MODAL SEISMIC CONTROL OF BUILDING FRAMES USING ANN

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ABSTRACT :

Target reduction of seismic response of a multi-storey frame with a neurocontroller (using Artificial Neural Network) is presented. The seismic response of the frame is controlled by controlling the significant modal contributions (modal control) to the overall response. ANN with a feed-forward architecture is used to construct, train and test the performance of the neurocontroller. Control methodology uses two sets of neural nets wherein output of first set acts as part of the input to the second set. Number of neural nets to be trained depends upon the number of modal response being controlled. The neurocontroller is designed to provide a target reduction of response by taking into account the time delay effect also. Inputs to this scheme are the measured accelerations only at few selected points of the structure, and the ground acceleration. The neural nets are trained for the synthetically generated input-output data with the help of simulated earthquake records having different frequency compositions. The effectiveness of the control scheme is tested for both known and unknown (El Centro and Treasure Island earthquake records) problems for a ten storey building frame. Results of the study show that the control scheme is highly effective in controlling both displacement and acceleration responses of the frame for the unknown El Centro and Treasure Island earthquake excitations.

KEYWORDS: Neurocontroller, ANN, Modal Control, Structural Acceleration, Frequency Composition.

1. INTRODUCTION

Active control of building frames subjected to earthquake excitation has been a topic of intense research in the recent past. The state of the art review papers on active control of structures (Datta 2003; Housner et al. 1997; Soong 1988; Spencer Jr. and Nagarajaiah 2003) provide a comprehensive knowledge on the subject.

The use of artificial neural network (ANN) for the active control of structures is now being researched and has provided alternative to analytical control algorithms for controlling the response of structures (Kim et al. 2001; Kim et al. 2000; Liut et al. 1999; Tang 1996). Potentially ANN is capable of tackling many of the practical problems in the implementation of active control strategies. However, the use of ANN for the control of building frames by considering the time delay effect and limited number of response feedback is not widely reported in the literature since it involves complex and computationally intensive training schemes. However, for a certain class of problem, the training scheme may be simplified. One such case is the control of the response of building frames where responses are predominantly governed by first few modes of vibration. For this type of building frames responses can be obtained by solving a few number of modal equations leading to a considerable simplification in the development of ANN based control schemes. Since many building frames respond primarily in the first few modes of vibration under seismic excitation, it is worthwhile to develop ANN based control schemes for such buildings.

Here in, an ANN based control scheme is developed which controls the contributions of a specified number of modes to the overall response of the structure so that a target reduction of response is achieved. Other features of the control scheme are that it takes measured accelerations of the structure from a limited number of points as feedback and can incorporate time delay effect in controlling the response. The control force is applied at the top of the building frame. The control scheme uses two sets of neural nets. The first set is used to obtain generalised acceleration from the actually measured acceleration of the structure. The second set of neural net provides the control force with input as the generalised accelerations of the structure and the ground acceleration. In the second set, only one neural net is trained. The control scheme is applied to control the response of a ten storey building frame.

2. ASSUMPTIONS

For the development of the control strategy, it is assumed that (i) the building frame is idealized as a shear frame with masses lumped at the floor level and first few modes contribute to the response of the structure, (ii) responses are measured at few locations, (iii) for training the neural nets, measured accelerations are assumed to be the same as the controlled accelerations obtained analytically from the simulation results, (iv) for testing the neural net (and the control scheme), the controlled responses obtained analytically by using the control force predicted by the ANN are assumed to be the same as the measured responses, and (v) control force is applied only at the top floor of the structure and is available for operation.

3. THEORETICAL BASIS OF THE CONTROL SCHEME

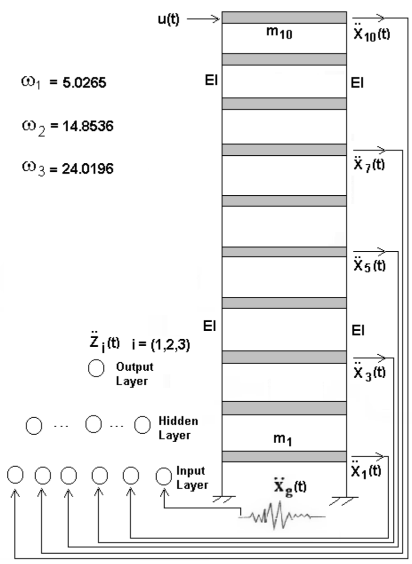

Figure 1 Schematic diagram of control scheme

For illustrating the theoretical basis of the scheme, consider the first three modes for the response analysis of the ten storey building frame shown in Figure 1. Further, it is considered that acceleration feedback measurements are taken from the first, third, fifth, seventh and tenth storeys i.e., from five points on the structure. Using modal analysis and assuming the contribution of the first three modes in the overall response, $\ddot{x}_i$ can be written as

$$\ddot{x}_i \approx \phi_i^1 \ddot{z}_1 + \phi_i^2 \ddot{z}_2 + \phi_i^3 \ddot{z}_3, \; i = 1, 3, 5, 7, 10 \tag{3.1}$$

in which, $\ddot{x}_i (i = 1,3,5,7,10)$ are the structural acceleration at the ith storey of the building; $\ddot{z}_1, \ddot{z}_2$ and $\ddot{z}_3$ are the first three modal accelerations and ϕ_i^1, ϕ_i^2, ϕ_i^3 are the mode shape coefficients of the ith storey in 1st, 2nd and 3rd modes. Thus, controlled structural acceleration could be obtained if the first three modal accelerations for the controlled structure are known. The first modal equation for the controlled structure can be written as

$$\ddot{z}_1 + 2\eta\omega_1\dot{z}_1 + \omega_1^2 z_1 + u_1(t) = -\rho_1\ddot{x}_g \tag{3.2}$$

in which, ω_1 is the first natural frequency of the structure, ρ_1 is the first mode participation factor, ϕ_1 is the first mode shape of the structure, I is a vector of unity, R is the location vector and $\ddot{x}_g$ is the ground acceleration. In Eqn. 3.2, $u_1(t) = k_1 u(t)$, where $u(t)$ is the control force applied at the top of the structure with the help of an active mass driver (pendulum type) and $k_1 = \phi_1^T R / \phi_1^T M \phi_1$. The second and the third modal equations can be similarly written as:

$$\ddot{z}_2 + 2\eta\omega_2\dot{z}_2 + \omega_2^2 z_2 + u_2(t) = -\rho_2\ddot{x}_g \text{ and } \ddot{z}_3 + 2\eta\omega_3\dot{z}_3 + \omega_3^2 z_3 + u_3(t) = -\rho_3\ddot{x}_g \tag{3.3), (3.4}$$

in which, ω_2 and ω_3 are the second and third natural frequencies of the structure, ρ_2 and ρ_3 are the second and third mode participation factors and

$$u_2(t) = \frac{\phi_2^T R u(t)}{\phi_2^T M \phi_2} = k_2 u(t) = \frac{k_2}{k_1} u_1(t),\ u_3(t) = \frac{k_3}{k_1} u_1(t) \tag{3.5), (3.6}$$

in which, k_2 and k_3 are defined similar to k_1. Let $\ddot{\bar{z}}_1$, $\ddot{\bar{z}}_2$ and $\ddot{\bar{z}}_3$ be the uncontrolled modal accelerations for the structure under base excitation $\ddot{x}_g$ and the target percentage reduction be p for the modal displacements and velocities for all the three modes. Note that the target percentage reduction of p is not specified for controlled accelerations. Thus, percentage reduction of acceleration achieved by the control scheme could be different than p. However, for obtaining $u_1(t)$ from Eqn. (3.2),

the controlled modal acceleration in first mode is assumed to have the same form as that of the uncontrolled acceleration $\ddot{\bar{z}}_1$ but with reduced value as

$$\ddot{z}_1 = (1-p)\ddot{\bar{z}}_1 \tag{3.7}$$

With this assumption $u_1(t)$ can be obtained from Eqn. 3.7 as

$$u_1(t) = -\rho_1\ddot{x}_g - (1-p)\left[\ddot{\bar{z}}_1 + 2\eta\omega_1\dot{\bar{z}}_1 + \omega_1^2\bar{z}_1\right] \tag{3.8}$$

Once $u_1(t)$ is known, $u_2(t)$ and $u_3(t)$ can be obtained from Eqns. 3.5 and 3.6. Using Eqns. 3.3 and 3.4, controlled accelerations in the other two modes are obtained as

$$\ddot{z}_2 = -\rho_2\ddot{x}_g - (1-p)\left[2\eta\omega_2\dot{\bar{z}}_2 + \omega_2^2\bar{z}_2\right] - u_2(t) \tag{3.9}$$

$$\ddot{z}_3 = -\rho_3\ddot{x}_g - (1-p)\left[2\eta\omega_3\dot{\bar{z}}_3 + \omega_3^2\bar{z}_3\right] - u_3(t) \tag{3.10}$$

Note that controlled modal accelerations in 2nd and 3rd modes do not have the same percentage of reduction as p. In a way, these two modal accelerations are penalised. Once controlled modal accelerations $\ddot{z}_1$, $\ddot{z}_2$ and $\ddot{z}_3$

are obtained, the structural acceleration $\ddot{x}_i$ (i=1,3,5,7,10) can be obtained from Eqn. 3.1. Further, $\ddot{z}_1$, $\ddot{z}_2$ and $\ddot{z}_3$ are related to the control force $u(t)$ through Eqns. 3.5 – 3.10. These, relationships are used for generating the input-output data pairs for training the neural nets. Note that the forces $u_1(t)$, $u_2(t)$, $u_3(t)$ are so called generalised modal control forces defined by Eqns. 3.5 and 3.6. In reality, they are not the realisable control forces; the realisable control force is the actual control force $u(t)$, which is applied to the structure. In order to obtain the modal accelerations $\ddot{z}_2$ and $\ddot{z}_3$, $u_2(t)$ and $u_3(t)$ are used (refer Eqns. 3.9 and 3.10) as intermediate variables. The calculation steps involve: (i) from target percentage reduction p and uncontrolled responses, $u_1(t)$ and hence $u(t)$ is obtained from Eqn. 3.8, (ii) then Eqns. 3.5 and 3.6 are used to obtain $u_2(t)$ and $u_3(t)$ and (ii) finally Eqns. 3.7, 3.9 and 3.10 are used to obtain controlled modal accelerations. The control force $u(t)$, which is applied at the top, bears relationship with the controlled modal accelerations, which are quite evident from Eqns. 3.9 and 3.10 (which do not bear simple proportional relationship).

4. TRAINING OF THE NEURAL NETS

For generating the data pairs for training the neural nets, the building frame is analysed for the simulated ground acceleration records from the double filtered power spectral density functions (PSDFs) of ground acceleration. Double filtered PSDF of ground acceleration is preferred over Kanai-Tajimi spectrum since it represents the PSDF ground displacements more realistically (Clough and Penzien 1993). The analysis is performed using mode superposition technique by considering the contributions of three modes to the response. Generally, for building frames the seismic responses are predominantly governed by first few modes of responses of the structure. For the type of building frame considered, the contribution of the first 3 modes provide the response quite accurately (the Max X_{10}(t) = 0.168 m considering all modes of vibration and Max X_{10}(t) = 0.166 m considering 3 modes). From the analysis, time histories of z_i, $\dot{z}_i$, $\ddot{z}_i$ (i = 1 to 3) are obtained.

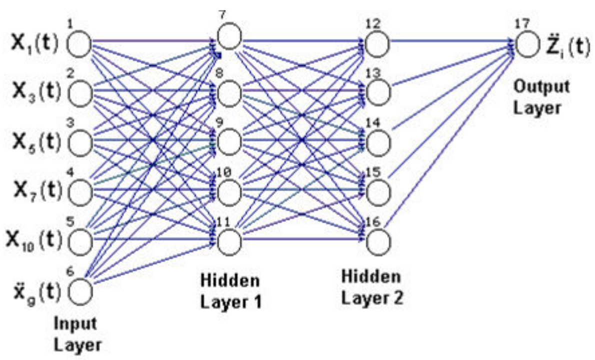

Figure 2a First set of neural nets

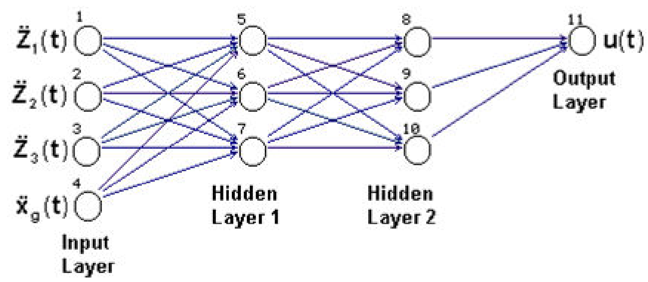

Figure 2b Second set of Neural nets

With the values of the above response quantities, the time histories of $u_1(t)$ are obtained from Eqn. 3.8 for a target percentage reduction *p* in displacement and velocity responses. $u_2(t)$, $u_3(t)$ and $u(t)$ are obtained from Eqns. 3.5 and 3.6. The time histories of controlled modal accelerations $\ddot{z}_1$, $\ddot{z}_2$ and $\ddot{z}_3$ are obtained from Eqns. 3.7, 3.9 and 3.10. The controlled structural accelerations $\ddot{x}_i$ (i=1,3,5,7,10) are obtained from Eqn. 3.1.

Once the time histories of the above quantities are determined, the training pairs for the first set of neural nets 1, 2, 3 (Figure 2a) are generated. These neural nets are trained for obtaining the modal accelerations ($\ddot{z}_1$, $\ddot{z}_2$, $\ddot{z}_3$). For training, three neural nets had to be trained separately mainly because one single neural net using three outputs could not be trained even when increasing intermediate hidden layers and nodes were attempted. The reason for this was due to the order of differences between the values of $\ddot{z}_1$, $\ddot{z}_2$ and $\ddot{z}_3$. Furthermore, it was realised that training of three separate neural nets may be better in the sense that each neural net captures the modal property of that mode only and hence, can be used for modal system identification. The training pairs for the second neural net (Figure 2b) are then obtained from the time histories of $\ddot{z}_1$, $\ddot{z}_2$, $\ddot{z}_3$ and the time history of control force $u(t)$ to be applied at the top of the building. Both sets of neural nets require the ground acceleration as input. The time delay effect is incorporated in training the second neural net. For training, the inclusion of time delay effect in control algorithm is complex and various literatures exist to include time delay compensation (Housner et al. 1997). Herein, a simple approach is adopted to train the neural net to provide a control force with a phase shift (only) with respect to that of the case of no time delay. It is found that the training scheme with simple time shift provides significantly different time histories of control forces for the cases of time delay and no time delay and are found to be quite effective in controlling responses when small time delay effect is considered. This is shown later in the example problem solved which verify the validity of the approach.

A fully connected feedforward neural net architecture with (a) six input nodes and one output node with 5 hidden nodes each in two hidden layers, (b) four input nodes and one output node, with 3 hidden nodes each in two hidden layers is used for training. 'Act_TanH' activation function, 'BackpropMomentum' learning function (learning parameter = 0.0001 and momentum factor = 0.01) 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 net.

5. NUMERICAL STUDY

A ten storeyed building fame is chosen for training and testing of the ANN with floor height as 4 m, bay width as 6.1 m and critical damping (η) as 0.02. Each floor mass from first to eight is taken as 4022 kg and for ninth and tenth floors as 2060 kg. A target percentage reduction (p) in displacement response is considered as 50%. The five time delays considered in the study are 0, Δt, 2Δt, 3Δt and 4Δt; Δt being equal to 0.02 s.

The data pairs for training the neural nets are generated from responses and control forces obtained for a set of artificially generated earthquake records. These records are simulated from the double filtered PSDFs (Clough and Penzien 1993) ranging from narrow to wide band. In all, five earthquake records, one from each type of PSDF (from frequency bands ω_1 = 3.1416, 6.2832, 10.9956, 15.7080, 31.4160; ω_2 = 0.1 ω_1) having 1501 data points sampled at an interval of 0.02 sec are generated. Thus, the generated earthquake records used for training have different frequency compositions (narrow to broad band). A total number of 7504 (5 × 1501 –1) training pairs are generated for each neural net sampled at 0.02 sec. With the above number of data pairs, it was seen that all neural nets were satisfactorily trained to provide the required results for the example problem. Note that for other problems, more number of data pairs may have to be generated from the earthquake records.

5.1. Testing Of Control Scheme For The Known Data Set

For testing the control scheme, the building frame is analysed for one segment (of duration 30 sec) of the synthetically generated time history (shown in Figure 3) by considering the contribution from the first three modes. Note that the synthetically generated time history shown in Figure 3 is only a segment of the total time history and shows the portion, which has predominantly narrow band frequency contents. Other portions of the time history have varied frequency compositions as mentioned before. For the target reduction of responses (displacement and velocity) of 50 percent, the time histories of $\ddot{z}_1$, $\ddot{z}_2$ and $\ddot{z}_3$ are obtained from the first set of three neural nets. These time histories are then used to obtain the time history of the control force from the second neural net using time delays of 0, Δt, 2Δt, Δt being equal to 0.02 s. Note that for incorporating the time delay, the second set of neural net had to be trained for each time delay separately. The time delay neural network was attempted so that it can train by considering all the time delays taken as parameter at one time. However, it was found that the nature of the sampled earthquake record and the response time history records at different sampled points are such that the time delay network did not work.

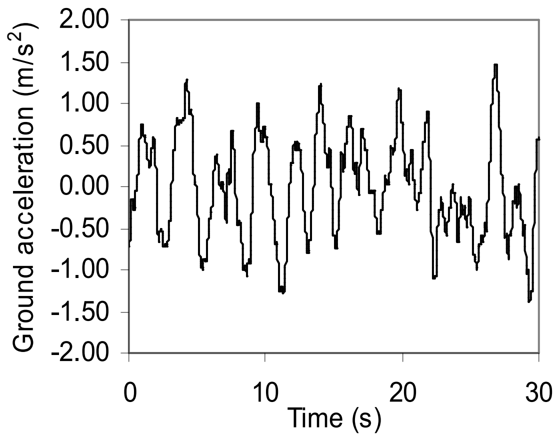

Figure 3 Segment of time history of artificial ground acceleration for which ANNs are trained

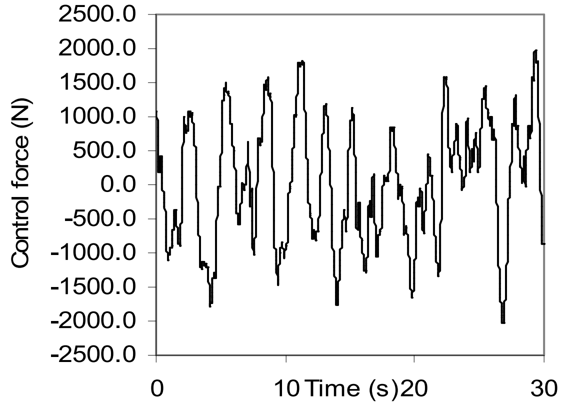

Figure 4 Segment of time history of ANN control force (target reduction = 50%)

The control force $u(t)$ is applied at the top of the building frame and it is analysed for the same synthetically generated time history of 30 sec (using contributions from three modes only). The displacement and acceleration responses are then compared with the target ones. For zero time delay, the time history of control force is shown in Figure 4. Figure 5 compares between the uncontrolled and controlled responses for the top storey for zero time delay. Reduction in peak displacement is 48.09% for top storey as against the 50% target reduction.

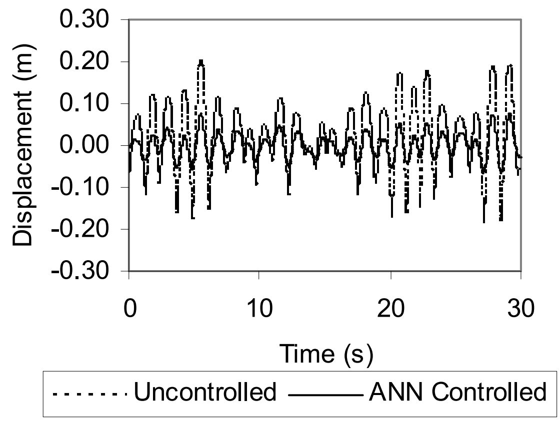

Figure 5 Time history of displacement for top story (target reduction = 50%)

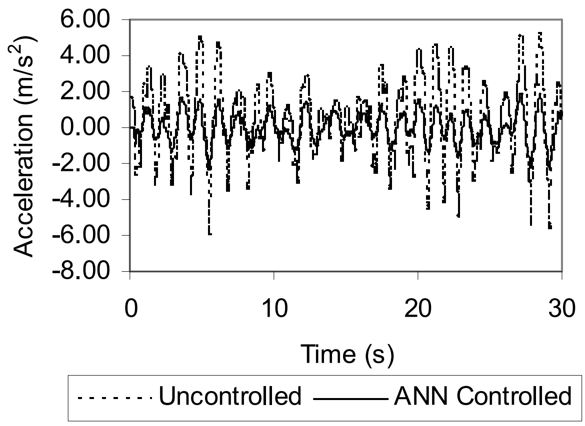

Figure 6 Time history of acceleration for top story (target reduction = 50%)

Although, the control scheme was developed for a target percentage reduction in displacement and velocity, it is seen from Figure 6 that the reduction in peak acceleration is also quite significant. For zero time delay, the percentage reduction in peak acceleration is 44.9% for the top storey. Thus, for the known problem, performance of the control scheme is highly satisfactory.

5.2. Testing For The Unknown Data Sets

In order to test the effectiveness of the control scheme, El Centro and Treasure Island earthquake records are considered as the unknown problems. Figures 7a, 7b, 8a and 8b compare ANN controlled responses for the time delays of 0 s (Δt) and 0.08 s ($4\Delta t$).

From Figure 7a, it is seen that for zero time delay the percentage reduction in peak displacement is 48.9% for the top storey as against 50% target reduction. For a time delay of 0.08 s ($4\Delta t$), the percentage reduction in peak displacement for the top storey is about 23.35%. Efficiency of the control scheme for the reduction of the top storey displacement (defined by percentage reduction in peak displacement per unit normalised peak control force) is about 6.35 for zero time delay and 6.07 for a time delay of 0.08 s. This shows that efficiency of the control scheme is more for zero time delay; however, the difference in efficiency of the control scheme for zero time delay and a time delay of 0.08 s is not very significant. Although, the control scheme was developed for a target percentage reduction in displacement and velocity, it is seen from Figure 7b that the reduction in peak acceleration is also quite significant. For zero time delay, the percentage reduction in peak acceleration is 47.9% and for a time delay of 0.08 s ($4\Delta t$) it is 27.06% as against 50% target reduction for the top storey.

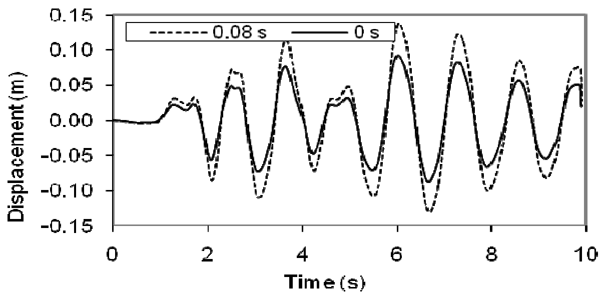

Figure 7a Time history of ANN controlled displacement for top storey (Earthquake = El Centro)

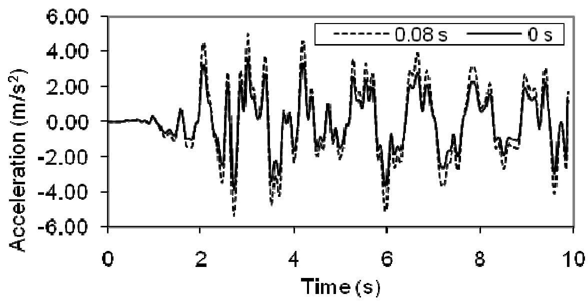

Figure 7b Time history of ANN controlled acceleration for top storey (Earthquake = El Centro)

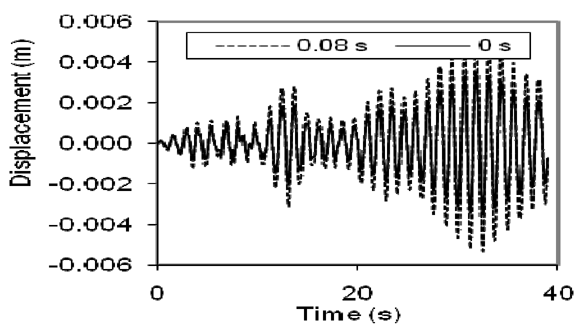

Figure 8a Time history of ANN controlled displacement for top storey (Earthquake = Treasure Island)

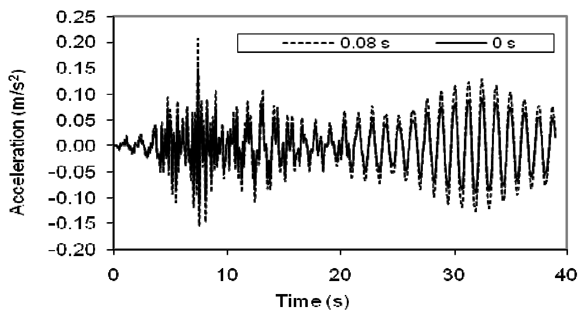

Figure 8b Time history of ANN controlled acceleration for top storey (Earthquake = Treasure Island)

It is observed that the peak control forces for 50% target reduction are about 7.39% of the building weight for the El Centro earthquake. Generally, the reported literature on the seismic control of building frame response show the peak control force requirement is of the order 5 to 10% of weight of the building depending upon the PGA (peak ground acceleration) value and frequency composition of the earthquake. For this particular example, the control force requirement for El Centro earthquake appears to be quite reasonable. Figures 8a and 8b show similar results for Treasure Island earthquake.

Thus, it is observed from the limited study made here that ANN control scheme is quite effective in seismic control of building frames. Since ANNs are trained off-line (much before the episode occurs) using synthetically generated data, the time requirement in providing control force at the time of actual episode is very small and is almost equal to that required in conventional control algorithms. Therefore, looking at the actual operational time and the tested level of reduction of responses of unknown problems, the ANN control scheme appears to be highly efficient.

6. CONCLUSIONS

ANN based control scheme for the response reduction of the multi-storey frame is presented. It is designed to suppress significant modal contributions to the overall response, provide a target reduction in responses and take care of time delay that exists between the actuation of control force and the measurement of feedback response. The effectiveness of the control scheme is tested for both El Centro and Treasure Island earthquake records. The results of the study show that (i) for the known problem, controlled top displacement responses are found to be very close to the target control; (ii) the performance and efficiency (measured by percentage reduction in response per unit normalised peak control force) of the control scheme decrease with the time delay; (iii) the performance of the control scheme for unknown problem (El Centro, Treasure Island) is nearly the same as known problem; (iv) although the control scheme has been developed with a target percentage reduction in displacement and velocity of the frame, significant control in the acceleration response of the frame is also achieved; (v) the control of responses is not uniform for all storeys; the control of responses for the first storey is found to be much lower than that for the top storey.

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