ANN-cum-Fuzzy Control of Seismic Response using MR Dampers

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ABSTRACT
An ANN-cum-fuzzy control scheme is developed here by training an ANN offline to establish a direct mapping of the control forces and command voltage (required to produce a target percentage of response control) from the structural response feedback. The training data set is generated by using a fuzzy logic control algorithm, which considers the dynamic characteristics of the MR damper by fuzzification (in place of the use of any analytical model) of the MR damper characteristics. These characteristics are represented by force-velocity and force-displacement curves of the MR damper under sinusoidal actuation test. A ten-storey building frame is taken as an illustrative example. Analytical results indicate that a back-propagation training algorithm with three layers architecture can be effectively used for training the ANN. A minimum number of response measurements are required to be provided as inputs to train the ANN so that it can capture the overall structural behavior and can effectively predict the command voltage for the MR dampers employed to control the responses.

Keywords: Semiactive Control; Fuzzy; Neural Network; MR Damper; Building Frame

1. INTRODUCTION

Structural control has emerged as a very effective technique for protecting structures from damage during earthquakes. One category of control algorithms are conventional methods which use mathematical models. The other category includes intelligent control algorithms which are based on the theories of fuzzy logic, neural networks or their combinations. The use of fuzzy inference system (FIS) in developing a semiactive controller or in modeling a MR damper calls for transforming human knowledge or experience into fuzzy rule bases or fuzzy if-then rules (Symans and Kelly, 1999; Choi *et. al.*, 2004; Wilson and Abdullah, 2005; Bhardwaj and Datta, 2006; Ok *et. al.*, 2007). Therefore, the effectiveness of the methods based on fuzzy logic depends on the choice different parameters defining the fuzzy rule bases. It cannot learn the rules by itself or cannot tune the parameters so as to minimize the output error or to maximize the performance effectiveness. This limitation of the fuzzy logic theory can, however, be overcome by using a neuro-fuzzy system. One such system is ANFIS (Adaptive-Network-Based Fuzzy Inference System). It is an architecture, functionally equivalent to a Sugeno type fuzzy rule base and is a method for training the existing rule base with a learning algorithm based on a collection of training data. However, the standard ANFIS algorithm available in the MATLAB becomes unsuitable for handling large size problems having many inputs. This problem can be addressed by separately training a neural-network and use it in the control theory (Ghaboussi and Joghataei, 1995; Chen *et. al.*, 1995; Ni *et. al.*, 2002; Xu *et. al.*, 2003).

In the present work, an ANN-cum-fuzzy control scheme is developed by training an ANN offline to establish a direct mapping of the control forces and command voltage (required to produce a target percentage of response control) from the structural response feedback. The control scheme does not require the use of either an emulator network or an observer. The training data set is generated using a control algorithm developed based on fuzzy logic. The reason for using fuzzy control algorithm for training the ANN is to consider the dynamic behaviour of the MR damper by directly fuzzyfying the hysteretic curve of the damper. The motivation for using the trained ANN is to replace control algorithms by ANN chips (weightages) in the LabVIEW for online control experiment or prototype use. In order to demonstrate the effectiveness of the control strategy, a ten storey building frame is taken and is subjected to earthquake ground excitations.

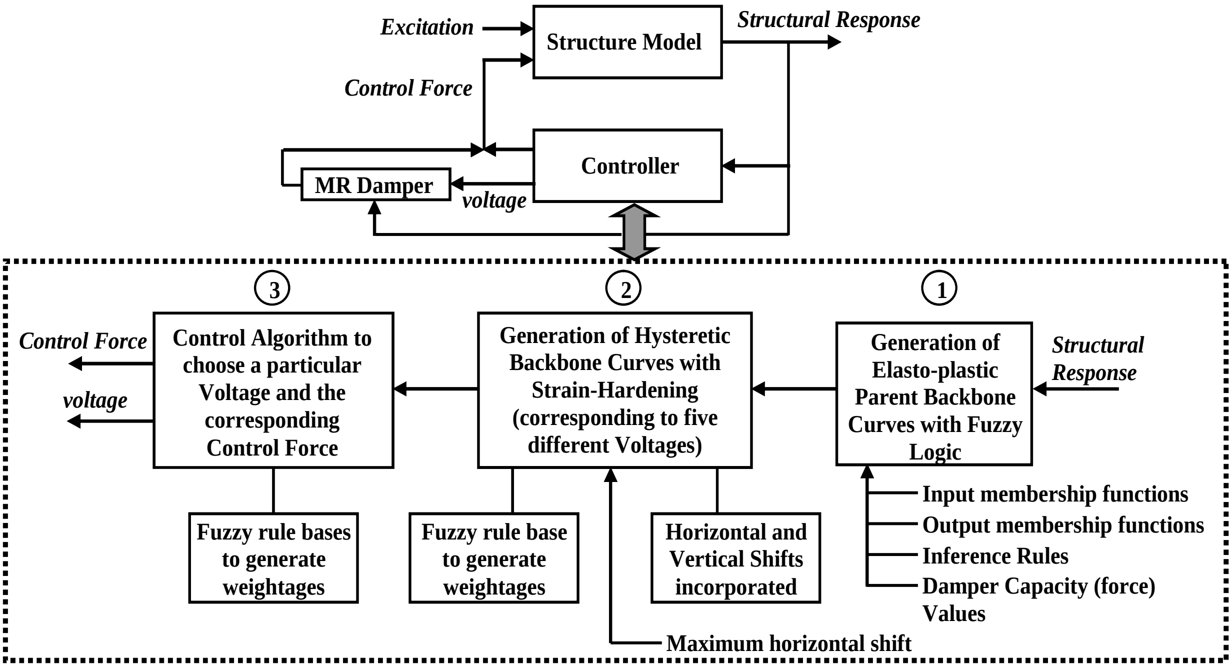


Figure 1. Schematic diagram of the fuzzy control system;

2. DYNAMIC BEHAVIOUR OF MR DAMPER

Mechanical model of MR damper, based on Bouc-Wen hysteresis relations, was developed by Spencer *et. al.* (1997). The dynamic behaviour of an MR damper is characterized by its response to sinusoidal displacement excitation and such experimental results are available in literature (Spencer *et. al.*, 1997; Dyke *et. al.*, 1996). In the present study, a target curve is generated by the fuzzy logic for voltage 1.5 volts for a sinusoidal actuation of frequency 2.5 Hz and amplitude 1.5 cm.

3. SEMIACTIVE CONTROL USING MR DAMPER

As mentioned before, the semiactive control using MR damper has been developed by utilizing the theory of bang-bang control or clipped-optimal control. In both the control theories, the control force, the voltage to be applied to the MR damper at any instant of time are obtained analytically for a given state of the system. For this purpose, either Lyapunov's stability criteria or Riccati equations are solved. The development of the theory requires the dynamic properties of the structure and a mathematical modelling of the MR damper. In fuzzy logic control algorithm, fuzzy rule base is used to obtain the control force and the voltage to be applied to MR damper for given damper characteristics. For this purpose, two sets of fuzzy rule bases and fuzzy algorithms are developed – one for fuzzification of the force – velocity characteristics of the MR damper, which is known from the experimental test, and the other for the development of the control algorithm, which will provide the desired control force to the structure for a given state of the system. Note that the desired control force applied to the structure is consistent with the voltage applied to the MR damper. This is achieved by integrating the two fuzzy algorithms as mentioned above.

The entire operation is described with the help of Fig 1. One or more of the response quantities of the structure, subjected to earthquake ground acceleration, is provided is provided as input to a fuzzy controller in the feedback loop. The controller performs the control operation in three stages:

Stage 1: The controller generates elasto-plastic backbone curves corresponding to different prescribed damper capacities. This is achieved with the help of a fuzzy logic, which is developed by defining sets of input and output membership functions and fuzzy inference rules.

Stage 2: In the next stage, hysteretic curves with strain hardening are generated by incorporating required horizontal and vertical shifts. The implementations of horizontal and vertical shifts are shown in Figs 2 and 3; the final backbone curve generated is shown in Fig 4. For this, a fuzzy rule base is developed to generate weightages. A value of the maximum horizontal shift is provided as input. In order to test the algorithms developed, the force-velocity hysteresis curves for voltage 1.5 volts obtained using the fuzzy rule base for a sinusoidal actuation of frequency 2.5 Hz and amplitude 1.5 cm is compared the target curve in Fig 5. It is seen from the figures that both these curves match well with each other.

Stage 3: In the last stage, a fuzzy control algorithm determines the control force and the corresponding voltage for a given state of the system. A fuzzy rule base generates the desired values of the weightages at different time steps. In case of real time experiments, this command voltage is supplied to the MR damper, which then produces the desired control force.

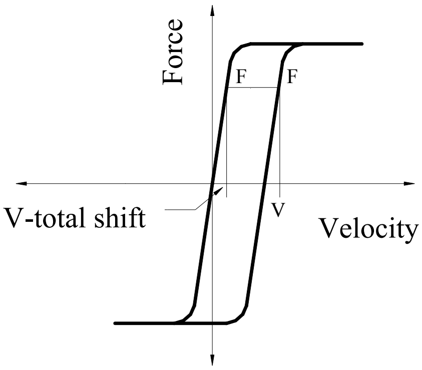


Figure 2. Implementation of horizontal shift

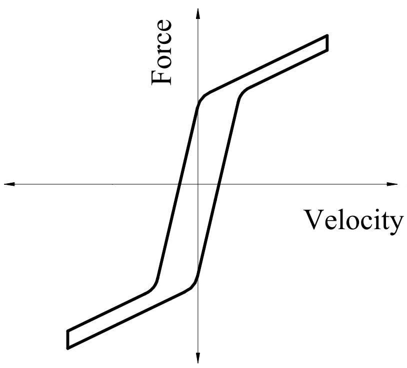


Figure 3. Vertical shift while modelling strain-hardening

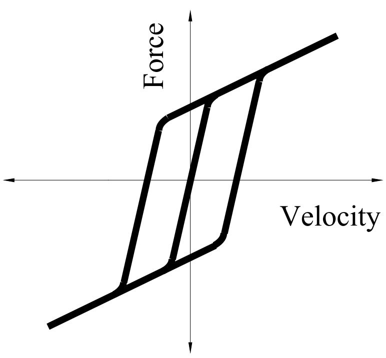


Figure 4. Backbone curve with post-yield slope and hysteresis loop

4. THEORETICAL DEVELOPMENT OF CONTROL SCHEME

Considering a MDOF structure with n degrees of freedom, subjected to earthquake ground acceleration $\ddot{x}_g(t)$ and assuming that the control forces $\boldsymbol{f}$ are adequate to keep the entire structure within the elastic range, the equation of motion can be written as

$$\boldsymbol{M}\ddot{\boldsymbol{x}} + \boldsymbol{C}\dot{\boldsymbol{x}} + \boldsymbol{K}\boldsymbol{x} = \Gamma\boldsymbol{f} - \boldsymbol{M}\Lambda\,\ddot{x}_g\,; \quad \dot{\boldsymbol{z}} = \boldsymbol{A}\boldsymbol{z} + \boldsymbol{B}\boldsymbol{f} + \boldsymbol{E}\,\ddot{x}_g; \quad \boldsymbol{y} = \boldsymbol{C}\boldsymbol{z} + \boldsymbol{D}\boldsymbol{f} + \boldsymbol{v} \tag{4.1}$$

where $\boldsymbol{x}$ is vector of relative displacement, $\boldsymbol{f}$ is a vector of control force corresponding to n_c number of dampers and $\ddot{x}_g$ is ground acceleration. $\boldsymbol{M}$, $\boldsymbol{C}$ and $\boldsymbol{K}$ are mass, damping and stiffness matrices of appropriate size. Γ represents an $n \times n_c$ matrix denoting the control force actuation on the structure due to the location of dampers and Λ is a vector of unity. In the usual state space form, $\boldsymbol{A}$ is a $2n \times 2n$ system matrix, $\boldsymbol{B}$ is a $2n \times n_c$ control matrix, $\boldsymbol{E}$ is a $2n \times 1$ disturbance matrix, $\boldsymbol{C}$ is a $p \times 2n$ measurement matrix and $\boldsymbol{D}$ is a $p \times n_c$ matrix. $\boldsymbol{z}$ is a $2n \times 1$ state vector, $\boldsymbol{y}$ is a $p \times 1$ vector of measured outputs, $\boldsymbol{v}$ is a $p \times 1$ measurement noise vector. A ten-story building frame available in literature (Yuen *et. al.*, 2007) is considered. The semiactive control using MR damper involves fuzzification of the MR damper hysteresis curve and consequently, the development of the fuzzy logic control algorithms. The control algorithm is described in detail in Das *et. al.* (2012). For training the neural networks, the fuzzy semiactive control algorithm described in the above-mentioned literature is used for generating the training data and real earthquakes of different peak ground accelerations are used. Since multiple dampers are used, separate training data sets are generated for each damper.

4.1 Training of Neural Network

For training the neural networks, the fuzzy semiactive control algorithm described earlier is used for generating the training data and real earthquakes of different peak ground accelerations are used. Since multiple dampers are used, separate training data sets are generated for each damper. To start with, inputs to be given to the networks were taken to be as fewer number of structural responses as was possible because the more the number of inputs, the more extensive and time consuming the training process becomes. It was, however, found that unless a minimum number of structural inputs were considered, the networks failed to capture the overall structural behaviour and hence, the training was not effective. Finally, the training data are generated by taking the response measurements taken from three points (first, sixth and tenth floors) in case of the ten storey building frame. The measured responses from each point include relative displacement, relative velocity and absolute acceleration. The ANN is trained for producing control signals for some percentage reduction of a response quantity such that the other response quantities are also controlled significantly. This requires experience and some trial runs. After giving some trial runs, a target reduction for base shear for the ten storey building are considered. The output quantities are the control force generated by the MR damper and the command voltage required to generate that force. For the case of ten storey frame, only control force is considered as output in order to keep the training time within reasonable limit. Each of the input and output variables is normalized by dividing it with the absolute maximum value of that particular variable in the entire training data set. Three layer back-propagation neural networks consisting of an input layer, a hidden layer and an output layer are considered in the study. Choosing a learning rate of 0.001, each network is initially trained for 10000 epochs; then, if required, the ANNs are further trained for more number of epochs. The ANNs are trained in offline mode with the help of SNNS (Stuttgart Neural Network Simulator) software.

4.2 Testing of Neural Network

The neural networks are tested for (i) one of the data sets for which it was trained (known data) and (ii) for an earthquake ground motion (unknown data), which was not included in the training data set. For testing the ANN with the known data, the time-histories of the input variables (the measured responses at different floor levels and the target percentage control of a particular response quantity) corresponding to this earthquake are provided at the input nodes of the trained ANN. Then, output values obtained are then compared with the time-histories of these same output variables in the original training data set. This can be termed as offline mode of testing the neural network. The ANNs are also tested in the online mode. In order to do that, a MATLAB function of the forward model of the network is written, extracting the values of the connection weights and bias from the trained network. Then, in the Simulink model of the structure, the block consisting of the fuzzy model of the MR damper is replaced with the forward model of the neural net. With the target percentage reduction of a response quantity as the additional input provided to the ANN, the Simulink model of the structure is analyzed for the ‘known’ earthquake excitation and the results are obtained. In both the modes of testing, the target percentage control is based on the percentage control, which is actually obtained by analyzing the structure using the fuzzy model. The measured responses (computed controlled responses) at different floors obtained from this analysis are compared with those obtained by analyzing the structure with the fuzzy model of the MR damper. The difference between the time histories of the control forces, voltage, and the response quantities serves as a measure of the efficiency of the neural network training. Another measure of efficiency is the difference between the target percentage reduction of the particular response quantity in the training data and that obtained for the same response quantity using the forward model of the ANN in the analysis.

The trained ANN is tested with the unknown data in the same way, *i.e.*, in the offline as well as in the online mode. For offline testing, the structure is first analyzed for the ‘unknown’ earthquake excitation. The measured responses (*i.e.*, the responses obtained analytically) at different floor levels and the percentage control (for the given response quantity) achieved become the input for the trained ANN, which is then tested and the efficiency of training is found out in the same way as described before. For online testing also, the same procedure as in the case of the ‘known’ data is followed. The unknown data sets are generated by finding the controlled responses of the structure for additional harmonic excitation, *i.e.*, with different combination of frequency and amplitude, which are not used in the training data set.

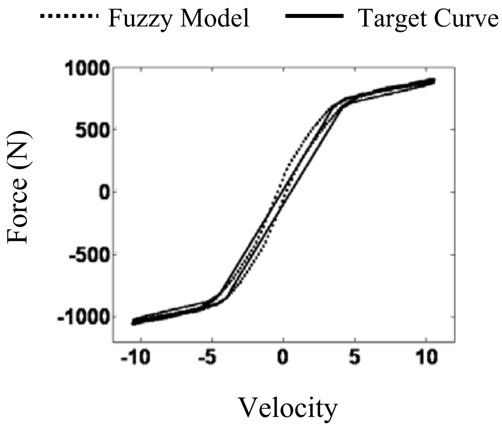
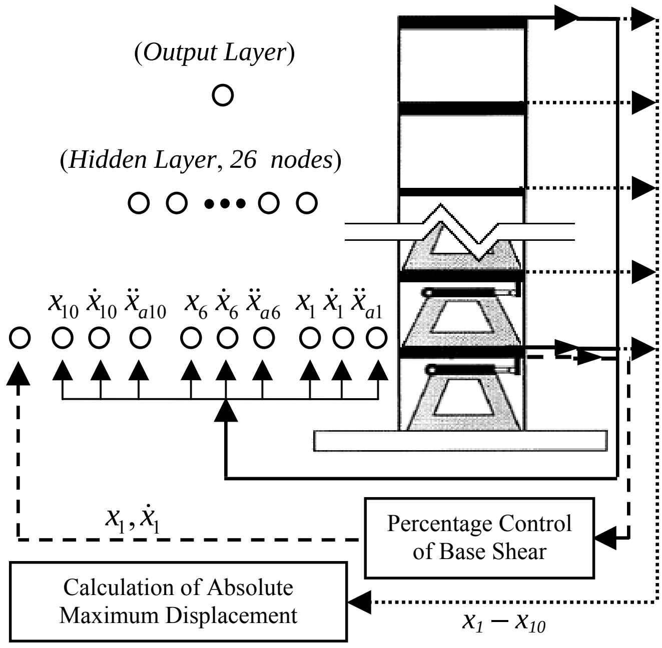


Figure 5. Comparison of backbone curve generated by the fuzzy model with the artificially generated target backbone curve for 1.5 volts



(b)

Figure 6. Schematic diagram of the neural network training methodology

5. NUMERICAL SOLUTION AND DISCUSSIONS

To verify the effectiveness of the proposed semiactive neurocontrol system using MR dampers, numerical simulations are performed. Simulation results of the proposed neurocontrol system are compared with those of a fuzzy control system as well as an uncontrolled system. A ten storey building frame available in literature (Yuen et. al., 2007) is considered. The mass of each floor of this building is 50 Kg and the interstorey stiffnesses are 948.70, 836.99, 886.11, 889.33, 925.77, 881.83, 833.79, 824.03, 872.11 and 829.86 N/cm for the first to the tenth storey, respectively. The values for the Rayleigh damping coefficients αm and αk are 0.1 s−1 and 7.36 × 10−4 s. Using the MR damper characteristics given by Spencer et. al. (1997), the control of responses of the under El Centro earthquake is obtained using reliability based control algorithm, using probabilistic concept. As a result, direct comparison of the controlled responses obtained by Yuen et. al. (2007) with the developed fuzzy control algorithm has not been possible because the latter is based on deterministic concept. When two dampers of 3000N capacity were installed at the bottom two storey levels, the percentage control was of the order of 50-55%. When more number of same dampers are used, the system became unstable. As a consequence, softer damper characteristics are used to control the same frame. In order to do that, softer backbone curves are artificially generated and with these curves as target curves, the fuzzy logic is modified. The target curve and the curve generated by the fuzzy logic for voltage 1.5 volts for a sinusoidal actuation of frequency 2.5 Hz and amplitude 1.5 cm are compared in Fig 5. It is seen from the figure that both the hysteresis curves compare well with each other. The control algorithm developed for the softer damper has been used to control the response of the frame. The architecture of these neural networks (*i.e.*, the number of nodes in the input, hidden and output layers, respectively) is also shown in Fig 6.

For the purpose of analysis, nine different earthquake excitations, are considered, namely Bhuj, Taiwan, Parkfield, Imperial Valley, Loma Prieta, Koyna, Coalinga, Tabas and San Fernando earthquakes. These excitations are scaled appropriately in order to have peak ground accelerations uniformly distributed over a range varying from 0.25g to 0.5g. In addition to these, N-S component of 1940 El Centro earthquake is also considered in the study. It is assumed that the responses of the ten storey building remains within the elastic range for the above mentioned earthquake excitations.

The Kobe Takatori and 1.5 times El Centro earthquakes are considered as ground excitations for testing the ANNs for generating the known and unknown data sets, respectively. Comparison of the time histories of first storey and fifth storey damper forces in the offline mode are shown in Fig 7. For the known earthquakes, the training data are used and for the unknown earthquake, the data is generated by analyzing the fuzzy model with the unknown earthquake as the ground excitation. It is seen from the figures that the outputs generated by the trained neural network compare well with those obtained analytically. The trained ANNs are also evaluated in the online mode. The response time histories are compared in Fig 8 for Parkfield earthquake (known data) and Figs 9-11 for 1.5 times El Centro earthquake (unknown data). Relative displacements, absolute acceleration and interstorey drifts are compared in these figures. The controlled responses obtained by using the trained ANN online are compared with those obtained by using the fuzzy model; the uncontrolled responses are also shown. It is seen from the figures that both responses agree well with each other both for known as well as for unknown data. Fig 12 compares the damper responses (force-displacement and force-velocity curves) in the online mode. It is clearly seen from these figures that the characteristics of the damper force computed by using the fuzzy model are reasonably close to those obtained by using the trained ANN.

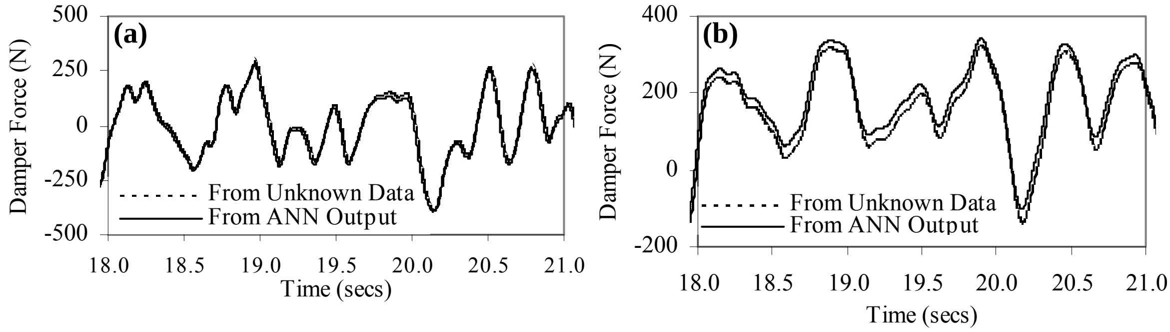


Figure 7. Comparison between the time-histories obtained from training data and from trained ANN output for 1.5 times El Centro earthquake (unknown data): (a) first storey damper force and (b) fifth storey damper force.

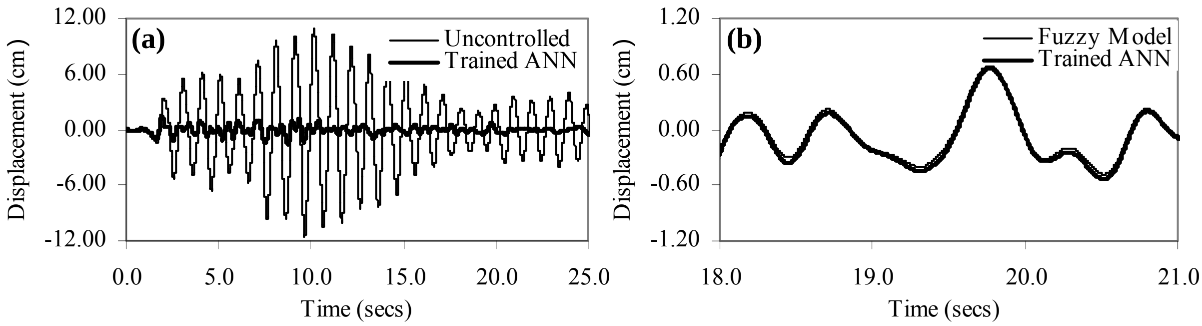


Figure 8. Top storey relative displacements of the ten storey building frame for Parkfield earthquake (known data): (a) time histories of responses and (b) comparison of responses

In order to evaluate the effectiveness of the neural network training, some numerical values of percentage reduction of responses and maximum control forces are listed for comparison in Table 1. The percentage control of different responses of the first, third, fifth, sixth and the tenth storeys, the base shear and the maximum control force of the first and the fifth storey dampers are considered. In the tables, the figures shown in brackets represent the target response control percentage values which have been provided as inputs to the ANNs. These values are based on response reductions obtained by analyzing the structures using fuzzy control algorithm. It is seen from the tables that the differences between the target percentage control and percentage of control achieved by using the trained ANN are not significant for all response quantities. Further, ANN predicted maximum control forces match quite well with those of the target ones.

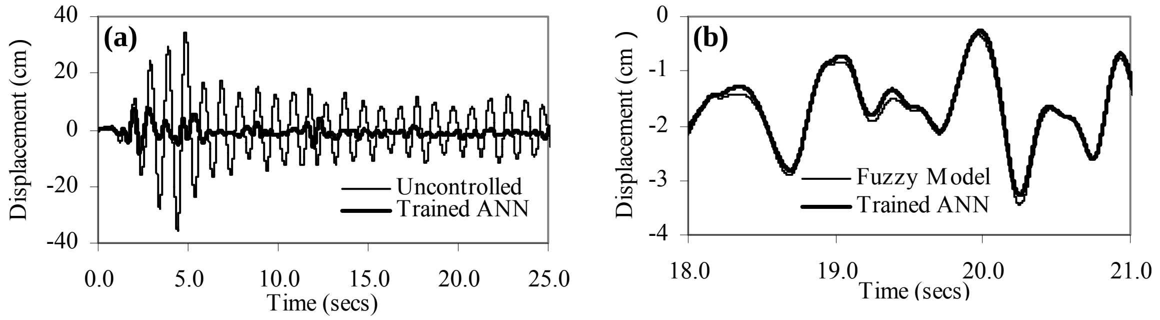


Figure 9. Top storey relative displacements of the ten storey building frame for 1.5 times El Centro earthquake (unknown data): (a) time histories of responses and (b) comparison of responses

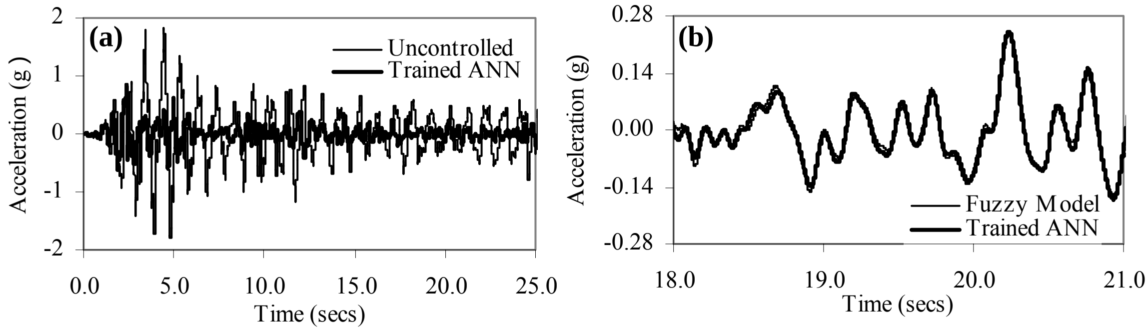


Figure 10. Top storey absolute acceleration of the ten storey building frame for 1.5 times El Centro earthquake (unknown data): (a) time histories of responses and (b) comparison of responses

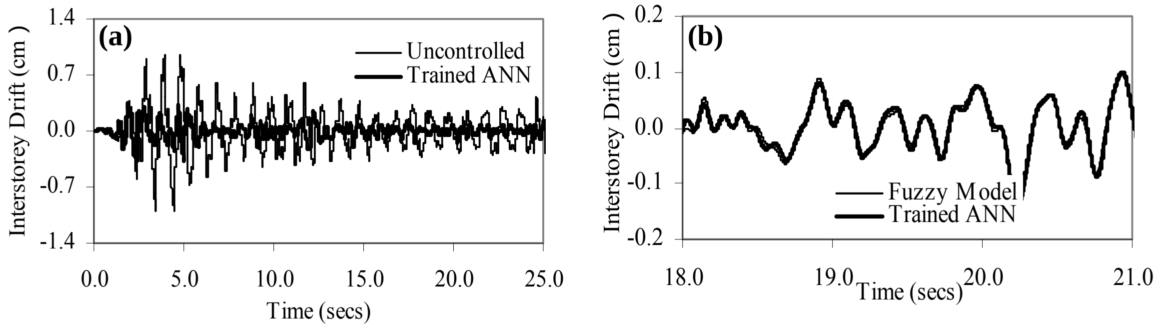


Figure 11. Top storey interstorey drift of the ten storey building frame for 1.5 times El Centro earthquake (unknown data): (a) time histories of responses and (b) comparison of responses

Thus, it is clearly evident that the trained ANNs work well for both known and unknown problems. The ANN-cum-fuzzy control scheme developed here is, thus, able to provide an ANN which can predict the required control force and/or input voltage to MR damper. The ANN can work well online and is trained to capture the experimentally obtained force-velocity characteristics of the MR dampers directly by fuzzification. In the subsequent chapter, use of the neural network developed by ANN-cum-fuzzy technique in the control experiment of model building.

6. CONCLUSIONS

An ANN-fuzzy control scheme is presented for the seismic control of building frames for future earthquakes. The control scheme has the advantages that it can consider (i) the characteristics of the dynamic behaviour of the MR devices, (ii) limited number of feedback measurements and (iii) a target reduction in response. The control scheme requires feedback of a limited number of floor displacements, velocities and acceleration, and a target percentage reduction to be provided as inputs to the ANN. The outputs of the ANN are the control forces. The control scheme is developed for a ten storey frame, with MR dampers in the first five storeys. Feedback measurements are taken from the first, sixth and the tenth floors. Following are the salient conclusions drawn from the study:

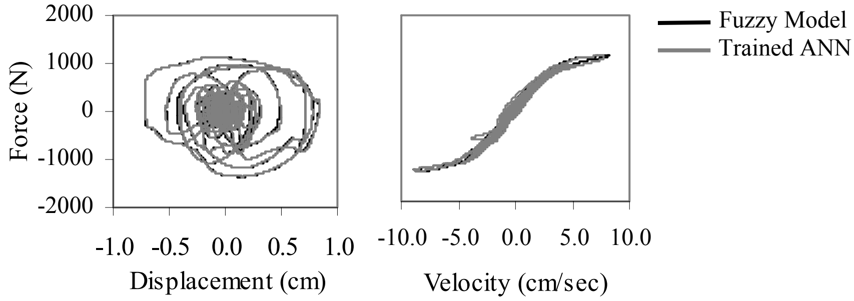


Figure 12. Comparison of the first storey damper responses for 1.5 times El Centro earthquake (unknown data)

Table 1. Comparison of the percentage control for different responses and the maximum control forces obtained by using the fuzzy model and the ANN for the ten storey building frame

Responses at storeys:	**Fuzzy Model**					**ANN**				
	Percentage Control (%)				**F (N)**	**Percentage Control (%)**				**F (N)**
	x^{+}	x_d^{++}	$\ddot{x}_a^{\#}$	V_b *		x	x_d	$\ddot{x}_a$	V_b	
Parkfield Earthquake (Known Data)										
1	91.9	…	31.1	…	432	91.6	…	29.3	…	440
3	…	90.4	…	…	…	…	89.6	…	…	…
5	…	…	…	…	259	…	…	…	…	253
6	90	76.6	45.8	…	…	89.6	76.1	45.0	…	…
10	86.5	55.4	61.0	…	…	86.2	55.0	60.9	…	…
BS	…	…	…	91.9	…	…	…	…	(92); 91.6	…
1.5 times El Centro Earthquake (Unknown Data)										
1	82.8	…	22.6	…	1364	82.0	…	12.2	…	1339
3	…	79.3	…	…	…	…	78.8	…	…	…
5	…	…	…	…	952	…	…	…	…	939
6	80.0	59.5	69.5	…	…	79.9	59.5	65.4	…	…
10	76.5	62.8	65.3	…	…	76.5	62.4	65.5	…	…
BS	…	…	…	82.9	…	…	…	…	(83); 81.9	…

Note: (+) Relative Displacement; (++) Interstorey Drift; (#) Absolute Acceleration; (*) Base Shear [Figure in bracket indicates Target Percentage Control]; (F) Maximum Control Force

1) A minimum number of response measurements is required to be provided as inputs to train an ANN so that it can capture the overall structural behaviour and can effectively predict for known and unknown data. In the present study, they are found to be displacement, velocity and acceleration from two floors.

2) Offline training of ANN with the generated data from fuzzy controller is found to be more efficient for large number of variables and data set than ANFIS. This is because ANFIS cannot be trained for large size problem due to lack of available memory for performing computation in MATLAB.
3) A back-propagation training algorithm with three layer (input, hidden and output) architecture can be effectively used for training an ANN for structural control applications. The earthquake ground acceleration records used for generating the training data, however, play a major role in proper training of the ANN.

4) Outputs obtained by using the trained ANN are in good agreement with those obtained from the fuzzy controller for the building frame, indicating that the ANNs are well trained.
5) Although the ANNs are trained offline, the effectiveness of the ANNs for online use is demonstrated with the help of the example problem.

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