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ANFIS optimized semi-active fuzzy logic controller for magnetorheological dampers

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Abstract: In this paper, we report on the development of a neuro-fuzzy controller for magnetorheological dampers using an Adaptive Neuro-Fuzzy Inference System or ANFIS. Fuzzy logic based controllers are capable to deal with non-linear or uncertain systems, which make them particularly well suited for civil engineering applications. The main objective is to develop a semi-active control system with a MR damper to reduce the response of a three degrees-of-freedom (DOFs) building structure. The control system is designed using ANFIS to optimize the fuzzy inference rule of a simple fuzzy logic controller. The results show that the proposed semi-active neuro-fuzzy based controller is effective in reducing the response of structural system.

Keywords: Fuzzy logic, MR damper, Semi-active control

1 Introduction

Neuro-adaptive learning techniques represent a simple methodology for the fuzzy modeling procedure to learn information about a dataset in order to compute the membership function parameters that best allow the associated fuzzy inference system to track a given input/output data. ANFIS uses a hybrid learning algorithm that combines the back-propagation 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 [1, 2]. The schematic of ANFIS architecture is shown in Figure 1.

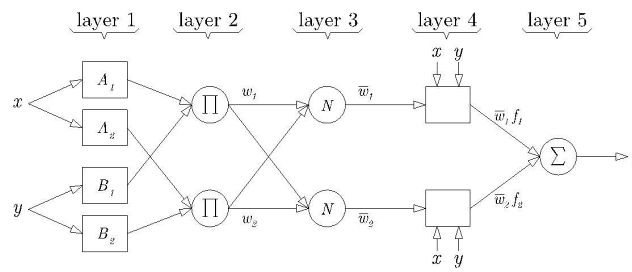

Figure 1: Adaptive Neuro-Fuzzy Inference System or ANFIS.

Soft computing methods represent a relatively recent modeling technique of control devices and controllers that have been shown to be effective in dealing with complex and non-linear behavior of structural control systems. The development of a neuro-fuzzy model for a control device or neuro-fuzzy based controller 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 control 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 descent method. The process ends when the error becomes less than the thresh-

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old value. The 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.

2 Numerical simulation

Consider a semi-active controlled system subjected to an earthquake ground motion with a control force applied to the first mass (or the first DOF, x_1) as illustrated in Figure 2. The control force provided by a MR damper intends to reduce the response of the system and can be achieved placing an actuator between the base and the first mass. The damper force can be changed using a control system comprising a controller that monitors the system response and computes the required damping force that should be applied to the system changes the system response in order to improve its structural performance. An effective semi-active control system involves an appropriate control algorithm that can take advantage of the dissipative properties of the control device, i.e., the MR damper [3, 4]. There are several approaches available in the literature to control semi-active devices including soft computing techniques such as neuro-fuzzy controllers.

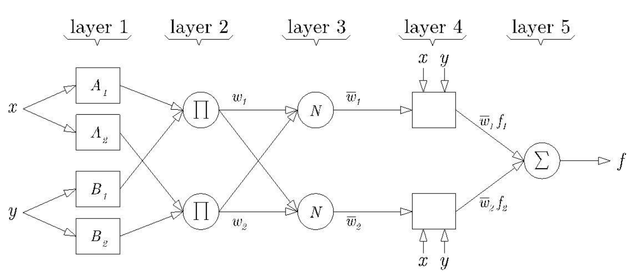

Figure 2: Schematic representation of a 3DOFs system under earthquake excitation - Semi-active control with a MR damper at the first floor.

In what follows, the results of the neuro-fuzzy semi-active control system are compared with the uncontrolled, passive OFF and passive ON responses to evaluate the efficiency of the semi-active control scheme in reducing the structural response. The mass, damping and stiffness matrices of the model structure are given by

$$M = \begin{bmatrix} m_1 & 0 & 0 \\ 0 & m_2 & 0 \\ 0 & 0 & m_3 \end{bmatrix} = \begin{bmatrix} 100 & 0 & 0 \\ 0 & 100 & 0 \\ 0 & 0 & 100 \end{bmatrix} \text{kg} \tag{1}$$

$$C = \begin{bmatrix} c_1 + c_2 & -c_2 & 0 \\ -c_2 & c_2 + c_3 & -c_3 \\ 0 & -c_3 & c_3 \end{bmatrix} = \begin{bmatrix} 175 & -50 & 0 \\ -50 & 100 & -50 \\ 0 & -50 & 50 \end{bmatrix} \text{N} \cdot \text{s/m} \tag{2}$$

$$CK = \begin{bmatrix} k_1 + k_2 & -k_2 & 0 \\ k_2 & k_2 + k_3 & -k_3 \\ 0 & -k_3 & k_3 \end{bmatrix} = \begin{bmatrix} 12 & -6 & 0 \\ -6 & 12 & -6 \\ 0 & -6 & 6 \end{bmatrix} 10^5 \text{ N/m} \tag{3}$$

In this study, the structure will be subjected to the *El Centro* ground motion (1940 N-S component with a peak acceleration of 3.42 m/s^2). Since the mechanical system seeks to represent a small-scale building, the earthquake signal needs to be decreased to represent the magnitude of displacements that would be observed in experimental tests. Thus, the time was scaled to 20% of the full-scale earthquake time history as shown in Figure 3.

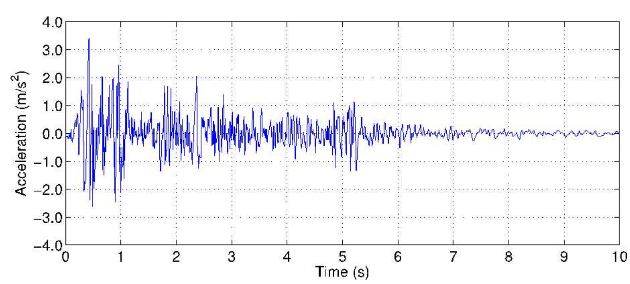

Figure 3: Time-scaled El-Centro NS earthquake ground motion (0.2 t).

The state space equation of motion is given by

$$\dot{z}(t)_{(6\times1)} = \begin{bmatrix} 0_{(3\times3)} & \mathrm{I}_{(3\times3)} \\ -\mathrm{M}^{-1}\mathrm{K}_{(3\times3)} & -\mathrm{M}^{-1}\mathrm{C}_{(3\times3)} \end{bmatrix} \begin{Bmatrix} \mathrm{X}(t)_{(3\times1)} \\ \dot{\mathrm{X}}(t)_{(3\times1)} \end{Bmatrix} + \begin{Bmatrix} 0_{(3\times1)} \\ -\lambda(t)_{(3\times1)} \end{Bmatrix} \underbrace{\ddot{x}(t)}_{\text{El Centro NS}} \tag{4}$$

where the column vector λ represents the location of the earthquake excitation (i.e., the seismic acceleration). Equation 4 can be written in a simplified form as

$$\dot{z}(t)_{(6\times1)} = A_{(6\times6)} z(t)_{(6\times1)} + E_{(6\times1)} \ddot{x}_g(t) \tag{5}$$

in which matrix A represent the system matrix

$$A_{(6\times6)} = \begin{bmatrix} 0_{(3\times3)} & \mathrm{I}_{(3\times3)} \\ -\mathrm{M}^{-1}\mathrm{K}_{(3\times3)} & -\mathrm{M}^{-1}\mathrm{C}_{(3\times3)} \end{bmatrix} \tag{6}$$

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and E is the disturbance locating vector given by

$$E_{(6\times1)} = \{0, 0, 0, -1, -1, -, 1\}^T \tag{7}$$

The response of the system can be computed using the state space output vector $y(t)$

$$y(t) = Cz(t) + Du(t) \tag{8}$$

If the system displacements, velocities and accelerations are required, then

$$C_{(9\times6)} = \begin{bmatrix} \mathrm{I}_{(3\times3)} & 0_{(3\times3)} \\ 0_{(3\times3)} & \mathrm{I}_{(3\times3)} \\ -\mathrm{M}^{-1}\mathrm{K}_{(3\times3)} & -\mathrm{M}^{-1}\mathrm{C}_{(3\times3)} \end{bmatrix},$$

$$D_{(9\times1)} = \begin{Bmatrix} 0_{(6\times1)} \\ -\lambda_{(3\times1)} \end{Bmatrix} \tag{9}$$

Using the state space formulation, the uncontrolled response of the 3DOFs system under the earthquake ground motion is displayed in Figure 4. It should be noted that the response was obtained with a high excitation level of the *El Centro* earthquake achieved by scaling up the amplitude of the earthquake signal in 150%.

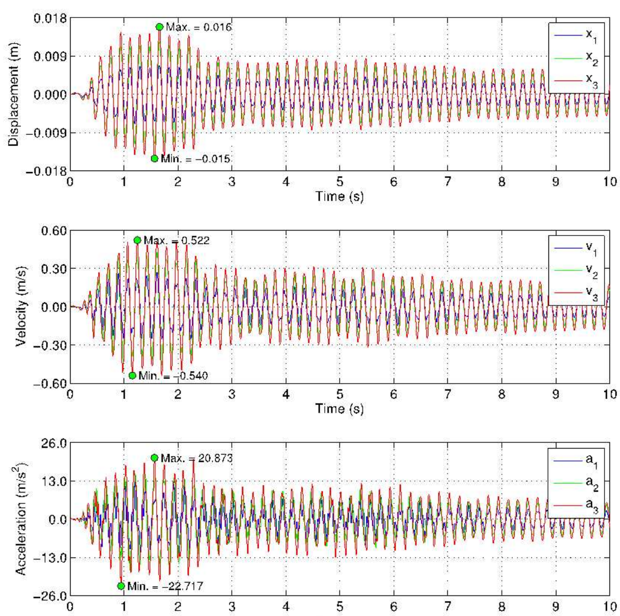

Figure 4: Uncontrolled response of the 3DOFs system.

The structure is equipped with a semi-active control system comprising a MR damper (Lord RD-1005-03 model) located between the ground floor and the first floor. The MR damper can operate in two modes:

1. As a passive energy dissipation device, i.e., without a control system (the properties of the actuator are constant during the simulation);
2. As a semi-active actuator whose control action is being commanded by a neuro-fuzzy based controller. In this case, the modified Bouc-Wen model was selected to simulate the behavior of the MR damper.

The numerical formulation and the corresponding model parameters are presented in Table 1 [5]. Besides, the first-order time lag involved in the current driver/electromagnet during a step command signal must be included in the numerical model of the device, which in this case is defined by a first order filter ($\eta = 130\ \mathrm{sec}^{-1}$).

The equation of motion of the controlled structure can be defined by a state space formulation as

$$\dot{z}(t)_{(6\times1)} = A_{(6\times6)}z(t)_{(6\times1)} + B_{c(6\times1)}f_{c1}(t) + E_{(6\times1)}\underbrace{\ddot{z}_g(t)}_{\text{El Centro NS}} \tag{10}$$

where B_c is an additional matrix accounting for the position of the control forces in the structure and f_c is a column vector with the control forces. The location of the control forces is defined by a location matrix Γ within B_c. In this case there is only one control force applied to the first mass and therefore, it follows that

$$\Gamma_{(3\times1)} = \{1, 0, 0\}^T \tag{11}$$

and then

$$B_{c(6\times1)}\left\{0, 0, 0, -\frac{1}{m_1}, 0, 0\right\}^T \tag{12}$$

Equation 10 can be written in a more compact form given that

$$B_{(6\times2)} = [B_{c(6\times1)} + E_{(6\times1)}] = \left[\begin{array}{cc} 0 & 0 \\ 0 & 0 \\ 0 & 0 \\ \hline -\frac{1}{m_1} & -1 \\ 0 & -1 \\ 0 & -1 \end{array}\right]$$

$$u(t)_{(2\times1)} = \begin{Bmatrix} f_{c1}(t) \\ \ddot{x}_g(t) \end{Bmatrix} \tag{13}$$

and finally

$$\dot{z}(t)_{(6\times1)}A_{(6\times6)}z(t)_{(6\times1)} + B_{(6\times2)} + u(t)_{(2\times1)} \tag{14}$$

The response of the system can be determined using the state space output vector

$$y(t)_{(9\times1)} = C_{(9\times6)}z(t)_{(9\times1)} + D_{c(9\times1)}f_c + F_{(9\times1)}\underbrace{\ddot{x}_g(t)}_{\text{El Centro NS}} \tag{15}$$

where $\ddot{x}_g(t)$ represents the seismic excitation loading.

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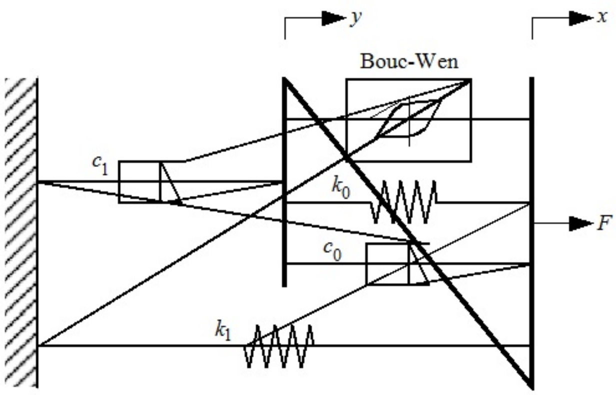
Table 1: Modified Bouc-Wen model - Parameters of the RD-1005-3 MR damper [5].



$$F = c_1\dot{y} + k_1(x - x_0)$$
$$\dot{y} = \frac{1}{c_0 + c_1}[\alpha s + c_0\dot{x} + k_0(x - y)]$$
$$\dot{s} = -\beta|\dot{x}|z|z|^{n-1} - \gamma\dot{x}|z|^n\delta\dot{x}$$

Current independent	δ [-]	β [mm^2]	γ [mm^2]	k_0 [N/m]	f_0 [N]	n
paramaters	10.013	3.044	0.103	1.121	40	2
Current dependent parameters	$\alpha(I) = -826.671I^3 + 905.14I^2 + 412.52I + 38.24$ [N]					
	$c_0(I) = -11.73I^3 + 10.51I^2 + 11.02I + 0.59$ [N·s/mm]					
	$c_1(I) = -54.40I^3 + 57.03I^2 + 64.57I + 4.73$ [N·s/mm]					

3 Semi-active control using a neuro-fuzzy controller

A fuzzy logic based controller was designed by using ANFIS modelling capabilities to find the nonlinear map that best fits the expected response of the control system. The fuzzy controller was developed based on the numerical results of the LQG controller whose response is used to define the training data-set for the neuro-fuzzy optimization procedure with ANFIS. Floor accelerations and the displacement across the MR damper are the responses of the controlled system used by the LQG controller to determine the desired control force. The control signal is determined from the predicted control force using an inverse Bingham model of the MR damper. The system responses and the desired control signal were recorded and then used to train the neuro-fuzzy controller.

The data-sets for training and validation were obtained by numerical simulations exposing the LQG controlled system to a set of amplitude-scaled versions of the ElCentro NS earthquake excitation (i.e., 100 gal, 200 gal, 335 gal and 500 gal seismic accelerations).

The LQG controller combines a LQR algorithm with a Kalman filter estimator. In this case the optimal controller uses floor accelerations and the displacement across the damper as the measured system outputs in determining the control signal. Identically distributed Gaussian white noise is used to simulate acceleration noise measurements. The LQR determines the state feedback and the Kalman filter estimates the state vector of a noisy system. Regarding the LQR controller, the state gain matrix G is tuned through the weighting matrices Q and r. In the present example different configurations of these parameters were evaluated by measuring the effect of each combination in the system response. The following weighting parameters provided the best performance in reducing the structural response

$$Q = \begin{bmatrix} K_{(3\times3)} & 0_{(3\times3)} \\ 0_{(3\times3)} & 0_{(3\times3)} \end{bmatrix}; \qquad R = r = 5\times10^{-7} \tag{16}$$

The observer gain L must be adjusted to achieve the required performance. A high gain allows the filter to follow the observations more closely while a low gain follows the predictions more closely. This is accomplished by setting

$$Q_w = q_w I_e, \quad R_v = r_v I_m \tag{17}$$

where I_e and I_m are identity matrices related with the number of excitation inputs and measurement signals, respectively. A common approach is to set one of the tuning parameters (e.g., $r_v = 0.001$) and adjust the other parameter until the result is satisfying. In this case $I_c = 1(\ddot{x}_g)$ and $I_m = I_{4\times4}(x, \ddot{x}_1, \ddot{x}_2, \ddot{x}_3)$.

The recorded velocity data and the control signal from the LQG controller were used to define the training data for the fuzzy controller. The first and third floor velocities are the FIS inputs while the command current represents the fuzzy outcome. Initially, increasing and decreasing step sizes of 0.12, 1.20 and 0.8, respectively during 200

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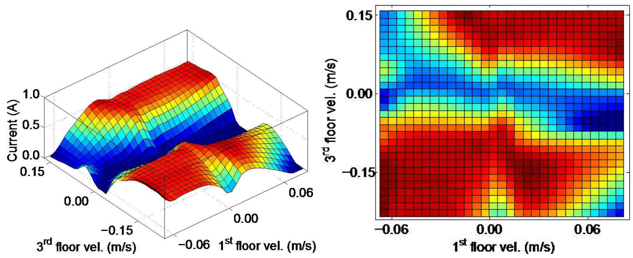

Figure 5: Uncontrolled response of the 3DOFs system.

epochs are the parameters involved in the ANFIS optimization procedure. The optimal number of membership functions (MFs) was defined through a trial and error process. In this case, six bell-shaped MFs were used to model each input variable (first and third floor velocities). The resultant fuzzy surface is shown in Figure 5.

It can be seen that when the first and third floor velocities are large and have the same signs, the required control signal that produces the damping force is also large. When both velocities are large but have opposite signs, the fuzzy controller delivers the lowest control signal. Besides, the minimum damping force requirement is located around the central zone comprising small floor velocities. It should be noted that the fuzzy controller can be enhanced using other excitation signals to define the training data-set for ANFIS optimization.

The damper force and the corresponding control signal during the numerical analysis is shown in Figure 6. As can be seen, the proposed fuzzy controller provides intermediate levels of control current instead of the bistate control signal used in many semi-active controllers allowing intermediate damping states over the full range of operation of the device. The results show that the proposed fuzzy logic controller is able to determine with sufficient reliability the required control action to reduce the response of the system.

Figure 7 displays the structural response of each floor obtained with the proposed fuzzy based control system along with the uncontrolled response of the third floor during the numerical simulation.

As can be seen, the proposed semi-active control system achieves a good performance in reducing the structural responses using only floor velocities as the reference (input) signals to compute the control action. In fact, the main advantage of this fuzzy logic based control system is that only the first and third floor velocities of the structure are required to determine the desired control signal. This means that the damping force generated during the control process does not need to be monitored, as happens in other controllers such as the clipped-optimal algorithm.

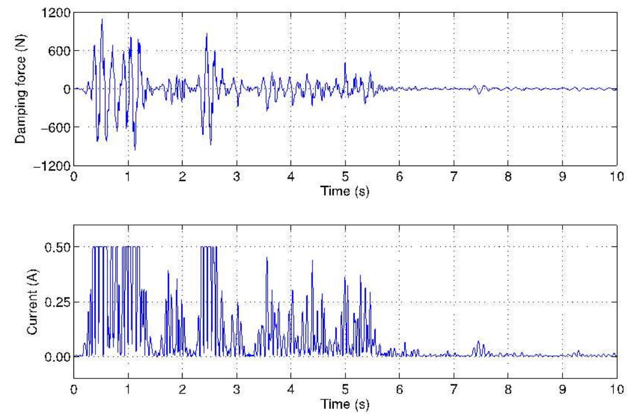

Figure 6: Damper force and corresponding operating current.

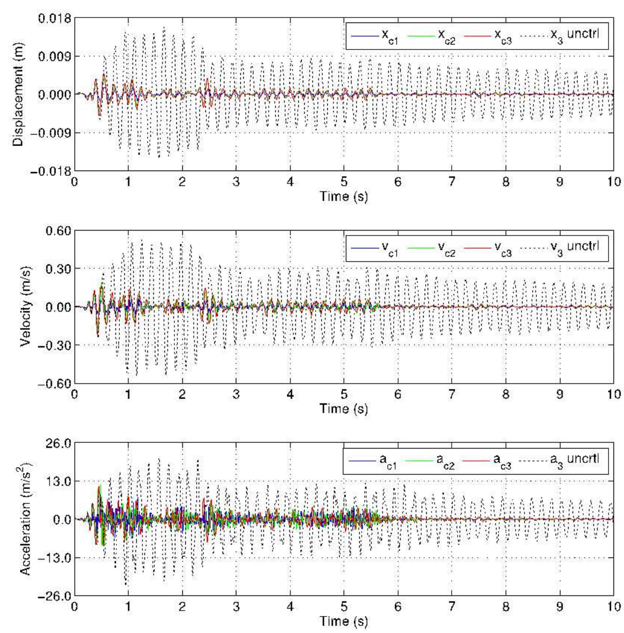

Figure 7: Uncontrolled response of the 3DOFs system.

Obviously, the main drawback of fuzzy controllers is related with the definition of the inference rules that relate the inputs with the desired control output. Structural systems usually include several sources of non-linearities and/or uncertainties that hinder the development of simple control rules based on human knowledge about the system behavior. In these cases, soft computing techniques are most appropriate to find the best set of fuzzy rules for a desired control action. For instance, an adaptive neuro fuzzy inference system (ANFIS) or a genetic algorithm (GA) constitute powerful optimization tools that allows for adjustment of a set of fuzzy parameters in accordance with a given training data to achieve the necessary control action.

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Table 2: 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		0.695	27.09	1305	—
		1.251	45.78	1736	
		1.587	54.02	2272	
Passive	Modified	0.518	20.02	999	166.4
OFF	Bouc-Wen	0.907	34.51	1358	
		1.191	42.79	1791	
Passive	**Modified**	**0.171**	**7.77**	**613**	**1048.9**
ON	**Bouc-Wen**	**0.423**	**19.36**	**1066**	
		0.560	**25.58**	**1366**	
Neuro-Fuzzy controller		0.164 (−4%)	7.07 (−9%)	739 (21%)	909.8
		0.410 (−3%)	17.59 (−9%)	963 (−10%)	
		0.529 (−6%)	23.64 (−8%)	1285 (−6%)	

A new numerical simulation was carried out to obtain the response of the three DOF structure using the MR damper in a passive OFF mode (zero voltage/current input) and passive ON mode (maximum value of the operating voltage/current).

The peak responses of the uncontrolled and controlled systems are listed in Table 2. The results show the effectiveness of the proposed fuzzy based controller in reducing the response of the structure. In this case the fuzzy controller outperforms the passive control modes in almost all peak responses (with exception of the 1st floor acceleration, although with a significant reduction compared with the uncontrolled case).

4 Conclusions

Comparing the controlled responses to those obtained in the uncontrolled and passive control systems, it was observed that both passive and semi-active control systems are effective in reducing the seismic responses. However, the semi-active controller allows a more efficient management of the control forces with a better performance in reducing the structural response. It was also verified that larger damping forces do not always produce better results (e.g., control forces achieved with the passive ON mode are larger than those obtained with the semi-active controller). It can be concluded that the proposed semi-active strategy is an efficient control approach outperforming the passive control modes.

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