Smart Control of Seismically Excited Highway Bridges

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Abstract This chapter proposes a novel smart fuzzy control algorithm for mitigation of dynamic responses of seismically excited bridge structures equipped with control devices. The smart fuzzy controller is developed through the combination of discrete wavelet transform, backpropagation neural networks, and Takagi-Sugeno fuzzy model. To demonstrate the effectiveness of the proposed smart fuzzy controller, it is tested on a highway bridge equipped with magneto rheological (MR) dampers. It controls the smart dampers installed on the abutments of the highway bridge structure. The 1940 El-Centro and Kobe earthquakes are used as disturbance signals. It is demonstrated that the smart fuzzy controller is effective in reducing the structural responses of the highway bridge under a variety of seismic excitations.

1 Introduction

In recent years, smart control strategies have attracted a great deal of attention from the structural engineering community [39, 3, 4, 5, 6, 10, 28, 29, 31]. However, a difficult problem in dealing with smart structures is creating an effective control model for a nonlinear dynamic structure under a variety of environmental forces [21, 23–26, 37, 6, 15]. Nonlinear systems occur when highly nonlinear hysteretic dampers, such as the magnetorheological (MR) dampers, are implemented into a structure to aid in the structure's ability to withstand the destructive environmental forces such as strong winds and earthquake loads [36]. Being able to mathematically model the structure-nonlinear damping system and its corresponding con-

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troller is a challenging task in smart control. Therefore, the challenge is to create a mathematical model to develop a relationship between the input and output of a smart structure that uses a nonlinear damping device. This chapter proposes a new smart control system for reducing nonlinear behavior of a seismically excited highway bridge structure with smart dampers.

The development of an effective smart control algorithm is essential in smart structures to operate the smart dampers within large civil structures. The goals of an effective smart controller is to reliably control how a system will behave under a variety of dynamic loading scenarios such as far- and near-field earthquakes, considering interactions between the structure and the smart dampers. Smart control algorithms can be separated into two categories: model-based and model-free algorithms [25]. The model-based control methods use the structural properties of the system, including stiffness and damping systems that are intrinsically imbedded in the structure and its materials [7, 8]. The model-free control approaches are implemented through training data to the input-output map of the structure employing the smart dampers [37, 38]. This model-free approach is useful to bridge the gap between the linear and nonlinear parts of the smart system. This has successfully been done with neural networks as well as fuzzy logic systems. In particular, the incorporation of the two systems provides a better learning model to use for training the model-free control models.

In this chapter, a new smart control model is developed through the integration of best features of discrete wavelet transform (WT), and fuzzy logic theory and neural network (NN). The first model used as a part of the proposed system in this chapter is a rule-based fuzzy logic. The fuzzy logic model has the main advantage of being used as a nonparametric method for system identification and control system design, and has been researched previously [44, 40, 21, 22, 27–33, 35], as well as general studies into the uncertainties and complexities of the dynamic system [34, 23]. Using a Takagi-Sugeno (TS) model for fuzzy logic theory allows for a representation of nonlinear systems using fuzzy rules and local linear models [40, 19, 41, 12, 20, 9, 11, 23, 42]. A disadvantage of using fuzzy inference systems as a control model is that it needs a time consuming optimization process of the parameters. The optimization process can be very complex, leading itself to the inclusion of NNs. The use of a NN is to develop a learning mechanism that emulates that of the human brain, such that it creates a network of interlinked nodes. These nodes, being connected, compute an output from the input to the node, and create a series of links between all nodes. As mentioned previously, the use of a fuzzy inference system can be complex and difficult in computations. Using a NN in combination with a fuzzy inference system can create a model that is more efficient. The NN adjusts parameters throughout the entirety of computation. The regulated parameters improve performance and decreases errors of the system. It is able to learn patterns and make adjustments as needed to further create a more improved model because it emulates the human brain and its cognitive mechanism. It has been studied previously to create a full model structure [16].

However, due to the complexities of training the using NNs, computation time can become excessive. Therefore, wavelet transform (WT) is used in conjunction with the combined fuzzy inference system, and NNs to compress input data and decrease computation time. WTs, combined with the neuro-fuzzy (NF) model, leads to a wavelet-based NF model (WNF). The WT can be used to filter out high or low frequency components from a time series. The WT improves upon previous methods due to its ability to incorporate an adjustable window function. It allows a user to analyze particular data points in a time series, rather than the entire time window, which is the case in Fourier transforms. Fast Fourier transforms (FFT) have been used previously for damage detection, system identification, and control systems, but require a fixed time-window for the entire data set [14]. This limitation of the FFT can induce difficulty when analyzing data for long periods of time, as in the case of real-time structural control, and can lead to missing key components, such as a particular control frequency. The WT allows for an adjustable window, and therefore is able to look into any portion of a time series. WTs can also be used as a means of filtering, which is critical in the use of the WNF control model. As previously mentioned, the NF system requires high computation time due to the stochastic learning mechanism of the NNs. Being able to decrease the amount of data points while still maintaining the important components allows for a reduced computational cost. The proposed model uses two levels of discrete WTs for compressing input data. Note that fuzzy logic controllers [2] and neuro-fuzzy controllers [13] have been widely researched previously. However, these controllers need extensive computation time to achieve adequate performance. Therefore, the creation of the new WNF system provides for decreased computation times while maintaining the performance. Thus, the creation of the WNF system for means of smart control algorithm is innovative in its application to smart damping systems for mitigation of responses of highway bridge structures.

2 Smart Highway Bridge Systems

2.1 Highway Bridge

To facilitate research in structural control, a benchmark bridge was developed based on an existing structure located at the crossing of the 91 and 5 highways in Orange County of California, USA [1]. A prestressed concrete box-girder is used with the span of 58.5 m. The deck has a width of 12.95 and 15 m for the east and west spans, respectively. The bridge carries four lanes of traffic atop columns of 6.9 m in height. The location of the bridge is within 20 km of two faults, the Whittier-Ellsinore and Newport-Inglewood fault zones, showing a great need for structural control due to its susceptibility to seismic events. Figure 1 shows the bridge schematic.

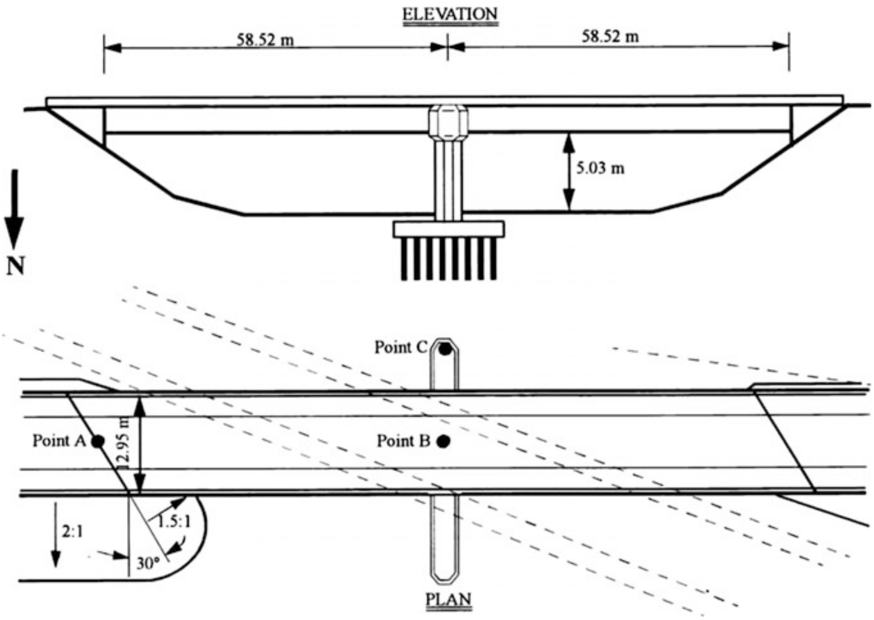

Fig. 1 Highway bridge structure

2.2 Magnetorheological (MR) Dampers

In recent years, smart structures have emerged from many engineering fields because the performance of structural systems can be improved without either significantly increasing the structure mass or requiring high cost of control power. They may be called intelligent structures, adaptive structures, active structures, and the related technologies adaptronics, structronics, etc. The reason to use these terminologies is that a smart structure is an integration of actuators, sensors, control units, and signal processing units with a structural system. The materials that are commonly used to implement the smart structure: piezoelectrics, shape memory alloys, electrostrictive, magnetostrictive materials, polymer gels, magnetorheological fluid, etc., researched in detail by Hurlebaus and Gaul [17].

Semiactive control systems have been applied to large structures because the semiactive control strategies combine favorable features of both active and passive control systems. Semiactive control devices include variable-orifice dampers, variable-stiffness devices, variable-friction dampers, controllable-fluid dampers, shape memory alloy actuators, piezoelectrics, etc., as described by Hurlebaus and Gaul [17]. In particular, one of the controllable-fluid dampers, magnetorheological (MR) damper has attracted attention in recent years because it has many attractive characteristics.

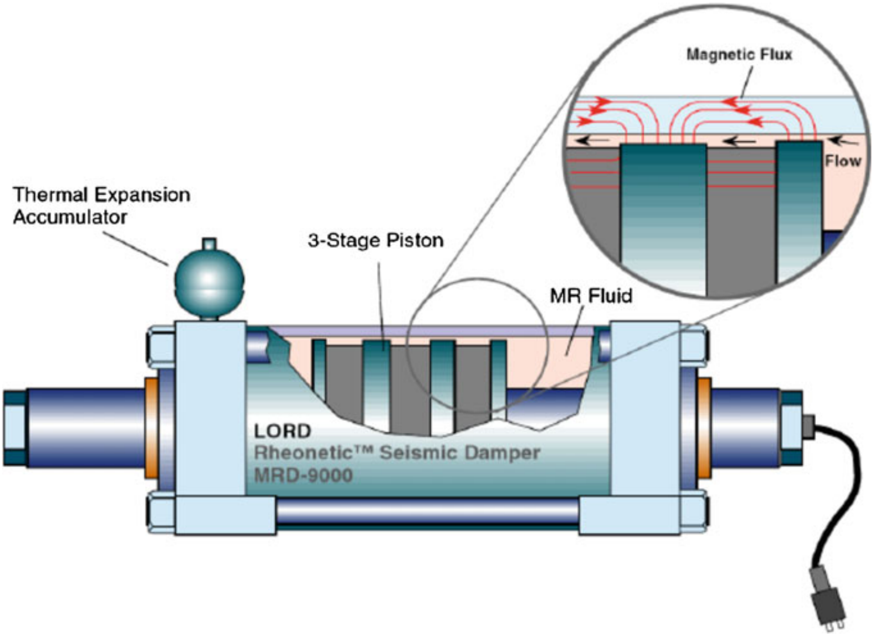

Fig. 2 Schematic of the prototype 20-ton large-scale MR damper

In general, a MR damper consists of a hydraulic cylinder, magnetic coils, and MR fluids that consist of micron-sized magnetically polarizable particles floating within oil-type fluids as shown in Fig. 2.

The MR damper is operated as a passive damper; however, when a magnetic field is applied to the MR fluids, the MR fluids are changed into a semi-solid state in a few milliseconds. This is one of the most unique aspects of the MR damper compared to active systems: the active control system malfunction might occur if some control feedback components, e.g., wires and sensors, are broken for some reasons during a severe earthquake event; while a semiactive system is still operational as at least a passive damping system even when the control feedback components are not functioning properly. Its characteristics are summarized by Kim et al. [23].

2.3 *Smart Controller*

In 1985, Takagi and Sugeno suggested an effective way for modeling complex nonlinear systems by introducing linear equations in consequent parts of a fuzzy model. It has led to reduction of computational cost because it does not need any defuzzification procedure. The fuzzy system used in the WNF model is of the form [22].

$$R_j : \text{If } u_{FZ}^1 \text{is } P_{1,j} \text{ and } u_{FZ}^2 \text{ is } P_{2,j} \ldots \text{and } u_{FZ}^i \text{ is } P_{i,j}$$
$$\text{Then } z = f_j\left(u_{FZ}^1, \ldots, u_{FZ}^i\right), \quad j = 1, 2, \ldots, N_r \tag{1}$$

where R_j is the jth fuzzy rule, N_j is the number of fuzzy rules, P_{ij} are fuzzy sets centered at the jth operating point, and u_{FZ}^i are premise variables that can be either input or output values. The equation of the consequent part $z = f(u_{FZ}^1, \ldots, u_{FZ}^i)$ can be any linear equation. Using fuzzy interpolation methods, all of the local subsystems are integrated

$$y = \sum_{j=1}^{N_r} W_j\left(u_{FZ}^i\right)\left[f_j\left(u_{FZ}^1, \ldots, u_{FZ}^i\right)\right] / \sum_{j=1}^{N_r} W_j\left(u_{FZ}^i\right) \tag{2}$$

where $W_j(u_{FZ}^i) = \prod_{i=1}^{n} \mu_{p_{i,j}}(u_{FZ}^i)$, n is the number of input variables and $\mu_{p_{i,j}}(u_{FZ}^i)$ is the membership grade of u_{FZ}^i in $P_{i,j}$. However, the main challenge in using a fuzzy model is the optimization of its parameters. Therefore, incorporating NNs to create a neuro-fuzzy system allows for these parameters to be optimized during computation.

The architecture of a NF model is shown in Fig. 3. This figure represents a two inputs, one output, and three membership functions (MFs). Each layer has particular tasks to complete before the data moves to the next layer.

In layer 1, the function of the node is represented by

$$F_{FZ}^{1,j} = \mu_{P_{i,j}}\left(u_{FZ}^i\right) \tag{3}$$

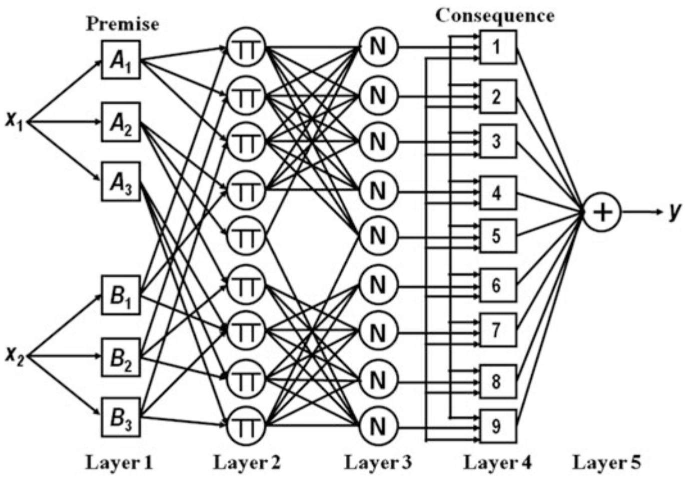

Fig. 3 Neuro-fuzzy model architecture

For a Gaussian MF used in this simulation,

$$\mu_{P_{i,j}}\left(u_{FZ}^{i}\right) = \exp\left[-(u-a_1)^2/2a_2^2\right] \tag{4}$$

where a_1 and a_2 are adjustable parameters of the Gaussian function. This MF is applied to each input in layer 1. Layer 2 then outputs the product of all inputs into layer 2, known as the firing strength

$$F_{FZ}^{2,j} = \mu_{P_{i,j}}\left(u_{FZ}^{1}\right) \times \mu_{P_{i,j}}\left(u_{FZ}^{2}\right) \times \cdots \times \mu_{P_{i,j}}\left(u_{FZ}^{i}\right) \tag{5}$$

Layer 3 takes a ratio of these layer 2 firing strengths in order to normalize the layer 2 outputs, such that

$$F_{FZ}^{3,j} = F_{FZ}^{2,j} / \sum_{j} \prod_{i=1}^{n} \mu_{P_{i,j}}\left(u_{FZ}^{i}\right) \tag{6}$$

Layer 4 then applies a node function to the normalized firing strengths

$$F_{FZ}^{4,j} = F_{FZ}^{3,j} \cdot f_j = F_{FZ}^{3,j}\left[f_j\left(u_{FZ}^{1}, \ldots, u_{FZ}^{i}\right)\right] \tag{7}$$

The last layer summates the layer inputs

$$F_{FZ}^{5,j} = \sum_{j} \prod_{i=1}^{n} \mu_{P_{i,j}}\left(u_{FZ}^{i}\right)\left[f_j\left(u_{FZ}^{1}, \ldots, u_{FZ}^{i}\right)\right] / \sum_{j} \prod_{i=1}^{n} \mu_{P_{i,j}}\left(u_{FZ}^{i}\right) \tag{8}$$

The output of this NF system is then used in a hybrid learning algorithm to create a linear combination of the consequent parameters. The key parameters for this simulation include the number of iterations, or epochs, the number of MFs and the type of MF, as well as the step size of the function. In this study, the premise part is determined by backpropagation algorithm while the consequent parameters are optimized using the least square estimator. Four Gaussian membership functions are adopted, the number of iterations is 300, the iteration step size is 0.9 and the increase rate of the step size is 1.2. Types of MFs can vary from a generalized bell function, Gaussian functions, sigmoidal functions, trapezoidal function, as well as other forms. Each change of variables will yield different output results [18, 43]. The fuzzy inference system sets up rules based on the number of MFs used in simulation. Fuzzy rules are set up for a five MF system. Each number represents one of the twenty-five fuzzy regions that are created through the use of five MFs in the neuro-fuzzy model. The fuzzy region is defined by the premise, and the output is generated through the consequent.

The inclusion of discrete wavelet transforms allows for an effective method to rid the control system of extraneous data, or noise. This methodology uses Daubechie wavelets filters in order to de-noise response data that are then used as inputs to the smart fuzzy control model. As mentioned earlier, the use of discrete wavelet transforms allows for a fixed time-frequency resolution. It means that the window function is chosen, and then the resolution is fixed through processing. A reduction in the number of data points required for accurate representation of the system is possible due to representation of the function with several discretization steps. The proposed algorithm for the smart fuzzy control is shown in Fig. 4.

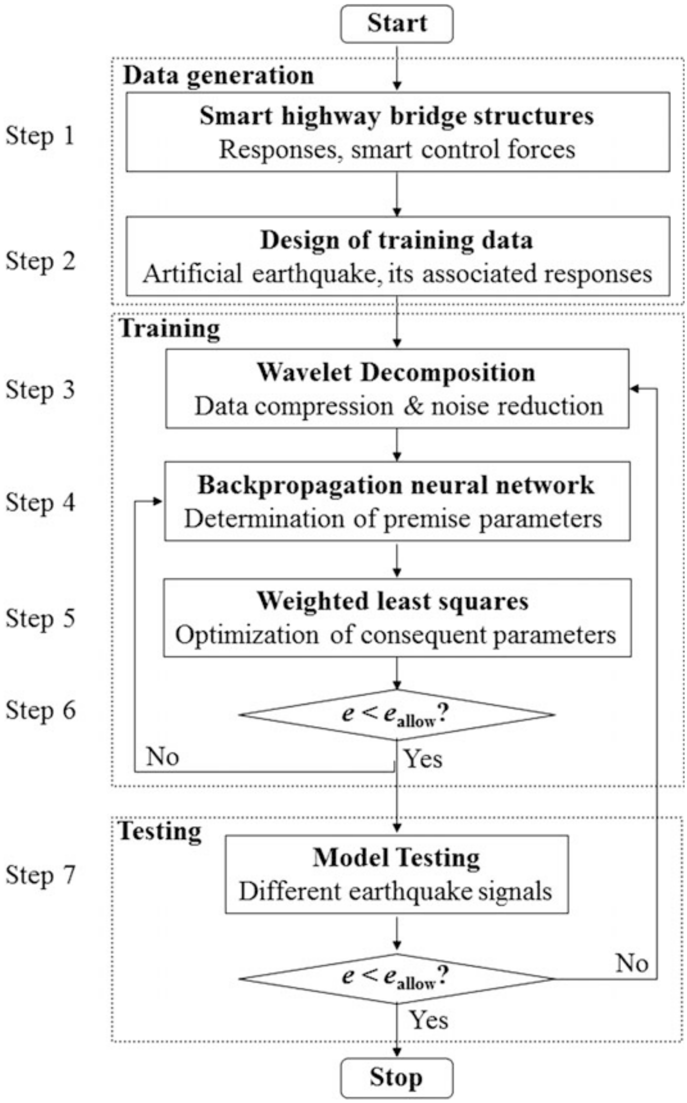

Fig. 4 Flowchart of the proposed algorithm

This control model proposes the use of two levels of discrete wavelet transform as a means of filtering as well as training the optimal control force. The architecture of this proposed smart fuzzy control system is depicted in Fig. 5. The smart fuzzy control algorithm is a two-input, one-output system to determine the control force of an MR damper. For this study, the inputs to the smart fuzzy control system are displacement and acceleration measurements. These were determined through an iterative process to maximize the results from training of the smart fuzzy control system, where velocity and drift responses were also studied to find the combination with the most favorable results. Next, simulations were performed on a highway bridge under a variety of earthquake loads to successfully reduce the seismic responses.

2.4 Simulation

Many simulations were performed to determine the best arrangement of control forces. It was found that the computation of only two control forces would need to be calculated for optimal voltage signals: x-direction and y-direction. This bridge is equipped with sixteen MR dampers in each *x*- and *y*-directions; all the MR dampers in each direction are commanded by a single control signal. To train the input-output mapping function of the smart fuzzy control model, an artificial earthquake signal that includes characteristics of the 1940 El-Centro and Kobe earthquake, as shown in Figs. 6 and 7.

Figures 8, 9, 10, 11, 12 and 13 show the simulation results. Figures 8 and 9 are the relative displacement responses to the 1940 El-Centro and Kobe earthquakes, respectively. Figures 10 and 11 are the absolute acceleration responses to the 1940 El-Centro and Kobe earthquakes, respectively. Figures 12 and 13 are the base shear

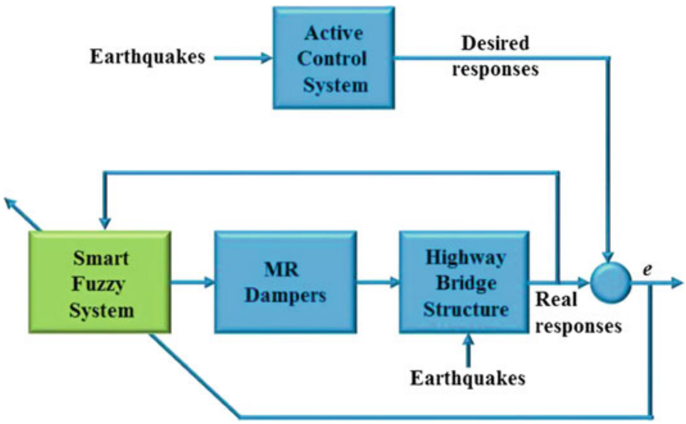

Fig. 5 Configuration of the proposed smart control

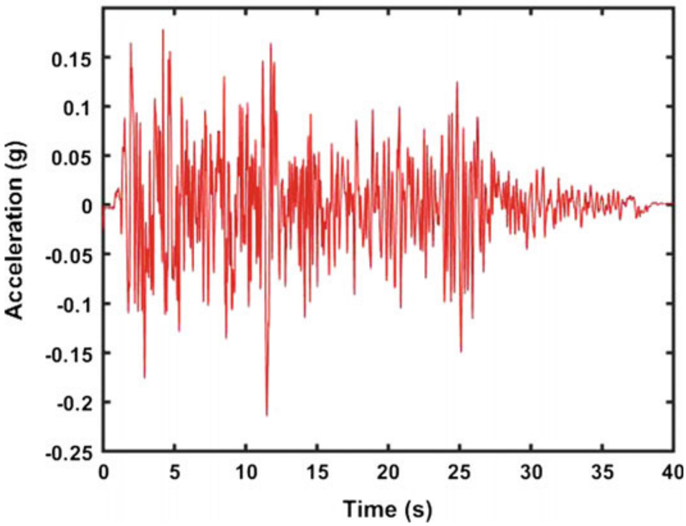

Fig. 6 1940 El-Centro earthquake

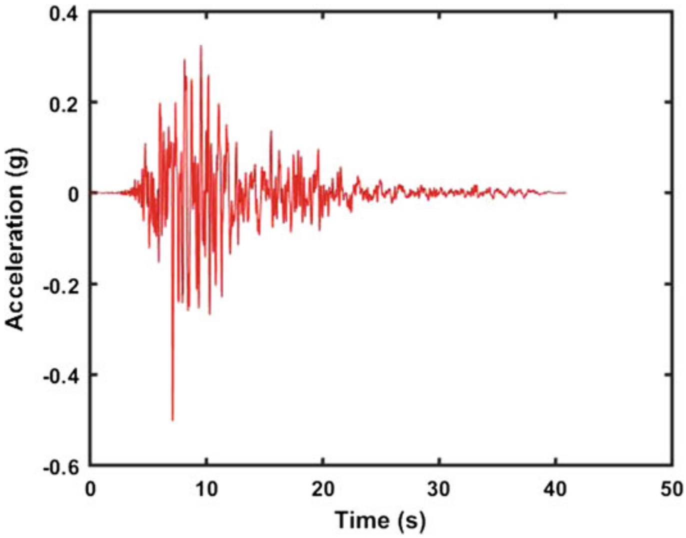

Fig. 7 Kobe earthquake

forces at the column to the 1940 El-Centro and Kobe earthquakes, respectively. The dotted lines represent the uncontrolled responses; while the solid red lines are the responses of the smart fuzzy control systems. As shown in figures, the proposed smart fuzzy control system is effective in mitigating the dynamic responses of highway bridge structures for most cases.

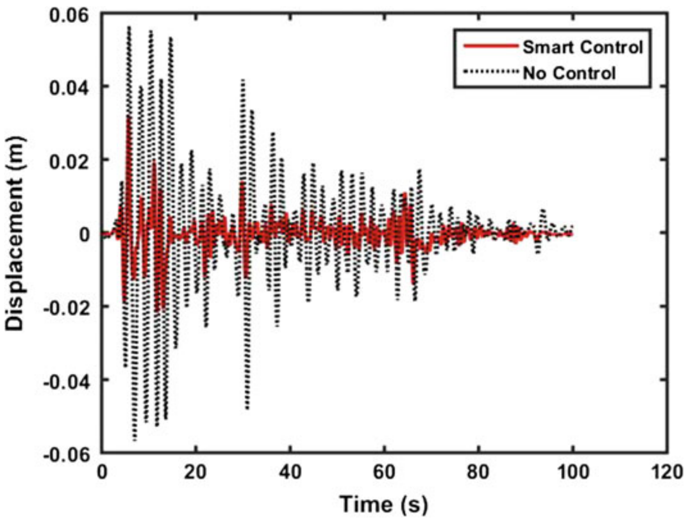

Fig. 8 Displacement: 1940 El-Centro earthquake

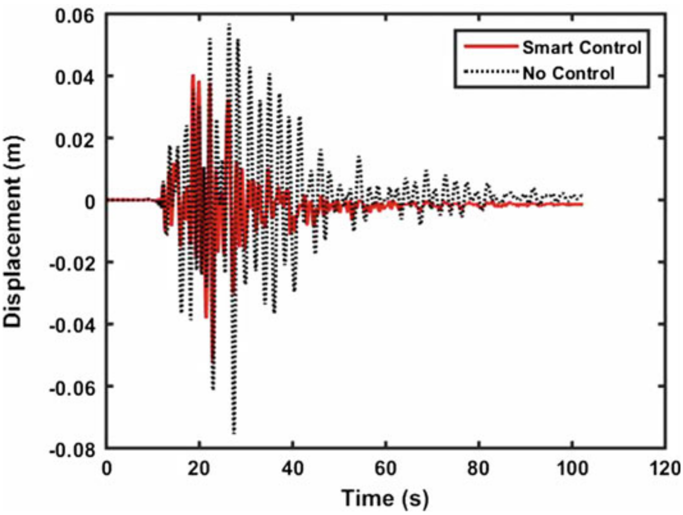

Fig. 9 Displacement: Kobe earthquake

As a means of validation and comparison, several evaluation indices are used. These indices compare structural responses and control outputs of the proposed smart control system to that of the uncontrolled structure, showing how much each index is reduced [1].

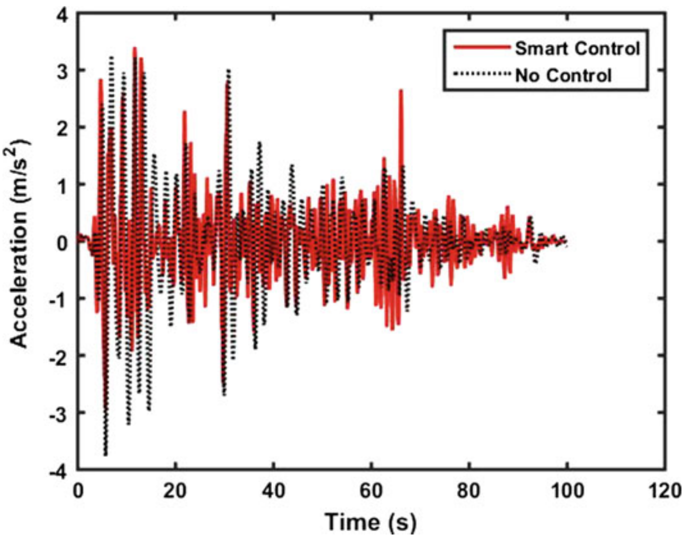

Fig. 10 Acceleration: 1940 El-Centro earthquake

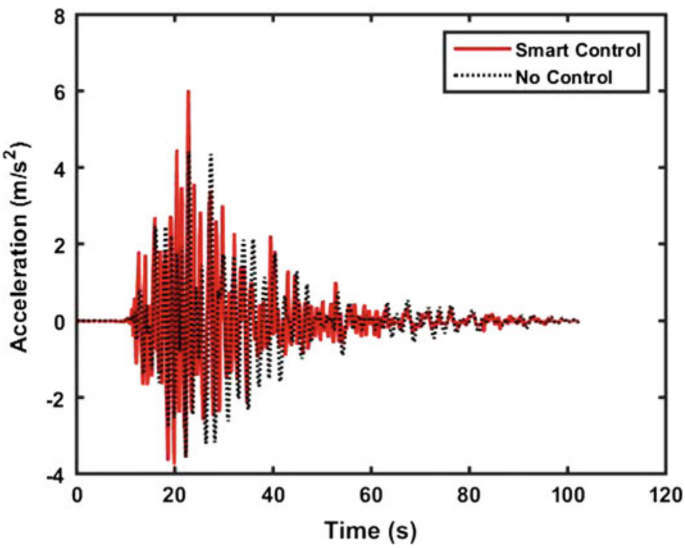

Fig. 11 Acceleration: Kobe earthquake

here $\hat{F}_{bi}(t)$ is the time history of shear force of the ith degree of freedom of the control system, $\hat{F}_{0b,\max}$ is the maximum shear force of the uncontrolled structure, $M_{bi}(t)$ is the time history of overturning moment, $M_{0b,\max}$ is the maximum overturning moment of the uncontrolled structure, $\hat{y}_{mi}(t)$ is the time history of the

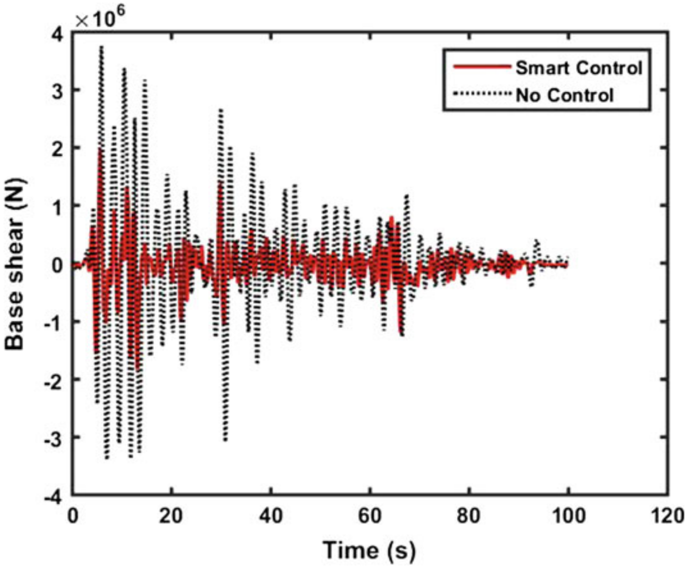

Fig. 12 Base shear: 1940 El-Centro earthquake

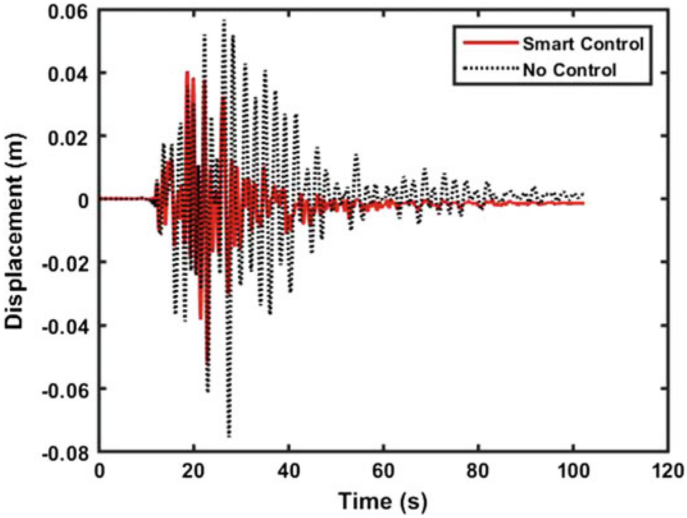

Fig. 13 Base shear: Kobe earthquake

midspan displacement, $\hat{y}_{0m,\max}(t)$ is the maximum midspan displacement of the uncontrolled structure, $\left|\ddot{\hat{y}}_{mi}(t)\right|$ is the time history of the midspan acceleration, $\ddot{\hat{y}}_{0m,\max}(t)$ is the maximum acceleration of the uncontrolled structure, $\hat{y}_{bi}(t)$ is the time history of the abutment displacement, $\hat{y}_{0b,\max}$ is the maximum abutment

Table 1 Control performance evaluation

	ElCentro	Kobe
$J_1 = \max\left\{\frac{\max\lvert\hat{F}_{bi}(t)\rvert}{\hat{F}_{0b,\max}}\right\}$	0.6967	0.8696
$J_2 = \max\left\{\frac{\max\lvert\hat{M}_{bi}(t)\rvert}{\hat{M}_{0b,\max}}\right\}$	0.5268	0.5901
$J_3 = \max\left\{\frac{\max\lvert\hat{y}_{mi}(t)\rvert}{\hat{y}_{0m,\max}}\right\}$	0.5627	0.6856
$J_4 = \max\left\{\frac{\max\lvert\ddot{\hat{y}}_{mi}(t)\rvert}{\ddot{\hat{y}}_{0m,\max}}\right\}$	0.9211	1.2205
$J_5 = \max\left\{\frac{\max\lvert\hat{y}_{bi}(t)\rvert}{\hat{y}_{0b,\max}}\right\}$	0.2942	0.5292
$J_6 = \max\left\{\frac{\max\lvert\hat{\Phi}_i(t)\rvert}{\hat{\Phi}_{\max}}\right\}$	0.5268	0.5901
$J_7 = \max\left\{\frac{\max\int d\hat{E}_i}{\hat{E}_{\max}}\right\}$	0	0
$J_8 = \max\left\{\frac{\hat{N}_{c,d}}{\hat{N}_d}\right\}$	0	0
$J_9 = \max\left\{\frac{\max\lVert\hat{F}_{bi}(t)\rVert}{\lVert\hat{F}_{0b,\max}\rVert}\right\}$	0.5679	0.7387
$J_{10} = \max\left\{\frac{\max\lVert\hat{M}_{bi}(t)\rVert}{\lVert\hat{M}_{bi,\max}\rVert}\right\}$	0.2954	0.5178
$J_{11} = \max\left\{\frac{\max\lVert\hat{y}_{mi}(t)\rVert}{\lVert\hat{y}_{0m,\max}\rVert}\right\}$	0.3052	0.5396
$J_{12} = \max\left\{\frac{\max\lVert\ddot{\hat{y}}_{mi}(t)\rVert}{\lVert\ddot{\hat{y}}_{0m,\max}\rVert}\right\}$	0.8069	1.0767
$J_{13} = \max\left\{\frac{\max\lVert\hat{y}_{bi}(t)\rVert}{\lVert\hat{y}_{0b,\max}\rVert}\right\}$	0.2330	0.4155
$J_{14} = \max\left\{\frac{\max\lVert\hat{\Phi}_i(t)\rVert}{\lVert\hat{\Phi}_{\max}\rVert}\right\}$	0.2954	0.5178
$J_{15} = \max\left\{\max\left(\frac{\hat{f}_l(t)}{\hat{W}}\right)\right\}$	0.0244	0.0248
$J_{16} = \max\left\{\max\left(\frac{\hat{d}_l(t)}{\hat{x}_{0m,\max}}\right)\right\}$	0.2705	0.5218
$J_{17} = \#$ of control devices	16	16
$J_{18} = \#$ of required sensors	12	12
$J_{19} = \dim(\hat{\mathrm{x}}_{\mathrm{c,k}})$	28	28

displacement of the uncontrolled structure, $\hat{\Phi}_i(t)$ is the time history of the ductility, $\hat{\Phi}_{\max}$ is the maximum ductility of the uncontrolled structure, $d\hat{E}_i$ is the dissipated energy of curvature at the column, $\hat{E}_{\max}$ is the maximum dissipated energy of the curvature at the column of the uncontrolled structure, $\hat{N}_{c,d}$ is the number of plastic connections of the control system, $\hat{N}_d$ is the number of plastic connections of the uncontrolled system, $|.|$ denotes the absolute value, $\|.\|$ denotes the normalized value, $\hat{f}_l(t)$ is the time history of the control force from the control device, $\hat{W}$ is the seismic weight of the system, $\hat{d}_l(t)$ is the stroke of the control device, $x_{0m,\max}$ is the maximum bearing deformation of the uncontrolled system, $\hat{P}_l(t)$ is the time history of the instantaneous power required for the control device, $\dot{\hat{x}}_{0m,\max}$ is the maximum velocity of bearing of the uncontrolled system, and $\hat{x}_{c,k}$ is the discrete state vector for the control algorithm. Table 1 shows the evaluation results of the proposed smart control systems. It is observed from Table 1 that the "Max" peak response quantities using the smart controller are quite effective in reducing structural vibration to both the El-Centro and Kobe earthquakes. In particular, peak evaluation criteria J_2, J_3, $J_5 \sim J_{11}$, and J_{13}, J_{14}, J_{16} and J_{18} are significantly reduced during both ground motions. It should be noted that structural displacement responses are directly related to safety of the bridge structures.

3 Conclusion

In this chapter, a novel smart control system is proposed for seismic response controls of seismically-excited bridge structures employing magnetorheological (MR) dampers. The smart control system is an integrated model of Takagi-Sugeno fuzzy model, wavelet transforms, and artificial neural networks. Using the smart fuzzy control system combines the positive attributes of the three described methodologies to create a system that is believed to yield more efficient results for system control of smart structures and shorter training times. To train the input–output mapping function of the smart fuzzy control model, an artificial earthquake signal and an MR damper force signal are used as a disturbance input signal and a control input, respectively, while acceleration response is used as output data. It is demonstrated from the simulation that the proposed smart fuzzy control model is effective in reducing the behavior of the seismically excited bridge-MR damper system.

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