SEMI-ACTIVE CONTROL OF BUILDING STRUCTURES USING A NEURO-FUZZY CONTROLLER WITH ACCELERATION FEEDBACK

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ABSTRACT

The present paper investigates the effectiveness of a neuro-fuzzy controller to reduce the response of building structures subjected to seismic excitations. The proposed controller was developed using an Adaptive Neuro-Fuzzy Inference System (ANFIS) to train a fuzzy logic system. In this case, floor acceleration measurements are used to compute the desired control signal to command a MR damper. A numerical example involving a three degrees of freedom building structure excited by the El Centro earthquake is presented to demonstrate the effectiveness of the proposed semi-active control system in reducing the response under seismic loading. A comparison between uncontrolled and controlled structural responses are used to validate the performance and efficiency of the proposed semi-active controller.

Keywords: Structural control, semi-active control, neuro-fuzzy, MR dampers.

INTRODUCTION

The present paper investigates the effectiveness of a neuro-fuzzy controller to reduce the response of building structures subjected to seismic excitations. A numerical analysis was carried out comprising the structural control of a three-story structure under the El Centro earthquake excitation using a single MR damper located between the base and the first floor. In this case, the sensors and the actuator are placed in different locations and therefore the control system has a non-collocated configuration. The uncontrolled response under harmonic excitation and seismic loading were obtained, which will be used as reference values for the remaining numerical simulations. Then, the seismic responses of the structure with one MR damper installed in the first floor and operating in a passive and semi-active configurations are obtained and analyzed. The numerical analysis was conducted with the aim of verify the efficiency of a neuro-fuzzy controller with acceleration feedback in reducing the seismic response of the structure.

NUMERICAL MODEL

Consider a controlled system subjected to an earthquake excitation as illustrated in Fig. 1. In this case the actuator is a MR damper that can be used as a passive dissipation device or in a semi-active control mode. In this last approach, 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 improve the structural performance. An effective semi-active control involves an appropriate control algorithm that can take advantage of the dissipative properties of the control device (Dyke, 1997; Jansen, 2000).
In this case the structure is equipped with a MR damper (Lord RD-1005-03 model) located between the ground floor and the first floor which can operate in two modes: as a passive energy dissipation device and as a semi-active actuator whose control action is being commanded by a neuro-fuzzy based controller.

The modified Bouc-Wen model was selected to simulate the hysteretic behavior of the MR damper. The numerical formulation and the corresponding model parameters are presented in Table 1 (Braz-César, 2013). 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 ($\eta = 130$ sec$^{-1}$).

Table 1 - Modified Bouc-Wen model - Parameters of the RD-1005-3 MR damper (Braz-César, 2013).

<p>| Modified Bouc-Wen model | \begin{equation} F(t) = c_i \dot{y} + k_i (x - x_0) \end{equation} | \begin{equation} \dot{y} = \frac{1}{c_a + c_i} \left[ \alpha z + c_0 \dot{x} + k_0 (x - y) \right] \end{equation} | \begin{equation} \ddot{z}(t) = -\beta \left| \dot{z}(t) \right| z(t) \left| z(t) \right|^{n-1} - \gamma \dot{z}(t) \right| z(t) \right|^{n} + A \ddot{z}(t) \end{equation} |
|------------------------|-----------------------------------------------------------------|-----------------------------------------------------------------|-----------------------------------------------------------------|</p>
<table>
<thead>
<tr>
<th>Current independent parameters</th>
<th>$A$ [-]</th>
<th>$\beta$ [mm$^{-1}$]</th>
<th>$\gamma$ [mm$^{-1}$]</th>
<th>$k_0$ [N/mm]</th>
<th>$f_0$ [N]</th>
<th>$n$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Current dependent parameters</td>
<td>\begin{equation} \alpha(I) = -826.67I^3 + 905.14I^3 + 412.52I + 38.24 \end{equation}</td>
<td>\begin{equation} c_0(I) = -11.73I^2 + 10.51I^2 + 11.02I + 0.59 \end{equation}</td>
<td>\begin{equation} c_0(I) = -54.40I^3 + 57.03I^3 + 64.57I + 4.73 \end{equation}</td>
<td></td>
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</tbody>
</table>
In what follows, the results of the semi-active control system are compared with the uncontrolled, passive OFF and passive ON responses to evaluate the efficiency of each semi-active control scheme in reducing the structural response. The mass, damping and stiffness matrices of the model structure can be determined as

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

(1)

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

(2)

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

(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/s²). 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 experiments tests. Thus, the time was scaled to 20% of the full-scale earthquake time history as shown in Fig. 2.

The state space equation of motion is given by

$$
\ddot{z}(t)_{(6x1)} = \begin{bmatrix}
0_{(3x3)} & I_{(3x3)} \\
-M^{-1}K_{(3x3)} & -M^{-1}C_{(3x3)} \\
\end{bmatrix} \begin{bmatrix} X(t)_{(3x1)} \\
\dot{X}(t)_{(3x1)} \\
\end{bmatrix} + \begin{bmatrix}
0_{(3x1)} \\
-\lambda_{(3x1)} \\
\end{bmatrix} \ddot{x}_{\text{El Centro NS}}(t)
$$

(4)

where the column vector $\dot{\lambda}$ represents the location of the earthquake excitation (i.e., the seismic acceleration). Equation 4 can be written in a simplified form as

$$
\ddot{z}(t)_{(6x1)} = A_{(6x6)} z(t)_{(6x1)} + E_{(6x6)} \ddot{x}_{\text{El Centro NS}}(t)
$$

(5)

where matrix $A$ represent the system matrix.
and \( E \) is the disturbance locating vector given by

\[
E_{(6 \times 1)} = \begin{bmatrix} 0, 0, 0, -1, -1, -1 \end{bmatrix}^T
\]

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

\[
y(t) = Cz(t) + Du(t)
\]

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

\[
C_{(9 \times 6)} = \begin{bmatrix} I_{(3 \times 3)} & 0_{(3 \times 3)} \\ 0_{(3 \times 3)} & I_{(3 \times 3)} \\ -M^{-1}K_{(3 \times 3)} & -M^{-1}C_{(3 \times 3)} \end{bmatrix}, \quad D_{(9 \times 1)} = \begin{bmatrix} 0_{(6 \times 1)} \\ -\lambda_{(3 \times 1)} \end{bmatrix}
\]

The uncontrolled response is displayed in Fig. 3.

Fig. 3 - Uncontrolled response of the 3DOFs system.
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%. This modification in the excitation signal was used only to amplify the magnitude of the displacements making the system response more compatible with the operating range of the MR damper. The equation of motion of the controlled structure can be defined by a state space formulation as

\[ \ddot{z}(t)_{(6 \times 1)} = A_{(6 \times 6)} z(t)_{(6 \times 1)} + B_{c(6 \times 6)} f_c(t) + E_{(6 \times 1)} \ddot{x}_g(t) \] (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 \( \Gamma \) within \( B_c \). In this case there is only one control force applied to the first mass and therefore, it follows that

\[ \Gamma_{(3 \times 1)} = \begin{pmatrix} 1, & 0, & 0 \end{pmatrix}^T \] (11)

and then

\[ B_{c(6 \times 1)} = \begin{pmatrix} 0, & 0, & 0, & - \frac{1}{m_1}, & 0, & 0 \end{pmatrix}^T \] (12)

Equation 10 can be written in a more compact given that

\[ B_{(6 \times 2)} = \begin{bmatrix} B_{c(6 \times 1)} & E_{(6 \times 1)} \end{bmatrix} = \begin{bmatrix} 0 & 0 \\ 0 & 0 \\ 0 & 0 \\ - \frac{1}{m_1} & -1 \\ 0 & -1 \\ 0 & -1 \end{bmatrix}, \quad u(t)_{(2 \times 1)} = \begin{bmatrix} f_c(t) \\ \ddot{x}_g(t) \end{bmatrix} \] (13)

and finally

\[ \ddot{z}(t)_{(6 \times 1)} = A_{(6 \times 6)} z(t)_{(6 \times 1)} + B_{(6 \times 2)} + u(t)_{(2 \times 1)} \] (14)

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

\[ y(t)_{(9 \times 1)} = C_{(9 \times 6)} z(t)_{(6 \times 1)} + D_{c(9 \times 6)} f_c + F_{(9 \times 1)} \ddot{x}_g(t) \] (15)

where \( C \) is the same matrix of Equation 9, \( D_c \) comprising the control forces is

\[ D_{c(9 \times 6)} = \begin{pmatrix} 0, & 0, & 0, & 0, & - \frac{1}{m_1}, & 0, & 0 \end{pmatrix}^T \] (16)

and the column vector \( F \) describing the location of the earthquake signal is given by

\[ F_{(9 \times 1)} = \begin{pmatrix} 0, & 0, & 0, & 0, & -1, & -1, & -1 \end{pmatrix}^T \] (17)

As for the state space equation, \( \ddot{x}_g(t) \) represents the seismic excitation loading.
NEURO-FUZZY CONTROLLER

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 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, 1993; Schurter, 2001). The reasoning scheme of ANFIS architecture is shown in Fig. 4.

![Adaptive Neuro-Fuzzy Inference System or ANFIS.](image)

Soft computing methods represent a relatively recent optimization/modeling techniques that have been shown to be effective in representing the non-linear behavior of structural systems. The development of a neuro-fuzzy controller for MR dampers involve four main steps:

1. Definition of input variables and the corresponding 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 neuro-fuzzy model controller;
4. Validation of the resulting fuzzy model.

In what follows, a neuro-fuzzy controller was designed by using an ANFIS model to find the nonlinear map (fuzzy inference system) that best fits the expected response of the control system. The proposed controller was developed based on the numerical results of the LQG control system whose response is used to define the training data set for the neuro-fuzzy optimization procedure with ANFIS. In this case, floor accelerations constitute the responses of the controlled system used by the LQG controller to determine the desired control force. Subsequently, the required control signal is determined from the predicted control force using an inverse Bingham model of the MR damper. The data set for training and validation was obtained through numerical simulations by exposing the LQG controlled system to a set of amplitude-scaled versions of the El Centro NS earthquake excitation, i.e., 100gal (30%), 200gal (60%), 335gal (100%) and 335gal (150%) seismic accelerations.
The system responses and the desired control signal were recorded and then used to train the neuro-fuzzy controller. In this case, floor accelerations are the FIS inputs while the command current represents the fuzzy outcome. An initial, increasing and decreasing step sizes of 0.12, 1.20 and 0.8, respectively during 200 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, three bell-shaped MFs were used to model each input variable. The universe of discourse of each fuzzy variable is not normalized displaying maximum and minimum values according with the results of the clipped-optimal LQG controller. The resultant fuzzy surfaces are shown in Fig. 5 to 7.

Although these fuzzy surfaces do not allow a fully interpretation of the fuzzy controller since all input variables must be combined in accordance with the trained fuzzy inference system to obtain a signal output, they provide crucial information about the interaction between the inputs and the effect of these on the corresponding model output.

![Fig. 5 - Fuzzy surface of the inference system - \( I(\text{acc}_1,\text{acc}_2) \).](image)

![Fig. 6 - Fuzzy surface of the inference system - \( I(\text{acc}_2,\text{acc}_3) \).](image)
One of the main problems that may arise is that ANFIS can determine an inference system whose output variable is outside the limits of the desired signal. This effect can be reduced selecting appropriate training data sets (e.g., remove sparse data points, extending and increasing the number of data points around the minimum and maximum values of the variable output, etc.) and also choosing the appropriate number and properties of the membership functions. This type of neuro-fuzzy systems can present high peaks near the corners of the surface. Depending on the fuzzy composition rules, these peaks can produce an incorrect output signal. If the surfaces are within the expected output range or if small peaks are visible only in very specific areas of the surface but the fuzzy system output has a small error, the fuzzy model can be easily tuned by adjusting the inputs and output variables. Otherwise, the optimization procedure of the fuzzy inference system should be reconsidered to improve the fuzzy system.

The corresponding Simulink block of the neuro-fuzzy controller is represented in Fig. 8. As can be observed, saturation blocks are used after the scaling factors to ensure that the structural accelerations are always within the range of values of the corresponding fuzzy variable ($K_c = 2.5$). Likewise, a saturation block was used to limit the minimum and maximum values of the FIS output, i.e., the control current to the operating range of the MR damper ($I_{\text{min}} = 0.0A$ and $I_{\text{max}} = 0.5A$).
A new numerical simulation was carried out to obtain the response of the three DOF structure to the time-scale earthquake excitation (i.e., El Centro NS). The system response for the passive OFF case along with the maximum and minimum values of each output variable is displayed in Figure 9 and the damper behaviour is characterized in Figure 10.

Fig. 9 - Results with the Modified Bouc-Wen model – Passive OFF case.

Fig. 10 - 3DOFs system - RD-1005-03 MR damper control force.
Passive OFF case – Modified Bouc-Wen model
Likewise, a numerical simulation was carried out to obtain the response of the three DOF structure to the time-scale earthquake excitation for the passive ON mode. The corresponding system response along with the maximum and minimum values of each output variable is displayed in Figure 11 and the damper behaviour is characterized in Figure 12.

Fig. 11 - Results with the Modified Bouc-Wen model – Passive ON case.

Fig. 12 - 3DOFs system - RD-1005-03 MR damper control force.
Passive ON case – Modified Bouc-Wen model
The Simulink model of the semi-active control system based on the neuro-fuzzy controller is displayed in Figure 13. As can be observed in this figure, floor accelerations of the building structure constitute the responses of the controlled system used by the controller to determine the desired control signal.

![Fig. 13 - Simulink model of the neuro-fuzzy control system.](image)

The structural responses obtained with the neuro-fuzzy based control system along with the uncontrolled response of the third floor are displayed in Figure 14. The peak responses of the both uncontrolled and controlled systems are listed in Table 2. The results show the effectiveness of the proposed controller in reducing the response of the structure.

Table 2 - Peak responses under the time-scaled El-Centro earthquake.

<table>
<thead>
<tr>
<th>Control strategy</th>
<th>$x$ (cm)</th>
<th>$\dot{x}$ (cm/s)</th>
<th>$\ddot{x}$ (cm/s$^2$)</th>
<th>$f$(N)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Uncontrolled</td>
<td>0.695</td>
<td>27.09</td>
<td>1305</td>
<td>----</td>
</tr>
<tr>
<td></td>
<td>1.251</td>
<td>45.78</td>
<td>1736</td>
<td></td>
</tr>
<tr>
<td></td>
<td>1.587</td>
<td>54.02</td>
<td>2272</td>
<td></td>
</tr>
<tr>
<td>Passive OFF</td>
<td>Modified Bouc-Wen</td>
<td>0.518</td>
<td>20.02</td>
<td>999</td>
</tr>
<tr>
<td></td>
<td></td>
<td>0.907</td>
<td>34.51</td>
<td>1358</td>
</tr>
<tr>
<td></td>
<td></td>
<td>1.191</td>
<td>42.79</td>
<td>1791</td>
</tr>
<tr>
<td>Passive ON</td>
<td>Modified Bouc-Wen</td>
<td>0.171</td>
<td>7.77</td>
<td>613</td>
</tr>
<tr>
<td></td>
<td></td>
<td>0.423</td>
<td>19.36</td>
<td>1066</td>
</tr>
<tr>
<td></td>
<td></td>
<td>0.560</td>
<td>25.58</td>
<td>1366</td>
</tr>
<tr>
<td>Neuro-fuzzy controller</td>
<td>0.164</td>
<td>7.07</td>
<td>739 (21%)</td>
<td>909.8</td>
</tr>
<tr>
<td></td>
<td>0.410</td>
<td>17.59</td>
<td>963 (-10%)</td>
<td></td>
</tr>
<tr>
<td></td>
<td>0.529</td>
<td>23.68</td>
<td>1285 (-6%)</td>
<td></td>
</tr>
</tbody>
</table>
As can be seen, the semi-active control system achieves a good performance in reducing the structural responses using floor accelerations as the reference signals to compute the control action. In fact, the main advantage of the proposed control system is that only acceleration responses are required to determine the control action. 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. Obviously, the main drawback regarding the implementation of the neuro-fuzzy controller is related with the optimization of the inference system. Fuzzy logic controllers are well known for its robustness against parameter variations or model uncertainties. In this context, an important characteristic of this type of controllers is their inherent ability to deal with possible sensor faults or measurement failures, thus enabling the deployment of a framework to design simple robust and reliable control systems with tolerance against sensor failures.

The damper force and the corresponding control signal are presented in Fig. 15. As can be observed, the control system uses a continuous control signal to command the MR damper. The hysteretic behavior of the MR damper during the numerical simulation is portrayed in the force-displacement and force-velocity plots presented in Fig. 16. The proposed control system is capable to explore the dissipative nature of this type of actuators.
CONCLUSION

The present paper presents a neuro-fuzzy controller with acceleration feedback for vibration control of building structures based on MR dampers. Comparing the controlled responses to those obtained in the uncontrolled and passive control systems, it is 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. It is 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. The proposed semi-active control system achieves a good performance in reducing the structural responses using only floor accelerations as the reference signals to compute the control action. Moreover, the proposed control system is capable to explore the dissipative nature of this type of actuators.
REFERENCES


