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NEURAL NETWORK-ENHANCED HYBRID VIBRATION CONTROL FOR BASE-ISOLATED STRUCTURES

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Abstract

In civil engineering, vibration control is crucial to protect structures, reduce damage and ensure comfort by reducing dynamic forces, which enhances stability. One effective approach is hybrid structural vibration control, which has made notable advancements in successfully mitigating undesired oscillations induced by external factors like wind and earthquakes. In our study, an advanced hybrid system that integrates a base isolator with an active tuned mass damper (ATMD) has been developed. The active control force for the ATMD is precisely determined through the use of an Artificial Neural Network (ANN) controller. The ANN controller is trained with a comprehensive database of forces generated by a linear quadratic regulator (LQR). To evaluate the hybrid control system's effectiveness, simulations were conducted on a six-degree-of-freedom base-isolated frame structure where the ATMD is strategically placed on the lowest floor of the structure. Notably, the hybrid control system demonstrates a significant reduction in vibration amplitudes in terms of base isolator displacement and maximum drifts while not adversely affecting the response of the superstructure, where it achieves an impressive reduction of up to 87 % in displacement responses. The results highlight the ANN algorithm's efficacy in reducing structural responses, emphasizing the substantial potential of hybrid systems in advancing structural vibration control. Furthermore, the system's performance was validated through simulations using real-time historical data from three earthquakes that were not included in the ANN training (Hector, Northridge, and Imperial Valley), confirming its capability to adapt and provide reliable vibration control in practical situations beyond the scope of its initial training. In conclusion, this approach represents a significant step forward in the field of seismic response reduction, offering both efficiency and adaptability.

Keywords: Active tuned mass damper, Artificial neural network, Based isolated structure, Hybrid system, Vibration control.

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1 INTRODUCTION

Earthquakes rank among the most devastating natural disasters, significantly impacting economies and posing a grave threat to human life. When the ground shakes, the consequences can be catastrophic, particularly for structures such as buildings, bridges, and offshore platforms.

In response to this looming threat, various seismic control methods have evolved over the years, broadly categorized into four main types: passive, active, semi-active, and hybrid systems [1]. While passive control systems are effective, they heavily rely on precise knowledge of system parameters, limiting their adaptability to variations and uncertainties. In contrast, active control dampens vibrations and structural motion by introducing control forces based on the structure's response [2].

Base Isolation (BI), achieved by strategically placing seismic isolators between the superstructure and the foundation, is an effective method for lengthening the natural period of a structure, thereby shifting its response away from the dominant frequencies of seismic ground motion and damping vibrations, providing additional energy dissipation, thus reducing structural vibrations. Numerous researchers have extensively studied and explored the implementation of this technology. [3-5]. However, a key challenge of this control method is the risk of excessive displacement, both within the structure and at the isolators, especially during strong seismic events. To address this, integrating active control devices with base-isolated structures can significantly improve the effectiveness of the BI system.

Yet, choosing the optimal control force is pivotal to ensuring that structural responses remain within acceptable bounds while minimizing control energy consumption. Artificial intelligence (AI) algorithms are increasingly at the forefront of research to mitigate building vibrations, particularly in active control [6-9]. This marks a fundamental advancement in the approach to structural dynamics and building safety.

In this context, an innovative approach is proposed in this study to reduce the base displacement response of a multi-degree-of-freedom (MDOF) rigid base-isolated frame structure. An artificial neural network-based (ANN) controller is employed to actuate an Active Tuned Mass Damper (ATMD), enhancing the efficiency and effectiveness of the BI system in the hybrid control process. This method is based on numerical analysis, which is built around the equations of motion and the active controller [10].

In recent years, driven by advancements in optimization technology and neural networks, active and semi-active control techniques have advanced rapidly [11]. Active and semi-active control systems exhibit a wider spectral range and greater efficacy [12] compared to passive control, which is crucial in addressing specific vibration control challenges. This method finds application across various structure types, including offshore platforms, buildings, and bridges.

Our study focuses on employing the ANN method to design a controller for an ATMD positioned at the base of a six-degree-of-freedom base-isolated building. The ANN controller is engineered to optimize the reduction of structural responses with fewer sensors, especially in the context of dynamic loads like earthquakes.

2 ACTIVE TUNED MASS DAMPER'S PRINCIPLE

While base isolation systems effectively mitigate the effects of seismic activity in buildings, they encounter certain limitations when applied to tall structures. However, incorporating an active mass damper can address these challenges, offering advantages such as enhanced damping capabilities and improved stability in high-rise constructions. ATMD consists of a mass suspended within a structure connected to springs and dampers. Sensors monitor vibrations, guiding actuators to adjust damping forces. This dynamic system effectively reduces structural oscillations, ensuring stability in tall buildings and large structures.

This paper aims to improve the effectiveness of a hybrid system, which combines a base isolation system with an ATMD controlled by ANN, during severe seismic events.

3 MATHEMATICAL MODEL

Consider a N-degrees of freedom structure equipped with a BI system of mass m_b, elastic stiffness k_b and viscous damping c_b, and an ATMD having mass m_d, elastic stiffness k_d and viscous damping c_d and active control force exerted by the controller f_u, as depicted in Figure 1.

The Equation of motion of the system can be written as follows:

$$\boldsymbol{M}\ddot{\boldsymbol{x}}_{\boldsymbol{t}} + \boldsymbol{L}\dot{\boldsymbol{x}}_{\boldsymbol{t}} + \boldsymbol{K}\boldsymbol{x}_{\boldsymbol{t}} = -\boldsymbol{M}\boldsymbol{r}\ddot{\boldsymbol{x}}_{\boldsymbol{g}} + \boldsymbol{d}f_u \tag{1}$$

Here, $\boldsymbol{M}$, $\boldsymbol{L}$, and $\boldsymbol{K}$ denote the system mass, damping, and stiffness matrices, respectively. The vector $\boldsymbol{x}_t$ and it first and second derivative correspond to the displacements, velocities and accelerations of the structure, respectively. The detailed form of the displacement vector is $\boldsymbol{x}_t = \{x_b \quad x_1 \quad x_2 \quad \cdots \quad x_n \quad x_d\}^T$ where the exponent T denotes a transposition, x_b represents the base displacement of the isolation system, x_i with i=1-N is the displacement of the generic i-DOF of the super structure and x_d is the displacement associated to the ATMD. $\boldsymbol{r}$ is the influence vector that captures the effect of ground acceleration $\ddot{x}_g$. The vector $\boldsymbol{d}$ specifies the location where the control force f_u is applied, representing the force generated by the active control system.

The matrices $\boldsymbol{M}$, $\boldsymbol{L}$ and $\boldsymbol{K}$ are presented as follows:

$$\boldsymbol{M} = \begin{bmatrix} m_b & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & m_1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & m_2 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & \ddots & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & m_{n-1} & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & m_n & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & m_d \end{bmatrix}$$

$$\boldsymbol{L} = \begin{bmatrix} c_b + c_1 + c_d & -c_1 & 0 & 0 & 0 & 0 & -c_d \\ -c_1 & c_1 + c_2 & -c_2 & 0 & 0 & 0 & 0 \\ 0 & -c_2 & c_2 + c_3 & -c_3 & 0 & 0 & 0 \\ 0 & 0 & -c_3 & \ddots & \ddots & 0 & 0 \\ 0 & 0 & 0 & \ddots & c_{n-1} + c_n & -c_n & 0 \\ 0 & 0 & 0 & 0 & -c_n & c_n & 0 \\ -c_d & 0 & 0 & 0 & 0 & 0 & c_d \end{bmatrix} \tag{2a-c}$$

$$\boldsymbol{K} = \begin{bmatrix} k_b + k_1 + k_d & -k_1 & 0 & 0 & 0 & 0 & -k_d \\ -k_1 & k_1 + k_2 & -k_2 & 0 & 0 & 0 & 0 \\ 0 & -k_2 & k_2 + k_3 & -k_3 & 0 & 0 & 0 \\ 0 & 0 & -k_3 & \ddots & \ddots & 0 & 0 \\ 0 & 0 & 0 & \ddots & k_{n-1} + k_n & -k_n & 0 \\ 0 & 0 & 0 & 0 & -k_n & k_n & 0 \\ -k_d & 0 & 0 & 0 & 0 & 0 & k_d \end{bmatrix}$$

By defining the state vector $\boldsymbol{z}(t)$ that collects the structural responses, including velocities and displacements, and the input vector $\boldsymbol{u}(t)$ that collects the force generated by the ATMD and the external excitation acceleration, respectively as:

$$\boldsymbol{z}(t) = \begin{bmatrix} \dot{\boldsymbol{x}}_t(t) \\ \boldsymbol{x}_t(t) \end{bmatrix}, \ \boldsymbol{u}(t) = \begin{bmatrix} f_u(t) \\ \ddot{x}_g(t) \end{bmatrix} \tag{3a-b}$$

The Equation (1) can be re-written using the state-space representation that is given as follows:

$$\begin{cases} \dot{\boldsymbol{z}}(\boldsymbol{t}) = \boldsymbol{A}\boldsymbol{z}(t) + \boldsymbol{B}\boldsymbol{u}(t) \\ \boldsymbol{y}(\boldsymbol{t}) = \boldsymbol{C}\boldsymbol{z}(t) + \boldsymbol{D}\boldsymbol{u}(t) \end{cases} \tag{4a-b}$$

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

$\boldsymbol{A}$, $\boldsymbol{B}$, $\boldsymbol{C}$, and $\boldsymbol{D}$ are matrices defining the system dynamics, whereas $\boldsymbol{E}$ and $\boldsymbol{0}$ are identity and zeros matrices of suitable dimensions, respectively.

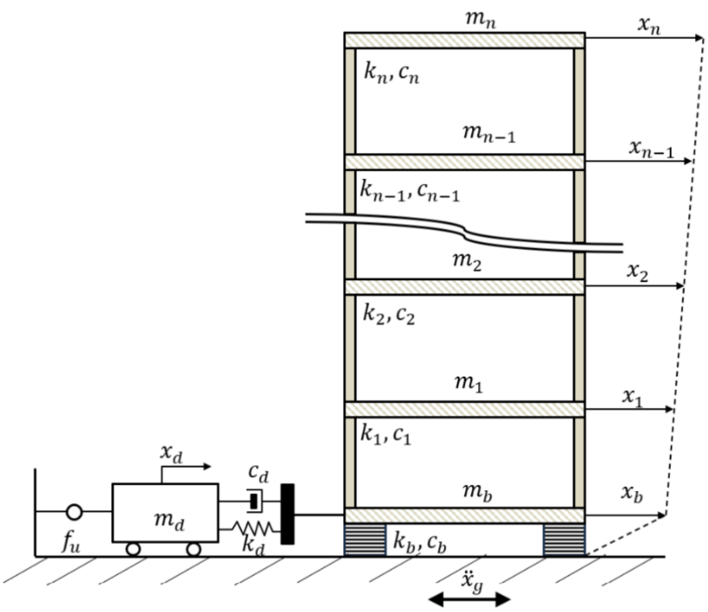

Figure 1: Base-isolated frame structure equipped with an active tuned mass damper.

4 CONTROL STRATEGY AND ANN IMPLEMENTATION

ANNs are a powerful tool for controller design, combining flexibility with innate learning capabilities. In the context of this study, the ANN is trained to emulate the optimal control force of the controller generated by a linear quadratic regulator (LQR) [9]. The LQR is a well-known optimal control method that minimizes a quadratic cost function, balancing state regulation and control effort to ensure stability and optimal performance in linear systems. It provides a reliable and efficient control signal, which serves as an ideal reference for training the ANN through supervised learning. The ANN learns an optimal control strategy that can be generalized to nonlinear systems and partially unknown dynamics providing a cost-effective solution by minimizing the number of required sensors while maintaining reliable performance in complex systems.

The process involves providing the ANN with input featuring the structural responses (displacement and velocity) and external excitation data (ground acceleration), which are mapped to their corresponding output (the control force). By minimizing the error between the ANN-predicted force and the LQR-generated optimal force during training, the network learns to replicate the desired control strategy. This approach enables the ANN to generate real-time control forces that adapt to changing environmental conditions, ensuring effective structural response mitigation. Figure 2 illustrates the architecture of an ANN model.

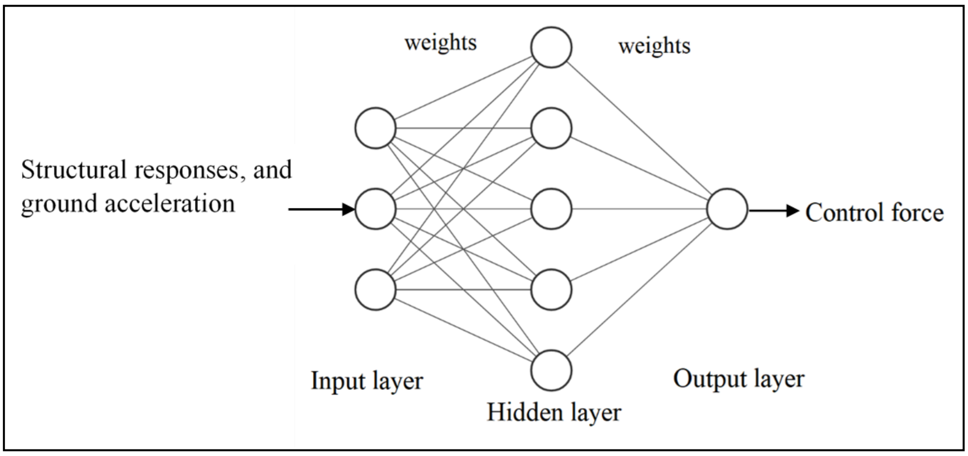

Figure 2: ANN random architecture.

In the current study, the ANN best model has 3 neurons in the input layer with normalized input data (structural responses of the base floor and El Centro ground motion), one hidden layer of 8 neurons. Random weights and biases are applied and the network predicts the output (the control forces produced by the LQR), which is evaluated using root mean squared error (*RMSE*). The training adjusts weights and biases to minimize prediction errors.

The minimized *RMSE* between the target and the actual output is defined as:

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(Y_{tar,i} - Y_{out,i})^2} \quad (5)$$

Where $Y_{tar,i}$ $Y_{out,i}$ denote the target and output control force values respectively for N data samples. Figure 3 represents the control diagram, illustrating a feedback loop between the structure and the ANN. During a seismic event, the neuro-controller receives live input from sensors monitoring the structure's response, it then computes the optimal control force in real time, directing the ATMD to counteract the seismic forces, accordingly ensuring effective vibration reduction through real-time adjustments.

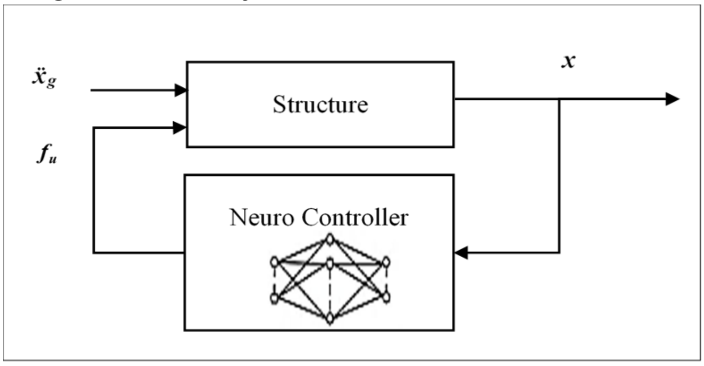

Figure 3: Active control diagram using ANN.

5 NUMERICAL STUDY

A six-DOF base-isolated structure taken from literature [13] was chosen as case study. The parameters of the structure and the base isolation system are reported in Table 1. The ATMD was designed to match the primary frequency of the base-isolated structure [3], having assumed a mass ratio between the TMD mass and the total mass of the structure equal to μ =0.05. The total mass of the adopted base-isolated structure is $M_T = 21000\ kg$, while, ts first natural frequency is $\omega_s = 3.15\ rad/s$. The design of the stiffness and damping coefficient of the ATMD are provided by following the design formulas proposed by Hartog and Ormondroyd [14]. According to this, having introduced the nondimensional quantities frequency ratio $\gamma = \frac{\omega_d}{\omega_s}$, as the ratio between the frequency of the ATMD denoted ω_d , the first frequency of the base-isolated structure ω_s , and the damping ratio of the ATMD ξ_d , these are evaluated as:

$$\gamma = \frac{1}{(1+\mu)^2} \tag{6}$$

$$\xi_d = \sqrt{\frac{3\mu}{8(1+\mu)^3}} \tag{7}$$

Once the designed nondimensional parameters of the ATMD are known, the mass, stiffness, and damping factor for the TMD are evaluated as follows:

$$m_d = \mu \cdot M_T \tag{8}$$

$$c_d = 2\xi_d \cdot \gamma \cdot m_d \cdot \omega_s \tag{9}$$

$$k_d = {\omega_d}^2 \cdot m_d \tag{10}$$

The parameters of the designed ATMD are reported in Table 1 as well.

Floor	Mass (kg)	Stiffness (kN/m)	Damping (kN.s/m)
ATMD	1050	8.55	0.76
BI	3500	210	2.66
1	3500	35×10^3	35
2	3500	35×10^3	35
3	3500	35×10^3	35
4	3500	35×10^3	35
5	3500	35×10^3	35

Table 1: Parameters of the structure and the isolator.

A MATLAB Simulink and Neural Network Toolbox were utilized for simulation purposes and for training the ANN. The structure was subjected to three natural earthquakes with different characteristics: Hector earthquake (Far-field), Imperial Valley earthquake (Near field with pulse), and Northridge earthquake (Near field without pulse), for testing and confirming the efficiency of the proposed model.

6 RESULTS AND DISCUSSION

The results presented in this section are derived from dynamic seismic analyses conducted on the case study structure. These analyses compare the performance of the base-isolated structure with that of the same structure equipped with the hybrid control system realized by adding to base isolation an ATMD, where the active control force is governed by a controller based on ANN, as illustrated in Section 4.

The presented results provide compelling evidence of the efficacy of the proposed Hybrid control system based on ANN in mitigating seismic responses. The values of the maximum base displacement and their reduction rate during the three seismic records are presented in Table 2.

The results presented in Table 2 clearly demonstrate the effectiveness of the ANN-based controller in reducing the maximum base displacement of the structure under seismic excitation.

For all three earthquakes considered, the hybrid controlled structure with ANN achieves significant displacement reductions compared to the isolated structure: for the Hector earthquake the displacement is reduced from 26.78 cm to 3.96 cm, corresponding to a reduction rate of 85.21%, for the Imperial Valley earthquake the displacement decreases from 24.99 cm to 3.20 cm, achieving a reduction rate of 87.19%, the highest among the three cases, for the Northridge earthquake, the displacement is reduced from 33.65 cm to 9.28 cm, with a reduction rate of 72.42%.

These findings highlight the ANN-based controller's superior ability to mitigate seismic impacts across different earthquake scenarios. The consistently high reduction rates demonstrate that the ANN approach is highly effective in improving structural performance during seismic events.

Earthquakes	Isolated structure (cm)	Controlled with ANN (cm)	Reduction Rate (%)
Hector	26.78	3.96	85.21
Imperial valley	24.99	3.20	87.19
Northridge	33.65	9.28	72.42

Table 2: Maximum base displacement with their reduction rate.

Figure 4 depicts the time history plots of the base displacement for the three earthquake scenarios, providing further insight into the dynamic behavior of the structure. These figures compare the base displacement of the isolated structure and the structure controlled with the ANN-based ATMD. The time histories of the base displacement demonstrate the significant impact of the ANN-based controller in reducing seismic response compared to the isolated structure across different earthquake scenarios. In all cases, the controller significantly reduces the amplitude of base displacement compared to the isolated structure. Additionally, it ensures faster decay of oscillations, highlighting its efficiency in damping vibrations. For the Hector and Imperial Valley earthquakes, the controller achieves substantial reductions in both peak displacement and oscillation duration. Even for the more intense Northridge earthquake, the ANN-based control strategy remains effective, providing notable reductions in displacement and stabilizing the structure's dynamic response. These results confirm the robustness and adaptability of the ANN-based controller in enhancing the structural performance of base-isolated structures.

Figure 5 presents the maximum inter-story drifts for the structure under the three earthquakes, offering additional insight into the structural response discussed in the time history of base displacement. The comparison between the isolated structure and the ANN-controlled structure reveals a consistent reduction in inter-story drifts across all stories when the ANN-based controller is applied.

These results align with the observations made for base displacement, as the ANN-based controller effectively limits not only the overall base motion but also the relative deformations between stories. This reduction is most noticeable in the upper stories, where seismic effects tend to amplify in the isolated structure. For the Hector and Imperial Valley earthquakes, the drifts in the controlled structure remain minimal, reinforcing the earlier conclusion about the controller's ability to mitigate seismic impacts. Even for the more intense Northridge earthquake, where base displacements were relatively higher, the ANN controller demonstrates its robustness by substantially reducing inter-story drifts and enhancing the structural performance.

Together, the time history of base displacements and the maximum inter-story drift results provide a comprehensive validation of the ANN-based control system's effectiveness in minimizing both global and local structural responses during seismic events.

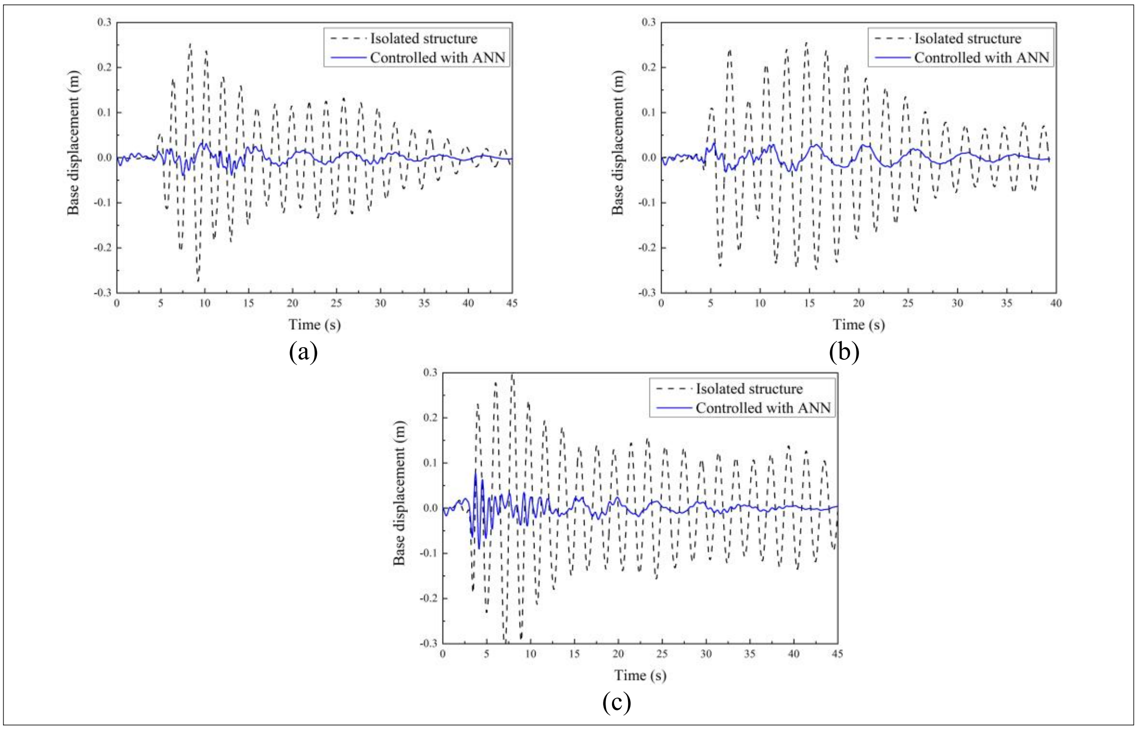

Figure 5: Base displacement under (a) Hector, (b) Imperial Valley, and (c) Northridge earthquakes.

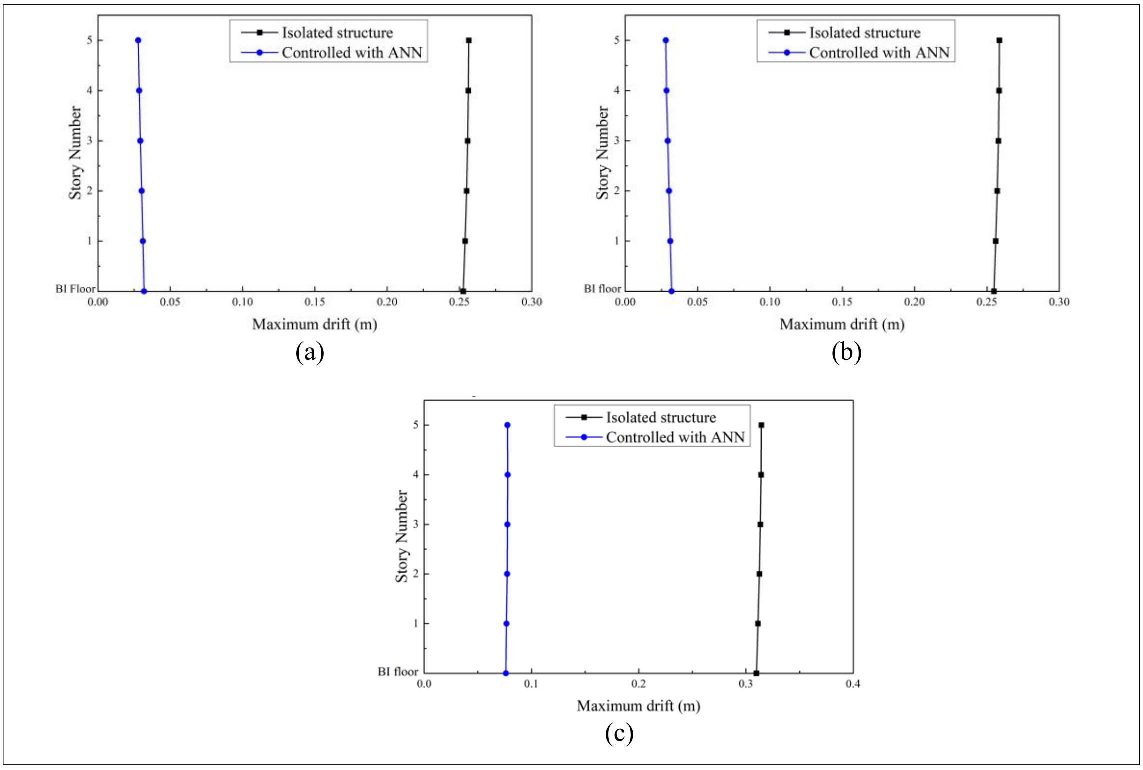

Figure 4: Maximum drifts under (a) Hector, (b) Imperial Valley, and (c) Northridge earthquakes.

These reductions in response are indicative of enhanced structural integrity and safety. The capability of the ANN control system to significantly diminish the seismic response of the structure is a testament to the potential of artificial intelligence in addressing complex and dynamic structural challenges. It underscores the shift towards more adaptive and effective seismic control strategies.

7 CONCLUSION

In this study, we have demonstrated the effectiveness of an optimal approach for seismic response reduction in a BI structure. This hybrid control combines a base isolator and an ATMD controlled with an ANN controller, trained to apply the necessary control force, resulting in efficient reductions in seismic responses. The primary goal of using the ANN controller was to train the ANN to replicate the behavior of the LQR using less number of sensors. The inherent adaptability of ANN control systems to changing conditions and their ability to improve performance over time without the need for precise structural models make them a promising tool for enhancing building resilience during seismic events.

These findings underline the potential of ANN control systems in mitigating earthquake damage and fortifying civil structures. By significantly reducing the base displacement and the maximum drift responses, the approach contributes to enhanced structural integrity, safeguards buildings, and ultimately plays a crucial role in ensuring the safety and resilience of communities in earthquake-prone regions.

This work represents a significant step forward in the field of structural engineering and artificial intelligence, highlighting the importance of interdisciplinary collaboration. We anticipate that these results will inspire future research, innovation, and the widespread adoption of more effective seismic control strategies.

While these results are encouraging, further investigation is warranted. Future research should delve into aspects such as controlling energy consumption, system robustness under different seismic conditions, and the potential for real-world implementation.

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