Fuzzy Control of Smart Base Isolation System using Genetic Algorithm

유전자알고리즘을 이용한 스마트 면진시스템의 퍼지제어

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국문요약

현재까지 많은 스마트 면진시스템이 제안되었고 연구되어 왔다. 본 연구에서는 스마트 면진시스템의 면진장치와 보조감쇠 장치로서 새로운 형태의 마찰진자시스템(FPS)과 MR 감쇠기를 각각 사용한다. 퍼지로직제어기(FLC)가 고유의 견실성과 비선형 및 불확실성을 쉽게 다룰 수 있는 능력이 있기 때문에 MR 감쇠기의 감쇠력을 조절하는데 FLC를 사용한다. 또한 FLC의 성능을 최적화 하기 위해서는 유전자알고리즘(GA)을 사용한다. GA를 사용함으로써 소속함수의 형상을 조절하는 것뿐만 아니라 적절한 퍼지제어규칙을 결정할 수 있다. 이를 위하여 본 연구에서는 부분개선 유전자알고리즘을 사용하였다. 이 방법은 유전자의 특정부분을 향상시키는데 효율적이다. FPS와 MR 감쇠기의 동적거동을 표현하기 위해서는 뉴로 퍼지 모델을 사용한다. FLC의 최적설계를 위하여 본 연구에서 제안된 방법의 효율성은 여러 가지 역사지진을 사용하여 계산된 동적응답을 기초로 하여 평가한다. 예제해석결과 제안된 방법은 적절한 퍼지규칙을 찾을 수 있고 GA로 최적화된 FLC는 수동제어기 뿐만 아니라 전문가의 지식에 기반한 FLC와 전통적인 준능동제어기보다 더 좋은 성능을 발휘한다.

주요어 : 스마트 면진장치, 마찰진자시스템, MR 감쇠기, 뉴로-퍼지 추론, 퍼지제어, 유전자 알고리즘

ABSTRACT

To date, many viable smart base isolation systems have been proposed and investigated. In this study, a novel friction pendulum system (FPS) and an MR damper are employed as the isolator and supplemental damping device, respectively, of the smart base isolation system. A fuzzy logic controller (FLC) is used to modulate the MR damper because the FLC has an inherent robustness and ability to handle non linearities and uncertainties. A genetic algorithm (GA) is used for optimization of the FLC. The main purpose of employing a GA is to determine appropriate fuzzy control rules as well to adjust parameters of the membership functions. To this end, a GA with a local improvement mechanism is applied. This method is efficient in improving local portions of chromosomes. Neuro fuzzy models are used to represent dynamic behavior of the MR damper and FPS. Effectiveness of the proposed method for optimal design of the FLC is judged based on computed responses to several historical earthquakes. It has been shown that the proposed method can find optimal fuzzy rules and the GA optimized FLC outperforms not only a passive control strategy but also a human designed FLC and a conventional semi active control algorithm.

Key words : smart base isolation, friction pendulum system, MR damper, neuro-fuzzy inference, fuzzy control, genetic algorithms

1. Introduction

Base isolation is one of the most widely used and accepted seismic protection systems. While standard base isolation techniques, such as insertion of rubber bearings or friction pendulum bearings between the ground and a structure that is to be protected, have been applied for a number of years, the addition of supplemental damping devices is being considered for large structures in order to reduce the base drift. However, the addition of damping to minimize base drift may increase both internal deformation and absolute accelerations of the superstructure, thus defeating many of the gains for which base isolation is intended.

Although significant studies have been conducted in recent years toward development and application of active and semi-active control schemes for vibration control of civil engineering structures in seismic zones, the application of intelligent controllers, including fuzzy logic controllers(FLC), has not been addressed extensively. Vibration control using fuzzy logic has attracted the attention of structural control engineers during the last few years. As an alternative to classical control theory, FLC allows the resolution of imprecise or uncertain information.

Because of the inherent robustness and ability to handle nonlinearites and uncertainties, FLC is used in this study to operate a large MR damper which is a key component of the smart base isolation system in this study. Not only has FLC has been demonstrated to be feasible, but knowledge of expert can be incorporated into fuzzy rules. Although FLC

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has been used to control a number of structural systems, selection of acceptable fuzzy membership functions has been subjective and time-consuming. To overcome this difficulty, many research studies have been reported on the acquisition of fuzzy rules using fuzzy neural networks. Fuzzy neural network systems usually require actual operating data for identification of control rules. In some cases, it is difficult to obtain the actual data in advance. Karr[(1),(2)] proposed application of a genetic algorithm(GA) to the design of a FLC and his work is now recognized as a pioneering effort in the application of GA to fuzzy control. To date, several studies using GA-optimized FLC[(1)~(5)] have been conducted; they have shown that performance of a GA-designed FLC appears to be better than that of the human-designed FLC.

Another advantage in the use of a GA is related to use of a wide range of fitness functions. The fitness function can include variables that are not the state variables of the controlled system. On the contrary, modern control theory that is based on the state space system can incorporate only state variables into the performance index. Karr et al. proposed use of a GA to adjust membership functions of fuzzy control rules. Most of these studies[(1)~(4)] did not utilize one of the main characteristics of a GA, namely that the algorithm would find unexpected and efficient rules.

Thus, the GA applied in this study focuses on finding appropriate fuzzy control rules as well as adjusting the membership functions. To this end, an effective method that uses a GA with a local improvement mechanism(Nagoya approach)[(6),(7)] is employed for efficient improvement of fuzzy rules. The Nagoya approach utilizes mechanisms of genetic recombination in bacterial genetics. It is efficient in improving local portions of chromosomes. However, the number of fuzzy rules that makes a FLC should be decided by the designer of the control system before applying this method. Sometimes an appropriate number of fuzzy rules cannot be readily selected. Therefore, in what follows, a weighting factor associated with each rule is introduced into the chromosomes in order to let the GA weaken or strengthen the contribution of each rule. Root mean squared(RMS) structural accelerations and base drifts that are normalized with respect to the uncontrolled RMS acceleration and drift responses, respectively, are used as the objective functions as well as normalized peak acceleration and drift responses. Moreover, a weighted sum approach is introduced to combine multiple objectives into a single fitness function. The level of priority of control for structural accelerations and base drifts can be adjusted by varying the weighting factors used in the fitness function.

The proposed design approach using the GA-optimized FLC for a smart base isolation system is demonstrated with the help of numerical simulations. Parameters from a large scale experimental model are employed as the basis for numerical simulation. The large scale experimental test was conducted at National Center for Research on Earthquake Engineering(NCREE) in Taipei, Taiwan. Powerful modeling capabilities of adaptive neuro-fuzzy inference system(ANFIS) are used to develop a neuro-fuzzy model of the MR damper and the four FPSs that support the mass. A neuro-fuzzy model is used to represent dynamic behavior of the MR damper for various displacement, velocity, and voltage combinations that are obtained from a series of performance tests. Modeling of the FPS is carried out with a nonlinear analytical equation and neuro-fuzzy training. A passive damping strategy, human-designed FLC and conventional semi-active controller(i.e. skyhook) are used to compare the efficiency of the proposed GA-optimized FLC. Based on computed responses to several historical earthquakes, the proposed approach is shown to provide an optimal FLC for a smart base isolation system that is equipped with FPS's and a controllable MR damper.

2. Model of the smart base isolation system

A series of large-scale experimental tests on a smart base isolated system was recently conducted at NCREE. The smart base isolation system consists of a set of four specially-designed FPSs and a 300 kN MR damper as shown in Fig. 1. The effectiveness of the hybrid base isolated system was experimentally verified. The system reduced base drifts without increasing accompanying accelerations that are manifested during use of a human-designed FLC. Although the expert's knowledge-based FLC controls the smart base isolation system effectively in comparison with passive control strategies during the experimental test, there seems to be considerable room for improvement through use of an optimal design method. Therefore, this experimental model of a smart base isolation system is employed as a numerical example in order to demonstrate improved performance of the FLC by using the proposed design approach.

3. Modeling of MR damper

Extensive performance testing of the 300-kN MR damper is conducted at NCREE using a dynamic actuator to collect a sufficient quantity of data that are evenly distributed over the operational range of the MR damper. These data enable training of neuro-fuzzy model that can be used to numerically simulate dynamic behavior of an MR damper. In this section, a neuro-fuzzy modeling procedure is presented to represent behavior of the 300-kN MR damper.

Special properties of an MR damper include relationships of parameters such as displacement, velocity, applied voltage, and resisting force. Because this relationship has been shown to provide sufficient information for operation of the damper and is suitable for control purposes, these three input and force output parameters are used in what follows to model the 300-kN MR damper. All numerical simulations for training a damper model are made by using the fuzzy logic toolbox of MATLAB 7.0. After extensive training through ANFIS, a satisfactory fuzzy model of the MR damper is obtained as shown in Fig. 2.

4. Modeling of FPS

An FPS is a mechanical device that isolates a structure from its support. It is often considered for use as an alternative to base isolation that employs high-density rubber bearings(HDRB). This can be accomplished by altering bearing material or by changing the radius of curvature of the spherical surface. For all data generated in this paper a coefficient of friction bearing material is considered to beas Teflon on steel with a coefficient of friction 0.03 and the radius is set at one meter. In order to establish pseudo-experimental data(i.e. data that can be taken as sufficiently similar to experimental behavior) that describes the nonlinear force-displacement relationship of a typical FPS system, the following equations can be employed. They are established by a simple analytical relationship from fundamental principles of mechanics[8].

$$F = W\left[\frac{u + \mathrm{sgn}(\dot{u})\mu\sqrt{R^2 - u^2}}{\sqrt{R^2 - u^2} - \mathrm{sgn}(\dot{u})\mu u}\right] \tag{1}$$

where F is the external force acting on the FPS, R is the radius of the spherical bearing surface, u is horizontal displacement, $\dot{u}$ is horizontal velocity, μ is the coefficient of friction, *sgn* indicates a positive or negative sign of its function, and W is the weight of the mass supported by the FPS.

Once a data set has been created, ANFIS can be used to create a FIS. A FIS is basically a black box that predicts the output from input data based on rules created by training on a set of known input and output data. The FIS for the FPS is designed with two inputs(displacement and velocity) and a single output(damping force) based on Eqs. (1) and (2). Fuzzy inference surfaces that represent evaluation of the membership functions for a range of input variables are shown in Fig. 3.

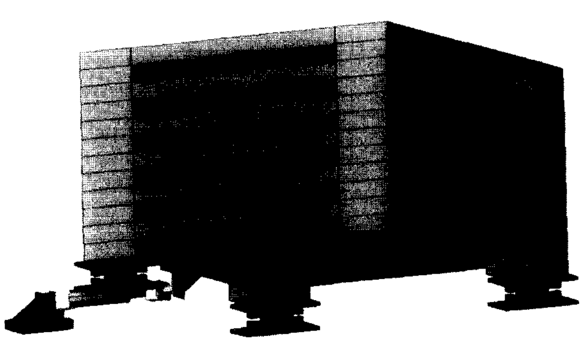

Fig. 1 Configuration of smart base isolation system.

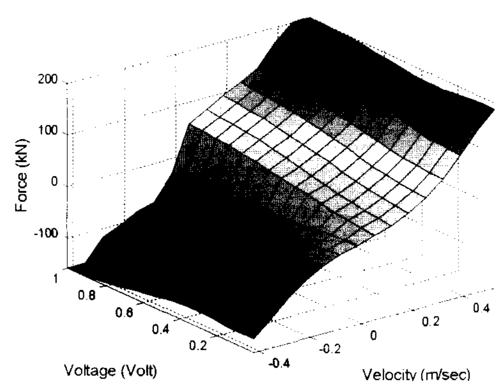

Fig. 2 Fuzzy inference surface of trained MR damper model.

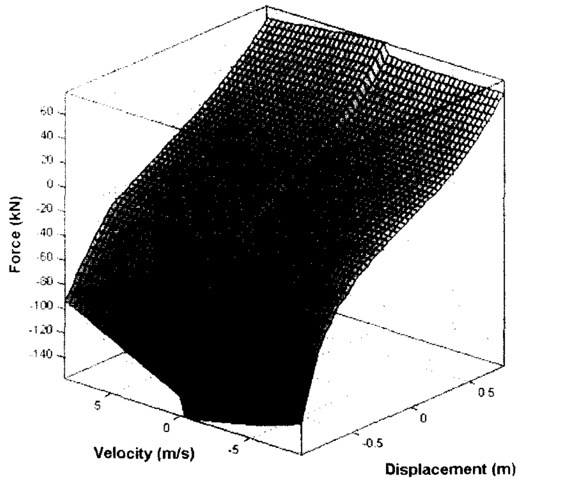

Fig. 3 Fuzzy inference surface for FPS model with μ = 0.03.

5. Optimization of FLC using GA

Since Karr first introduced a GA approach to design of FLCs in 1991, many researchers have optimized FLC using a GA. In this study, a GA with a local improvement mechanism is employed to find unexpected and effective fuzzy control rules as well as to adjust the membership functions. Moreover, a weighting factor associated with each fuzzy rule is introduced to optimize the contribution of the rule to the FLC.

5.1 Encoding method

Encoding is the genetic representation of a FLC solution. All of the information represented by the FLC parameters is encoded in a structure called a chromosome or string. Each chromosome is made up of a sequence of genes from a certain alphabet. Gaussian membership functions are used for all input and output variables because they can approximate almost all other types of membership functions by changing the parameters shown in Eq. (2).

$$\mu = \exp\left(-\frac{(x-c)^2}{2\sigma^2} \right) \tag{2}$$

The shape of the Gaussian membership function can be defined by two parameters: c and σ[9]. Here c is the central position, and σ is the width(standard deviation). Using these two parameters, various types of knowledge can be expressed. These two parameters are encoded into the gene with a real-valued representation as shown in Fig. 4.

Figure 4 shows the encoding method employed for each chromosome. There are two inputs $x1$, $x2$ and one output $x3$ in each rule. A rule has the parameters of Eq. (2), i.e. the central position $c1$ and $c2$ and the width $\sigma1$ and $\sigma2$, for inputs $x1$ and $x2$, respectively. For output $x3$, the central position $c3$ and the width $\sigma3$ are encoded. The parameter t specifies the connective used in the antecedent of the rule. If the connective is "AND," t = 1 and if the connective is "OR," t = 2. According to the original Nagoya approach, the appropriate number of fuzzy rules should be decided by the designer before optimizing the parameters. However, too many or too few fuzzy rules may decrease efficiency of the FLC. That is, it is difficult to select an appropriate number of fuzzy rules a priori. Therefore, a weighting factor, w, associated with each rule is introduced into each gene in order to let the GA optimize the contribution of rules through weakening or strengthening the weight of each rule. An adequate number of fuzzy rules can be found using this encoding method. In addition, for application of the Nagoya approach each chromosome is divided into four parts as explained in

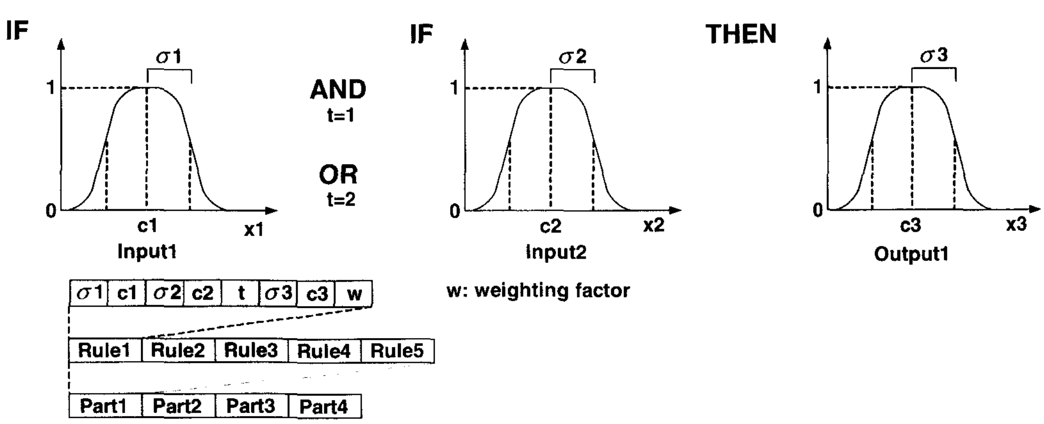

Fig. 4 Encoding structure of a chromosome.

following section. Each part consists of five rules - the number five being determined by previous experience with numerical simulation of similar problems[7].

5.2 GA with a local improvement mechanism

One of the drawbacks in using a GA for control is that it often needs a huge population. For example, the size of the population is recommended to be at least equal to the number of variables in a chromosome[9]. Also a GA often takes a very large number of generations to achieve a satisfying performance. The latter drawback can be surmounted by using a GA with a local improvement mechanism[6,7]. Fig. 5 shows the flow of the modified Nagoya scheme used in this study. The basic idea is to evaluate mutations of the chromosomes in shorter intervals so as to improve the effectiveness of the mutation operator.

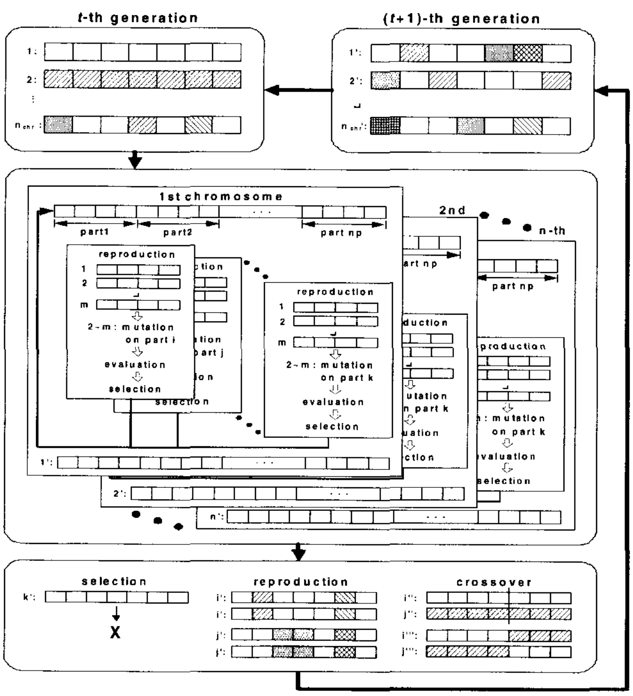

Fig. 5 Flow of GA with a local improvement mechanism.

To this end, each chromosome is divided into several parts. GA operations proceed as follows: First, chromosome 1 in the current population is copied m times and m-1 clones are mutated. The mutation operation is applied to the randomly chosen i^{th} part. The m clones are then evaluated using the GA fitness function and the fittest clone survives. The i^{th} part once selected is never selected again in the same generation. This procedure is repeated for all parts of the chromosome and for all chromosomes. After this process, other genetic operators such as selection, reproduction and crossover operators are applied to whole chromosomes in the population. This GA is efficient in local improvement of chromosomes, since the evolution is carried out on the level of chromosomal genes. The approach mainly focuses on finding control rules and adjusting membership functions.

5.3 Fitness function

The fitness function is the main criterion that is used to evaluate each chromosome. It provides an important connection between the GA and the physical system that is being modeled. A good fitness function can embody requirements of the base isolation system and evaluate the chromosomes properly. As stated earlier a good base isolation system simultaneously reduces base drift and structural acceleration thereby limiting or avoiding damage, not only to the structure but also to its contents. Therefore, the objectives in the design of a FLC for a smart base isolation system are to minimize both base drift and structural acceleration. In other words, optimization of the FLC for a smart base isolation system is a multi-objective optimization problem. There are several methods that can combine multiple objective functions to make a single fitness function in a multi-objective optimization problem. One of these methods, a weighted sum approach, is employed in this study as shown in Eq. (3).

$$F(x) = \sum_{i=1}^{k} w_i f_i(x) \tag{3}$$

where, $F(x)$ is fitness function, $f_i(x)$, i = 1, ..., k, are objective functions, w_i are weighting factors and

$$\sum_{i=1}^{k} w_i = 1$$

Base drift and structural acceleration responses normalized with respect to the uncontrolled base drift and structural acceleration responses, respectively, are used here as the multi-objectives. These objectives include RMS responses as well as peak responses. Therefore, the fitness function which has to be minimized, has been obtained by combining normalized peak base drift ($f_{peak\ drift}$), normalized RMS base drift (f_{RMS_drift}), normalized peak acceleration (f_{peak_accel}) and normalized RMS acceleration (f_{RMS_accel}) with two weighting factors as follows:

$$F = w_1 \times (f_{peak\_drift} + f_{RMS\_drift}+) + w_2 \times (f_{peak\_accel} - f_{RMS\_accel}) \tag{4}$$

where, w_1 and w_2 are the drift and acceleration weighting(importance) factors, respectively. A summary of the objectives used in this study is given in Table 1, where, d is controlled base drift, $\hat{d}$ is uncontrolled base drift, a is controlled acceleration, $\hat{a}$ is uncontrolled acceleration, σ_d is controlled RMS base drift, $\sigma_{\hat{d}}$ is uncontrolled RMS base drift, σ_a is controlled RMS acceleration and $\sigma_{\hat{a}}$ is uncontrolled RMS acceleration. The maximum value is obtained from the structural response to a series of historical earthquakes and is selected as the value of the corresponding objective function.

Table 1 Objectives of FLC optimization for smart base isolation system

Description	Objectives
Normalized Peak Base Drift	$f_{peak\_drift} = \max\limits_{earthquakes} \left\{ \dfrac{\max\limits_t \lvert d(t) \rvert}{\max\limits_t \lvert \hat{d}(t) \rvert} \right\}$
Normalized Peak Acceleration	$f_{peak\_accel} = \max\limits_{earthquakes} \left\{ \dfrac{\max\limits_t \lvert a(t) \rvert}{\max\limits_t \lvert \hat{a}(t) \rvert} \right\}$
Normalized RMS Base Drift	$f_{RMS\_drift} = \max\limits_{earthquakes} \left\{ \dfrac{\sigma_d(t)}{\sigma_{\hat{d}}(t)} \right\}$
Normalized RMS Acceleration	$f_{RMS\_accel} = \max\limits_{earthquakes} \left\{ \dfrac{\sigma_a(t)}{\sigma_{\hat{a}}(t)} \right\}$

Eleven optimization runs where w_1 varies from 0 to 1 in steps of 0.1 are conducted to determine the shape of the trade-off curve and select an appropriate FLC that can reduce both base drift and structural acceleration. If w_1 is smaller than w_2, namely smaller than 0.5, the weight of the normalized base drift decreases in comparison with the weight of the normalized acceleration. Also, if the weight of the normalized base drift is significantly smaller than the weight of the normalized acceleration, the normalized acceleration becomes a dominant factor in the fitness function. In that case, the GA mainly decreases the normalized acceleration instead of the normalized base drift. Therefore, the priority of the control objectives between base drift and structural acceleration can be adjusted by varying w_1 and w_2. As the weighting factor w_1 increases from 0 to 1, the dominant factor moves from acceleration to base drift.

6. Comparative controllers

6.1 Human Designed FLC

In order to verify control performance of the GA-optimized FLC, a comparative FLC is used that is based on the knowledge of a human expert. For a comparative FLC, the absolute acceleration and base drift of the structure are selected as inputs and the output is the command voltage. The number of membership functions used for the acceleration and drift inputs are five and six, respectively, while seven membership functions are used for the output. The input and output subsets are: PH = huge positive, PB = big positive, PS = small positive, Z = zero, NS = small negative, NB = big negative, and NH = huge negative. Table 2 shows the corresponding fuzzy rules in a succinct format.

Table 2 Fuzzy rules

		Base Drift					
		PH	PB	PS	NS	NB	NH
Structural Acceleration	PH	PB	PS	PS	NS	NS	NB
	PS	PH	PH	PS	NS	NH	NH
	Z	PS	PS	Z	Z	NS	NS
	NS	PH	PH	PS	NS	NH	NH
	NH	PB	PS	PS	NS	NS	NB

The fundamental approach to design of the human-designed FLC is to minimize both the structural acceleration and the base drift of the isolated structure. As a result, this controller divides the response of the isolation system into three types. First, when the absolute acceleration is very large, the command voltage is specified to be small when base drift is small and large when the base drift is very large. In this situation, the command voltage is suppressed to prevent exciting the acceleration responses except when the base drift is also very large. Secondly, when the absolute acceleration is small, the command voltage is increased in proportion to the base drift. That is, the command voltage is as large as possible except for the small response zone. Thirdly, when the absolute acceleration is almost zero, the command voltage is zero when base drift is small and small when the base drift is large. This approach provides a zero command voltage zone around acceleration responses that are minuscule and softens the MR damper when seismic excitation is over. Fig. 6 shows the corresponding control surface.

6.2 Skyhook controller

A skyhook controller is also employed as a comparative semi-active controller. As opposed to conventional dampers that tend to reduce the relative acceleration of the mass, the skyhook controlled damper attempts to reduce absolute acceleration of the mass[10]. As the damping coefficient of the skyhook damper is optimized, the response of the system near its resonant frequency is reduced and the response at higher frequencies also can be reduced somewhat. However, in a conventional damper, a reduced response at resonant frequency is obtained at the cost of degraded response at higher frequencies. The skyhook control algorithm used in this study is given by

$$V(t) = \begin{cases} V_{\max} & \text{if } \dot{u}_a \dot{u}_r > 0 \\ V_{\min} & \text{if } \dot{u}_a \dot{u}_r < 0 \end{cases} \tag{5}$$

where, $V(t)$ is the command voltage; V_{max} is the maximum voltage, namely 1 volt; V_{min} is the minimum voltage, 0 volt; $\dot{u}_a$ is the absolute velocity and $\dot{u}_r$ is the relative velocity.

7. Numerical studies

A numerical model of the smart base isolation system with a FPS and MR damper is implemented in SIMULINK as shown in Fig. 7. The FLC has been designed using the fuzzy logic tool box in Matlab[9]. Quantization error and saturation of the analog to digital converter(ADC) and digital to analog converter(DAC) and sensor noise have been included in the SIMULINK model in order to simulate a realistic representation of the control system. The ADC and DAC have 16-bit precision, a span of ±10 V, and sensor noise of 0.03 V RMS i.e. 0.3% of the range of the ADC signal. Excitation records that are used for numerical simulation include three commonly used earthquakes: El Centro(18 May 1940); Kobe(17 January 1995); and Northridge(17 January 1994). An integration time step of 0.01 sec is used and the control signal is computed every 0.01 sec. A GA with a local improvement mechanism, discussed in Section 5.2, is employed for optimization of the control system. The population size is taken to contain 10 individuals. An upper limit on the number of generations is taken to be 50.

As mentioned previously, priorities among the objectives of the GA-optimized FLC can be adjusted by varying weighting factors in Eq.(4). In order to find the appropriate weighting factor that can effectively reduce both base drift and absolute acceleration, a series of numerical simulations is conducted with various weighting factors from 0 to 1. Variation of the objective f_{peak_drift} with the corresponding value of the objective f_{peak_accel} is shown in Fig. 8. Fig. 9 shows the results of RMS responses. The objectives f_{peak_drift} and f_{RM_drift} can be improved at the cost of the degraded objectives f_{peak_accel} and f_{RM_accel} , respectively. Therefore, an engineer needs to choose a proper FLC that can satisfy the desired performance requirements by selecting appropriate

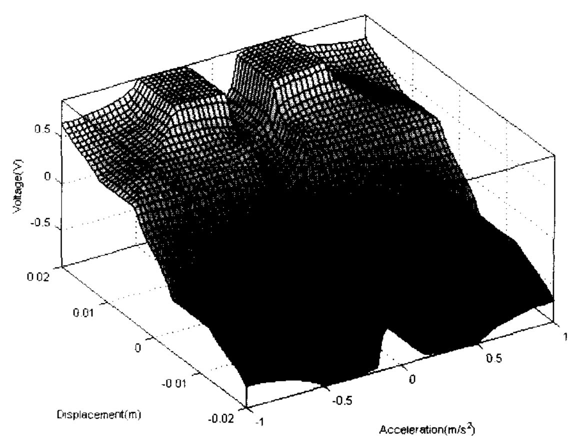

Fig. 6 FIS surface for human-designed FLC.

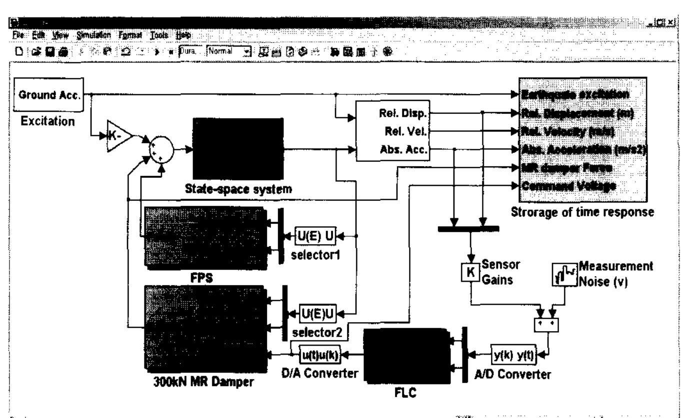

Fig. 7 SIMULINK block diagram for the smart base isolation system.

weighting factors. Results from the human-designed FLC, passive-on case and skyhook control are also shown in Figs. 8 and 9. The passive-on case can be thought of as the best passive case for the reduction of base drift. As expected, normalized peak and RMS base drift for the passive-on case are smaller than those of human-designed FLC and skyhook controller. On the other hand, the skyhook controller shows better performance for the normalized structural acceleration compared to the passive-on case. It can be seen that the control performance of the human-designed FLC is intermediate between passive-on and skyhook controller results; namely, it can reduce base drift better than the skyhook controller and it can reduce structural acceleration better than the passive-on controller.

Performance of the GA-optimized FLC in controlling base drift has been found to be better than that of the best passive case by tuning the weighting factor. In other words, the GA-optimized FLC using w_1 with values greater than 0.7 can reduce the base drift of the isolated structure more effectively than for passive-on control. The skyhook controller shows good performance in reducing peak and RMS structural acceleration due to its fundamental design. More importantly, use of the GA-optimized FLC with w_1 less than 0.9(0.7 for RMS response) can reduce structural acceleration much better than even the skyhook controller. Moreover, the GA-optimized FLC using a w_1 of 0.6~0.9 for peak responses(0.6 and 0.7 for RMS responses) shows an improved performance for both the base drift and absolute acceleration simultaneously in comparison with the human-designed FLC. Therefore, 0.6 and 0.7 are selected for the weighting factor w_1 (i.e. 0.4 and 0.3 for w_2) in the following numerical simulation that compares the control performance for six evaluation criteria($J1$~$J6$).

Peak base shear normalized by the corresponding shear in the uncontrolled structure and peak force generated by the MR damper normalized by the weight of the structure are employed as the performance indices for each controller as well as the four objectives that are included in the fitness function shown in Eq. (4). Table 3 lists these performance indices where V is controlled base shear, $\hat{V}$ is uncontrolled base shear, F is device force, t is time, q is earthquake, W is weight of the structure(235.2 kN) and the other notations have the same meaning as described in Table 1.

Table 3 Evaluation criteria for smart base isolation system

Description	Performance index
Normalized Peak Base Drift	$J1(q)=\dfrac{\max_t \lvert d(t,q)\rvert}{\max_t \lvert \hat{d}(t,q)\rvert}$
Normalized Peak Acceleration	$J2(q)=\dfrac{\max_t \lvert a(t,q)\rvert}{\max_t \lvert \hat{a}(t,q)\rvert}$
Normalized RMS Base Drift	$J3(q)=\dfrac{\sigma_d(t,q)}{\sigma_{\hat{d}}(t,q)}$
Normalized RMS Acceleration	$J4(q)=\dfrac{\sigma_a(t,q)}{\sigma_{\hat{a}}(t,q)}$
Normalized Peak Base Shear	$J5(q)=\dfrac{\max_t \lvert V(t,q)\rvert}{\max_t \lvert \hat{V}(t,q)\rvert}$
Normalized Peak Device Force	$J6(q)=\dfrac{\max_t \lvert F(t,q)\rvert}{W}$

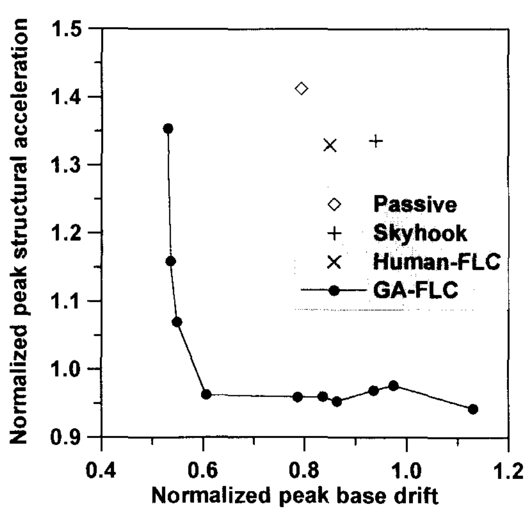

Fig. 8 Comparison of the peak responses

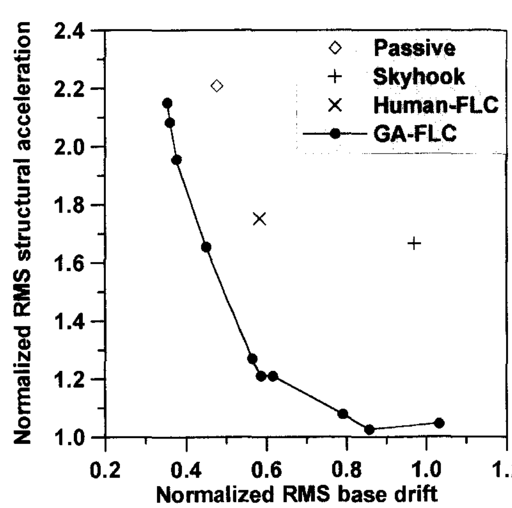

Fig. 9 Comparison of the RMS responses

Table 4 summarizes the control performance indices($J1 \sim J6$) for each controller, namely the passive-on case, the skyhook controller, the human-designed FLC and the GA-optimized FLC. The base-isolated structure is subjected to the three historical earthquakes mentioned earlier. Because the numerical model used in this study is a single degree of freedom system, normalized peak base shear is a constant multiple of the normalized peak acceleration. From Table 4 it can be seen that passive-on case can reduce peak base drifts from approximately 21% to 88%. However, these reductions in base drift come at the expense of increased structural accelerations. Peak structural accelerations for passive-on control were increased from approximately 2% to 41%. Especially peak structural acceleration for the moderate earthquake(El Centro) is significantly increased. The skyhook controller can control peak and RMS structural accelerations better than passive-on operation of the damper, and also provides between 6% ~ 36% decreased peak base drift in comparison with the uncontrolled case although the reduction amount is smaller than for the passive-on control. Performance of the human-designed FLC for acceleration is similar and in some cases better than the skyhook controller. Moreover, the human-designed FLC can reduce base drifts much better than the skyhook controller in 5 out of 6 cases.

As mentioned in the previous section, the performance indices of the GA-optimized FLC are presented using w_1 of 0.6 and 0.7. For most cases the GA-optimized FLC shows superior performance in comparison with the human-designed FLC. Especially, the GA-optimized FLC can effectively control the worst largest performance indices better than the other controllers. This is the case because the GA-FLC was optimized in order to reduce the maximum value of the objective values obtained from a series of historical earthquakes as described previously. Thus, GA-optimized FLCs not only reduce large structural acceleration for the El Centro earthquake but they also substantially ameliorate base drift resulting from the Northridge earthquake. In other words, not only does the GA-optimized FLC control structural accelerations for moderate levels of excitation, but it also concomitantly mitigates base drifts for large excitations and near-fault earthquakes. SinceNote that the force in the MR damper generated by each of the every FLC($J6$) is smaller than that of the passive and skyhook controllers. Therefore, through use of modulated current, FLCs may reduce the temperature of the MR fluid which is an important factor for reliable operation of the damper in practical applications.

8. Conclusions

This study investigates performance of a GA-designed FLC for a hybrid base isolation system consisting of an FPS isolator and an MR damper. The FLC is designed using a GA with a local improve-

Table 4 Control performance comparison

EQ	Controller	J1	J2	J3	J4	J5	J6
El Centro	Passive on	0.1152	1.4125	0.1168	2.2088	1.4125	0.3231
	Skyhook	0.6406	1.3358	0.3937	1.6666	1.3358	0.3127
	Human Fuzzy	0.4150	1.3268	0.3553	1.7503	1.3268	0.2971
	GA Fuzzy(w_1 = 0.6)	0.4517	0.9438	0.4426	1.2696	0.9438	0.2082
	GA Fuzzy(w_1 = 0.7)	0.3746	0.9834	0.1979	1.6692	0.9834	0.2260
Kobe	Passive on	0.7940	1.0171	0.4756	1.3238	1.0171	0.7956
	Skyhook	0.9393	0.9958	0.5206	1.0757	0.9958	0.8039
	Human Fuzzy	0.6229	0.9185	0.5346	1.2350	0.9185	0.7154
	GA Fuzzy(w_1 = 0.6)	0.7515	0.9065	0.5385	1.1729	0.9065	0.7235
	GA Fuzzy(w_1 = 0.7)	0.5932	0.9412	0.4167	1.2889	0.9412	0.7500
Northridge	Passive on	0.5383	1.0359	0.4081	1.3185	1.0359	0.7957
	Skyhook	0.8792	1.0315	0.9690	1.1286	1.0315	0.8122
	Human Fuzzy	0.8495	0.9542	0.5795	1.1553	0.9542	0.7714
	GA Fuzzy(w_1 = 0.6)	0.7865	0.9589	0.5635	1.1241	0.9589	0.7721
	GA Fuzzy(w_1 = 0.7)	0.6081	0.9623	0.4563	1.2188	0.9623	0.7615

ment mechanism. A weighted sum approach is employed to combine multiple objectives, namely reduction of base drift and structural acceleration, into a single fitness function. By varying weighting factors in the fitness function, priorities of the control goal can be adjusted. An adaptive neuro-fuzzy inference system is employed to model the control device and isolator of the smart base isolation system. Behavior of the FPS and MR damper can be successfully estimated using these neuro-fuzzy models.

Passive, skyhook, and a human-designed FLC are used as comparative controllers to investigate the effectiveness of the GA-optimized FLC. In the passive-on control case, base drift can be significantly reduced but structural acceleration is not well controlled. The skyhook controller reduces structural acceleration in comparison with passive-on control, but only at the expense of larger base drifts for all earthquakes that are numerically simulated. A human-designed FLC can reduce base drift better than the skyhook approach and it can reduce structural acceleration better than passive-on operation of the MR damper. That is, a human-designed FLC can appropriately control both base drift and structural acceleration. Finally, a GA-optimized FLC shows better performance in comparison with the human-designed FLC for most evaluation criteria. Furthermore, performance of the GA-optimized FLC can be easily adjusted by selecting an appropriate weighting factor according to desired performance requirements.

Based on numerical studies, a smart base isolation system consisting of a large MR damper and a novel FPS with an appropriate controller is shown to achieve significant decreases in base drift without accompanying increases in acceleration that accompany passive base isolation systems.

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