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SEISMIC RESPONSE REDUCTION USING AN ACTIVE TUNED MASS DAMPER DRIVEN BY AN ARTIFICIAL NEURAL NETWORK CONTROLLER

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Abstract

Active structural vibration control techniques are effective ways to lessen undesirable vibrations that are caused by external disturbances such as earthquakes. This study uses an artificial neural network-based (ANN) controller to actuate an active tuned mass damper (ATMD) to attenuate the response of a scaled three-storey shear frame structure. The ANN controller has shown its ability to mimic the classical controller behavior with fewer sensors. The controller used in this study is trained using a database of controller force generated based on a linear quadratic regulator controller. The results show that the neural network algorithm successfully reduced the structural responses compared to those of an uncontrolled system.

Keywords: Vibration control, Artificial neural network, ATMD, Structural response, Linear quadratic regulator.

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1 INTRODUCTION

Earthquakes are among the most catastrophic natural disasters that result in significant loss of lives and properties. The prospect of using various control systems in structural engineering has received a lot of attention over the last few decades [1, 2].

Different control devices are now widely utilized worldwide, specifically in civil engineering constructions to improve their resistance and survivability against powerful earthquakes [3]. These later can be classified into three types: passive, semi-active, and active. Passive control filters the transmission of forces in the structure. It loses its ability to reduce vibrations when the properties of the system are not exactly known since it has no other support, making it unable to respond to the loading changes. Furthermore, semi-active control reduces vibration by changing the mechanical properties of the control device with a small power supply. However, active control is the most powerful and effective strategy out of the three. Active control has been extensively researched and developed for civil engineering applications [4]. Its principle is to produce the necessary control force to reduce induced vibrations; this force is calculated using a control algorithm based on a set of response feedbacks. An active tuned mass damper (ATMD) is one of the active devices made by attaching an actuator to a regular tuned mass damper (TMD).

Over the past two decades, various classical control strategies have been used to control various active dampers. These classical controllers have a common drawback related to their dependence on an extensive and complicated sensor network. Recently, intelligent approaches have become more widespread, especially artificial neural network (ANN) algorithms. ANN was the initial concept of developing theories of biological learning; it was carried out by Mcculloch and Pitts (1943) [5] when they first applied an artificial neuron model that represents perceptron's mathematical model. The artificial neural network was brought to structural engineering back in the 1980's Adeli and Yeh (1989) [6]. It has gained a lot of interest in designing active control schemes in vibration control [7-10]; due to their parallelism and learning capabilities, they can produce good performance with a limited number of sensors. The self-learning capability of artificial neural network control above traditional control is a benefit since it eliminates the requirement for the previous system's information, where it must adapt to environmental changes.

This work used a neural network technique to train and deploy a controller that drives an ATMD placed on top of a scaled three-storey building shear frame. The ANN controller provides an optimum response reduction against dynamical loadings, precisely earthquakes.

2 ARTIFICIAL NEURAL NETWORK CONTROL STRATEGY

2.1 Artificial neural network

Similar to the biological brain network of the human body, artificial neural networks have layered architecture with an input layer, one or more hidden layers, and an output layer. Every node in the network is connected to one another and can process input and send weighted output to other nodes.

The figure below represents the architecture of an artificial neural network, including its inputs and outputs.

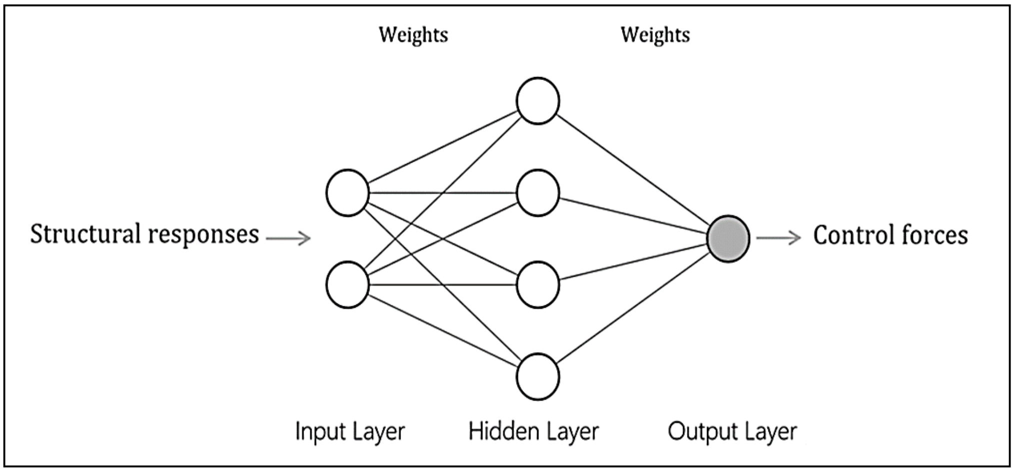

Figure 1: artificial neural network architecture.

The idea behind a neural network is that it takes data as inputs, produces a prediction as an output, compares it to the desired result by calculating the error, and then uses the results of the comparison to change or alter its internal parameters to produce a better prediction the next time.

2.2 Active tuned mass damper design model

The following equation defines the design parameters of the ATMD proposed by Sadek et al 1997 **[11]**, including the mass ratio (μ), frequency ratio (γ), damping ratio (ζ), and the state parameters of the ATMD (m_d, c_d, and k_d).

$$\mu = \frac{m_d}{M_T} \tag{1}$$

$$\gamma = \frac{1}{1+\mu}\left[1-\xi_s\sqrt{\frac{\mu}{1+\mu}}\right] \tag{2}$$

$$\zeta = \frac{\xi_s}{1+\mu}+\sqrt{\frac{\mu}{1+\mu}} \tag{3}$$

$$m_d = \mu \times m_T \tag{4}$$

$$\omega_d = \gamma \times \omega_{s(1)} \tag{5}$$

$$c_d = 2\times\gamma\times m_d \times \omega_d \tag{6}$$

$$k_d = {\omega_d}^2 \times m_d \tag{7}$$

Where m_T, ω_d, ξ_s, and $\omega_{s\,(1)}$ are the total structure's mass, the frequency of the ATMD device, the system's damping ratio, and the system's natural fundamental frequency, respectively. m_d, c_d, and k_d are the damper's mass, damping, and stiffness.

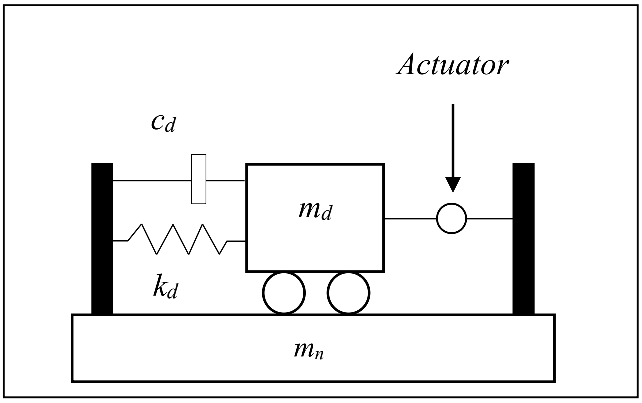

Figure 2: Active mass damper model.

Table 1 contains the data that defines the damper for our structure.

Parameters	Value [Unit]
μ	0.05
γ	0.942
ζ	0.2658
ω_d	32.92 [rad/s]
m_d	14.745 [kg]
c_d	253.15×10^3 [N.s/m]
k_d	15.38×10^3 [N/m]

Table 1: Parameters of the ATMD.

In this work, the ATMD equations were implemented in a MATLAB Simulink model to understand how the device functions.

2.3 Artificial neural network method using ATMD

An ANN training is supplied with input-output data from the building-damper system to model the structure's dynamic behaviour, which will take the same input signal as the structure (ground acceleration) and the structural response data. At the same time, the outputs are control forces based on a linear quadratic regulator controller; it then learns to make predictions that have the smallest possible error compared to the actual target values. This is achieved by repeatedly adjusting the network's parameters during the training phase, leading to more effective vibration control and improved overall building performance.

Figure *3* illustrates the control diagram for the ANN control system.

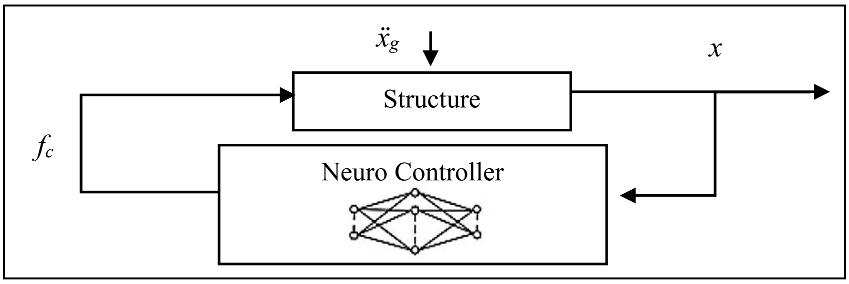

Figure 3: ANN control diagram using ATMD.

Where f_c is the control force of the ATMD, $\ddot{x}_g$ is the ground acceleration, and x is the displacement of the structure.

3 NUMERICAL RESULTS

A three-storey shear building structure was analyzed to evaluate the efficiency of the active ANN control system with an ATMD damper. The simulated results of the suggested control system were compared with those of an uncontrolled one.

3.1 System's equation of motion

Figure 4 displays a three-storey building model with a single ATMD damper placed on the roof. This system represents a straightforward version of the scaled three-storey test structure outlined in Reference [12], which was utilized in earlier active control studies at the University of Notre Dame's Structural Dynamics and Control Earthquake Engineering Laboratory (SDC/EEL) [13]. The equation of motion of the system is represented as follows:

$$[M_t]\{\ddot{x}_t\}+[C_t]\{\dot{x}_t\}+[K_t]\{x_t\}=-[M_t]\{r\}\{\ddot{x}_g\}+\{d\}(f_u) \tag{8}$$

Where f_u is the control force, $\ddot{x}$**,** $\dot{x}$ and are the system acceleration, velocity, and displacement vectors, respectively. Table 2 represents the matrices of the system,

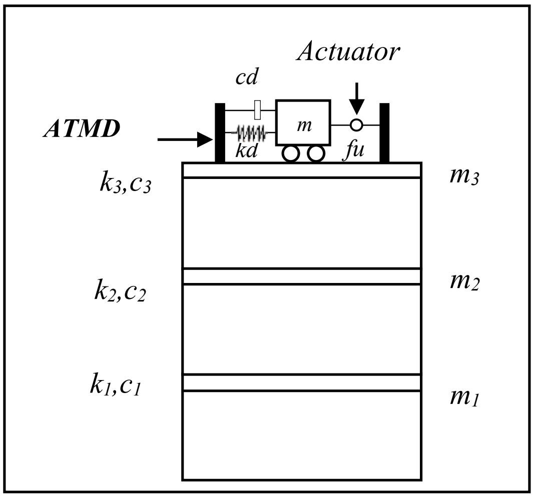

Figure 4: Three-storey model building equipped with ATMD on the top floor.

Mass Matrix	$M = \begin{bmatrix} 98.3 & 0 & 0 \\ 0 & 98.3 & 0 \\ 0 & 0 & 98.3 \end{bmatrix} kg$
Stiffness Matrix	$K = \begin{bmatrix} 12.0 & -6.84 & 0 \\ -6.84 & 13.7 & -6.84 \\ 0 & -6.84 & 6.84 \end{bmatrix} 10^5\ N/m$
Damping matrix	$C = \begin{bmatrix} 175 & -50 & 0 \\ -50 & 100 & -50 \\ 0 & -50 & 50 \end{bmatrix} N.s/m$
Location matrix of ATMD	$d = [0 \;\; 0 \;\; 1]^{\mathrm{T}}$
External force distribution matrix	$r = [1 \;\; 1 \;\; 1]^{\mathrm{T}}$

Table 2: Three-storey shear building system matrices.

The equation of motion can also be written as:

$$\begin{cases} \dot{z}(t) = Az(t) + Bu(t) \\ y(t) = Cz(t) + Du(t) \end{cases} \tag{9}$$

Where:

$$A = \begin{bmatrix} -M^{-1}C & -M^{-1}K \\ E & 0 \end{bmatrix}, \qquad B = \begin{bmatrix} -M^{-1}d & -E \\ 0 & 0 \end{bmatrix}, \qquad C = [E], \qquad D = [0]$$

[E] and **[0]** are identity and zeros matrices of convenient sizes. The vectors in this case, are:

$$z = \begin{bmatrix} \dot{x} \\ x \end{bmatrix} \tag{10}$$

$$u = \begin{bmatrix} f_u \\ \ddot{x}_g \end{bmatrix} \tag{11}$$

3.2 ANN control algorithm

A neural network is modelled based on how the human brain functions, emphasizing neurons and synapses.

Numerous tools and features for designing, developing, and testing neural networks are available in the MATLAB toolbox. Artificial neurons are stacked in layers and function as a network to analyze and send data. The weights, or connections between these neurons, may be changed to enable the network to learn from instances and generate predictions. In this study, the neural network inputs are the structure and ground acceleration state, and the outputs are the control forces generated by the LQR control algorithm. The model consists of one hidden layer with three neurons. After defining and normalizing the inputs, random weights and biases are selected, at which point the biases are added to the product of the weights and inputs. The result is renormalized to obtain the output, and the root mean squared error (RMSE) performance indicator is chosen and calculated. This process is repeated to find the optimal and desired output.

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(Y_{tar,i} - Y_{out,i})^2} \qquad (0 < RMSE < \infty) \tag{12}$$

Where $Y_{tar,i}$, $Y_{out,i}$, represent the target, output for N data samples.

3.3 Simulated results

The structure's response is investigated under El Centro, 1940 earthquake, with the excitation scaled up to five times the recorded rate since the system being analyzed is a scaled model.

A new method for reducing seismic response in a three-storey shear building using an active Artificial Neural Network (ANN) control system with an ATMD damper is proposed. The performance of the proposed adaptive control system will be compared to an uncontrolled system. The comparison will be based on the maximum peak accelerations of the structure, as shown in Table 3. The controller is designed using the response variables of the top floor as input and an active external control force produced by the LQR as the output variable.

Control strategy	**Uncontrolled**	**Controlled with ANN**	**Reduction rate**
ẍ(cm/s²)	1005	711.85	29%
	1072.6	453.86	58%
	1458.8	750.97	48%

Table 3: Maximum Acceleration Response during the El Centro Earthquake.

According to Table 3, the maximum response in the controlled system with ANN on the top floor has been significantly reduced by around 48% compared to the uncontrolled system. This result indicates that the ANN control system was highly effective in reducing the seismic response.

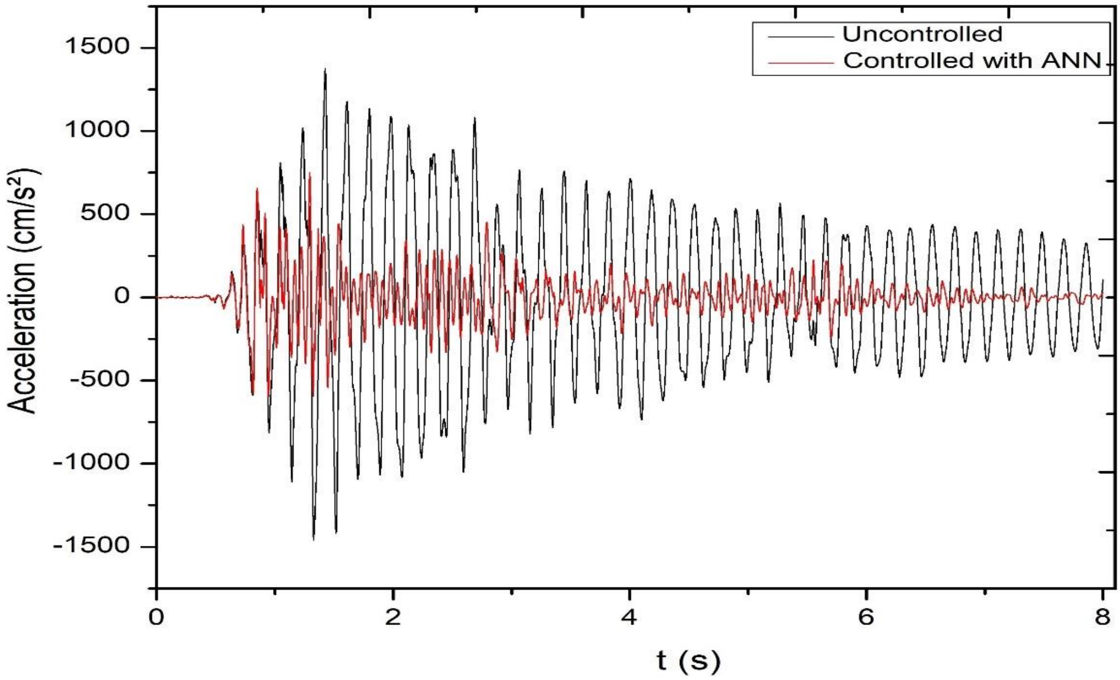

Figure 5: Acceleration responses of the top floor under El Centro earthquake.

Figure 5 displays the structural response of both the uncontrolled and actively ANN-controlled systems in terms of acceleration. As demonstrated in the figure, the acceleration on the third floor is significantly decreased compared to the case where the ATMD damper was not utilized.

The effectiveness of the active ANN control system in reducing structural responses caused by the El Centro earthquake is established.

4 CONCLUSION

An active Artificial Neural Network (ANN) control technique incorporating the ATMD damper is proposed for decreasing seismic responses in a three-storey shear building. The proposed controller employs training to learn and implement the desired control force. The results clearly show the efficiency of the ANN control system in reducing seismic responses and emphasize its capacity for enhancing the overall safety and stability of structures during earthquakes. Also, it indicates that ANN control systems could play a vital role in minimizing the damage caused by earthquakes and improving the overall aseismic performance of structures.

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