

Neuro-Fuzzy Control of Structures using MR dampers

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Abstract

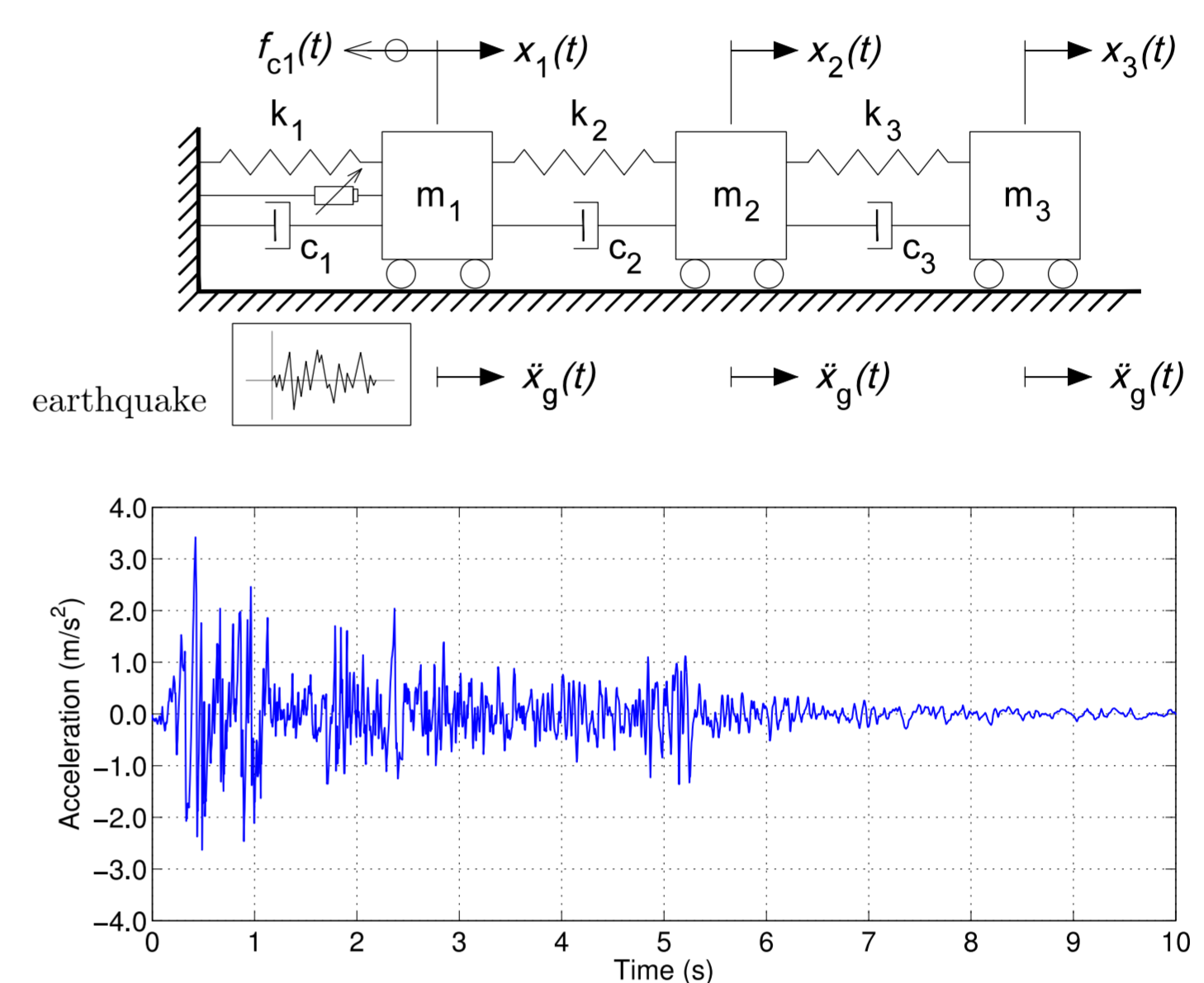
Over the last decades, soft computing based controllers have been widely explored as an alternative to conventional control systems in many engineering applications. The ability of intelligent and adaptive control systems to deal with uncertain systems and to change the controller behavior at different operating conditions constitute decisive advantages over conventional control systems that allows for the development of robust controllers for complex vibration engineering problems. In this regard, this paper aims to analyze the performance of a neuro-fuzzy controller in reducing seismic-induced vibrations in building structures using a MR damper.

Numerical Simulation

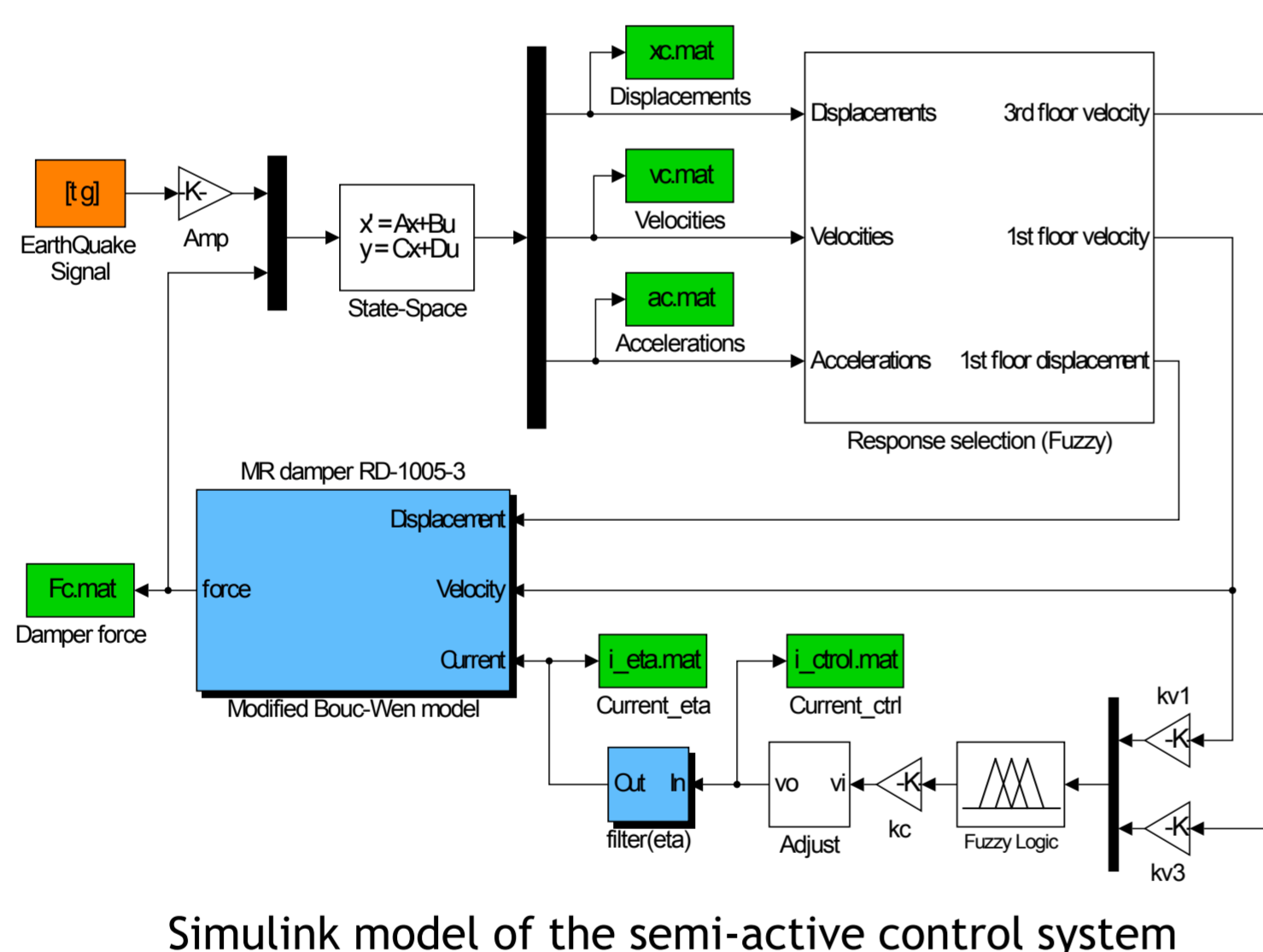
The plant is a three degree-of-freedom system, which represents a three-story shear building structure. The semi-active control system is derived from an optimal controller. This controller is used to command a MR damper (RD-1005-3 model) located between the ground and the first floor, i.e., in a non-collocated configuration. The data obtained from the optimal controller is used as a reference to train a fuzzy based controller via an Adaptive Neuro-Fuzzy Inference System (ANFIS). The uncontrolled response is compared with passive (OFF and ON modes) and semi-active controlled responses in order to assess the effectiveness of the proposed neuro-fuzzy controller.

$$M = \begin{bmatrix} m_1 & 0 & 0 \\ 0 & m_2 & 0 \\ 0 & 0 & m_3 \end{bmatrix} = \begin{bmatrix} 100 & 0 & 0 \\ 0 & 100 & 0 \\ 0 & 0 & 100 \end{bmatrix} \text{ kg} \quad C = \begin{bmatrix} c_1 + c_2 & -c_2 & 0 \\ -c_2 & c_2 + c_3 & -c_3 \\ 0 & -c_3 & c_3 \end{bmatrix} = \begin{bmatrix} 175 & -50 & 0 \\ -50 & 100 & -50 \\ 0 & -50 & 50 \end{bmatrix} \text{ N} \cdot \text{s/m}$$

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



Fuzzy modelling



Simulink model of the semi-active control system

Results

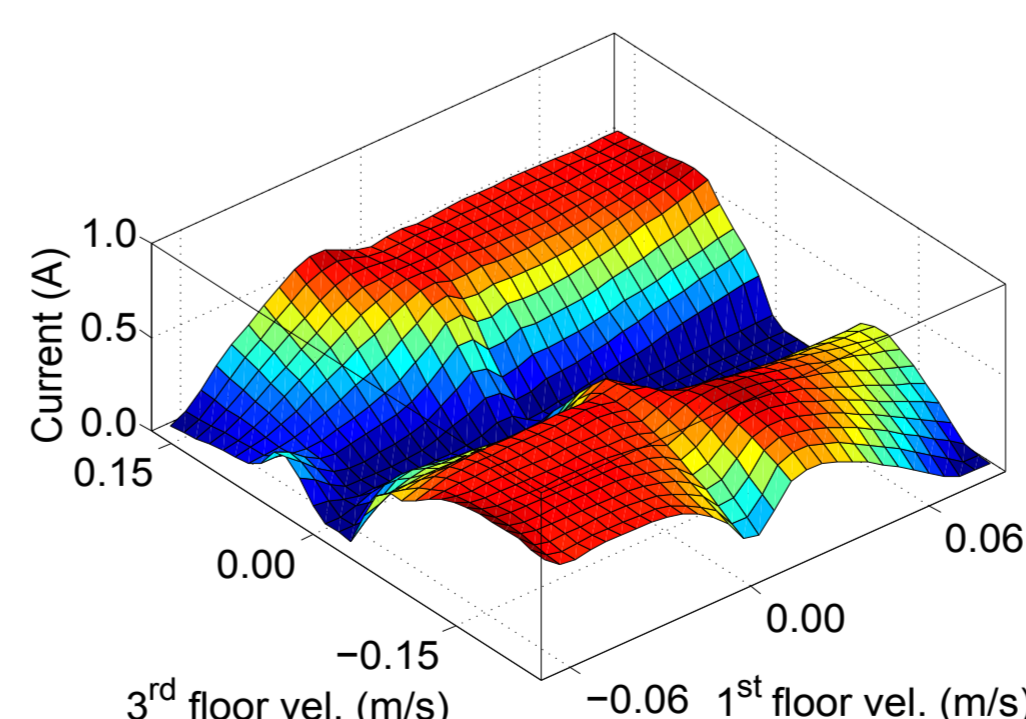
| Control strategy | | x (cm) | \dot{x} (cm/s) | \ddot{x} (cm/s ²) | drift (cm) | f (N) |
|--------------------------------|----------------------|-------------|------------------|---------------------------------|------------|---------|
| Uncontrolled | | 0.695 | 27.09 | 1305 | 0.695 | --- |
| | | 1.251 | 45.78 | 1736 | 0.581 | --- |
| | | 1.587 | 54.02 | 2272 | 0.371 | --- |
| Passive OFF | Modified Bouc-Wen | 0.518 | 20.02 | 999 | 0.518 | 166.4 |
| | | 0.907 | 34.51 | 1358 | 0.443 | |
| | | 1.191 | 42.79 | 1791 | 0.292 | |
| Passive ON | Modified Bouc-Wen | 0.171 | 7.77 | 613 | 0.171 | 1048.9 |
| | | 0.423 | 19.36 | 1066 | 0.253 | |
| | | 0.560 | 25.58 | 1366 | 0.208 | |
| Fuzzy logic control (ANFIS) | | 0.164 (-4%) | 7.07 (-9%) | 739 (0.21) | 0.164 | 909.8 |
| | | 0.410 (-3%) | 17.59 (-9%) | 963 (-0.10) | 0.247 | |
| | | 0.529 (-6%) | 23.64 (-8%) | 1285(-0.06) | 0.194 | |

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.

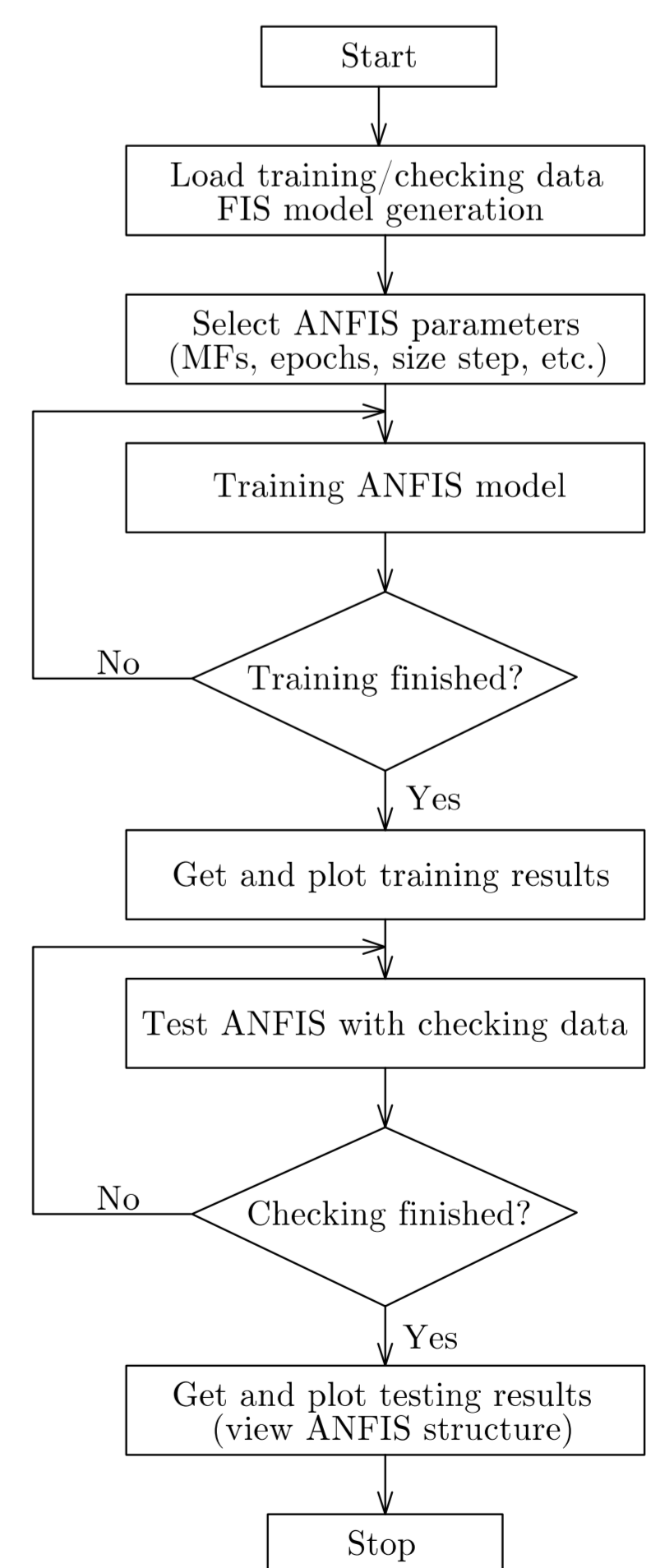
The fuzzy controller was developed based on the numerical results of a LQG controller whose response is used to define the training data set for the neuro-fuzzy optimization procedure with ANFIS. The control signal is determined from the predicted control force using an inverse Bingham model of the MR damper. The system responses and the desired control signal were recorded and then used to train the neuro-fuzzy controller.

The development of a neuro-fuzzy model of a control device or a neuro-fuzzy based controller typically involve four main steps:

1. Definition of input variables and the corresponding fuzzy inference system (FIS) membership functions;
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 to generate a fuzzy model;
4. Validation of the resulting fuzzy model.



Optimized fuzzy surface (ANFIS)



Flowchart of ANFIS training