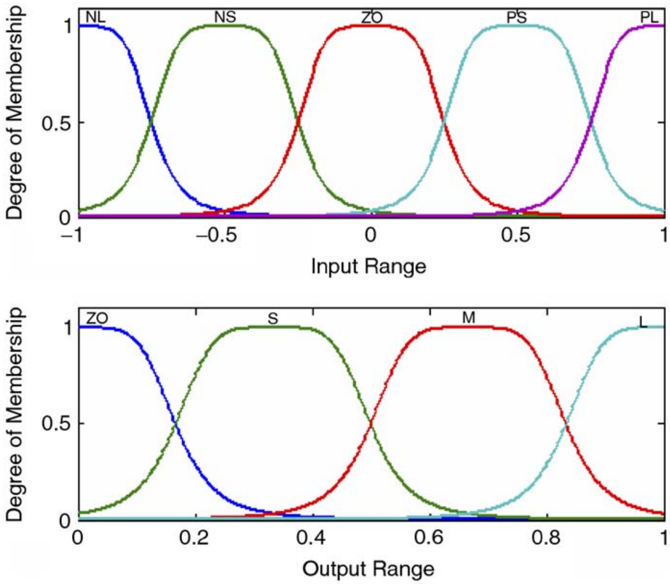

Fig. 2. Membership functions used for input and output variables.

4.2. Define fitness function for GA

As mentioned previously, GA uses a fitness function value for the genetic operators, and this function reflects the desired objective. The control objective is to minimize both the peak displacement and acceleration responses of the structure to ensure the security of the building and maintain the comfort level of the occupants. A set of evaluation criteria based on those used in the second generation linear control problem for buildings to evaluate the various control algorithms are given in Refs. [26,27]. In this study, two of these criteria which are also regarded as the objectives in GA are selected to evaluate effectiveness of the proposed method. The first evaluation criterion is a measure of the normalized maximum floor displacement relative to the ground, given as

$$J_1 = \max_{t,i}\left(\frac{|x_i(t)|}{x^{\max}}\right), \tag{2}$$

where $x_i(t)$ is the relative displacement of the ith floor over the entire response, and $x^{\max}$ denotes the uncontrolled maximum displacement response. The other evaluation criterion is a measure of the normalized peak floor accelerations, given by

$$J_2 = \max_{t,i}\left(\frac{|\ddot{x}_{ai}(t)|}{\ddot{x}_a^{\max}}\right), \tag{3}$$

where the absolute accelerations of the ith floor $\ddot{x}_{ai}(t)$ are normalized by the peak uncontrolled floor acceleration, denoted as $\ddot{x}_a^{\max}$.

For simplicity, the objective function that reflects the above objectives in this study is defined as follows

$$J = \alpha J_1 + (1-\alpha)J_2, \tag{4}$$

where J_1 and J_2 are the evaluation criteria defined above representing normalized maximum floor displacement relative to the ground and normalized peak floor accelerations, respectively. α is a weighting coefficient reflecting the relative importance of the two objectives. Then the objective value is converted to fitness value given by

$$F = C - J, \tag{5}$$

where C is a proper constant to make sure the fitness value is positive. This fitness function forms the basis of the genetic operations in this study.

4.3. Encode the input– output region into bit-strings

Encoding information is the most important step in the design of a GAF controller. One of the biggest differences between GA and other optimization methods is that GA works in the genetic space; therefore, it is necessary to code the fuzzy input and output sets into genetic space represented by chromosomes. Here for simplicity, the most common coding strategy, binary bit-string coding, is used. In this coding strategy, a set of fuzzy rules mapping fuzzy inputs to fuzzy outputs is represented by a binary bit-string, called a chromosome [24].

Suppose a FLC system with two inputs and single output represents a single damper case that is to be designed. This two-input-single-output case is chosen to simply clarify the basic ideas of how to represent a fuzzy rulebase using bit-strings. Extension of this technique to more input and output variables is straightforward. Because each input is divided into five fuzzy sets in this study, in such a system a fuzzy rulebase consists of 25 fuzzy rules for the two fuzzy inputs. These rules can be organized in a five-by-five table with each cell to hold the corresponding outputs. When the table is empty, namely there is no rule in the initial condition of the fuzzy rulebase, there are four choices for each of the voltage outputs corresponding to each rule. For example, using "IF–THEN" form, IF Input1 is NS and Input2 is PS, THEN Output is ZO or S or M or L (Input1 and Input2 represent the two input variables, respectively, and Output represents the output variable). Because in a population, each individual chromosome, i.e. a complete bit-string, consists of all the fuzzy rules and has the same input conditions but different output control signals assigned to it, it is needed only to encode the output signals of the fuzzy rule [24]. There are totally 25 rules that form the fuzzy control rulebase, thus totally 100 bits can be used to represent a whole rulebase for single output. Each four consecutive bits are coded to represent the output for each rule. Each four bits from left to right represents the output linguistic variables ZO, S, M and L, respectively. An output signal is selected by GA by setting the corresponding bit to 1 while other three bits are 0 s. For example, the following rules

- IF Input1 is NL and Input2 is NL, THEN Output is L;
- IF Input1 is NL and Input2 is NS, THEN Output is M;
- IF Input1 is ZO and Input2 is PS, THEN Output is ZO;
- IF Input1 is PL and Input2 is PL, THEN Output is S
  (totally 25 rules)

can be represented by a chromosome as

$$0001\,0010\,\ldots\,1000\,\ldots\,0100\ (\text{totally 100 bits}).$$

The multiple damper case is similar to the single damper case, except that the bit number that represents the corresponding output voltages has a longer length.

However, the problem in this coding strategy is that it is hard to perform a mutation operation since it may result more than one choice for each output in one rule. So in this study, only the selection and crossover operators are used to perform GA operations while neglecting the mutation operator because crossover is the main evolution operator in GA and mutation is secondary.

4.4. Generate fuzzy rules using GA operations

GA is used to make the choice of the output control voltages that are to be set for each fuzzy rule. GA randomly initializes a population of complete bit-strings. Each of these bit-stings is then decoded into fuzzy rules and evaluated by the objective function defined in Eq. (4) which is determined by the maximum displacement and acceleration responses under control. Each bit-string's fitness is defined in Eq. (5). According to the fitness value, the GA then performs a self-directed search, learning to look for improved fuzzy rules, until the stopping criterion is met. It is clear that the fuzzy rules generated by GA depend on the fitness function, namely depend on the objective function. And since there is a weighting coefficient α in the objective function defined in Eq. (4) that reflects the relative importance of the two objectives, the fuzzy rules are different if α is changed.

5. Numerical results

To illustrate the effectiveness of the proposed control strategy, numerical results are given in this section. The simulation procedure is implemented using MATLAB (2002) [25]. Single and multiple damper cases are reported to show that the proposed integrated fuzzy logic and GA control strategy can effectively generate an effective and reliable fuzzy control system. This is especially true for a MIMO system in which the correlation between the multiple inputs and multiple outputs is difficult to determine using a conventional design approach.

5.1. Single damper case

The example used for this study is a simple model of a three-story building configured with a single MR damper. The MR damper is rigidly connected between the ground and the first floor of the structure. Details of this model are given in Dyke et al. [2]. The structural matrices are

$$\boldsymbol{M} = \begin{bmatrix} 98.3 & 0 & 0 \\ 0 & 98.3 & 0 \\ 0 & 0 & 98.3 \end{bmatrix} \text{kg}, \quad \boldsymbol{C} = \begin{bmatrix} 175 & -50 & 0 \\ -50 & 100 & -50 \\ 0 & -50 & 50 \end{bmatrix} \text{Ns/m},$$

$$\boldsymbol{K} = 10^5 \begin{bmatrix} 12 & -6.84 & 0 \\ -6.84 & 13.7 & -6.84 \\ 0 & -6.84 & 6.84 \end{bmatrix} \text{N/m}.$$

The first 20 s of the NS component of the 1940 El Centro ground acceleration record is used as the excitation. However, the acceleration is reproduced at five times the recorded rate to account for structural similitude. The parameters for the prototype MR damper used in this case are given by Spencer et al. [4]. For GA, the population size is taken as 80 members, and the upper limit on the number of generations is taken as 20. Proportional selection and one-point crossover are chosen to perform evolutionary operations based on an elitist model. An elitist model replaces the worst individual of the current generation by the current best individual to accelerate convergence of GA. The probability of crossover is set to 0.6, and the constant C in Eq. (5) is chosen to be 1.

As the emphasis in this study is on the MIMO system, the single damper case only considers the situation when $\alpha = 1$, namely, the multi-objective problem degenerates into a single-objective problem. However, as shown later, the proposed integrated control strategy has the capability to reduce the acceleration response dramatically while keeping the displacement response at a low level. Table 1 shows the fuzzy rules generated

Table 1
Fuzzy rulebase generated by GA in single damper case when $\alpha = 1$

Accel1	Accel2				
	NL	NS	ZO	PS	PL
NL	L	S	ZO	S	ZO
NS	ZO	ZO	ZO	L	S
ZO	L	L	L	L	ZO
PS	L	S	L	L	S
PL	L	S	S	S	ZO

by GA that establish the correlation between the selected acceleration responses and the command voltage sent to a single MR damper when $\alpha = 1$ (Accel1 and Accel2 represent the accelerations of the second and third floors, respectively; Vol represents the command voltage sent to the MR damper). Table 2 presents the maximum structural responses to the El Centro earthquake. Here x_i is the maximum relative displacement of ith floor with respect to ground, d_i is the maximum inter-story displacement (i.e., x_i–x_{i-1}), and $\ddot{x}_{ai}$ is the maximum absolute acceleration of the ith floor, and F is the applied control force. For purposes of comparison, the uncontrolled responses, responses under two passive control modes named *Passive-Off* and *Passive-On* whose operation voltage is set to zero and maximum, respectively, and results given by a *Clipped-Optimal* control strategy [2], are also listed in Table 2.

GA generates a set of fuzzy rules for each input and output as shown in Table 1 when $\alpha = 1$. In an adaptive manner, the correlation between the building accelerations and the command voltage applied to MR damper has been constructed. This correlation forms the basis for semi-active control of the structure using an MR damper. Numerical results given by the last column in Table 2, whose control strategy name is *GAF*, shows the effectiveness of the newly generated fuzzy rules. The GAF control strategy achieves a significant reduction of both displacement and acceleration responses, even though when $\alpha = 1$ only the displacement objective is pursued. Figs. 3 and 4 illustrate the time histories of the relative displacements and absolute accelerations of the structure, respectively, with the proposed GAF control strategy and without control, showing that the correlation established by GA is proper and effective. Thus, the fuzzy control system based on this correlation can significantly reduce structural responses. Fig. 5 shows the force produced by MR damper and command voltage sent to the damper in the GAF control strategy.

5.2. Multiple damper case

As mentioned previously, the proposed integrated fuzzy logic and GA control strategy is especially suitable for designing an MIMO system. This section presents a multiple damper case to show its effectiveness in achieving the multi-objectives. The case taken for this study is a simple model of a six-story building configured with four MR dampers. Two devices are rigidly connected between the ground and the first floor of the structure and two devices are rigidly connected between the first and second floors. Fig. 6 shows the structural model used for this study. It is defined that the mass of each floor m_i is 0.227 N/(cm/s^2), the stiffness of each floor k_i is 297 N/cm, and the damping ratio for each mode is 0.5%. Details of this model are given by Jansen and Dyke [26,27] and Yi et al. [28]. The MR dampers used in this study are the same as the prototype shear-mode MR damper modeled by Yi et al. [28,29] and Dyke et al. [30]. The equations governing the force f predicted by this model are as follows

$$f = c_0\dot{x} + \alpha z, \tag{6}$$

$$\dot{z} = -\gamma|\dot{x}|z|z|^{n-1} - \beta\dot{x}|z|^n + A\dot{x}, \tag{7}$$

Table 2
Peak responses due to El Centro earthquake in single damper case

Control strategy	Uncontrolled	Passive–Off	Passive–On	Clipped–Optimal	GAF
x_i (cm)	0.538	0.211	0.076	0.114	0.100
	0.820	0.357	0.196	0.185	0.169
	0.962	0.455	0.306	0.212	0.255
d_i (cm)	0.538	0.211	0.076	0.114	0.100
	0.319	0.153	0.158	0.090	0.120
	0.201	0.103	0.110	0.101	0.102
$\ddot{x}_{ai}$ (cm/s^2)	856	420	281	696	499
	1030	480	494	739	586
	1400	717	767	703	709
F (N)	—	258	979	941	867

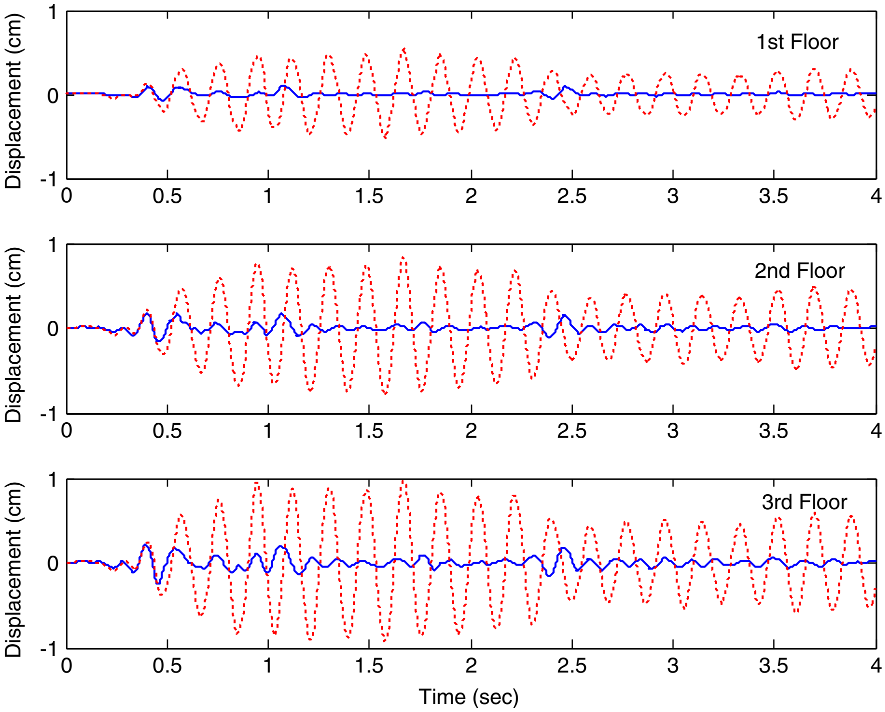

Fig. 3. Relative floor displacement time histories with and without fuzzy control in single damper case when $\alpha = 1$.

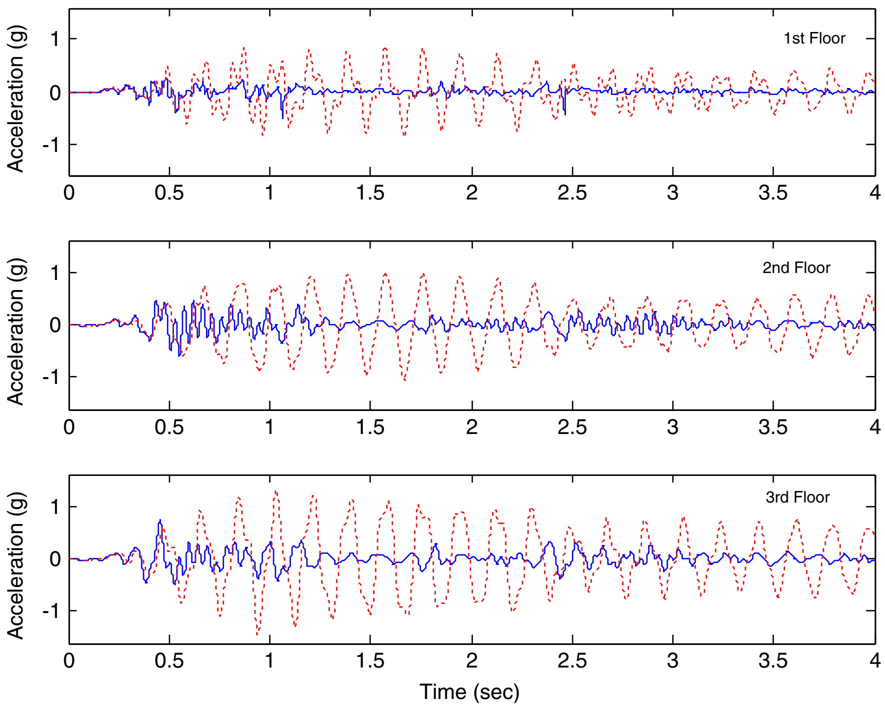

Fig. 4. Absolute floor acceleration time histories with and without fuzzy control in single damper case when $\alpha = 1$.

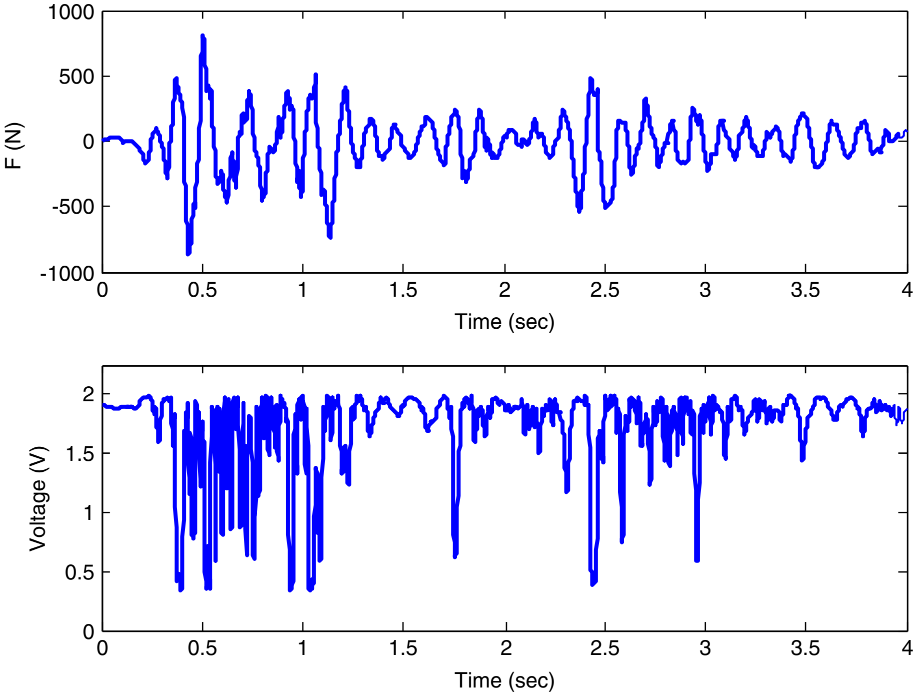

Fig. 5. Force produced by MR damper and command voltage sent to MR damper in single damper case when $\alpha = 1$.

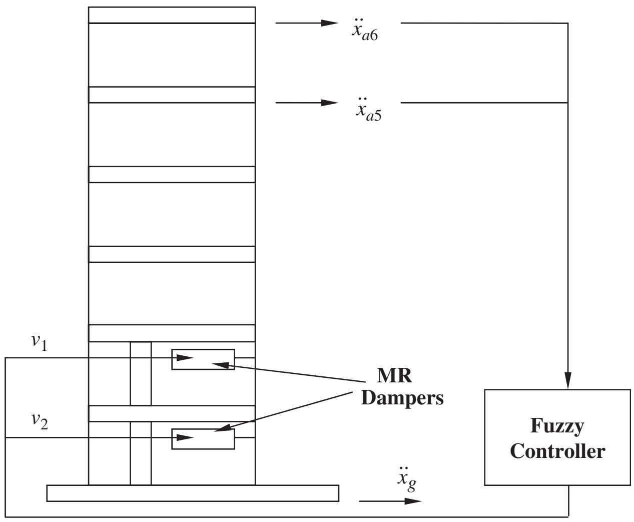

Fig. 6. Illustration of structure model used in multiple damper case.

where z is the evolutionary variable that accounts for history dependence of the responses. The model parameters depend on the voltage v to the current driver as follows

$$\alpha = \alpha_a + \alpha_b u, \quad c_0 = c_{0a} + c_{0b} u, \tag{8a,b}$$

where u is given as the output of the first-order filter

$$\dot{u} = -\eta(u - v). \tag{9}$$

Eq. (9) is used to model the dynamics involved in reaching rheological equilibrium and in driving the electromagnet in the MR damper [28–30].

The MR damper parameters used in this case are $c_{0a} = 0.0064\,\mathrm{Ns/cm}$, $c_{0b} = 0.0052\,\mathrm{Ns/cmV}$, $\alpha_a = 8.66\,\mathrm{N/cm}$, $\alpha_b = 8.86\,\mathrm{N/cmV}$, $\gamma = 300\,\mathrm{cm}^{-2}$, $\beta = 300\,\mathrm{cm}^{-2}$, $A = 120$, $n = 2$ and $\eta = 80\,\mathrm{s}^{-1}$. The parameters used for GA are the same as those for single damper case except the constant C is chosen to be 2.

In simulation, the NS component of the 1940 El Centro ground acceleration record is again used as the excitation. Because the building system considered is a scaled model, the amplitude of the El Centro earthquake is scaled to 10% of the full-scale earthquake acceleration to represent the magnitude of displacements that would be observed in laboratory experiments with the structure [26]. The acceleration responses of the highest two floors are selected as the inputs of the fuzzy controller, and the fuzzy controller outputs voltages to control the MR dampers. The goal is to generate proper forces to reduce the structural

Table 3
Fuzzy rulebase generated by GA in multiple damper case when $\alpha = 0.6$

Accel1	Accel2				
	NL	NS	ZO	PS	PL
NL	M/ZO	S/S	L/S	S/L	L/ZO
NS	L/L	L/ZO	ZO/ZO	ZO/L	ZO/M
ZO	L/M	S/ZO	L/M	L/ZO	M/S
PS	S/S	L/ZO	L/L	L/S	L/S
PL	S/ZO	ZO/ZO	ZO/S	L/ZO	S/L

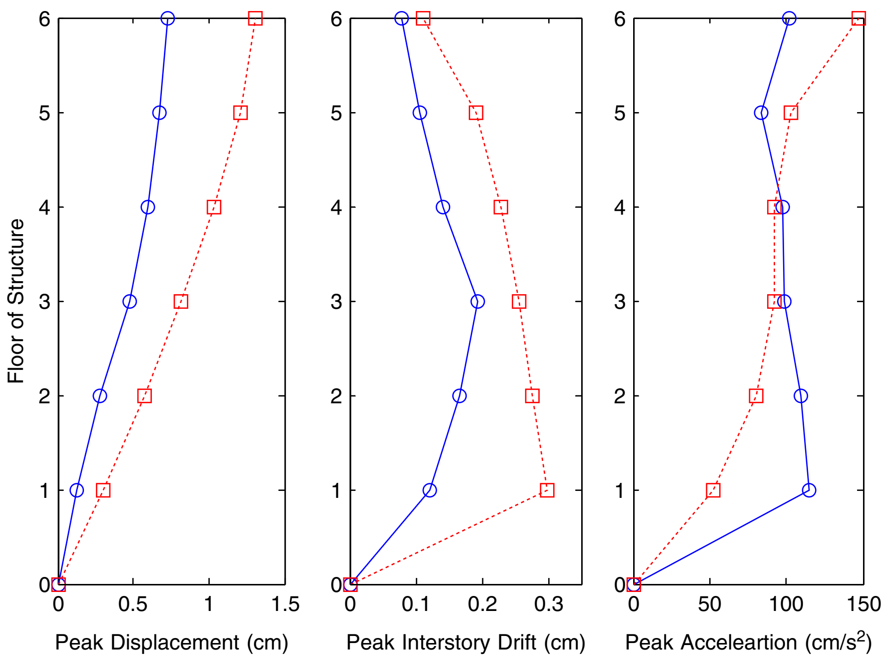

Fig. 7. Peak responses of each floor with and without fuzzy control in multiple damper case when $\alpha = 0.6$.

responses under earthquake. The two devices installed on the same floor are assumed to produce the same forces. It can be noted that the correlation between the accelerations and the voltages is not a simple matter to determine using conventional means because of the high degree of nonlinearity of the building-damper system and due to uncertainties during an earthquake event.

Table 3 presents a typical set of fuzzy rules generated by the adaptive GA when $\alpha = 0.6$ (Accel1 and Accel2 represent the accelerations of the fifth and sixth floors, respectively; Vols represent the command voltages sent to the MR dampers of the first and second floors, respectively). Fig. 7 shows the peak responses of each floor of the structure under the scaled El Centro earthquake with the GAF control strategy using the fuzzy rulebase presented in Table 3. The corresponding uncontrolled peak responses are: $x_i = 1.3113\,\text{cm}$, $d_i = 0.299\,\text{cm}$, $\ddot{a}_{ai} = 146.95\,\text{cm/s}^2$. From Fig. 7, it can be seen that the maximum displacement response of the structure relative to ground is dramatically reduced with the measure criterion $J_1 = 0.551$, which is almost a 45% reduction. A by-product of reduction of the relative displacement response is that the maximum interstory drift which is defined as $d_i = x_i - x_{i-1}$, is reduced by 37%. The other objective, namely the reduction of the peak absolute acceleration response is also presented in this figure. Although the acceleration of the lower floors increases, it is permissible since the criterion evaluating the maximum acceleration reduction among all of the floors, namely $J_2 = 0.780$, means that the proposed GAF control strategy is effective in reducing both the maximum displacement and acceleration responses as was expected. Fig. 8 shows the command voltages sent to the MR dampers calculated by the fuzzy controller and the control force produced by dampers installed on different floors.

Jansen and Dyke [26,27] give a comparative study for semi-active control strategies using MR dampers. They show that the performance of the controlled system is highly dependent on the choice of the control

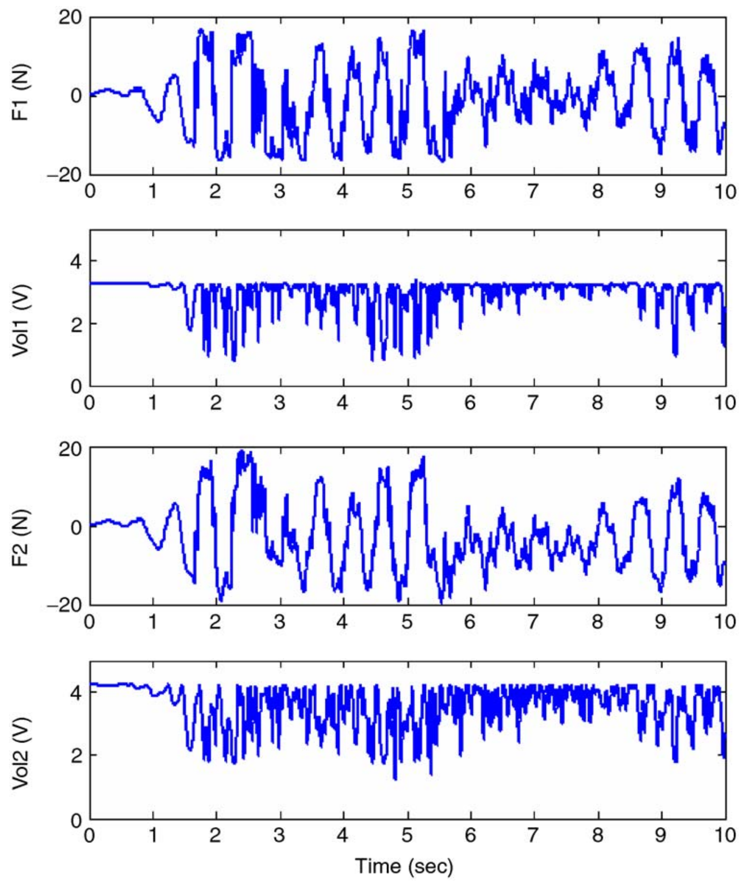

Fig. 8. Force produced by MR dampers and command voltages sent to MR dampers in multiple damper case when $\alpha = 0.6$.

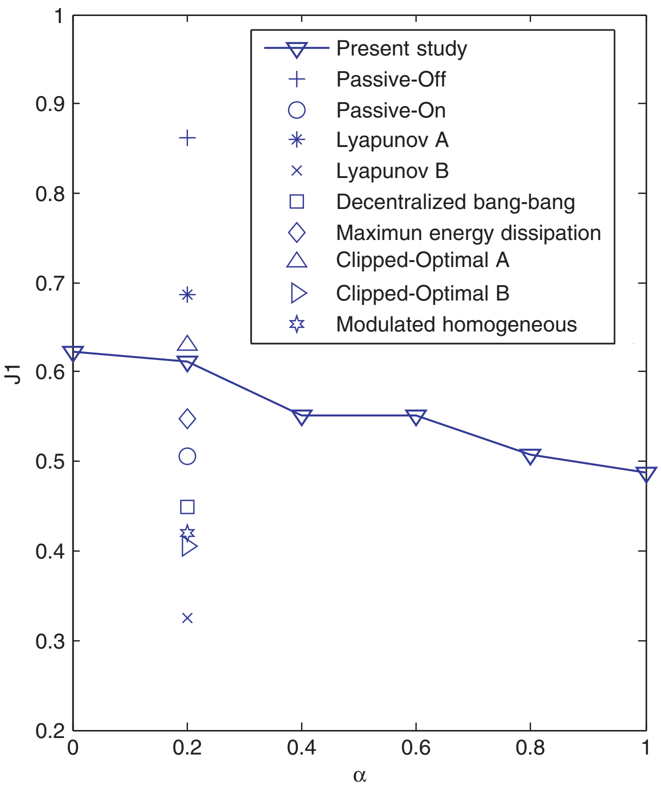

Fig. 9. Ratio of controlled to uncontrolled maximum displacement responses due to scaled El Centro earthquake with variation of α in multiple damper case.

algorithm. For purposes of comparison, results are given in Figs. 9 and 10 to show the variation of the criteria J_1 and J_2, with the weighting coefficient α. The results given by Jansen et al. are also presented in Figs. 9 and 10. These figures clearly show that when using other nonlinear control strategies, the maximum displacement response and the maximum acceleration response cannot be reduced simultaneously. In some situations, the reduction of displacement even means an unacceptable increment of acceleration. However, the intelligent control strategy proposed in this study effectively solves this problem as shown in Figs. 9 and 10.

6. Concluding remarks

This study presents a design strategy based on GA for semi-active fuzzy control of structures that have MR dampers installed to prevent damage from severe dynamic loads. Based on the advantages of FLC in dealing with uncertainties and nonlinearities, GA is used to further enhance the capacity of FLC with its powerful optimization capability. It can be seen that this FLC-GA architecture successfully establishes a fuzzy relationship between the input and the output of the controller which is almost impossible to accomplish using conventional design of a fuzzy controller, especially for a MIMO system. At the same time, the displacement and acceleration responses of the structure are simultaneously reduced to a low level using its powerful multi-objective optimization capability. It also offers flexibility and simplicity for designing a fuzzy controller for control of civil engineering structures using MR dampers that are full of nonlinearities and uncertainties, since a limited number of measurements are used. Future research is needed to further combine GA and fuzzy control, focusing on advanced and highly efficient coding strategy of GA. Experiments verifications are also needed to be conducted to verify the numerical results.

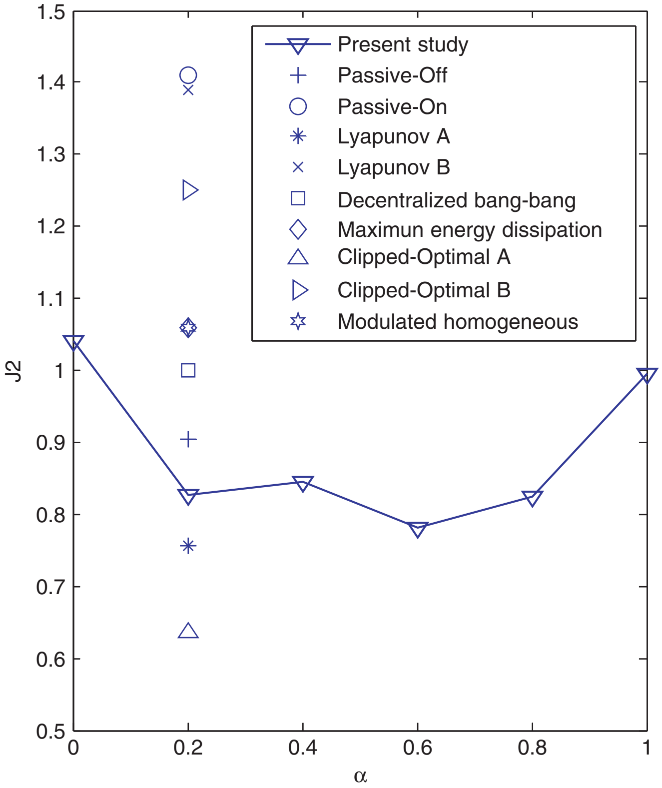

Fig. 10. Ratio of controlled to uncontrolled maximum acceleration responses due to scaled El Centro earthquake with variation of α in multiple damper case.

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