

Semi-active fuzzy based control system for vibration reduction of a SDOF structure under seismic excitation

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(Received November 26, 2017, Revised November 11, 2017, Accepted March 9, 2018)

Abstract. This paper presents the application of a semi-active fuzzy based control system for seismic response reduction of a single degree-of-freedom (SDOF) framed structure using a Magnetorheological (MR) damper. Semi-active vibration control with MR dampers has been shown to be a viable approach to protect building structures from earthquake excitation. Moreover, intelligent damping systems based on soft-computing techniques such as fuzzy logic models have the inherent robustness to deal with typical uncertainties and non-linearities present in civil engineering structures. Thus, the proposed semi-active control system uses fuzzy logic based models to simulate the behavior of MR damper and also to develop the control algorithm that computes the required control signal to command the actuator. The results of the numerical simulations show the effectiveness of the suggested semi-active control system in reducing the response of the SDOF structure.

Keywords: structural control; fuzzy logic based control; semi-active system; MR damper

1. Introduction

As is well-known, structural control systems are designed to reduce or mitigate the response and damage in civil engineering structures. Over the last decades many passive, active, semi-active and also hybrid control systems have been studied for wind and seismic protection of building and bridge structures. Among them, semi-active control systems based on “smart” damping devices such as MR dampers have shown to be a promising technology for civil engineering applications due to their perceptible advantages over passive and active control methods, in particular low power requirements and the adaptability of fully active systems (Carlson 2007, Bana *et al.* 2012).

On the other hand, soft-computing techniques such as fuzzy logic systems seem to be adequate to develop control systems to handle the inherent non-linear and/or uncertain behavior of civil structures (Casciati and Rossi 2003, Choi *et al.* 2004, Wilson and Abdullah 2005). The application of these soft-computing techniques also allows for the development of model free control systems, i.e., they no longer require an exact mathematical model of the structural system to determine the desired control action. In fact, fuzzy control does not need an accurate model of the system, which can be represented by a set of fuzzy variables and fuzzy rules (Casciati *et al.* 1996, Casciati *et al.* 1999, Faravelli and Rossi 2000, 2002, Askari *et al.* 2016). However, establishing reasonable fuzzy rules is a very

challenging task mainly because there is no systematic method to define those rules. Fuzzy rules can be defined using human reasoning based only on the knowledge about the dynamics of the system, or can be optimized by using learning/searching techniques (Jang and Sun 1997, Passino and Yurkovich 1998, Braz-César and Barros 2015a,b, Huang *et al.* 2009, Wang and Wu 2009, Ghaffarzadeh 2013, Pourzeynali *et al.* 2016).

This paper presents a semi-active fuzzy based control approach to reduce the vibration of a SDOF structure equipped with a MR damper. These actuators present a highly non-linear behavior that should be replicated using a precise numerical model. In this case, a neuro-fuzzy optimized model will be used to reproduce the hysteretic behavior of the MR damper. This type of actuators can be operated as passive devices or as semi-active systems in which the damping level of the MR damper can be modified in accordance with the system response. In this study, the damping force is determined by means of a fuzzy based control algorithm that computes the required control action providing a continuous control instead of the bi-state type control offered in typical controllers. The proposed control approach provides a model-free and robust control strategy that can be used to reduce the response of civil structures subjected to seismic loading. The numerical results have demonstrated that the proposed fuzzy based control system is effective in reducing seismic-induced vibrations of the SDOF structure equipped with a MR damper and therefore it is suitable for semi-active structural control applications.

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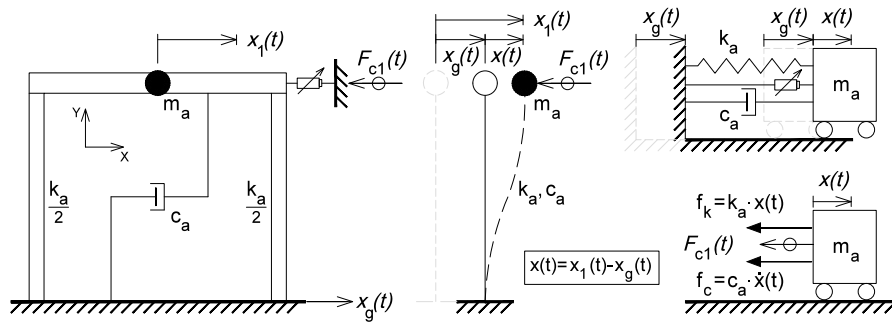


Fig. 1 SDOF control system under seismic loading

2. Numerical model

The numerical simulation are carried out using a one story shear frame excited by a seismic ground motion as shown in Fig. 1.

The system represents a SDOF structure with the following properties: $m=1000$ kg; $k=404200$ N/m and $\zeta=0.02$. The structure is subjected to the 1940 El-Centro earthquake ground motion (N-S component with a peak acceleration of 3.42 m/s²). The time was scaled to 50% of the full-scale earthquake time history as shown in Fig. 2.

The equation of motion of the SDOF system can be written as

$$m\ddot{x}(t) + c\dot{x}(t) + kx(t) = f_c(t) - m\ddot{x}_g(t) \quad (1)$$

where $f_c(t)$ is the control force of a generic actuator and $\ddot{x}_g(t)$ is the ground excitation (earthquake acceleration). Using a state space formulation, Eq. (1) can be rewritten as

$$\dot{z}(t) = Az(t) + Bf_c(t) + F\ddot{x}_g(t) \quad (2)$$

in which $z(t) = \{x(t), \dot{x}(t)\}$ is the state space vector and

$$A = \begin{bmatrix} 0 & 1 \\ -k/m & -c/m \end{bmatrix}, \quad B = \begin{bmatrix} 0 \\ 1/m \end{bmatrix}, \quad F = \begin{bmatrix} 0 \\ -1 \end{bmatrix} \quad (3)$$

The motion of the mass can be defined by the absolute displacement $x_1(t)$. The relative displacement between the mass and the ground is given by $x(t) = x_1(t) - x_g(t)$, where $x_g(t)$ represents the absolute displacement of the ground. The system response is given the state space output vector

$$y(t) = Cz(t) + Df_c(t) + E\ddot{x}_g(t) \quad (4)$$

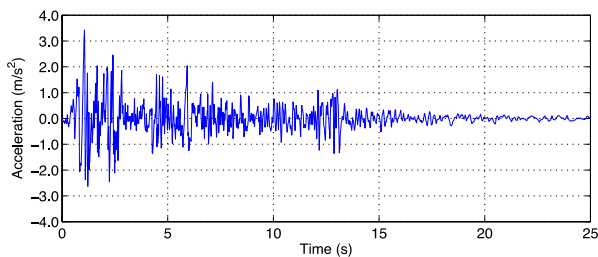


Fig. 2 El-Centro earthquake ground motion (N-S component scaled by 0.5t)

where

$$C = \begin{bmatrix} 1 & 0 \\ 0 & 1 \\ -k/m & -c/m \end{bmatrix}, \quad D = \begin{bmatrix} 0 \\ 0 \\ 1/m \end{bmatrix}, \quad E = \begin{bmatrix} 0 \\ 0 \\ -1 \end{bmatrix} \quad (5)$$

In this study, the control force is produced by a MR damper located between the ground and the first floor (mass). The viscosity of the MR fluid inside the damper can be controlled changing the input current applied to an electromagnet in the piston rod. Hence, the damper can be operated as a passive device when a constant current is applied or as a semi-active actuator when a controllable operating current is used to drive the electromagnet within the damper (Spencer *et al.* 1997).

3. Semi-active fuzzy logic control system

The main objective of this study is to use fuzzy logic systems to develop a semi-active control system. The fuzzy based theory is used to construct a numerical model of the MR damper and also to design a semi-active controller to drive the actuator based on the system response. Due to the non-linear hysteretic behavior of the MR damper, the fuzzy model of the actuator was obtained using an Adaptive Neuro-Fuzzy Inference System (ANFIS) while the semi-active controller was defined explicitly using simple human reasoning (Braz-César and Barros 2016).

3.1 Fuzzy model of the actuator

The present section describes the application of ANFIS to develop a neuro-fuzzy model for a MR damper (RD-1005-3 model by Lord, USA). The mechanical simplicity of MR dampers represents a considerable advantage to design reliable semi-active control systems. However, its complex hysteretic behavior hinders the development of simple numerical models. Fuzzy logic models represent an appropriate approach to deal with such non-linear systems. In this regard, neuro-adaptive learning technique such as ANFIS presents the advantage of providing automatic tuning of fuzzy inference systems (FIS) to model the relationships of the input variables and their important parameters. This approach uses a hybrid learning algorithm

that combines the backpropagation gradient descent and least squares methods to create a fuzzy inference system whose membership functions are iteratively adjusted according to a given set of input and output data (Jang *et al.* 1997, Kim *et al.* 2006). The development of a neuro-fuzzy model typically involves four main steps:

1. Definition of input variables and the corresponding fuzzy inference system (FIS) membership functions (the FIS output is the desired output signal);
2. Selection of experimental or artificial data sets to generate training and checking data;
3. Use of ANFIS optimization algorithm for training the FIS membership function parameters to model the set of input/output data by mapping the relationship between inputs and outputs in order to generate a fuzzy model of the systems;
4. Validation of the resulting fuzzy model.

The process begins by obtaining a training data set and checking data sets. The training data is used to find the premise parameters for the membership functions (MFs are dependent on the system designer). A threshold value for the error between the actual and desired output is determined. The consequent parameters are found using the least-squares method. If this error is larger than the threshold value, then the premise parameters are updated using the gradient decent method. The process end when the error becomes less than the threshold value.

Checking data set can then be used to compare the model with the actual system. The fuzzy model is obtained after ANFIS training process and is based on the training data, training options and type/number of membership functions previously defined by the user.

In this case, it is intended to optimize a fuzzy inference system by training a family of membership functions according to a predetermined input and output data set related with the damper behavior. Thus, the piston displacement and velocity, and the operating current represent the three fuzzy variables assigned to the input membership functions and the damper force represents the fuzzy output variable. Generalized bell-shaped membership functions are used to represent the input variables. The fuzzy parameters assigned to each fuzzy input variable, i.e., the properties of the selected membership functions are summarized in Table 1.

Table 1 Fuzzy MFs parameters (RD-1005-3 MR damper by Lord, USA)

Data	Fuzzy variable	Type	No. of MFs	Universe of discourse*
Input MFs	Piston displacement	Generalized bell-shaped	2	$[-\dot{x}_{\max}, \dot{x}_{\max}]$ with $\dot{x}_{\max}=20$ mm
	Piston velocity		4	$[-\dot{x}_{\max}, \dot{x}_{\max}]$ with $\dot{x}_{\max}=18$ cm/s
	Operating current		3	$[0, I_{\max}]$ with $I_{\max}=1.00$ A

* For a normalized universe of discourse

The fuzzy model was developed from the numerical results of the modified Bouc-Wen model (Spencer *et al.* 1997) which in turn was developed from experimental data obtained from several experimental tests (Braz-César and Barros 2012). The training data should cover those ranges of values with a comprehensible data set over the entire spectrum operation of the MR damper. A series of training sequences comprising five types of artificial displacement sequence inputs were used to generate the data set for training the fuzzy inference system of the proposed numerical based fuzzy model. Constant displacement (CD), triangular wave (TW), amplitude-modulated (AM) and frequency-modulated (FM) are the displacement sequences used to represent the MR damper dynamics and the hysteresis behavior under changes in the magnitude and frequency of excitation for stepped increments of the operating current level.

The fuzzy model was obtained after an iterative trial and error process to determine the appropriate number of membership functions and the corresponding training parameters. Several training parameters (number of epochs, initial step size, error tolerance, etc.) must be defined before starting the learning process. The ANFIS training options used in the present study are given in Table 2.

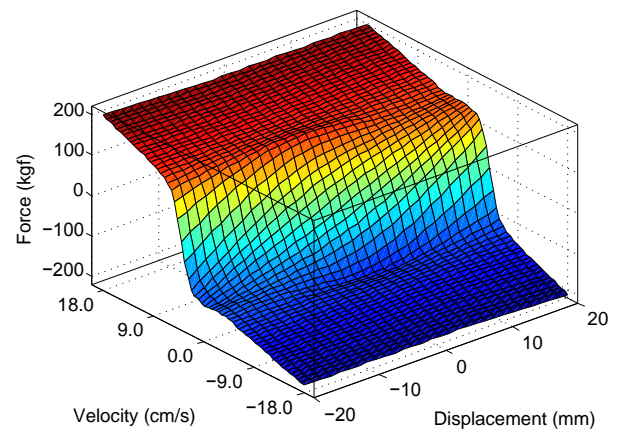


Fig. 3 ANFIS estimated fuzzy surfaces $f_c(x-\dot{x})$

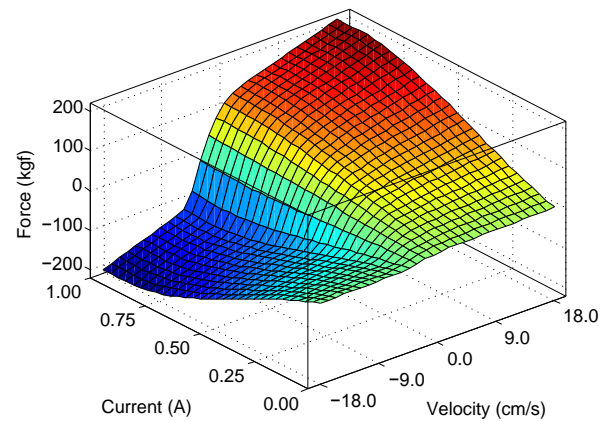


Fig. 4 ANFIS estimated fuzzy surfaces $f_c(\dot{x}-I)$

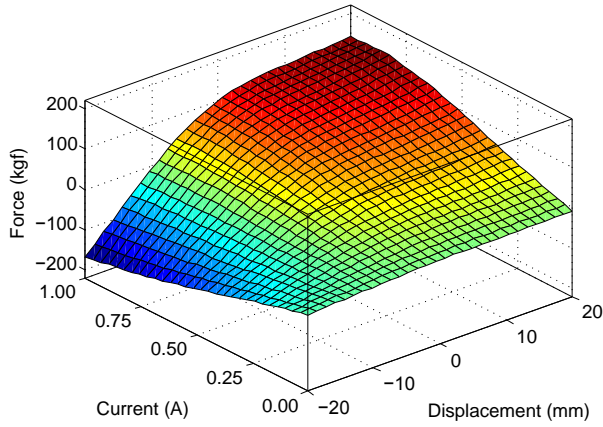
Fig. 5 ANFIS estimated fuzzy surfaces $f_c(x-l)$

Table 2 ANFIS optimization parameters

No. of epochs	Initial step size	Increasing step size	Decreasing step size	Error tolerance
200	0.10	1.20	0.80	0.1

The resultant fuzzy surfaces for the trained FIS model representing the relationship between the inputs and output are shown in Fig. 3 to Fig. 5. The resultant mapping surfaces highlights the highly non-linear relationship between the damping force and the piston displacement and velocity. Besides it can be seen that increasing the operating current level will increase the resultant damping force of the MR damper.

3.2 Fuzzy model of the controller

The fuzzy controller is developed to determine the control current to command the MR damper. Hence, the controller computes directly the required control current signal providing a continuous control instead of the bi-state type control offered by typical controllers.

The fuzzy controller requires the definition of input variables to compute the required control action. In this case, floor displacements and velocities will be used as the fuzzy input variables. The universe of discourse or range of the membership functions can be normalized or defined as the minimum and maximum expected values for each fuzzy input/output. In this last case, fuzzifiers and defuzzifiers (scale factors) are used to adjust the variables to the universe of discourse of the fuzzy controller. In this study, the maximum floor displacement and velocity for the passive off mode (MR damper without applied current) are used to define the basic domain for these variables. The universe of discourse of the current is the current range of the MR damper ($I_{\max} = 1.0\text{A}$). The inputs, outputs and the corresponding scale factors are summarized in Table 3.

To control of the MR damper with voltage output, seven membership functions were chosen for both of the two inputs, i.e., displacement and velocity $\{NL, NM, NS, ZO, PS, PM, PL\}$ and four membership functions were considered for the control voltage output $\{ZO, PS, PM, PL\}$

where these labels stands for NL is Negative Large, NM is Negative Medium, NS is Negative Small, ZO is Zero, PS is Positive Small, PM is Positive Medium and PL is Positive Large. To compute the degree of membership, the input membership functions were defined by seven identical triangles (50% overlap) as shown in Fig. 6.

The output MFs are presented in Fig. 7. As can be seen, four triangular functions with the same overlapping as the previous ones were used. Observing the structure of the output variable it is clear that this controller will allow intermediate levels of operating current instead of the traditional bi-state control algorithm, i.e., a step control signal which will switch on and off the current supplied to the MR damper at any instance.

The next stage requires the definition of the rules that combine the input variables to obtain a specific output variable. Simple logic reasoning is used to define the FIS: if the structure is moving away from its neutral position, then the current should be progressively increased. When the structure is moving towards the neutral position, little or no current needs to be provided. This simple reasoning allows defining a “human-designed” inference rule system shown in Table 4.

Table 3 Control parameters and scale factors

Type	Description	Range	Fuzzifier*
Inputs	Floor displacement	$[-x_{\max}, x_{\max}]$ with $x_{\max} = 0.022\text{ m}$	$K_d = 85.0$
	Floor velocity	$[-\dot{x}_{\max}, \dot{x}_{\max}]$ with $\dot{x}_{\max} = 0.42\text{ m/s}$	$K_v = 4.0$
Outputs	Control current	$[0, I_{\max}]$ with $I_{\max} = 1.00\text{ A}$	$K_c = 0.625$

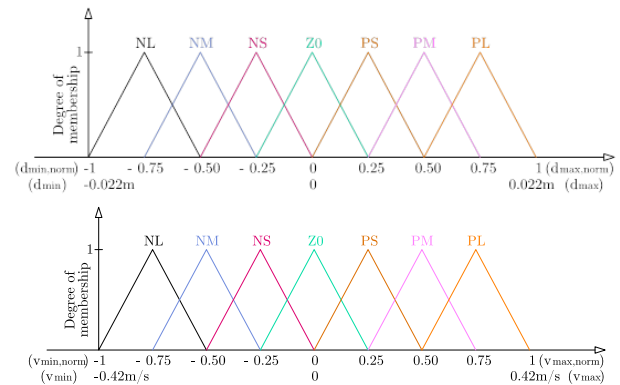


Fig. 6 Displacement and velocity fuzzy variables (input)

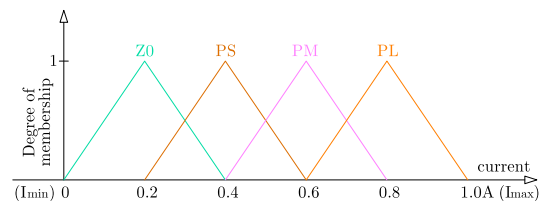


Fig. 7 Output fuzzy variable (control signal)

Table 4 Inference fuzzy rules matrix (proposed fuzzy logic controller)

Inputs		Velocity						
		NL	NM	NS	ZO	PS	PM	PL
Displacement	NL	PL	PL	PL	PM	ZO	ZO	ZO
	NM	PL	PL	PL	PS	ZO	ZO	PS
	NS	PL	PL	PL	ZO	ZO	PS	PM
	ZO	PL	PM	PS	ZO	PS	PM	PL
	PS	PM	PS	ZO	ZO	PL	PL	PL
	PM	PS	ZO	ZO	PS	PL	PL	PL
	PL	ZO	ZO	ZO	PM	PL	PL	PL

The output signal must be a crisp value that could actually be applied to the MR damper. Thus, the fuzzy information must be defuzzified and in this case the center of gravity method (COG) was used to obtain the control current output (limited to 0.5A). The fuzzification factor K_c adjusts the FIS output to the desired maximum value of the control signal.

4. Numerical simulation

A set of numerical simulations were carried out to obtain the response of the SDOF system equipped with the MR damper. The Simulink model of the proposed semi-active fuzzy based control system is shown in Fig. 8. The damper force and the corresponding control signal times histories obtained with the proposed fuzzy based control approach are shown in Fig. 9.

It should be noted that the fuzzy logic controller (FLC) outputs a non-zero current output ($I_{\min}=0.125\text{A}$) as the minimum operating current instead of a null value, which could be adjusted by applying an output offset and a new fuzzification factor.

The hysteretic behavior of the MR damper is shown in Fig. 10. The effect of the fuzzy control output signal in the velocity response is visible in the force-velocity plot in which the velocity scale had to be modified (*i.e.*, increased) to represent the system response.

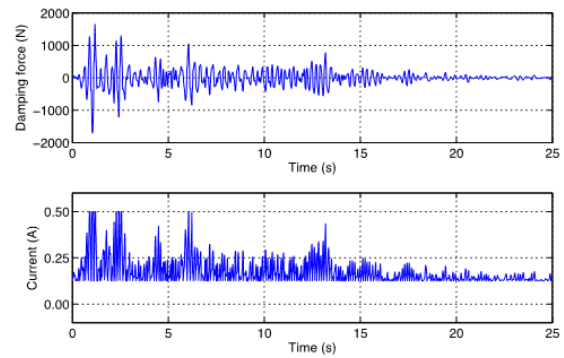


Fig. 9 Damper force and corresponding operating current

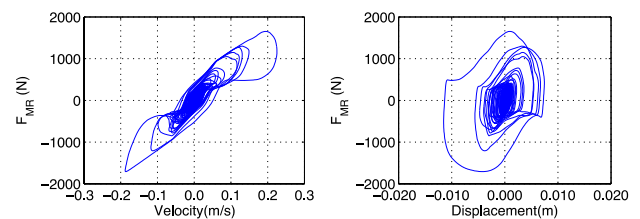


Fig. 10 Damper control force generated during the numerical simulation

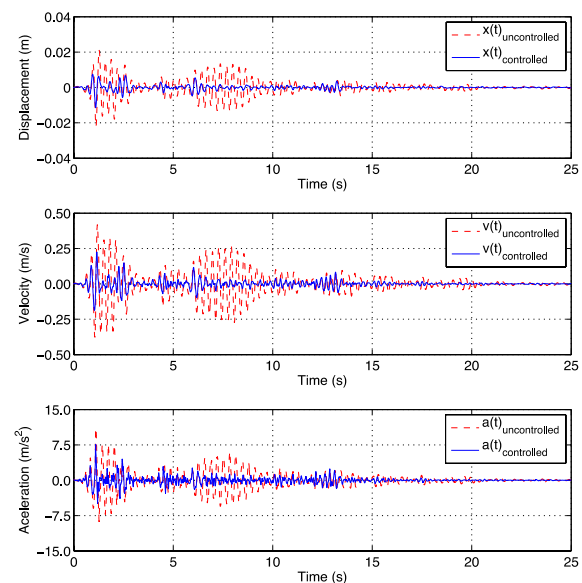


Fig. 11 Structural response obtained with the proposed fuzzy based control system

The controlled responses obtained with the proposed fuzzy control system along with the uncontrolled responses are displayed in Fig. 11.

The results show that the proposed semi-active control system is able to compute and apply the required damping force to control the response of the structural system. It can be seen that both displacement, velocity and acceleration responses are significantly reduced when compared with the uncontrolled response.

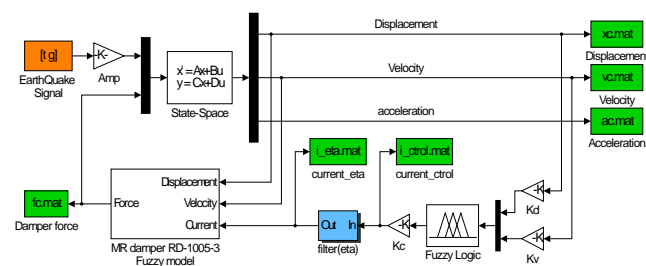


Fig. 8 Simulink model of the fuzzy based semi-active control system

Table 5 Peak responses under the time-scaled El-Centro earthquake

Control strategy	x (cm)	\dot{x} (cm/s)	\ddot{x} (cm/s ²)	f (N)
Uncontrolled	0.0221	0.4184	10.761	----
Passive OFF	0.0203	0.3859	10.511	261.5
Passive ON	0.0093	0.1573	6.8376	1542.9
Fuzzy based control system	0.0115	0.2254	7.5933	1708.2

The MR damper can be used as a passive energy dissipation device instead of a semi-active actuator. Two damping states are defined for the passive control mode: passive off mode in which no operating current is applied to the electromagnet within the MR damper (i.e., working as a typical passive device), and a passive on mode in which the maximum operating current is applied. To better evaluate the performance of the MR damper, peak responses of both uncontrolled and controlled systems are listed in Table 5.

Besides, a new set of evaluation criteria including normalized and RMS responses, and also control requirements was also used to better evaluate the effectiveness of the proposed semi-active control system (Table 6). In these equations, $|\cdot|$ denotes the absolute value and $\|\cdot\|$ is the L_2 norm.

Table 6 Evaluation criteria (normalized and RMS responses)

Evaluation criterion	Description
$J_1 = \max_{t,i} \left(\frac{ x_i(t) }{x_{\max}} \right)$	Normalized peak floor displacement relative to the ground. Where $x_i(t)$ is the relative displacement over the entire response and x_{\max} represents the uncontrolled maximum displacement
$J_2 = \max_{t,i} \left(\frac{ \dot{x}_i(t) }{\dot{x}_{\max}} \right)$	Normalized peak floor velocity relative to the ground. Where $\dot{x}_i(t)$ is the relative velocity of the floor over the entire response and \dot{x}_{\max} is the uncontrolled maximum velocity
$J_3 = \max_{t,i} \left(\frac{ \ddot{x}_i(t) }{\ddot{x}_{\max}} \right)$	Normalized peak floor accelerations relative to the ground. Where $\ddot{x}_i(t)$ is the absolute accelerations of the floor are normalized by the peak uncontrolled floor acceleration \ddot{x}_{\max}
$J_4 = \max_{t,i} \left(\frac{\ x_i(t)\ }{\ x_{\max}\ } \right)$	Maximum normed value of the floor displacement. Where $\ x_i(t)\ $ represents the normed displacement over the entire response and $\ x_{\max}\ $ is the uncontrolled maximum normed displacement
$J_5 = \max_{t,i} \left(\frac{\ \dot{x}_i(t)\ }{\ \dot{x}_{\max}\ } \right)$	Maximum normed value of the floor velocity. Where $\ \dot{x}_i(t)\ $ is the normed velocity of the floor over the entire response and $\ \dot{x}_{\max}\ $ represents the uncontrolled maximum velocity
$J_6 = \max_{t,i} \left(\frac{\ \ddot{x}_i(t)\ }{\ \ddot{x}_{\max}\ } \right)$	Maximum normed value of the floor acceleration. Where $\ \ddot{x}_i(t)\ $ is the normed acceleration of the floor over the entire response and $\ \ddot{x}_{\max}\ $ represents the uncontrolled maximum acceleration
$J_7 = \max_{t,i} \left(\frac{ f_i(t) }{W} \right)$	Measure of the maximum control force generated during the control action, normalized by the weight of the structure W (where W represents the total weight of the structure)

Table 7 Evaluation criteria for each control strategy (time-scaled EL Centro NS time history)

Control strategy	Normalized responses			Normed Responses			Control requirements
	J_1	J_2	J_3	J_4	J_5	J_6	J_7
Passive OFF	0.93	0.92	0.97	0.75	0.76	0.77	0.027
Passive ON	0.43	0.38	0.64	0.21	0.21	0.29	0.157
Fuzzy control system	0.46	0.41	0.67	0.25	0.25	0.32	0.166

The first three criteria are based on the peak displacement ratio (J_1), peak velocity (J_2) and peak floor acceleration (J_3) while the next three criteria are related with normed structural responses, i.e., the normalized peak displacement (J_4), velocity (J_5) and acceleration (J_6). The final parameter (J_7) is used to assess the performance of the actuator and is related with the peak control force. The results obtained with these criteria are shown in Table 7 (numbers in bold are reference values that represent the best solution).

It can be seen that the proposed fuzzy based control system is not as effective as using the MR damper in a passive on control mode (passive dissipation device with the maximum allowable operating current). This behavior was already expected since the structure under control is a SDOF system. Thus, increasing the damping of the actuator will increase the energy dissipation leading to a direct reduction of the motion of the mass (only one mass is being controlled in a collocated configuration, i.e., a passive device with a high damping state can be used to reduce the system response).

It is important to notice that the fuzzy logic controller was defined using human reasoning resulting in a simple and straightforward control approach. Hence, the controller could be enhanced defining new optimized membership functions or by using a learning procedure to optimize the inference rules system.

Nevertheless, the results show that the proposed fuzzy logic control approach is effective in reducing seismic-induced vibrations of a SDOF structure compared with the uncontrolled and passive control modes, although in this system the passive control on mode is slightly better than the semi-active control approach.

5. Conclusions

This paper presents the application of a fuzzy based semi-active control system to reduce the response of a SDOF structure using a MR damper. Fuzzy based models were used to define the numerical model of the MR damper and to design the semi-active controller. It was verified that the proposed control approach was able to improve significantly the structural response over the uncontrolled case. The advantage of fuzzy logic systems lies on the fact that they can be applied to highly non-linear and uncertain response systems, such as is the case of MR dampers. Nevertheless the membership functions and the application rules of the fuzzy logic controller are difficult to define

using only human-like reasoning. Thus, although the results obtained with the proposed semi-active fuzzy based control system are promising, they could be improved by optimization of the fuzzy parameters as well as applying soft computing techniques such as genetic algorithms or neural networks. Further research is required to assess the effectiveness of the proposed fuzzy control system, in particular with multi-DOF structures with several MR devices.

References

- Askari, M., Li, J. and Samali, B. (2016), "Semi-active control of smart building-MR damper systems using novel TSK-Inv and max-min algorithms", *Smart Struct. Syst.*, **18**(5), 1005-1028.
- Banna, K., Asan, G.A., Muthalif, M., Mahbubur, R. and Sharmila, F. (2012), "Fuzzy-PID controller for semi-Active vibration control using magnetorheological fluid damper", *Procedia Eng.*, **41**, 1221-1227.
- Braz-César, M. and Barros, R. (2015a), "Neuro-fuzzy modeling of a sponge-type MR damper", *Proceedings of the 5th International Conference on Computational Methods in Structural Dynamics and Earthquake Engineering* (COMPdyn 2011), Corfu, Greece, May.
- Braz-César, M. and Barros, R. (2015b), "Neuro-fuzzy control of structures using MR dampers", *Proceedings of the 13th International Conference Dynamical Systems – Theory and Applications* (DSTA2015), Lodz, Poland, December.
- Braz-César, M. and Barros, R. (2016), "Fuzzy based control and modelling of a MR damper for vibration reduction of SDOF structural systems", *Proceedings of the 5th International Conference on Integrity, Reliability and Failure*, Porto, Portugal (IRF2016), Porto, Portugal, July.
- Braz César, M. and Barros, R. (2012), "Experimental behaviour and numerical analysis of MR dampers", *Proceedings of the 15th World Conference on Earthquake Engineering*, Lisbon, Portugal, September.
- Carlson, J.D. (2007), "Semi-active vibration suppression", In *CISM Course: Semi-Active Vibration Suppression-the Best from Active and Passive Technologies*, Udine, Italy, October.
- Casciati, F. and Rossi, R. (2003), "Dynamics of structural systems with devices driven by fuzzy controllers understanding fuzzy rules", *IUTAM Symposium on Dynamics of Advanced Materials and Smart Structures*, **106** (Solid Mechanics and Its Applications), 29-40.
- Casciati, F., Faravelli, L. and Torelli, G. (1999), "A fuzzy chip controller for nonLinear vibrations", *Nonlinear Dynam.*, **20**(1), 85-98.
- Casciati, F., Faravelli, L. and Yao, T. (1996), "Control of nonlinear structures using the fuzzy control approach", *Nonlinear Dynam.*, **11**(2), 171-187.
- Choi, K., Cho, S., Jung, H. and Lee, I. (2004), "Semi-active fuzzy control for seismic response reduction using magnetorheological dampers", *Earthq. Eng. Struct. D.*, **33**(6), 723-736.
- Faravelli, L. and Rossi, R. (2000), "Fuzzy chip controller implementation", (Eds., F. Casciati and G. Magonette), *Proceedings of the 3rd International Workshop on Structural Control – Structural Control for Civil and Infrastructure Engineering*, World Scientific, Singapore.
- Faravelli, L. and Rossi, R. (2002), "Adaptive Fuzzy Control: Theory versus Implementation", *J. Struct. Control*, **9**(1), 59-73.
- Ghaffarzadeh, H. (2013), "Semi-active structural fuzzy control with MR dampers subjected to near-fault ground motions having forward directivity and fling step", *Smart Struct. Syst.*, **12**(6), 595-617.
- Huang, Z., Wu, C. and Hsu, D. (2009), "Semi-active fuzzy control of MR damper on structures by genetic algorithm", *J. Mech.*, **25**(1), 1-6.
- Jang, J., Sun, C. and Mizutani, E. (1997), *Neuro-Fuzzy and Soft Computing*, Prentice Hall Inc.
- Kim, H., Roschke, P., Lin, P. and Loh, C. (2006), "Neuro-fuzzy model of hybrid semi-active base isolation system with FPS bearings and a MR damper", *Eng. Struct.*, **28**(7), 947-958.
- Passino, K.M. and Yurkovich, S. (1998), *Fuzzy control*, Addison Wesley Longman Inc.
- Pourzeynali, S., Salimi, S., Yousefisefat, M. and Kalesar, H. (2016), "Robust multi-objective optimization of STMD device to mitigate buildings vibrations", *Earthq. Struct.*, **11**(2).
- Schurter, K.C. and Roschke, P.N. (2001), "Neuro-fuzzy control of structures using acceleration feedback", *Smart Mater. Struct.*, **10**, 770-779.
- Spencer, Jr., B.F., Dyke, S.J., Sain, M.K. and Carlson, J.D. (1997), "Phenomenological model of a magnetorheological damper", *J. Eng. Mech.*, **123**, 230-238.
- Wang, H. and Wu, H. (2009), "The neuro-fuzzy identification of MR damper", *Proceedings of the 6th International Conference on Fuzzy Systems and Knowledge Discovery*, Tianjin, China, August.
- Wilson, C. and Abdullah, M. (2005), "Structural vibration reduction using fuzzy control of magnetorheological dampers", *Proceedings of the ASCE structures congress*, New York, USA, April.

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