Predictive Safe Control of Non-Linear Seismic Response of Building Frames Using Neuro-Modal Controllers

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SUMMARY:
Neuro-modal control schemes for the reduction of nonlinear (uncontrolled) response of multi-storey building frames subjected to seismic excitations are presented using a combination of modal analysis and artificial neural net (ANN), known as neuro-modal controllers. Application of the control scheme is restricted to building frame which has widely spaced frequencies and whose controlled response (elastic) is predominantly governed by the first mode response. A feedback control scheme is adopted in which feedback of the responses is considered as input to the neural net incorporating time delay. The neural nets are trained for a predetermined reduction of response for an assumed time delay between the measurement of response and the application of control force. The data pairs for training the neural nets are generated from responses and control forces obtained for a set of artificially generated earthquake records. Performance of neuro-modal control schemes is tested for the Treasure Island earthquake data.

Keywords: Artificial Neural Networks, Neuro-modal Controller, Predictive control

1. INTRODUCTION

For large earthquakes, the structure may undergo inelastic response. Control of inelastic response of structure is relatively less reported in the literature. Some control schemes have been developed based on feedback algorithm for response reduction of nonlinear structural response [Wu et al., 1995; Meirovitch and Stemple, 1997]. For control of nonlinear structural response, the equations of motion and the control algorithms are developed based on incremental solution. Control of nonlinear response of structure using ANN is not widely reported.

In this paper, ANN based control schemes for the reduction of nonlinear response of multi degree of freedom system is presented. Three types of control schemes are developed i.e., displacement, velocity and acceleration feedback control scheme; displacement, velocity, acceleration and ground acceleration feedback control scheme; and acceleration and ground acceleration feedback control scheme.

Application of the control schemes is restricted to building frames whose response is predominantly governed by the first mode response in the elastic range. Application of the ANN based control schemes developed in this paper is applied to the nonlinear response reduction of a building frame.

2. THEORY

For the multi-storey frame as shown in Fig. 2.2 which has widely spaced frequencies and whose response (elastic) is predominantly governed by the first mode response, the control scheme is developed here for controlling the nonlinear response of the frame. The force deformation behaviour of the members of the frame under cyclic loading is assumed to remain the same. The storey yield force depends upon the storey stiffness k and the permissible yield displacement x_y (Fig. 2.1). The value of x_y may be assigned as n times the root mean square (rms) response of a specified floor by performing an elastic analysis of the frame. In the present case n is taken as unity and top floor response has been considered. With the elastoplastic characteristic of Fig. 2.1 defined like this, the multi-storey frame is analysed by incremental solution of the equation of motion. C matrix is taken to be proportional to mass and initial stiffness matrix K and is constructed by considering first two modes of the structure. The equation of motion (uncontrolled) in incremental form takes the form

$$M\Delta\ddot{\bar{x}} + C\Delta\dot{\bar{x}} + (K_e + K_p)\Delta\bar{x} = -MI\Delta\ddot{x}_g \tag{2.1}$$

in which K_e and K_p are the elastic and plastic components of the total stiffness; I is the vector of unity and $\bar{x}$, $\dot{\bar{x}}$, $\ddot{\bar{x}}$ and $\ddot{x}_g$ are the vectors of uncontrolled displacement, velocity, acceleration and ground acceleration. The controlled equation of motion is given by

$$M\ddot{x} + C\dot{x} + K_e x + \{r\}u(t) = -MI\ddot{x}_g \tag{2.2}$$

in which x etc., are the controlled responses of the structure and $\{r\}^T$ is $[1 \quad 0 \quad 0 \quad 0 \quad 0 \quad . \quad . \quad .]$ assuming that the actuator is placed at the top of the frame. Eqn. 2.1 is solved using the procedure given by Chopra (1998) to obtain x , $\dot{x}$ and $\ddot{x}$.

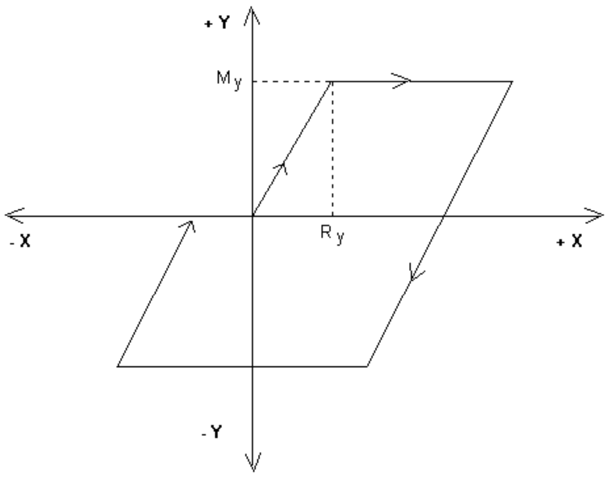

Figure 2.1. Elastoplastic deformation relationship

For a predetermined p percentage reduction of response, the displacement response of the top storey of the frame is $(1-p)\bar{x}_n$, where $\bar{x}_n$ is the uncontrolled displacement of the top storey obtained from the solution of Eqn. 2.1. Since it is assumed that the controlled responses remain within the elastic range, Eqn. 2.2 can be solved by modal analysis and the first modal equation will be

$$\bar{m}_1\ddot{z}_1 + \bar{c}_1\dot{z}_1 + \bar{k}_e z_1 + \phi_1^T r u(t) = -\phi_1^T MI\ddot{x}_g \tag{2.3a}$$

or

$$\ddot{z}_1 + 2\eta\omega_1\dot{z}_1 + \omega_1^2 z_1 + \bar{u}(t) = -\lambda_1\ddot{x}_g \tag{2.3b}$$

in which, $\bar{u}(t) = \dfrac{u(t)}{m_1}$. Eqn. 2.3b and z_1 is equal to x_n if mode shape coefficient for the top of the building frame is made equal to unity. Thus, z_1 can be equated to $(1-p)\bar{x}_n$; $\dot{z}_1$ to $(1-p)\dot{\bar{x}}_n$ and $\ddot{z}_1$ to $(1-p)\ddot{\bar{x}}_n$. With the above considerations, $\bar{u}(t)$ can be obtained from Eqn. 2.3b and then ANN can be trained to obtain $\bar{u}(t)$.

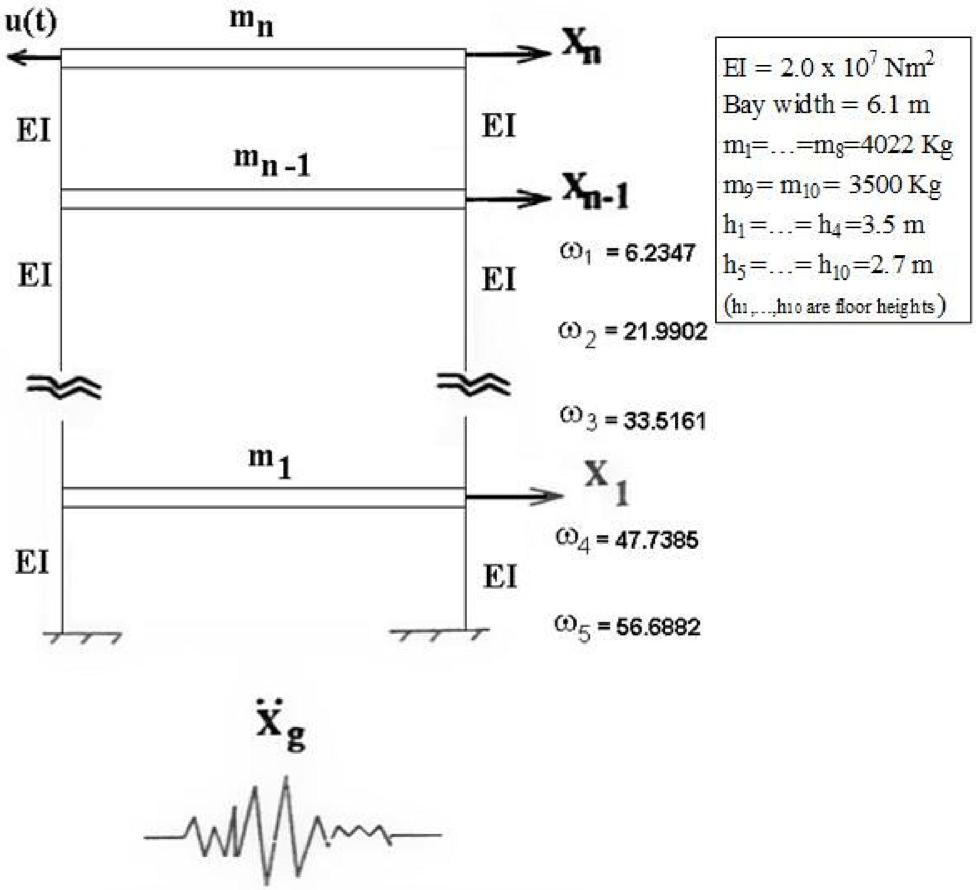

Figure 2.2. Shear frame model with earthquake excitation and control force

3. ANN BASED CONTROL SCHEME

Assuming that only the control of the first mode response is desired $u(t)$ is obtained from the trained neural net. Neural net is trained using the following methodology.

A feedback control scheme is adopted in which the feedback of the responses is considered as input to the neural net. Three types of neural nets as shown in Fig. 3.1 are trained. The inputs to the three neural nets are:

(a) Structural displacement, velocity and acceleration (Scheme-1 – closed loop).
(b) Structural displacement, velocity, acceleration and ground acceleration (Scheme-2 – open-closed loop).
(c) Acceleration and ground acceleration (Scheme-3 – open-closed loop).

Last control scheme is important since in real life, accelerations are directly measured. The velocity and displacement are the derived processes. The output of the neural net is $u(t)$. The neural nets are trained for a predetermined reduction of response, called the target reduction and for an assumed time delay between the measurement of response and the application of control force.

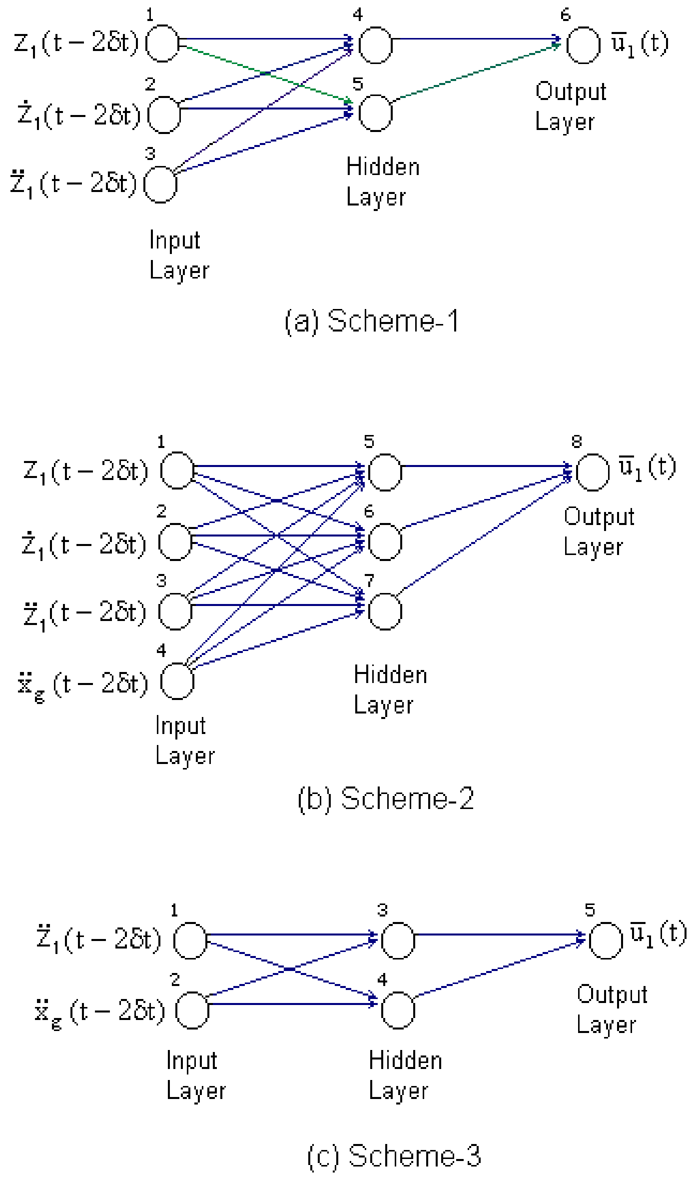

Figure 3.1. Typical input-output pairs for 3 schemes

The data pairs for training the neural nets are generated from the nonlinear responses obtained for the 10 storey frame using control forces obtained for a set of artificially generated earthquake records having different frequency compositions. These records are simulated from the double filtered power spectral density functions (PSDF) [Clough and Penzien, 1993].

In all, five earthquake records (as shown in Fig. 3.2), one from each PSDF having 1501 data points sampled at an interval of 0.02 s are generated. Using the generated earthquake records, uncontrolled responses x, $\dot{x}$ and $\ddot{x}$ are obtained by solving Eqn. 2.1 without $u(t)$. The controlled responses and the corresponding control force $u(t)$ are obtained from Eqns. 2.2 and 2.3b. 7504 data pairs are generated in all and used for training the neural nets. The time delay is caused due to the computational time and implementaional time required for the generation and application of the control force respectively. Zero time delay denotes the hypothetical case of instantaneous control.

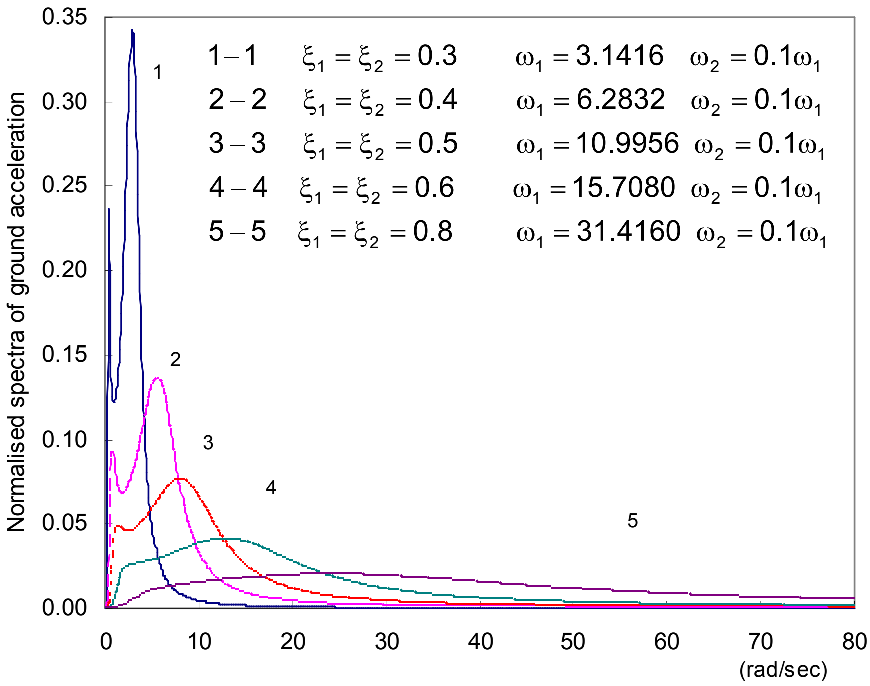

Figure 3.2. PSDF of ground acceleration

A fully connected feedforward neural net architecture with 3 input nodes and one output node with 8 hidden nodes in each of the two hidden layers is used for training in case of scheme-1. A fully connected feedforward neural net architecture with four input nodes and one output node with 4 hidden nodes each in each of the two hidden layers is used for training in case of scheme-2. A fully connected feedforward neural net architecture with 2 input nodes and one output node with 8 hidden nodes in each of the two hidden layers is used for training in case of scheme-3. 'Act_TanH' activation function, 'BackpropMomentum' learning function and 'Topological_order' update function along with 'Randomize_weights' initialising function are used for the training. SNNS [Zell et al., 1989] package is utilised for training the neural nets.

4. TESTING OF NEURAL NET AND DISCUSSION OF RESULTS

Target percentage reductions (p) in response are considered as 30, 50 and 80. The five time delays considered in the study are 0, δt, $2\delta t$, $3\delta t$ and $4\delta t$; δt being equal to 0.02 s. With the help of 45 generated data sets (15 for each scheme) 45 neural nets are trained. Each neural net is trained for a combination of target percentage reduction (p) and the time delay $n\delta t$ (n=0, 1, 2, 3, 4).

4.1. Testing for Known Data Set

After the neural nets are trained, each neural net is tested with an input data set taken from a segment of the data pairs used for training the ANN. The output control force is compared with that obtained theoretically. Also, the responses obtained with value of $u(t)$ taken as that obtained from ANN are compared with the target controlled responses. The comparisons are obtained for a target percentage reduction equal to 30 and time delay equal to zero and for a segment of time histories of ground acceleration corresponding to narrowband process. The control forces and responses are obtained from the neural net corresponding to scheme-3. It is seen that the control force predicted by the ANN compares very well with that obtained analytically. Also, it is seen that the controlled displacement and acceleration responses obtained with $u(t)$ predicted by ANN compare fairly well with the target controlled responses. The difference between the absolute peak responses is of the order of 0.21%. The same comparisons are obtained for a time delay of 2δt. The difference between the absolute peak responses is of the order of 1.62%.

4.2. Testing for the Unknown Data Sets

The trained neural nets are tested for unknown data sets generated from Treasure Island (E – W) earthquake records for controlling the nonlinear response of the ten storey building. The elastoplastic force deformation relationship adopted for the nonlinear analysis is shown in Fig. 2.1. The controlled responses of the frame by considering contribution from all modes and by using the same control force as obtained for the single mode control is also determined.

The responses are designated as target single mode (one mode) and all modes. While comparing between the time histories of uncontrolled, controlled (target) and controlled (ANN) for 50% reduction of responses with zero time delay and for Treasure Island earthquake, ANN predicted responses are found about 15% more than the target reduction for scheme-1. Note that scheme-1 does not incorporate ground acceleration as feedback for schemes 2 and 3, in which feedback of the ground acceleration is taken for predicting the control force provide the responses very close to the target responses. Thus, is seen from the results that the performance of scheme-1 is inferior to that of schemes 2 and 3. It is interesting to note that scheme-3 which considers only structural acceleration and ground acceleration as feedbacks perform extremely well.

Comparison between the controlled (target) and controlled (ANN) for 50% target reduction with time delay of 2δt (0.04 s) and for Treasure Island earthquake record, it is seen from the results that the performance of scheme-1 is inferior to the other two control schemes. So far as the displacement control is concerned, the ANN controlled responses provide 2.65% more values for the absolute maximum displacement. For control schemes 2 and 3 the ANN controlled responses are almost same as the target values. For acceleration response, the values at the peaks are over estimated by all three ANN control schemes; scheme-1 provides more error. At other points, however, the difference between the ANN controlled accelerations are nearly the same as the target values.

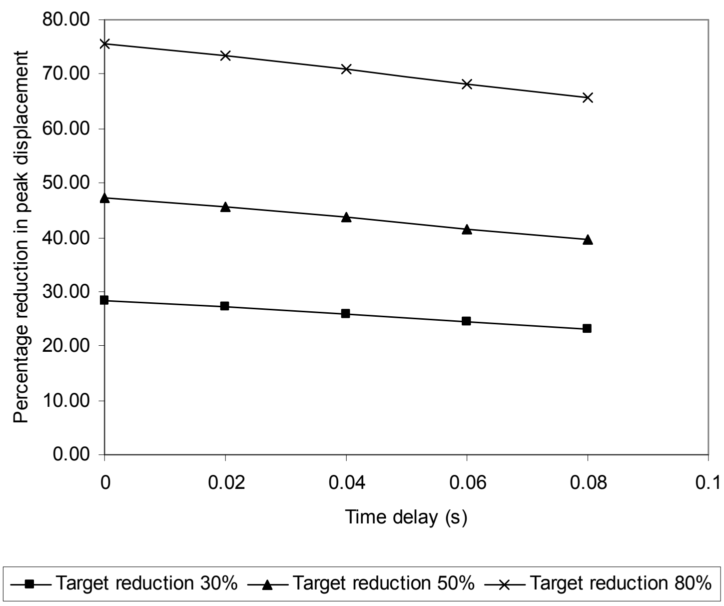

Figure 4.1. Performance of trained neural net with time delay (Scheme-1, Earthquake = Treasure Island)

Figs. 4.1 – 4.3 show the performance of the trained neural net with time delay for Treasure Island earthquake. The percentage reduction in the absolute peak displacement obtained by the ANN control schemes is plotted against the time delays incorporated in feedback information. It is seen from the figures that the efficiency of the control schemes does not significantly decrease with time delay for schemes 2 and 3 up to 4δt (0.08 s). For the scheme-1, the percentage reduction in peak displacement decreases with time delay. For example, for a time delay of 0.08 s, the reduction in peak displacement is about 65% for a target reduction of 80%.

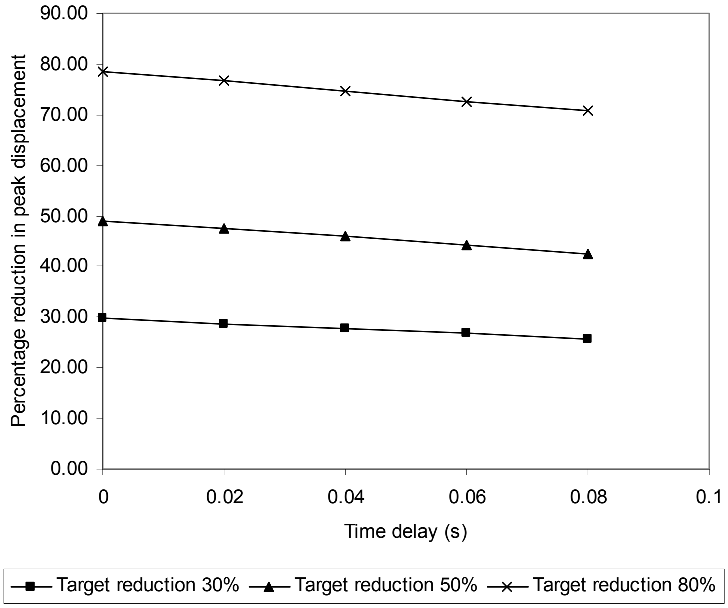

Figure 4.2. Performance of trained neural net with time delay (Scheme-2, Earthquake = Treasure Island)

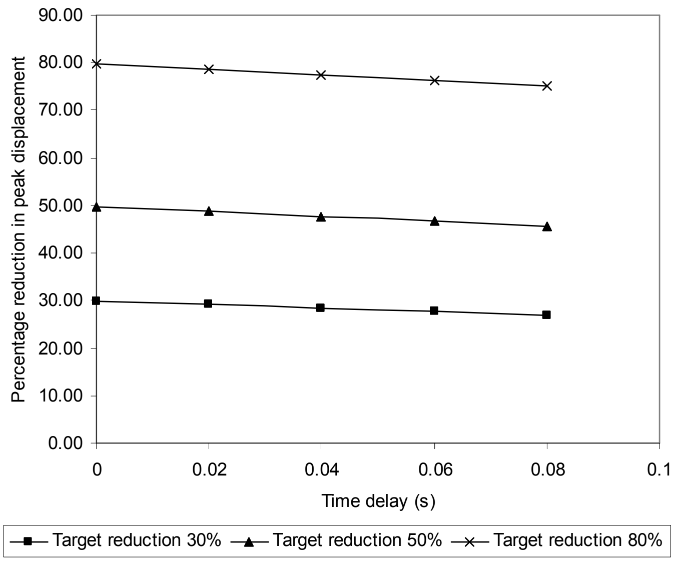

Figure 4.3. Performance of trained neural net with time delay (Scheme-3, Earthquake = Treasure Island)

From the above figures it is clear that a time delay up to 4δt (0.08 s) can be accommodated in the ANN control schemes (2 and 3) without loss of much efficiency.

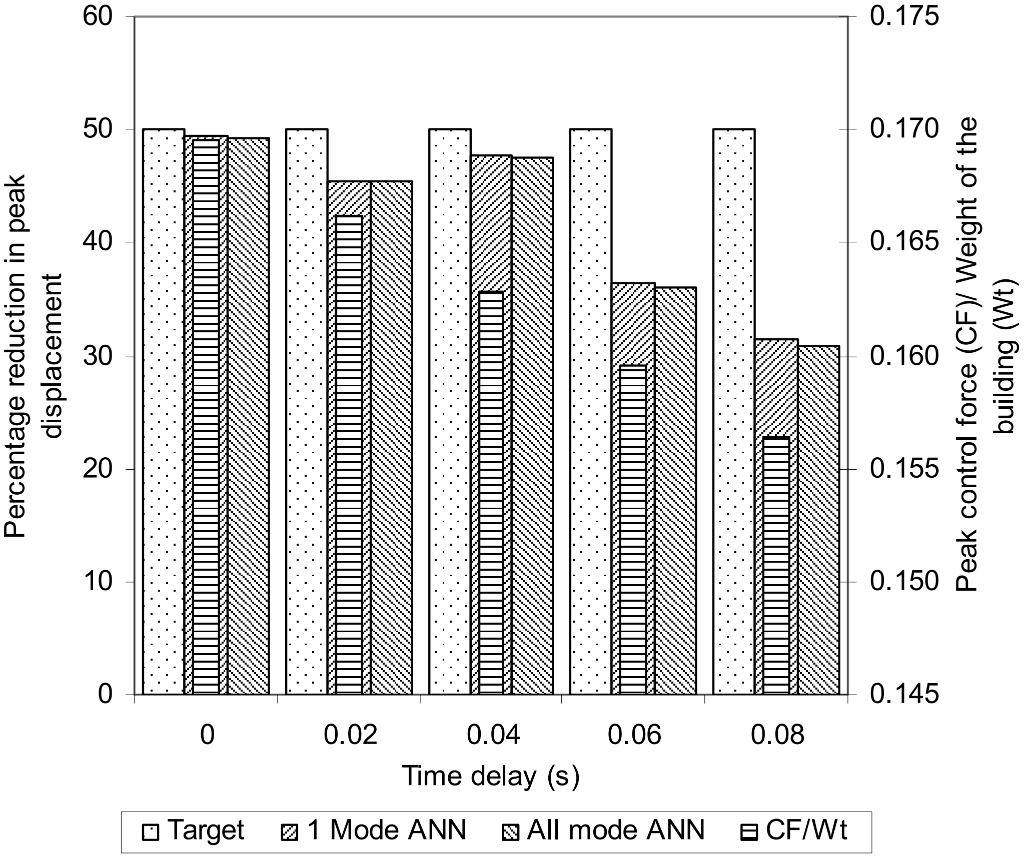

Figure 4.4. Top storey displacement control
(Scheme-3, Earthquake = Treasure Island)

Fig. 4.4 compares between the target reduction (target control) and the reduction obtained by the control scheme (ANN control) for peak displacement response of the top storey for different time delays for Treasure Island earthquake data. It is seen from the figure that up to the time delay of 2δt, they are nearly the same. For time delays of 3δt and 4δt, the ANN control is lower than the target control. For a time delay of 4δt, ANN control is about 32% as compared to the target value of 50%. The controlled response obtained by considering all modes and the single mode are practically the same, as it would be expected since the elastic response is primarily governed by the first mode of response. The efficiency of the control scheme for zero δt is 0.291 while that for a time delay of 4δt is 0.197. In order to investigate the control of displacement response at other storeys, it is observed for first storey that it is similar to the top storey displacement.

Fig. 4.5 compares between the target control and ANN control for the acceleration response of the top storey for different time delays. ANN control for acceleration gradually decreases with time delay and for a time delay of 4δt, the ANN control is about 31.16% as against the target control of 50%. For the time delay of 4δt, the ANN control is about again 31.36% as against 50% target control. The efficiency of the control scheme for zero δt is 9.88 while that for a time delay of 4δt is 7.1.

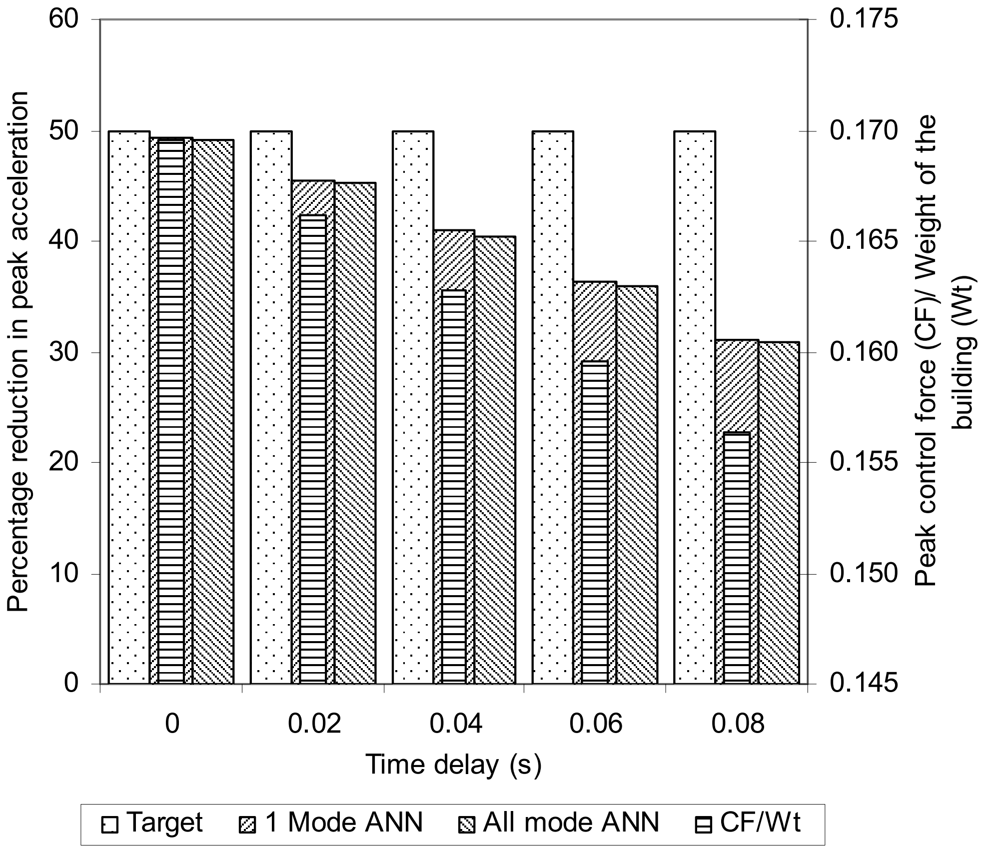

Figure 4.5. Top storey acceleration control
(Scheme-3, Earthquake = Treasure Island)

5. CONCLUSIONS

Efficient control scheme using neural net is presented for the reduction of nonlinear response of building frame subjected to support excitation. The uncontrolled response undergoes nonlinear excursion due to the elastoplastic behaviour of the restoring force under cyclic loading. The three types of control scheme are presented for the control of the nonlinear response. In the development of the control schemes, it is assumed that the control response remains within the elastic range and the control schemes can handle the time delay effect. Neurocontrollers are trained for the synthetically generated ground motions. The performance of the control schemes are tested for the Treasure Island earthquake data. The third control scheme, which takes ground acceleration and structural acceleration as feedbacks, is implemented to control the nonlinear response of a ten storey shear building frame for a predetermined percentage reduction in response. For this purpose, nonlinear response of the ten storeyed building frame is obtained for the synthetically generated earthquake data. The reduced responses for a predetermined percentage reduction of the uncontrolled response are then utilised to train the neurocontroller for providing the control force for the response reduction of the top storey displacement of the frame. For the development of the control scheme it is assumed that the controlled response of the frame remains within the elastic range and is predominantly governed by the first mode response. The ten storey building frame is used for testing the control scheme for Treasure Island earthquake data. The results of the numerical studies show that

i. Schemes 2 and 3 perform better than scheme-1 i.e., neurocontroller predicts better control force when the ground acceleration is also taken as input.

ii. The reduction in responses is generally reduced as time delay increases. The decrease in controlling the response depends upon the response quantity of interest and the nature of ground acceleration.
iii. Control of the displacement response is generally better than control of acceleration response when the time delay is taken into consideration; for large time delays like $4\delta t$ (0.08 s) the acceleration response can even get amplified for certain ground motion.
iv. For certain system there may not be any appreciable change in the control of displacement responses when time delay up to 0.08 s is considered. The use of neurocontroller trained for a target percentage reduction in response may provide higher reduction of response, especially for zero time delay, for unknown excitations (for which the neurocontroller is not trained).
v. The efficiency of the control scheme denoted by maximum peak reduction per unit maximum control force.
vi. Out of the schemes 2 and 3, scheme-2 provides better reduction of maximum response per unit maximum control force i.e., for achieving a better efficiency all the three response quantities along with the ground acceleration must be measured and taken as inputs.
vii. The proposed control scheme-3 can be effectively used for the reduction of nonlinear response of building frames in which the controlled responses remain within the elastic range and are predominantly governed by first mode response. Even for the displacement reduction of the first storey, the control scheme performs well.
viii. Unlike linear control, the nonlinear control of the frame provides a good reduction in acceleration response even for a time delay of $4\delta t$.

The performance of the proposed control scheme for the control nonlinear response of the building frames must be tested for more unknown problems for verifying its effectiveness.

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