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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 contents, it is likely that the control force of the system will be most effective. Based on that premise, it is assumed that the shape of the PSDF of the control force is the same as that of the PSDF of ground motion representing the future earthquake. This assumption makes also the control problem to be site specific. 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-story building frame is taken as an illustrative example. Feedback responses are taken from 1st, 5th and 10th stroys 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.

Keywords: ANN Control, Active control, AMD, El Centro earthquake, response reduction,

1. Introduction

Active control of building frames using artificial neural network (ANN) has been a subject of intensive research. In the past, numerous applications of ANN for structural control are reported in the literature. In the earlier works Ghaboussi and Joghataie, Chung et al., Bani-Hani and Ghaboussi, Yu-Ao He and Jianjun [1-6] developed online control using ANN with emulator neural network. Dong – Hyawn Kim et al. [7] replaced the emulator neural network with a sensitivity evaluation algorithm and applied it to a multi -degree of freedom structure. Chang et al. [8] used recurrent neural network models for structural control. Alok Madan [9] used steepest gradient descent scheme for minimizing a cost function for training of multilayer feed forward neural networks for active control in multi-degree of freedom systems. Hyun Cho et al. [10] presented neural network active control of structures under earthquake excitation in which optimum number of the neurons in the hidden layers was determined considering the control performance criteria. Rao et al. [11] have developed a procedure for active control of structures using two sets of neural networks for general stochastic simulations of earthquake based on Kanai Tajmi power spectral density function. Sridhar and Hasan [12] proposed an adaptive output feedback scheme that uses radial basis function neural nework for the control of a class of non linear systems. Jagannathan [13] developed a multilayer neural nework controller again for a class of non linear systems.

Some of the recent works on the structural control using ANN combined with the genetic algorithm and fuzzy logic include the work of Chen et al. [14] on modified intelligent genetic algorithm based adaptive ANN control of uncertain system structures; Chen C.W. [15] on neural network based fuzzy logic parallel controller for structural system; Wang et al. [16] on self constructing wavelet ANN algorithm for non linear control of large structures; Chang et al. [17] on active control of building structures using probabilistic ANN and Baghban et al. [18] on nonlinear control of structures using neuropredictive algorithm.

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, a target percentage reduction and site specific condition 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 ANN based controller duly takes into account the site specific future earthquake represnted by its PSDF. 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.

2. 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 story displacement response.
The controlled responses are obtained by solving the following equation of motion:

$$M\ddot{Y} + C\dot{Y} + KY = -M\,I\,\ddot{x}_g + H\,u \tag{1}$$

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 nth 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 generated 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 [19] 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 $\omega_g, \zeta_g, \omega_s$ and ζ_s are the filter coefficients for the second and the first filters, respectively. The parameters $\omega_g, \zeta_g, \omega_s$ 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 a 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. 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.

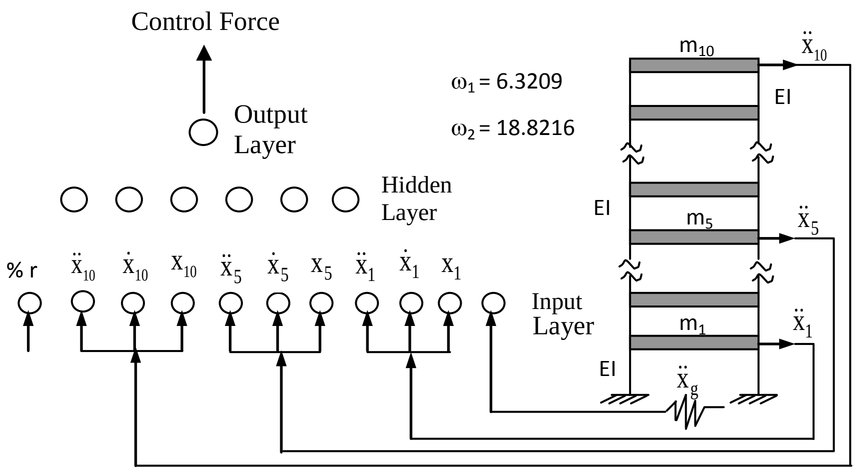

Fig. 1: Schematic diagram of control scheme for MDOF system

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 simulated excitations and the corresponding control forces. For each case, the percentage reduction of top floor displacement is obtained. This percentage reduction goes to one of the input nodes as % r as shown in the Figure 1. With these sets of time histories, the training data for the neural-net is prepared in the following way.

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 $n\Delta t$ ($n = 1,2$). This means that at time t, $u(t)$, the output from ANN, acts on the structure instantaneously with the values of $x(t-n\Delta t)$, $\dot{x}(t-n\Delta t)$, $\ddot{x}(t-n\Delta t)$ and $\ddot{x}_g(t-n\Delta t)$ 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 $n\Delta t$. Clearly, the data set for time delay of $2\Delta t$ is prepared such that the control force at the third time step from the generated time history of control force corresponds to 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 zero and the control force at the third time station is the same as that for the simulated time history of the control force.

2.1 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. 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.

2.2 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 with the time delay as described before. For the testing of the neural net with the known data set, the trained ANN is fed with delayed response i.e. $x(t -n\Delta t)$ etc. and delayed excitation along with the percentage reduction of top floor displacement taken from the data sets used for training the ANN. The time history of control force obtained from the output node of the ANN is compared with that of the training dataset. Further, the time history of control force as obtained from the ANN is used to determine the percentage control of top story displacement by solving Eq. 1. This percentage reduction is compared with the target percentage reduction used in the input node of ANN.

For the unknown problem, the time history of control force used for the computation of response is obtained by normalizing the time history record of the El Centro ground acceleration with respect to its peak value and then multiplying it by the assumed peak value of the control force so that excitation and control force have the same frequency contents. Note that the control forces are set to zero for the first two time steps if time delay of $2\Delta t$ is considered. The percentage reduction in peak controlled displacement obtained with the applied control force by solving Eq. 1 is taken as the target reduction. With inputs as the delayed measured responses (computed controlled responses), target reduction and the delayed 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 used to obtain the target percentage reduction.

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. Note that for no time delay, the instantaneous control is assumed i.e. there is a perfect time matching for input and output node parameters.

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 peak percentage reduction of the controlled responses of all the floors.

3. 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 by solving the equation 1 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. The training and testing of the ANN are done for the time delay of nΔt with n = 0, 1, 2. n= 0 specifies no time delay i.e. instantaneous control (termed as ideal control).

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%

3.1 Testing of 10-Storey Frame

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 which is used to obtain the target responses from analysis. It is seen from the figure that the two time histories of control force are practically the same for the case of known problem (dataset) for no time delay. Therefore, it is expected that the target responses and the ANN controlled responses will be nearly the same.

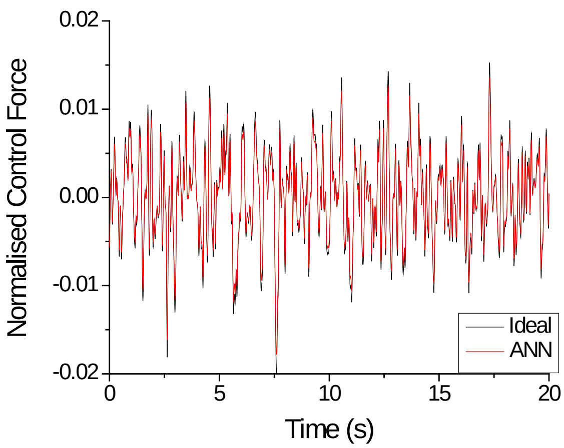

Fig. 2:Time histories of ideal and ANN control force (peak control force = 0.02 W; time delay = 0; known excitation)

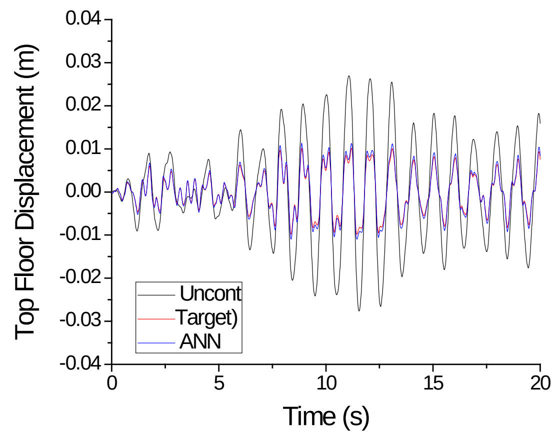

Fig. 3:Time histories of 10th floor uncontrolled, target and ANN controlled displacements (peak control force = 0.02 W; time delay = 0; known excitation)

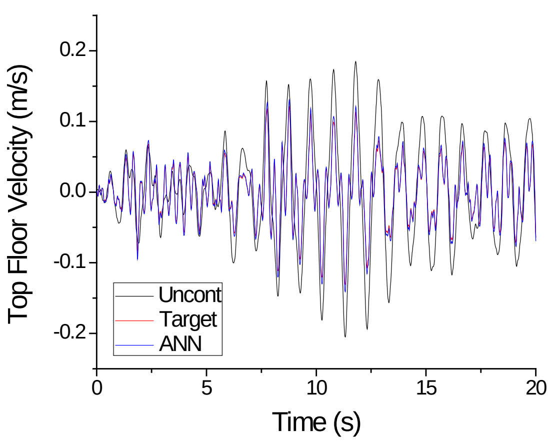

Figure 4: Time histories of 10th floor uncontrolled, target and ANN controlled velocity (peak control force = 0.02 W; time delay = 0; known excitation)

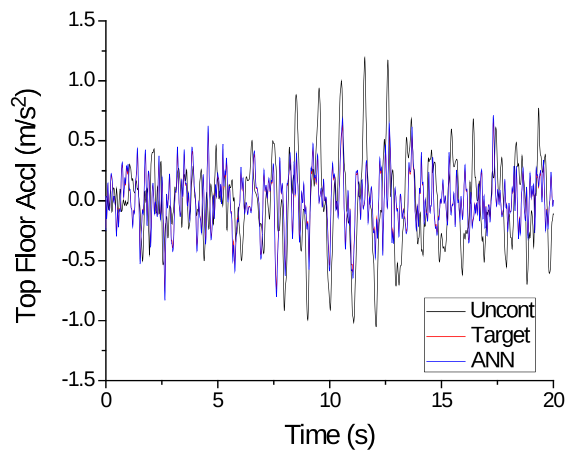

Figure 5: Time histories of 10th floor uncontrolled, target and ANN controlled acceleration (peak control force = 0.02 W; time delay = 0; known excitation)

Figs. 3 - 5 compare between the uncontrolled, target and ANN controlled time histories of response for the 10th storey. It is seen from the figures that difference between the target and the ANN controlled responses is insignificant. 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 El Centro excitation. The two time histories match quite well. Therefore, it is expected that the difference between the target and ANN controlled responses will be small.

Figs. 7 -9 compare between the uncontrolled, target and ANN controlled responses of the top floor. It is seen from the figures that difference between the target and the ANN controlled responses is not very significant. 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 of interest occur at different floors. However, it is generally observed that percentage reductions in peak responses for all response quantities of interest become less towards the bottom floors. For the present example, it is seen that the percentage reductions in peak responses are 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.

Table 2: Comparison of target percentage reduction in responses and that obtained from ANN for 10-storey frame (peak control force = 0.02 W; known data set; time delay = 0)

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

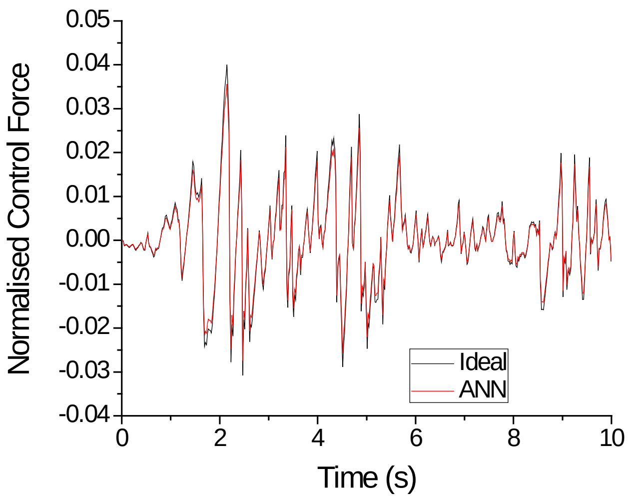

Figure 6: Time histories of ideal and ANN control force (peak control force = 0.04 W; El Centro; no time delay)

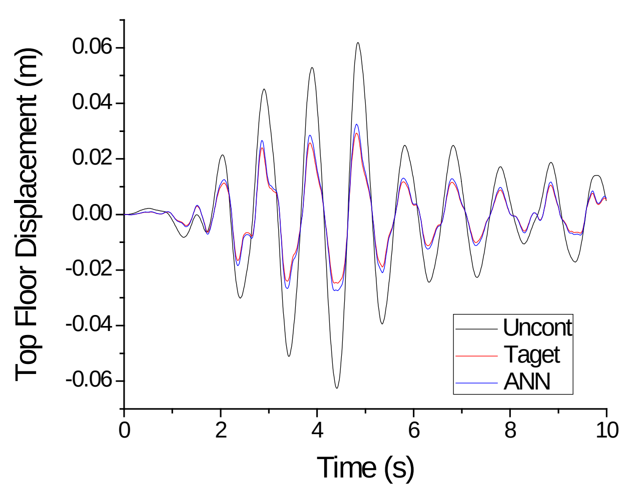

Figure 7: Time histories of 10^{th} floor uncontrolled, target and ANN controlled displacement (peak control force = 0.04 W; El Centro; no time delay)

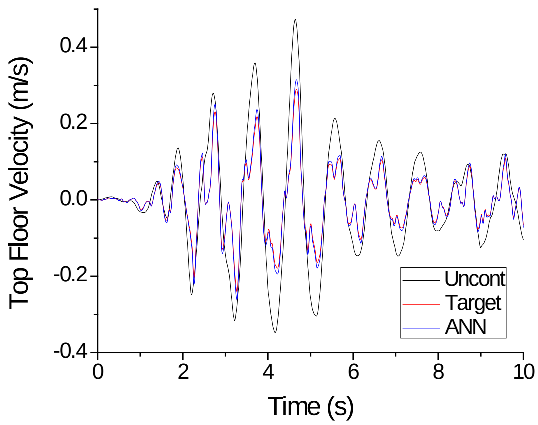

Figure 8: Time histories of 10th floor uncontrolled, target and ANN controlled velocity (peak control force = 0.04 W; El Centro; no time delay)

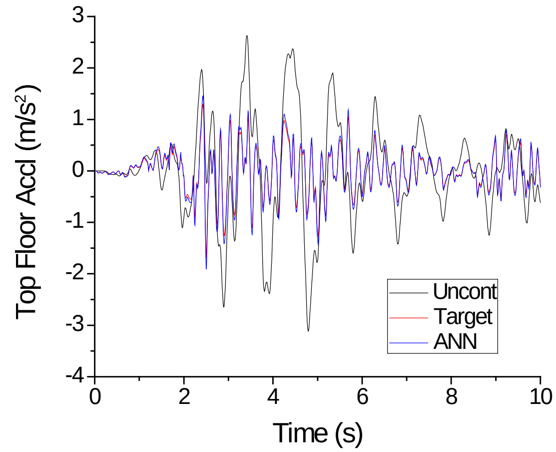

Figure 9: Time histories of 10th floor uncontrolled, target and ANN controlled acceleration (peak control force = 0.04 W; El Centro; no time delay)

Table 3: Comparison of target percentage reduction in responses and that obtained from ANN for 10-storey frame (peak control force = 0.04 W; El Centro earthquake; time delay = 0)

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

Fig. 10 compares between the time histories of control force as obtained from ANN with a time delay of 0.02 s (2Δt) 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 10th story. Note that the target responses are obtained with the time history of ideal control force (i.e. without time delay). This comparison is shown to illustrate the effect of time delay on the control algorithm. A time delay of Δt = 0.02 s is selected for comparison since it is expected that between the measurement of responses and the application of control force the time delay will not exceed 0.02s.It is seen from the figures that the two time histories of 10th floor responses for different response quantities of interest differ by different degrees. However, the difference between the two is not very large.

Tables 4 and 5 compare between the percentage reductions for peak target responses and those for the ANN controlled responses for time delays of 0.01 s (Δt) and 0.02 s (2Δt) for El Centro earthquake. Along with the percentage reductions shown in the tables, the ideal percentage peak reduction in responses i.e. the target percentages of reduction for no time delay are shown for reference.

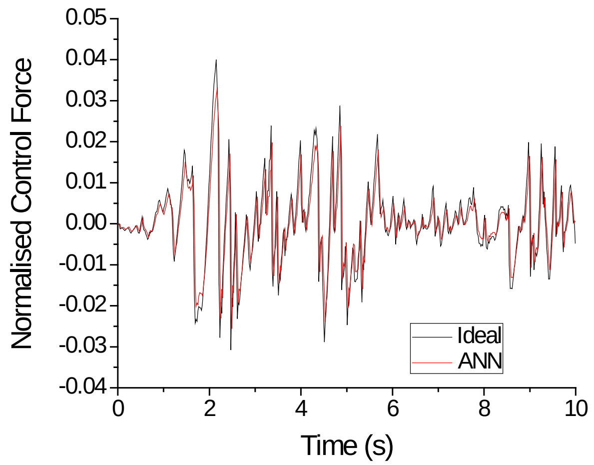

Figure 10: Time histories of ideal and ANN control force (time delay = 0.02 s, peak CF= 0.04 W; El Centro)

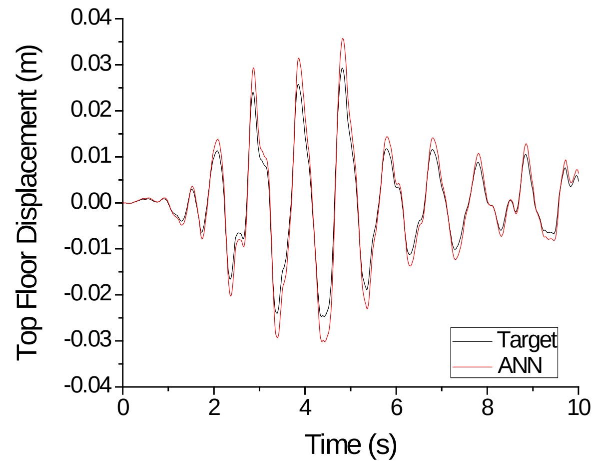

Figure 11: Time histories of 10th floor target and ANN controlled displacement (time delay = 0.02 s, peak CF= 0.04 W; El Centro)

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 = 0.01 s)

Floor	**Percentage Reduction in Responses**								
	Displacement			**Velocity**			**Acceleration**		
	Ideal	**Target**	**ANN**	**Ideal**	**Target**	**ANN**	**Ideal**	**Target**	**ANN**
10	53.2	48.5	44.5	38.7	38	33	45.0	43	41.5
9	55.6	50	45.6	44.4	43.6	39.6	46.9	45	44
8	58.3	53.5	48.5	51.0	50	46	49.2	49	47
7	56.7	49	45	58.5	55.7	51.5	52.0	49	46.2
6	55.0	49	45	55.6	54.5	50	48.5	47	43.5
5	53.5	50	46	41.1	42.6	38	43.8	42	38
4	52.4	49	44	29.6	30.2	25.6	35.9	35	33.8
3	49.3	44.5	40.5	18.3	21.6	17	24.8	34	22
2	44.2	42	38	9.6	10.5	6	14.5	13	11
1	41.0	37	33	–1.1	-1	-1.5	3.6	1.2	-1.8

It is seen from the tables 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 7th 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 floors as compared to ideal one. For some of the response quantities, it is observed that the percentage reduction in peak response is maximum for the 7th 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 7th to 9th floor, like the case of no time delay. No significant difference is observed for percentage reduction in responses (ANN) between time delay of 0.02 s and 0.01 s.

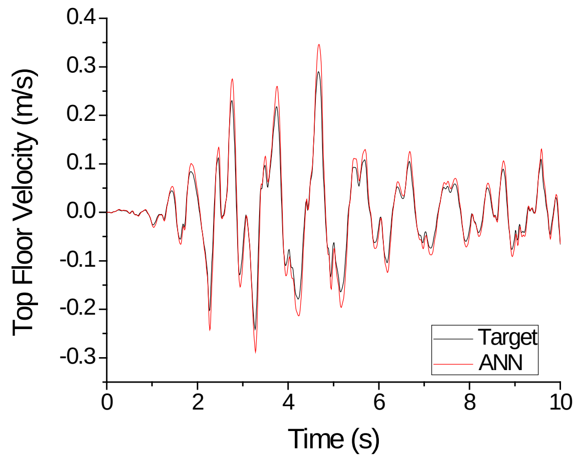

Figure 12: Time histories of 10th floor target and ANN controlled velocity (Time delay = 0.02 s, peak CF= 0.04 W; ElCentro)

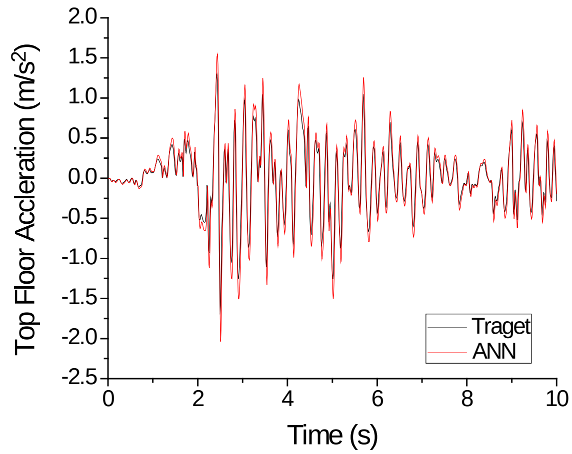

Figure 13: Time histories of 10th floor target and ANN controlled acceleration (Time delay = 0.02 s, peak CF= 0.04 W; ElCentro)

Table 5: 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**								
	Displacement			**Velocity**			**Acceleration**		
	Ideal	**Target**	**ANN**	**Ideal**	**Target**	**ANN**	**Ideal**	**Target**	**ANN**
10	53.2	48	43	38.7	31	25.8	45.0	39.5	34.6
9	55.6	49	44.2	44.4	37.6	32.6	46.9	41	36.2
8	58.3	51	46.5	51.0	43.4	38.6	49.2	44	38.4
7	56.7	47.6	42.8	58.5	48.2	43.7	52.0	43.5	38.2
6	55.0	47.2	42.5	55.6	48	42.9	48.5	41.3	36.6
5	53.5	47	42.3	41.1	35	30.3	43.8	35.8	31.5
4	52.4	46	40.9	29.6	23.6	18.9	35.9	31.2	26.6
3	49.3	43	38.3	18.3	14	8.2	24.8	21.2	15.5
2	44.2	38	35.3	9.6	4	0.5	14.5	12	6.3
1	41.0	35	30.5	–1.1	-2.5	-7.9	3.6	-2.2	-5.9

3.2 Implementation

The ANN controller is fed with the measured responses taken from the frame for which the controller was trained. Depending upon the time delay used for training, delayed responses are provided to the controller to produce the command signal for control force at any instant of time t. The trained controller acts online during earthquake excitation.

4. 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, (iii) site condition 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 1st, 5th and 10th 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 no time delay.
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 for no time delay.
3. With time delay, the efficiency of the ANN control is reduced compared to ideal response reduction (i.e. with no time delay); however, compared to target response reduction, the efficiency does not significantly deteriorate for all response quantities of interest.
4. There is no appreciable change in the percentage reduction of responses when the time delay of 0.01 s is increased to 0.02 s.

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

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

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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