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ANN CONTROL OF BUILDING FRAMES FOR FUTURE EARTHQUAKES

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ABSTRACT

An active control scheme using ANN is presented for seismic control of building frames for future earthquakes. It is based on the premise that if the desired control force and the future earthquake excitations have the similar frequency content it is likely that the control force of the system will be most effective. The control scheme developed has the advantage that it can consider limited number of feedback measurements, time delay effect, and target reduction in response. The ANN control scheme requires feedback responses (displacement, velocity and acceleration), ground excitation and a target percentage reduction as inputs to the ANN. The output of the ANN is the time history of control force. A ten-storey building frame is taken as an illustrative example. Feedback responses are taken from 1st, 5th and 10th storeys of the frame. The control is affected by a single control force applied at the top of the building frame with AMD. The results of the study show that (i) the control scheme is very effective in controlling the response of the building frame for excitations under El Centro earthquake taken as an unknown problem; (ii) The peak control force required to obtain a significant percentage reduction in response is not very large.; and (iii) Time delay (of the order of 2Δt; Δt time step interval) does not significantly deteriorate the performance of control scheme.

Introduction

Active control of building frames using artificial neural net (ANN) has been a subject of intensive research in the recent past. In the earlier works (Ghaboussi and Joghataie 1995, Chung et al. 1989, 1997, Bani-Hani and Ghaboussi 1998, Yu-Ao He and Jianjun 1998) neural nets were trained with and without emulator network. Whenever emulator network is used, the training of neural net becomes extensive. There have also been attempts to use fuzzy rules with ANN for control of structures (Joghataie and Ghaboussi 1994, Tani et al., 1998). Not much work on the use of ANN for structural control using single ANN and limited measurements of feedback responses with direct incorporation of time delay effect, and a target percentage reduction are reported in the literature. Keeping these in view, a simple ANN based control scheme using a single ANN is presented here. It is capable of handling directly the time delay effect, working with a limited number of feedback measurements and providing a target reduction of response quantity of interest. The proposed method is developed and tested for multistorey frame controlled by an AMD placed at its top. The effectiveness of the control scheme is evaluated by taking a 10-storey building frame as an illustrative example.

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Theory

The control scheme is illustrated with the help of a multistorey building frame as shown in Fig 1. The control force is applied at the top of the frame using an AMD. The feedback responses, measured from three points, are shown in the figure. Inputs to the ANN are the feedback controlled responses from the three points, the ground acceleration and the target percentage reduction of the top storey displacement response.
The controlled responses are obtained by solving the following equation of motion:

$$M\ddot{Y} + C\dot{Y} + KY = -MI\ddot{x}_g + Hu \tag{1}$$

where *M*, *C* and *K* are, respectively, mass, damping and stiffness matrices corresponding to the sway degrees of freedom of the frame; *u* is a single time history of the control force applied through AMD; *H* is a vector of size *n* whose all elements are zero except the *n*th element which is unity; *Y* is a vector of sway displacements of the frame and $\ddot{x}_g$ is the ground acceleration.

The controlled equation of motion is solved using SIMULINK toolbox of MATLAB. For using the SIMULINK, the mass, stiffness and damping matrices need to be defined explicitly. For this purpose, damping matrix is obtained by assuming it to be mass and stiffness proportional and is determined by using the first two undamped modes and frequencies of the MDOF system.

In Eq. 1, $\ddot{x}_g$ is the record of ground acceleration for earthquake. In case of instantaneous control, depending upon the measured responses at any time *t*, the control force, *u(t)*, acts on the system. The inputs to the ANN are the measured responses, i.e. displacement, velocity and acceleration at time *t*, and the measured ground acceleration at the same time. When the control scheme is not an instantaneous one but incorporates time delay in it, then *u(t)* is the predicted control force at time *t* from the neural-net with input to the ANN as structural displacement, velocity, acceleration and ground acceleration recorded at a previous time station (may be at $t - \Delta t$ or $t - 2\,\Delta t$, depending upon the time delay considered in the study). The training data is obtained from possible future earthquakes at the site of interest.

Possible future earthquakes at the site is generated by assuming the future earthquakes to be a stationary random process, having a power spectral density function (PSDF), $S_{\ddot{X}_g}$, of the form

$$S_{\ddot{X}_g} = S_0 \frac{\left[1 + (2\rho_s \zeta_s)^2\right]\rho_g^4}{\left[(1-\rho_s^2)^2 + (2\rho_s \zeta_s)^2\right]\left[(1-\rho_g^2)^2 + (2\rho_g \zeta_g)^2\right]} \tag{2}$$

Eq. 2 is after Clough and Penzein (1993) which they used to represent the double filtered ground motion, in which S_0 is the PSDF of the white noise; $\rho_s = \omega/\omega_s$, and $\rho_g = \omega/\omega_g$, and ω_g, ζ_g, ω_s and ζ_s are the filter coefficients for the second and the first filters, respectively. The parameters ω_g, ζ_g, ω_s and ζ_s duly take care of the site soil condition. The future earthquakes are synthetically generated from the PSDF given by Eq. 2 using Monte Carlo simulation. Depending upon the site condition, different forms of PSDF may be considered. Even non-stationary model of future earthquakes may be incorporated by using a modulation function.

If the desired control force and the future earthquake excitations have the similar frequency contents, it is likely that the control of the system will be most effective. Therefore, for effective control of the system to future earthquakes, the desired control force may be assumed also to be stationary random process with a PSDF (S_u) having the same form as given by Eq. 2. Thus, time histories of control forces can be synthetically generated from the PSDF of the control force. Note that both $S_{\ddot{X}_g}$ and S_u can be expressed by the same expression (Eq. 2), by simply changing the parameter S_0, i.e. for ground acceleration S_0 may be denoted by S_{0g}, and for control force it may be denoted by S_{ou}. For a given PGA, S_{0g} can be determined using the standard procedure explained in Appendix - I. For given PGA, S_{ou} for the control force can be obtained for different assumed values of peak control force (taken as a fraction of the weight of the mass of MDOF system). The procedure is similar to that given in Appendix - I.

In simulating the time history of control forces, and the time histories of ground accelerations from their respective PSDFs, the time lag between the two is assumed to be zero. For each set of simulated time histories of control force and ground acceleration, the equation of motion of the controlled response given by Eq. 1, is solved and the time histories of displacement, velocity, acceleration responses are generated. Several sets of such responses are generated for different sets of excitations and the corresponding control forces. With these sets of time histories, the training data for the neural-net is obtained. When time lag is incorporated between the response measurement and application of control force, the training data is generated by assuming that the time delay between the response measurement and the actual application of the control force on the structure is 2 Δt. This means that at time *t*, *u(t)*, the output from ANN, acts on the structure instantaneously with the values of $x(t-2\Delta t)$, $\dot{x}(t-2\Delta t)$, $\ddot{x}(t-2\Delta t)$ and $\ddot{x}_g(t-2\Delta t)$ applied at the input nodes of the neural net. All time delays including computational time of the neural net, conversion time from digital to analog signal and implementation time of actual control force are incorporated in the time interval 2 Δt. Clearly, the data set is prepared such that the control force at the third time step from the generated time history of instantaneous control force corresponds with the values of controlled displacement, velocity, acceleration of the structure and ground acceleration at the first time step. Note that while finding out the controlled responses, control force at the first two time stations are set to be zero and the control force at third time station is same as that of the instantaneous control.

Training of Neural Net

With the input and output nodes as described above, the ANN is trained with the generated data set, using a single hidden layer. A fully connected feedforward neural net architecture with five input nodes and one output node with three hidden nodes in a single hidden layer is used for training. “Act_TanH’ activation function, ‘BackpropMomentum’ learning function and ‘Topologic_order’ update function along with “Randomize_weights’ initialising function are used for the training. SNNS package is utilized for training the neural net.

Testing of Neural Net

The neural nets are tested for (i) one of the data sets for which it was trained, and (ii) for ElCentro earthquake (unknown problem). For testing the neural net, the computed response of the system for the input ground motion and the control force applied to the system are taken as the measured responses which are fed to the neural net. The time history of control force used for the computation of response is obtained by normalizing the time history record of the ground acceleration with respect to its peak value and then multiplying it by assumed peak value of the control force so that excitation and control force have the same frequency contents. The percentage reduction in peak controlled displacement obtained with the applied control force is taken as the target reduction and is used along with controlled responses as inputs to the ANN. With inputs as the measured responses (computed controlled responses), target reduction and the ground acceleration, the time history of control force as obtained from the output node of the ANN is compared with the applied time history of the control force.

The difference between the time histories of the two control forces is taken as one measure of the efficiency of the control scheme. The other measure of the efficiency of the control scheme includes differences between the target percentage reduction and the percentage reduction for the peak controlled displacement obtained using the time history of control force obtained from ANN. Also, the two sets of time histories of controlled responses, one obtained by using control force from ANN and the other used as input to ANN, are compared for studying the efficiency of the control scheme.

A fully connected feedforward neural net architecture with eleven input nodes (nine nodes from feedback responses from three point, one node for ground acceleration and the other node for the target reduction) and one output node with six hidden nodes in a single hidden layer is used for training. For training and testing, the target percentage reduction of displacement is considered only for the top floor displacement. The efficiency of the control scheme is studied by considering also the controlled responses of the floors from which no feedback was fed to the ANN.

Numerical Study

The time histories of ground accelerations (excitations) are generated from the power spectral density functions (PSDFs) as mentioned above. In all, 7 sets of time histories of excitation sampled at an interval of 0.01s with 2001 number of sampled points in each set are used for training the neural net. The set of time histories of excitation is generated such that it covers a wide range of PGA, i.e. from 0.05g to 0.35 g and covers frequency contents whose PSDF corresponds to neither narrow nor wide band condition ($\omega_g = 5\pi$, $\omega_s = 0.5\pi$, $\zeta_g = 0.6$, $\zeta_s = 0.6$). The time histories of the control force are generated from the PSDF of similar shape having peak control force ranging from 0.5% to 10% weight of the 10-storey frame. With these data, 35 sets of time histories of controlled responses are generated using SIMULINK and are used for training the neural net. Table 1 shows the different combinations of PGA of excitation and peak control force used for generating the data sets. The control scheme using the trained neural-net is tested for one set of known data (i.e. the data used for training) and one unknown set of data obtained for ElCentro earthquake.

Testing of 10-Storey Frame

The testing of the ANN is done with one known excitation (which is used for training of the neural net) and the ElCentro earthquake. For testing the ANN, the ANN controlled responses of the different storeys are compared with the target ones. Fig. 2 compares between the time histories of control force as obtained from the ANN and that (ideal one) which is used to obtain the target responses. It is seen from the figure that the two time histories of control force are practically the same for the case of known excitation. Therefore, it is expected that the target responses and the ANN controlled responses will be nearly the same. Figs. 3 - 5 compare between the uncontrolled, target and ANN controlled responses for the 10^{th} storey. It is seen from the figures that difference between the target and the ANN controlled responses is almost indistinguishable. The difference between the ANN controlled peak displacement and the target peak displacement is about 12%. Table 2 compares between the percentage reductions in peak target responses and those for the ANN controlled responses. It is seen from the table that the percentage reductions in peak responses for the two do not significantly differ; ANN provides less reduction in responses.

Fig. 6 compares between the time histories of control force obtained from the ANN and that is used for obtaining the target responses for ElCentro excitation. The two time histories match quite well. Therefore, it is expected that the difference between the target and ANN controlled response will be small. Figs. 7 -9 compare between the uncontrolled, target and ANN controlled responses for the 10^{th} storey. It is seen from the figures that difference between the target and the ANN controlled responses is almost indistinguishable in the figures. The difference between the ANN controlled peak displacement and the target peak displacement is about 11%. Table 3 compares between the percentage reductions in peak target responses and those for the ANN controlled responses. It is seen from the table that the percentage reductions in peak responses for the two do not significantly differ; ANN provides less reduction in responses. In fact, comparison of controlled responses of all floors shows that the maximum percentage reductions in peak response for different response quantities occur at different floors. However, it is generally observed that percentage reductions in peak responses for all response quantities become less towards the bottom floors. For the present example, it is seen that the percentage reductions in peak responses are very high (nearly maximum) between 7^{th} to 9^{th} floor. Further it is important to note that the peak control force required to obtain a significant percentage reduction in response in not very large. For a peak control force of 4% of building weight the reduction in peak displacement, velocity and acceleration of the top floor are 48.8%, 33.4% and 38.6% respectively.

Fig. 10 compares between the time histories of control force as obtained from ANN with a time delay of 0.02 s ($2\Delta t$) and the ideal one (without time delay). It is seen from the figure that the two time histories differ and the difference is more prominent near the peaks. The difference between the peak values of the control forces is about 17%. Figs. 11 - 13 compare between the target and ANN controlled responses of 10^{th} storey. Note that the target responses are obtained with the time history of ideal control force (i.e. without time delay). It is seen from the figures that the two time histories of responses for different floors and different response quantities differ by different degrees. However, the difference between the two is not very large. Table 4 compares between the percentage reductions for peak target responses (without time delay) and those for the ANN controlled responses (with time delay). It is seen from the table that the time delay deteriorates the efficiency of the control scheme. The maximum effect of the time delay is observed for the velocity response; there is about 15% less reduction in peak velocity of 7^{th} floor due to the effect of time delay. Further, it is observed from the table that the percentage reductions in responses are not uniform for all the four floors. For some of the response quantities, it is observed that the percentage reduction in peak response is maximum for the 7^{th} floor. In fact, comparison of controlled responses of all floors shows that the maximum percentage reductions in peak response for different response quantities occur at different floors. However, it is generally observed that percentage reductions in peak responses for all response quantities become less towards the bottom floors. For the present example, it is seen that the percentage reductions in peak responses are very high (nearly maximum) between 7^{th} to 9^{th} floor, like the case of no time delay.

Conclusions

An active control scheme using ANN is presented for the seismic control of building frame for future earthquakes. The control scheme has the advantage that it can consider (i) limited number of feedback measurements, (ii) time delay effect, and (iii) a target reduction in response. The ANN control scheme requires feedback responses (displacement, velocity and acceleration), ground excitation and a target percentage reduction as inputs to the ANN. The output of the ANN is the time history of control force. A 10-storey building frame is taken as the illustrative example. Feedback responses are taken from 1^{st}, 5^{th} and 10^{th} storeys of the building frame. The control is affected by a single control force applied at the top of the building frame with AMD. Following conclusions are drawn from the numerical study.

1. The ANN control scheme is found to be quite effective in controlling the response of a ten-storey building frame taken as an illustrative example. The difference between the peak control force predicted by the ANN and the ideal control force for the ElCentro earthquake is of the order of 10%; the maximum difference between the target response and the ANN controlled response is of the order of 11% for instantaneous control.
2. The peak control force required to obtain a significant percentage reduction in response in not very large. For a peak control force of 4% of building weight the reduction in peak displacement, velocity and acceleration of the top floor are 48.8%, 33.4% and 38.6% respectively.
3. When the time delay is taken into consideration, the performance of the control scheme deteriorates. For a time delay of 0.02s ($2\Delta t$), the percentage reduction in the top floor responses (peak displacement, velocity and acceleration) decreases by about 10%, 13% and 11%. The peak control force also decreases by 17% from its ideal value.

Table 1. Combinations of PGA of excitation and peak control force used for obtaining training data for neural net.

PGA of Excitation	Peak Control Force (as percentage of weight of the frame)
0.05 g	0.5%, 1%, 1.5%, 2%, 2.5%, 3%
0.10 g	1.5%, 2.5%, 3.5%, 4.5%, 5.5%
0.15 g	1%, 2%, 4%, 6%, 8%
0.20 g	3%, 5%, 7%, 9%
0.25 g	2%, 4%, 6%, 8%, 10%
0.30 g	2%, 4%, 6%, 8%, 10%
0.35 g	2%, 4%, 6%, 8%, 10%

Table 2. Comparison of target percentage reduction in responses and that obtained from ANN for 10-storey frame (peak control force = 0.02 W and known excitation).

Floor	Percentage Reduction in Responses (Target)			Percentage Reduction in Responses (ANN)		
	Disp	Vel	Accl	Disp	Vel	Accl
10	63.3	36.2	40.5	59.5	31.1	35.4
9	64.1	42.1	43.2	61.2	37.2	39.6
8	65.9	50.8	48.5	60.8	44.8	45.6
7	63.9	60.6	51.0	57.8	55.7	46.0
6	58.2	49.6	42.1	53.5	45.3	38.3
5	52.6	37.2	31..0	48.2	33.6	27.0
4	47.8	25.3	20.3	43.5	22.0	17.2
3	43.1	14.8	10.6	41.2	11.3	6.7
2	39.2	6.8	5.9	36.7	4.9	3.3
1	36.1	–0.14	0.04	33.0	–2.4	–2.3

Table 3. Comparison of target percentage reduction in responses and that obtained from ANN for 10-storey frame (peak control force = 0.04 W; ElCentro earthquake).

Floor	Percentage Reduction in Responses (Target)			Percentage Reduction in Responses (ANN)		
	Disp	Vel	Accl	Disp	Vel	Accl
10	53.2	38.7	45.0	48.8	33.4	38.6
9	55.6	44.4	46.9	50.7	39.9	42.3
8	58.3	51.0	49.2	54.1	46.8	44.6
7	56.7	58.5	52.0	50.5	53.2	46.4
6	55.0	55.6	48.5	49.9	51.6	44.3
5	53.5	41.1	43.8	48.3	37.0	38.2
4	52.4	29.6	35.9	47.8	26.2	31.3
3	49.3	18.3	24.8	45.1	15.2	21.3
2	44.2	9.6	14.5	41.2	6.5	13.6
1	41.0	–1.1	3.6	36.2	–3.2	1.1

Table 4. Comparison of target percentage reduction in responses and that obtained from ANN for 10-storey frame (peak control force = 0.04W; ElCentro earthquake; time delay = 0.02 s).

Floor	Percentage Reduction in Responses (Target)			Percentage Reduction in Responses (ANN)		
	Disp	Vel	Accl	Disp	Vel	Accl
10	53.2	38.7	45.0	42.9	25.8	34.6
9	55.6	44.4	46.9	44.2	32.6	36.2
8	58.3	51.0	49.2	46.5	38.6	38.4
7	56.7	58.5	52.0	42.8	43.7	38.2
6	55.0	55.6	48.5	42.5	42.9	36.6
5	53.5	41.1	43.8	42.3	30.3	31.5
4	52.4	29.6	35.9	40.9	18.9	26.6
3	49.3	18.3	24.8	38.3	8.2	15.5
2	44.2	9.6	14.5	35.3	0.5	6.3
1	41.0	–1.1	3.6	30.5	–7.9	-5.9

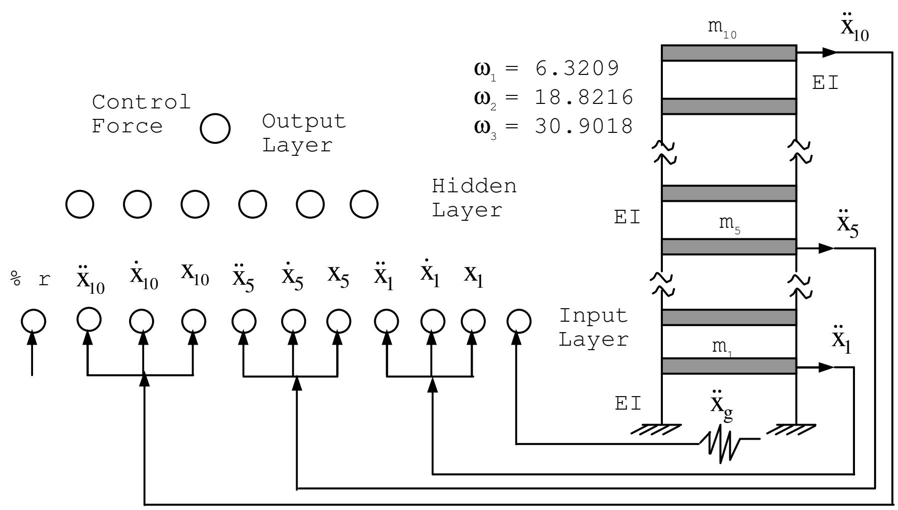

Figure 1. Schematic diagram of control scheme for MDOF system.

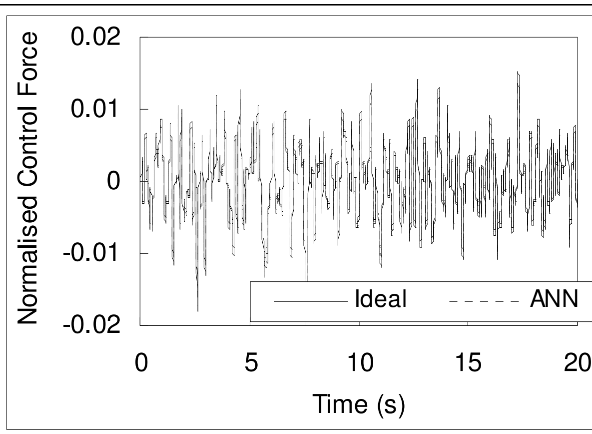

Figure 2. Time histories of ideal and ANN control force (peak control force = 0.02 W; known excitation).

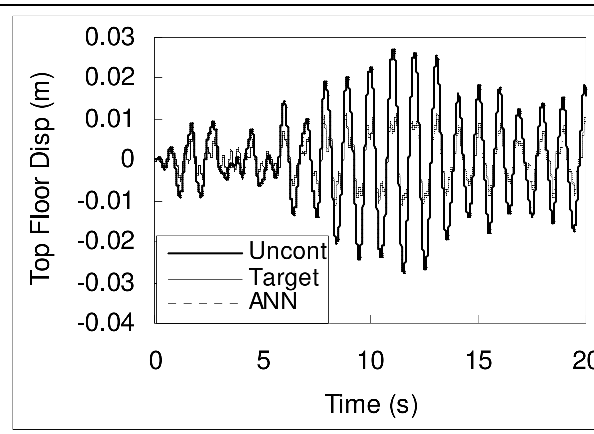

Figure 3. Time histories of 10th floor uncontrolled, target and ANN controlled displacements (peak control force=0.02 W; known excitation)

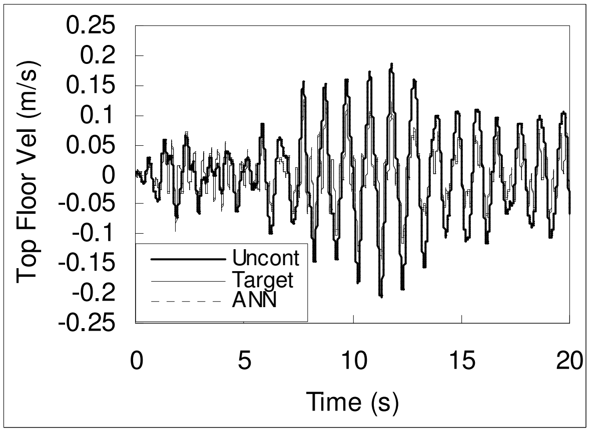

Figure 4. Time histories of 10th floor uncontrolled target and ANN controlled velocity (peak control force = 0.04 W; known excitation).

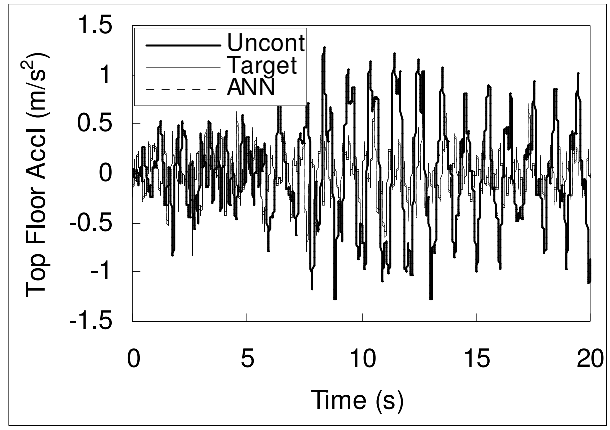

Figure 5. Time histories of 10th floor uncontrolled target and ANN controlled acceleration (peak control force = 0.02 W; known excitation).

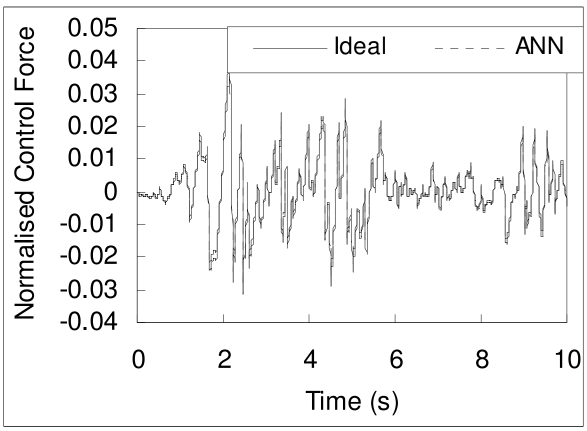

Figure 6. Time histories of ideal and ANN control force (peak control force = 0.04 W; ElCentro).

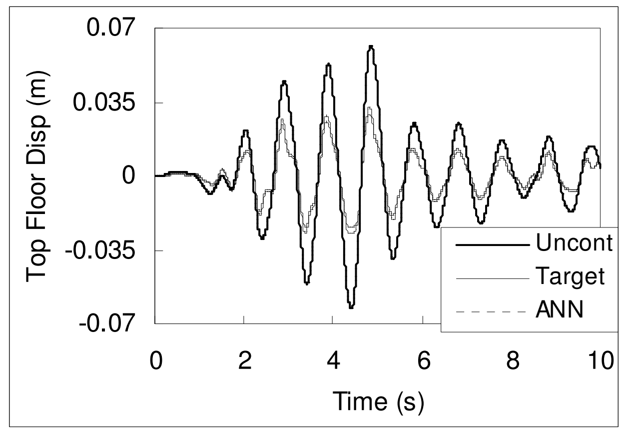

Figure 7. Time histories of 10th floor uncontrolled target and ANN controlled displacement (peak control force = 0.04 W; ElCentro).

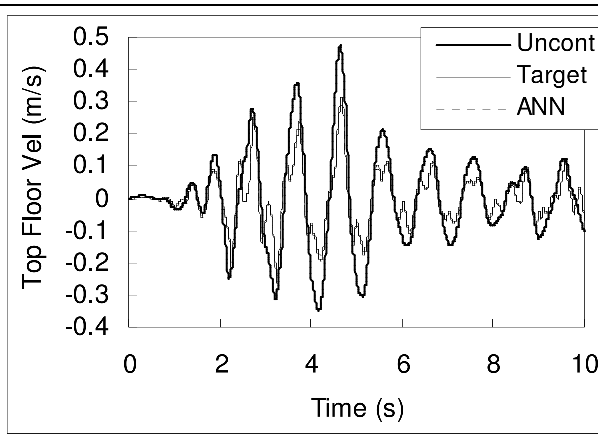

Figure 8. Time histories of 10th floor uncontrolled target and ANN controlled velocity (peak control force = 0.04 W; ElCentro).

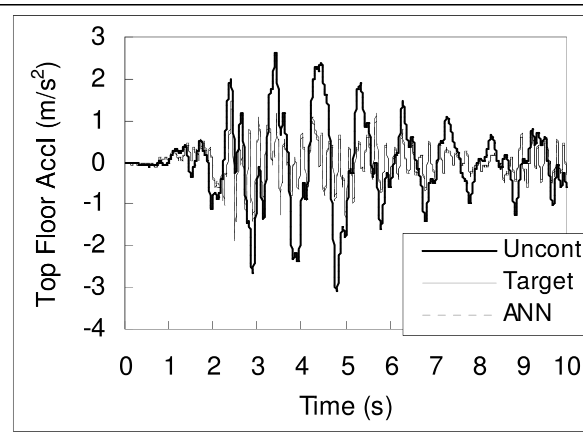

Figure 9. Time histories of 10th floor uncontrolled target and ANN controlled acceleration (peak control force = 0.04 W; ElCentro).

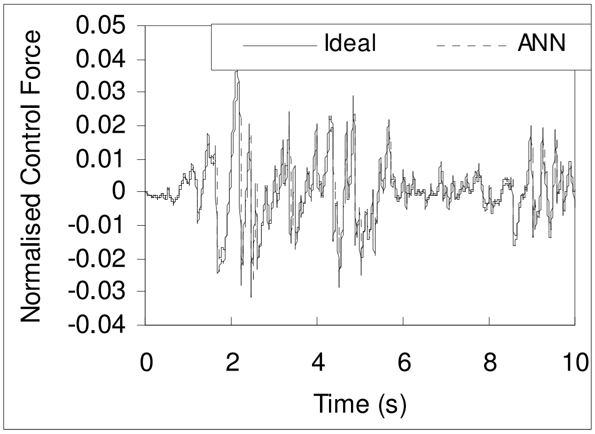

Figure 10. Time histories of ideal and ANN control force (time delay = 0.02 s, peak CF= 0.04 W; ElCentro).

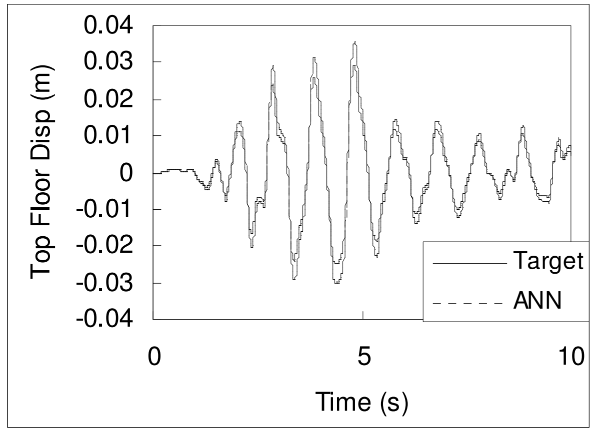

Figure 11. Time histories of 10th floor target and ANN controlled displacement (time delay = 0.02 s, peak CF= 0.04 W; ElCentro).

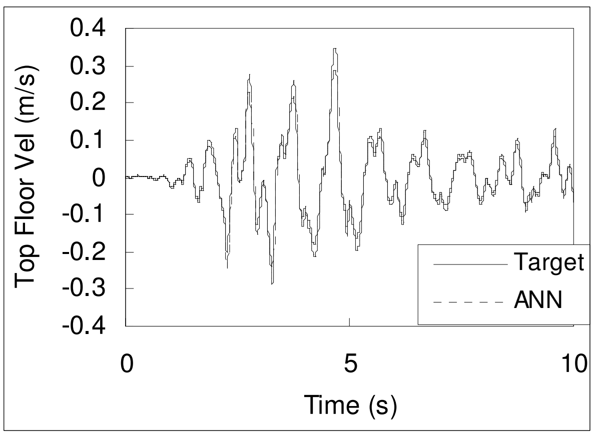

Figure 12. Time histories of 10th floor target and ANN controlled velocity (Time delay = 0.02 s, peak CF= 0.04 W; ElCentro).

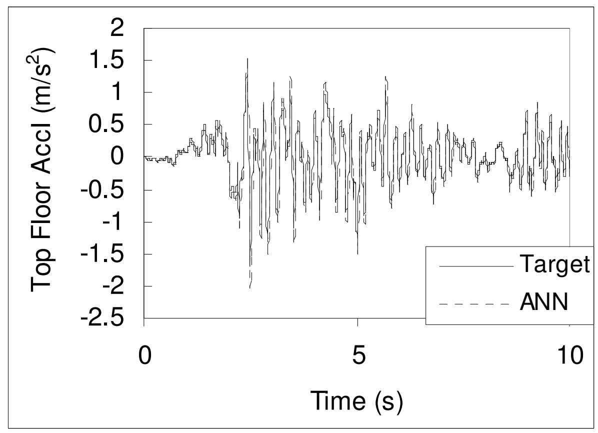

Figure 13. Time histories of 10th floor target and ANN controlled acceleration (Time delay = 0.02 s, peak CF= 0.04 W; ElCentro).

APPENDIX - I

For the known shape of PSDF of ground excitation

$$S_{og} = \frac{\sigma_{sg}^2}{\int_{0}^{\infty} \frac{(1 + (2\rho_s \zeta_s)^2)\ \rho_g^4}{[(1-\rho_s^2)^2 + (2\rho_s \zeta_s)^2]\,[(1-\rho_g^2)^2 + (2_{\rho_g} \zeta_g)^2]}} \tag{I.1}$$

here σ_{sg}^2 is the variance which is equal to the area under the PSDF curve of ground excitation. For an assumed value of peak ground acceleration (PGA)

$$\sigma_{sg} = \frac{PGA}{p} \tag{I.2}$$

where p is the peak factor given in terms of the first three spectral moments (λ_0, λ_1, λ_2) and the duration τ of earthquake (Kiureghian, 1981).

$$p = \sqrt{2 \ln(\upsilon_e \tau)} + \frac{0.5772}{\sqrt{2 \ln \upsilon_e \tau)}} \tag{I.3}$$

where υ_e is an equivalent rate of statically independent zero crossings expressed as

$$\upsilon_e = (1.63\,\delta^{0.45} - 0.38)\,\upsilon \qquad \text{for } \delta < 0.69$$
$$= \upsilon \qquad \text{for } \delta \geq 0.69 \tag{I.4}$$

in which υ is the mean zero crossing rate of the process given by

$$\upsilon = (1/\pi)\sqrt{\lambda_2 / \lambda_0} \tag{I.5}$$

and δ is the shape-factor for the excitation PSDF (with a value between 0 and 1) given by

$$\delta = \sqrt{1 - \frac{\lambda_1^2}{\lambda_0\,\lambda_2}} \tag{I.6}$$

in which λ_0, λ_1 and λ_2 are respectively the zeroth, first and second moments of the PSDF about the frequency origin.

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