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Hybrid Geno-Fuzzy Controller For Seismic Vibration Control

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***Abstract*— This paper evaluates the possibility of applying a geno-fuzzy control strategy to a magnetorheological semi-active damper for seismic vibration control. The proposed control starategy is designed and then tested and validated in a simulated environment. The control strategy is validated by considering a more destructive seismic disturbance as input for the damper-structure system. The proposed geno-fuzzy hybrid controller offers improved performance and implementability for real-time applications.**

Keywords: *semi-active control, fuzzy controller, magnetorheological fluid damper, seismic response, genetic algorithms, hybrid geno-fuzzy controller.*

I. INTRODUCTION

Earthquake induced vibration of civil structures is a current topic of high interest. As buildings rise and materials are sought to be lighter and cheaper, the limitations of structural design are visible in buildings subjected to seismic and wind disturbance. A common approach is using additional structural vibration damping devices, be they passive, active, or semi-active. The technological advancements in computer and information technology make possible the real-time implementation of complex, advanced or non-linear control systems.

This article focuses on the use of magnetorheological (MR) dampers for semi-active seismic vibration control, by means of a hybrid geno-fuzzy non-linear controller. Using MR actuators for their dissipative properties is not a new idea. However, the applied control strategies vary in structure and performances. MR and ER (electrorheologic) bracing systems' analysis of seismic response with a linear controller based on ground acceleration is performed in [1], the authors showing showed that placing dampers near the base of a structure, as opposed to the upper levels, gives a better response reduction. Instead, in [2] a non-linear fuzzy control system is successfully employed for a base isolation MR damper.

Due to the non-linear intrinsic character of the MR dampers and of the fuzzy controllers, researchers have attempted evolutionary optimization of the fuzzy control systems for active and semi-active dampers. A base isolation system is designed in [3], combining a MR damper with a passive friction pendulum system. The authors have obtained a neuro-fuzzy model of the MR damper and have performed a genetic algorithm optimization of the fuzzy rules and the associated membership functions' parameters. A decrease in base displacements was observed, without increasing the acceleration, as seen in fully passive systems.

Another base isolation system was developed for a benchmark structure using MR dampers and a fuzzy controller, in [4]. Numerically simulated genetic algorithms were used to optimize the control system's performance. The genetic algorithm chromosomes have been used to code the membership functions' parameters, as well as a set of weighting factors for the fuzzy rules, the authors obtaining structural response reduction in both the base and the supra-structure. The evolutionary optimization of fuzzy controllers is also applied to an active tuned mass damper (ATMD) system in [5], where a genetic algorithm was used to optimize membership functions, rule weighting coefficients and three of the ATMD parameters.

In recent years, development of optimized fuzzy control systems for structural vibration control has taken a turn towards implementation of these algorithms. Thus, in [6], genetic algorithms are used to optimize model parameters of a benchmark building and a fuzzy model of a MR damper is obtained. Genetic algorithms are also used to optimize the fuzzy controller rules, that are considered to be described by membership functions and their parameters, reaching a chromosome length of 80 to 100 genes.

Computation time was still an issue in [7], where genetic algorithms and particle swarm optimization are used for the optimization of a fuzzy rule base and membership functions' parameters. The considered damping system was a semi-active MR actuator, obtaining a computing time between 2 and 60 hours for the tuning of the fuzzy controller.

Genetic algorithms also are used for determining the rule base of a fuzzy control system for seismic vibration control with an MR semi-active damper in [8]. In comparison with an adaptive controllers, the authors have obtained a better response reduction of the structural system from the optimized fuzzy controller.

This paper is organized as follows: in section 2, the authors present the models for the magnetorheological damper and structure, along with the principle of semi-active vibration control. In section 3, the proposed control strategy is presented, while section 4 contains a case study along with its results. Finally, section 5 contains the conclusions.

II. MAGNETORHEOLOGICAL SEMI-ACTIVE DAMPER

A. Magnetorheological Damper Model

A magnetorheological damper is a hydraulic-class actuator used in seismic protection design [9]. This device is used to generate the necessary control forces using as an input a command current and the velocity of the story on which it is mounted. The damper is a hydraulic cylinder filled with MR fluid – a magnetically polarizable micron size suspension in oil or other fluids [2]. The damping coefficient of this device is controlled by varying a magnetic field, thus changing the fluid from viscous to semi-solid in milliseconds. In this specific case, the command signal is a current between *0-2 A*.

In order to obtain a satisfactory vibration control of a given structure, it is necessary that the actuators perform inside a set of strict performance criteria, such as response time and robustness versus uncertainties. The output force generated by these dampers is required to be maintained into specific limits, as not to induce instability into the structure. Therefore, a control loop for the actuator is required. In this paper, a magnetorheological damper (figure 1) is controlled via a geno-fuzzy hybrid controller.

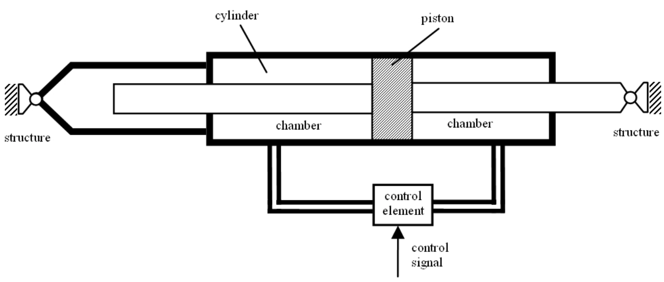

Figure 1. Magnetorheological damper.

A MR (magnetorheological) damper is analyzed. Due to uncertainties in modeling of the damper, a two velocity domain approximation is performed. The behavior of the semi-active MR damper used in this paper has is given by [10]:

$$\begin{cases} f = c_0\dot{x} + \alpha z \\ \dot{z} = -\gamma|\dot{x}|z|z|^{n-1} - \beta\dot{x}|z|^n + A\dot{x} \\ \alpha = \alpha_a + \alpha_b u \\ c_0 = c_{0a} + c_{0b}u \\ \dot{u} = -\eta(u - v) \end{cases} \tag{1}$$

where f is the force generated by the damper, u is the command signal and v is the command voltage. The control element is modeled by the fourth equation with first order dynamic. This research makes use of the following parameter values [11]: c_{0a} = 0.0064 Ns/cm, c_{0b} = 0.0052 Ns/cmV, a_a = 8.66 N/cm, a_b = 8.86 N/cmV, $\gamma = 300\text{cm}^{-2}$, $\beta = 300\text{cm}^{-2}$, A = 120, n = 2 and $\eta = 80\text{s}^{-1}$.

B. Structure Model

The damper is considered to be mounted in the base of a building. Thus, the equation used to describe a structural system with a damper that is subject to earthquake disturbances is:

$$M\ddot{x} + C\dot{x} + Kx = F_d + F_u \tag{2}$$

where x is a vector containing the displacements x_i of each story, F_d is the force induced by the earthquake and F_u is a vector containing the control forces for each story. Due to physical connection of each damper, this vector consists of pairs of control forces, equal in value, but in opposing directions, each pair corresponding to one damper. M, C and K are mass, damping and stiffness matrices, respectively, as follows: M is a diagonal matrix that contains the stories' masses, C and K are tri-diagonal matrices describing the codependency between adjacent stories [12].

C. Semi-Active Vibration Control

Semi-active vibration control allows the damping system behaves as a passive one while the structural vibration remains in specified constraints, otherwise the control is active. Advantages of these type of actuators show low costs and little need for auxiliary power sources. Semi-active dampers can efficiently respond with precision, to strong wind or damaging earthquakes. The necessary control forces are generated based on the information received from the sensor distribution throughout the structure. The performance levels are comparable to the ones offered by active control strategies, without their major drawbacks and with minimal risk to generate unstable behaviour. The principle of the semi-active control is presented in the figure 2. Earthquake induced ground motion information is submitted to a switch module which disables or enables the passive and active modes accordingly.

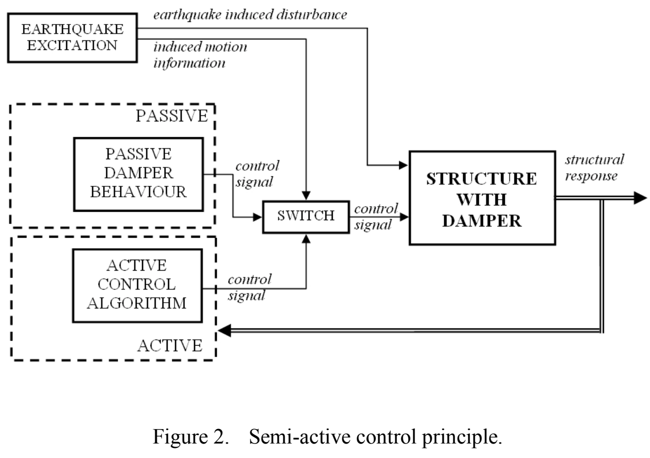

Figure 2. Semi-active control principle.

III. PROPOSED CONTROL STRATEGY

Fuzzy sets are generally used to reflect vague information of the real world environment. Due to model nonlinearities and uncertainties, it is difficult to accurately describe the structural response or even the damper behavior. Nevertheless, fuzzy logic presents a viable solution, its main advantage being high performance when dealing with non-linear systems and vague information.

To this extent, the fuzzy controller implemented in this paper is constructed with a set of rules that would have been extracted from human experience. The authors propose an evolutionary learning strategy for the fuzzy controller. Because of the non-linear nature of these controllers, genetic algorithms (GAs) are used for tuning the existing "knowledge" of the fuzzy controller. The general strategy is presented in [13]. Figure 3 illustrates the control architecture proposed in this paper, where: x is the displacement of the structure; $\dot{x}$ and $\ddot{x}$ are the velocity and acceleration of the structure, respectively; F is the control force; i is the command current, , i_P is the passive command current, i_A is the active command voltage; I is the performance index for the genetic algorithm; Φ represents a vector containing the fuzzy controller parameters that are optimized via genetic algorithm; a and v are the earthquake induced ground acceleration and velocity, respectively.

The proposed strategy is structured on two levels. One level deals with damper control and building displacement reduction, while the other level deals with tuning the implemented fuzzy controller. The scheme functions online only through the first level, GA tuning being an offline procedure. The output is a generated control force. The main loop implements a hybrid geno-fuzzy controller.

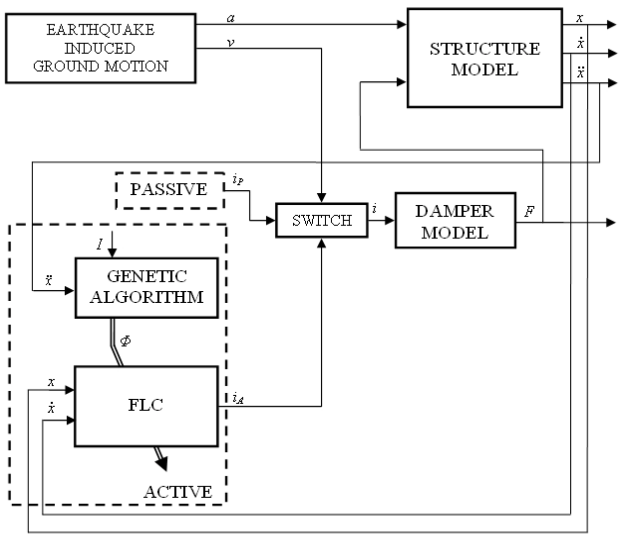

Figure 3. The proposed control architecture.

Fuzzy logic controllers (FLCs) make use of linguistic terms to describe process variables. The main characteristic of fuzzy systems is the use of vague notions instead of crisp numerical values. The linguistic information is represented through words like *small*, *medium*, *large* etc, and makes for a valuable tool in control systems design when the numerical information is incomplete. A FLC is comprised of a fuzzification module, a rule base, an inference mechanism, and a defuzzification module. The fuzzification module transforms the crisp variable into their vague counterparts, while the defuzzifier performs the inverse operation, allowing the controller to generate commands that are compatible with the real life plant. The inference mechanism retrieves the rules from the rule base according to the current inputs of the controller.

Genetic algorithms (GAs) are evolutionary optimization algorithms, also suited for searching problems, specifically when the solution pool is vast and the information is little. GAs are able to perform multi-dimensional searches, even in conditions of uncertainty, and impartial to the strictness of the constraints. The main steps of a GA [14] require first an initialization of the solution pool, knows as a population. Then, for each generation, each individual is evaluated based on a problem-specific fitness function and thus is either selected or eliminated from the current population, followed by a recombination of the selected individuals. The loop repeats until a termination condition is met, either considering a maximum number of generations, or a specified population fitness. The fitness function models the objective of the algorithm, its purpose being the rejection of unfit/unwanted solutions from the gene pool.

The genetic learning of fuzzy controllers is a fine tuning procedure for the parameters of the latter. The procedure requires two steps. First, an algebraic model (AM) for the fuzzy controller is obtained, by fitting a non-linear function over the fuzzy input-output dependency using GAs. Next, the AM's coefficients are tuned in closed loop in order to obtain a better system response, again by means of GAs. The structure of a hybrid geno-fuzzy controller is presented in figure 4, pointing out the inputs and outputs of the closed loop tuning genetic algorithm.

The algebraic model (AM) of the FLC has the following general structure:

$$\delta = \sum_{i=1}^{N} \frac{f_{i0} + f_{i1} \cdot \varepsilon + f_{i2} \cdot d\varepsilon}{f_{i3} + f_{i4} \cdot \varepsilon + f_{i5} \cdot d\varepsilon} \tag{3}$$

where δ is the controller output (command), ε is the control deviation between the setpoint and the system's output, $d\varepsilon$ is the derivative of ε, and N is the number of terms in the AM, dependant on the complexity of the designed FLC.

The parameters f in the model represent the algebraic model coefficients. In order to find the AM coefficients, a GA was implemented that minimizes a performance index I as the sum of the square errors between the AM output δ and the actual fuzzy controller output.

Further tuning of the AM is required, by means of GA. This time around, the GA searches the adjiacent space of the previously found solutions in order to obtain a better performance from the control system. Since the AM has numerical coefficients, the tuning procedure is much faster than if human operator would apply modifications to the fuzzy membership functions or rulebase.

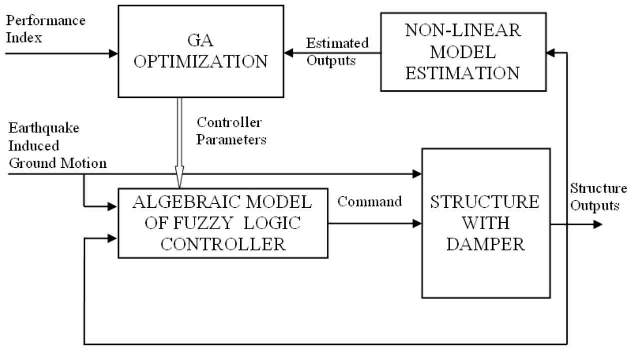

Figure 4. Geno-fuzzy controller.

IV. CASE STUDY

The case study presented here implements the proposed control architecture and analyzes the hybrid geno-fuzzy controller's performance in conditions of model uncertainties and external disturbances. The authors considered a base mounting of the MR damper. Since the destructive effect of the earthquake is a result of its horizontal vibrational components, the vertical load on the ground story is not taken into account, and all spring and damper structural elements are considered in a horizontal direction. The masses cover both the floors and the associated walls.

This paper implements a geno-fuzzy control strategy for seismic vibration mitigation. Considering non-linearities and model uncertainties, the authors approached a hybrid geno-fuzzy controller, which was included in a semi-active control strategy. The fuzzy controller input variables are the displacement and velocity of the structure and the output is the command voltage used for the elecrohydraulic damper. The discourse universes for each input variable are normalized to [-1, 1], while the output is generated in the interval [0, 5]. The scaling factors used were obtained by analyzing the structure output. The input and output variables and the rulebase are presented in figure 5, in which all membership functions are triangular, with a 50% overlap. The linguistic terms are coded as follows: E - displacement (deviation from zero), D - velocity (derivative of first input), C - command (output), N - negative, P- positive, L - large, M - medium, S - small, Z - zero.

disp. / vel.	ELN	EMN	ESN	EZ	ESP	EMP	ELP
DLN	CPL	CPL	CPM	CPS	CZ	CZ	CZ
DMN	CPL	CPL	CPM	CPS	CZ	CZ	CZ
DSN	CPL	CPM	CPS	CZ	CZ	CPS	CPM
DZ	CPM	CPM	CPS	CZ	CPS	CPM	CPM
DSP	CPM	CPS	CZ	CZ	CPS	CPM	CPL
DMP	CZ	CZ	CZ	CPS	CPM	CPL	CPL
DLP	CZ	CZ	CZ	CPS	CPM	CPL	CPL

Figure 5. Rulebase of the fuzzy controller.

The control methods described above have been simulated together with a 3-story structure. For the design of the hybrid geno-fuzzy controller, the structure is modeled as a system which integrates the damper in its base (figure 6).

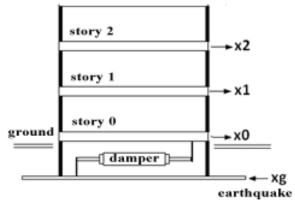

Figure 6. Base isolation of the structure.

The three story building has the following parameters:

$$\begin{cases} M = \begin{bmatrix} 98.3 & 0 & 0 \\ 0 & 98.3 & 0 \\ 0 & 0 & 98.3 \end{bmatrix} [kg] \\ C = \begin{bmatrix} 175 & -50 & 0 \\ -50 & 100 & -50 \\ 0 & -50 & 50 \end{bmatrix} [Ns/m] \\ K = 10^5 \begin{bmatrix} 12 & -6.84 & 0 \\ -6.84 & 13.7 & -6.84 \\ 0 & -6.84 & 6.84 \end{bmatrix} [N/m] \end{cases} \quad (4)$$

Details of this model are given in [15].

A set of evaluation criteria [8] has been chosen:

$$\begin{cases} J_1 = \dfrac{\max|x_i(t)|}{x_{open}} \\ J_2 = \dfrac{\max|d_i(t)|}{d_{open}} \\ J_3 = \dfrac{\max|\ddot{x}_i(t)|}{\ddot{x}_{open}} \end{cases} \quad (5)$$

where $x_i(t)$, $\ddot{x}_i(t)$ are the relative displacement, acceleration of the *i*-th story, while $d_i(t)$ is the interstory drift and the notation *open* designates the overall maximum absolute displacements, accelerations and drifts of the uncontrolled structure.

The control system of the MR damper is simulated by means Matlab (Simulink). Figure 8 presents the response of the MR damper-structure system when excited with an earthquake input signal (Northridge 1994 - the earthquake accelerogram is presented in figure 7), controlled with the geno-fuzzy controller vs. the uncontrolled response of the ground story. The performance criteria is to reduce ground story movement.

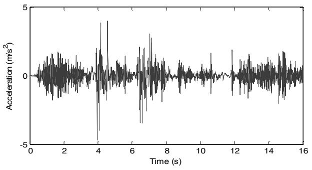

Figure 7. Northridge earthquake accelerogram.

For the fuzzy controller designed, the maximum controlled displacement and acceleration was observed to be 15.22% lower than for the open loop simulation.

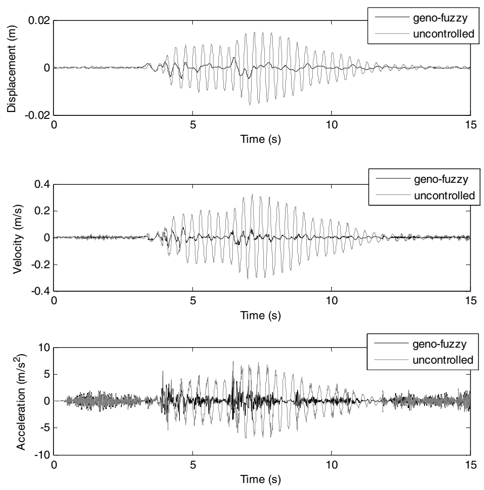

Figure 8. Comparative base structural responses: geno-fuzzy.

The fuzzy logic controller (FLC) designed in this paper has a set of rules, with a rule base created based on human experience. The AM obtained in this paper is:

$$\delta = \frac{0.113 + 0.415 \cdot d + 0.743 \cdot v}{-0.4 + 0.843 \cdot d + 0.167 \cdot v} + \frac{0.005 + 0.86 \cdot d + 0.434 \cdot v}{0.02 + 0.054 \cdot d + 0.7 \cdot v} + \frac{-0.88 \cdot d \cdot v}{0.04 - 0.4 \cdot d - 0.9 \cdot v} \quad (6)$$

where v is the velocity, ε is the deviation and $d\varepsilon$ is the difference of the deviation at two consecutive time samples as inputs of the controller, δ is the output, a current between 0 and 5 V, with a performance index $I = 0.0039$.

Equation (6) presents an approximate model for the FLC. Further tuning of the AM parameters is necessary. Using GA optimization once more, the model for the fuzzy controller is:

$$\delta_{tuned} = \frac{0.113 - 0.28 \cdot d + 0.74 \cdot v}{-0.4 + 0.83 \cdot d + 0.167 \cdot v} + \frac{0.764 + 0.4 \cdot d + 0.464 \cdot v}{0.02 + 0.054 \cdot d + 0.7 \cdot v} + \frac{0.75 \cdot d \cdot v}{0.04 - 1.03 \cdot d + 0.02 \cdot v} \quad (7)$$

with a performance index of $J = 0.0087$ (J is computed as the normalized sum of square acceleration deviations in closed loop).

The responses of the system using both the AM and the tuned geno-fuzzy controllers, versus the uncontrolled structural responsem show an acceleration reduction of the ground story of 39.25% for the tuned controller relative to the uncontrolled system and 37.5% for the AM controller relative to the uncontrolled system.

Further validation of the hybrid geno-fuzzy controller has been obtained by using a different set of external disturbances: the Vrancea 1977 earthquake accelerogram is presented in figure 9.

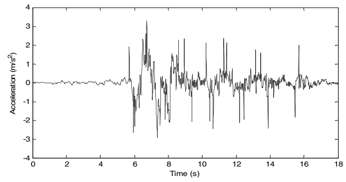

Figure 9. Vrancea earthquake accelerogram.

Results for each case are presented in Table I, for the following cases: using the fuzzy controller, using the algebraic model of the fuzzy controller and finally using the tuned geno-fuzzy controller. A comparative analysis of the proposed control strategy has been performed, using bang-bang and skyhook controllers [16]. Although these two controllers offer a good displacement reduction, their effect on the acceleration of the building is massive, adding up to 63% acceleration. In opposition, the geno-fuzzy controller reduces both acceleration and displacements, as well as inter-story drifts.

TABLE I. PERFORMANCE EVALUATION

Disturbance	Controller	J_1	J_2	J_3
Northridge	Fuzzy	1.2419	1.2385	1.3227
	AM	0.9032	0.8979	1.0433
	Geno-Fuzzy	0.4729	0.4373	0.6317
	Bang-bang	0.1770	0.1570	1.5442
	Skyhook	0.7772	0.8101	1.6285
Vrancea	Fuzzy	1.3022	1.3541	1.2934
	AM	0.7802	0.7995	0.7563
	Geno-Fuzzy	0.5989	0.5959	0.7470
	Bang-bang	0.1760	0.1455	1.3737
	Skyhook	0.9076	0.9540	1.4363

For the Northridge earthquake, the tuned hybrid geno-fuzzy controller offers the best performances: 39.25% acceleration reduction, 75.32% velocity reduction and 70.1% displacement reduction. For the Vrancea earthquake, the hybrid geno-fuzzy controller offers the best performances: 12.6% acceleration reduction, 33.3% velocity reduction and 7.8% displacement reduction.

Figures 10 and 11 show the displacements, the inter-story drifts and the accelerations on each story, for the Northridge and Vrancea earthquakes, respectively. The designed geno-fuzzy controller offers a good performace for an earthquake with a maximum displacement amplitude approximately 4.5 times greater than the one it was originally designed for: maximum displacement for the Northridge earthquake is 27.9mm, while the maximum displacement for the Vrancea earthquake is 124.6mm. It was thus shown that the designed geno-fuzzy controller can still offer acceptable performances in conditions of high uncertainties regarding the seismic magnitude of the region for which the controller is meant to be implemented.

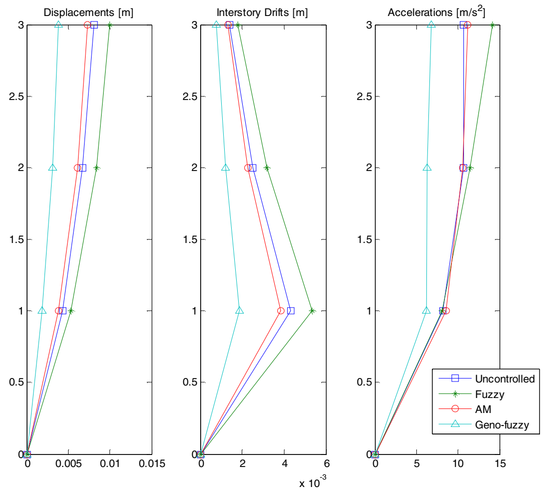

Figure 10. Maximum displacements, inter-story drifts and accelerations for the Northridge earthquake.

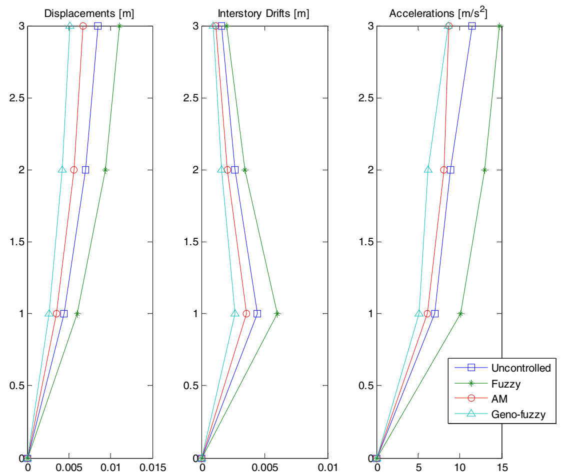

Figure 11. Maximum displacements, inter-story drifts and accelerations for the Vrancea earthquake.

The total computing time, including generating the algebraic model and the subsequent tuning procedure, is between 50 and 60 seconds, using an Intel Pentium Dual CPU 2.16 GHz processor. Through optimization of the GA code on a dedicated processor, the total computing time can be significantly reduced, thus making possible the real-time implementation of the geno-fuzzy tuning procedure.

V. CONCLUSIONS

By means of genetic algorithms, the learning capabilities of a fuzzy logic controller have been enhanced. The designed hybrid geno-fuzzy controller offered better performance than the equivalent fuzzy controller.

Moreover, by changing the basic implementation form of the fuzzy controller from a heterogenic entity to an algebraic model, the computing time decreases exponentially, making the obtained geno-fuzzy controller easy to implement without removing its non-linear essence.

The proposed geno-fuzzy hybrid controller can offer improved performance and increased implementability in real life buildings.

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