Optimization of tuned mass dampers parameters using Artificial Neural Networks

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Abstract. Control systems are usually employed to minimize the dynamic effects on structures. These controllers must be designed according to the physical and geometric characteristics of the system and the environmental loads to which the structure will be subjected. Passive control is the most suitable for extreme events because it does not depend on an external power source to function properly. The use of a linear attenuator, such as the tuned mass damper (TMD), allows for dynamic analysis in the frequency domain, which provides a reduction in the computational cost of the analysis. Among the several methods used to determine the optimal parameters of the damper, analytical methods in their closed form can be applied to simpler structures. In structures with several degrees of freedom or complex geometry, the optimal TMD parameters, as well as its optimal position, can be acquired by methods based on stochastic optimization. This kind of problem is commonly solved in the state-of-the-art by Metaheuristic algorithms. However, generaly, these procedures require high computational costs, which makes Artificial Neural Networks (ANN) a viable alternative to minimize the processing time. Thus, this paper proposed a methodology based on ANN in comparison with the Circle-Inspired Optimization Algorithm (CIOA) to determine the optimal parameter of tuned mass dampers, i.e., the damper period. Neural networks training was performed with a dataset of optimal TMD values, which were obtained in the frequency domain. The model developed from these results was subsequently tested on different shear-building models, including the influence of seismic excitation. Structural displacements was evaluated with the optimal values obtained through ANN and compared with the structures without the control device. In addition, the optimal parameters obtained by ANN were also compared with the closed analytical formulations. Results obtained by the neural networks were as effective as the CIOA metaheuristic algorithm but required up to 0.02% of its processing time.

Keywords: Tuned Mass Damper (TMD), Artificial Neural Networks (ANN), Metaheuristic Algorithms.

1 Introduction

Tuned mass damper (TMD) has been extensively researched by various researchers over the years and has found wide application in various real-world structures to mitigate vibrations. Examples of such structures include bridges [1], offshore platforms [2], and ships [3]. In addition, TMDs have been employed in buildings to control dynamic responses to wind and earthquake loads, with well-known examples such as the Taipei 101 building in Taiwan and The Citicorp Center in New York City [4].

TMDs were initially investigated by Frahm in 1909 [5]. Subsequently, these devices were employed in buildings a few decades later. Den Hartog conducted the first studies on the optimal design of TMDs, developing analytical expressions for single degree of freedom (SDOF) systems [6]. Later, Warburton expanded on this work by considering damping in the primary system [7]. To facilitate the utilization of TMDs in the seismic control of buildings, Tsai and Lin proposed curve-adjusted formulas based on Den Hartog's findings [8]. The recommended optimal TMD parameters from these formulas were designed to support both excited and damped systems.

Traditional methods commonly derive optimal TMD parameters based on a single mode of an elastic structure, but this approach may not always yield optimal results for structures with multi degrees of freedom (MDOF) and multiple TMDs [9]. Hence, to achieve an optimal design for structures with MDOF subjected to seismic actions, metaheuristic methods can be utilized [10–12]. One such metaheuristic algorithm is the Circle-Inspired Optimization Algorithm (CIOA) [13], which will be employed in this paper.

Optimization procedures in dynamic analysis can be computationally expensive in the time domain. To mitigate this, a mathematical subterfuge can be employed by performing the analysis in the frequency domain, particularly for linear systems. Alternatively, machine learning techniques such as Artificial Neural Networks (ANN) can be employed. A notable advantage of ANN is its ability to consider uncertainties related to the excitation and/or structural properties of the system. This allows the identification of an optimal control system for multiple structural systems subjected to random excitations.

Thus, the aim of this study is to obtain and optimize accurately the responses of building structures equipped with TMD subjected to seismic excitation. Dynamic analysis is conducted in the frequency domain using the shear-building model to formulate the structures. Seismic excitation is artificially generated, and the optimal parameters' results are compared using closed-form solutions, the CIOA metaheuristic algorithm, and ANN.

2 Frequency domain analysis of SDOF structure with TMD

For a SDOF structure with a TMD on top, as shown in Figure 1 (a), the stiffness, the mass and the damper are represented, respectively, by k, m and c. The damper's mass and stiffness are represented as m_d and k_d. To perform frequency domain analysis, modal decomposition is necessary, thus, modal stiffness is defined as $K_i (i = 1, 2)$ and the equilibrium equation for each mode may be written as:

$$S_{u_i}(\omega) = |H_i(\omega)|^2 S_{p_i}(\omega). \tag{1}$$

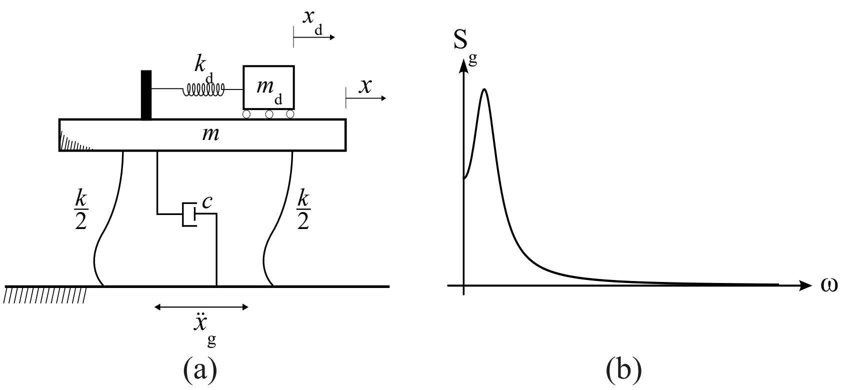

Figure 1. (a) SDOF structure with TMD on top and (b) power spectrum density of the ground acceleration

Where $S_{u_i}(\omega)$ is the displacement power spectrum density of the i-mode, $H_i(\omega)$ is the mechanical admittance function and $S_{p_i}(\omega)$ is the power spectrum density of the i-mode force. Mechanical admittance function and the power spectrum density of the i-mode force may be written as:

$$|H_i(\omega)|^2 = \left\{K_i^2 \left[1 + \left(4\zeta^2 - 2\right)\beta^2 + \beta^4\right]\right\}^{-1}. \tag{2}$$

$$S_{p_i}(\omega) = S_g(\omega)\overrightarrow{\phi_i^t}\mathbf{M}\overrightarrow{b}\,\overrightarrow{b}^t\mathbf{M}\overrightarrow{\phi_i}. \tag{3}$$

Where $S_g(\omega)$ is the power spectrum density (PSD) of the ground acceleration (Figure 1 (b)), defined by [14, 15], ϕ_i is the i-mode of the structure, $\mathbf{M}$ is the mass matrix, $\overrightarrow{b}$ is a directional vector, β is the frequency ratio (ω/ω_i), and ζ is the damping factor.

The analysis aims to minimize the root mean square (r.m.s) displacement of the structure, thus the objective function of this paper is presented in eq. (4). In this equation, corresponds to the r.m.s displacement of the i-mode, and can be evaluated as shown in equation eq. (5):

$$\overrightarrow{U}_{\text{rms}} = \sum_{i=1}^{2} \sigma_i \overrightarrow{\phi_i}. \tag{4}$$

$$\sigma_i = \left[\int_0^\infty S_{u_i}(\omega)\mathrm{d}\omega \right]^{\frac{1}{2}}. \tag{5}$$

Since $\overrightarrow{U}_{\mathrm{rms}}$ is a vector, the objective is to minimize the first component of this vector, which will be designed as $U_{rms,1}$. An optimal TMD divides the fundamental frequency of the original structure into two close natural frequencies around the original one, as shown in Figure 2. It is possible to visualize that system with TMD has a smaller resonant response and a smaller r.m.s value.

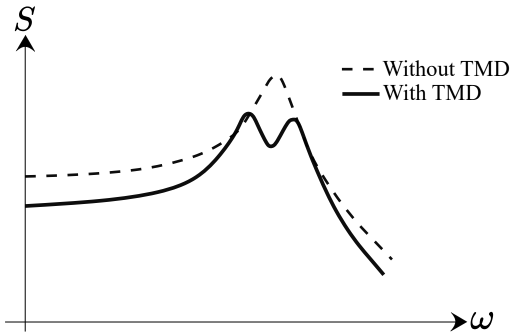

Figure 2. Displacement PSD of structure with and without TMD

3 Circle-Inspired Optimization Algorithm (CIOA)

The CIOA is a metaheuristic optimization algorithm inspired by the formulations of the trigonometric circle. Each search agent moves along arcs according to an angle θ and radius r. Initially, the search agents receive a random value to evaluate the objective function, and the results are classified in a ranking according to the solutions obtained. Afterward, the parameters θ and r of each agent are updated to improve the classification in the next iteration. When the movement of a search agent worsens its radius increases, and when the movement of a search agent improves its radius is reduced (Figure 3). The algorithm promotes a global and local search concomitantly, i.e., agents producing the best optimal solutions describe small movements (local search), while those with less effective solutions often describe large movements (global search) [13].

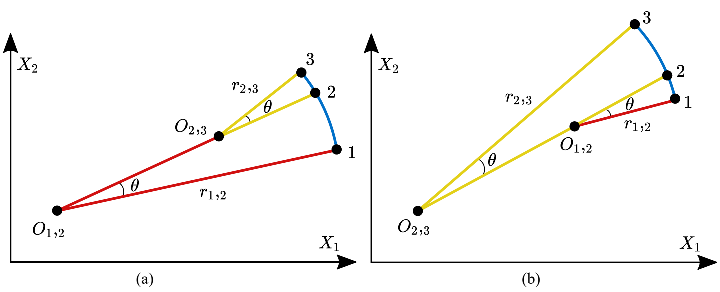

Figure 3. Changing the radius and updating the center of the circle: (a) improvement of search agent classification and reduction of the radius size, (b) worsening of search agent classification and increase of the radius size

This algorithm was used to solve the optimization problem of eq. (4) and find the best parameters of the tuned mass damper for systems with different conditions. The optimization process involved 100 search agents and was limited to a maximum of 60 iterations. Therefore, only the damper natural period (relationship between stiffness and mass) was optimized. The results were employed to create a training dataset for the artificial neural networks model, which posteriorly was used to predict the optimal TMD parameters of structural systems with MDOF.

4 Artificial neural networks

The ANN is a type of Machine Learning algorithm that mimics the behavior of the human brain reproducing the neural network learning process. The artificial neurons (processing elements) are interconnected performing operations and transmitting their results to adjacent neurons. Input data are applied to each element and these values are weighted according to the network structure generating the respective output data. Thus, the artificial neural network is used to predict the relationship between inputs and outputs.

In this work, the Feedforward neural network was chosen to solve the problem. The information processing in this type of ANN flows towards the output layer, i.e., the signals do not return to previous layers. For the training, T_s and μ were used as input data and T_d as output. The training dataset was divided as follows: 70% for training, 20% for validation, and 10% for testing. One hidden layer with 5 neurons was adopted (Figure 4). In addition, the training parameters considered were the Levenberg-Marquardt algorithm as the training function, a maximum of 1000 epochs, 10 maximum validation failures, a minimum performance gradient of 10^{-8}, and a stopping criterion based on a mean squared error goal of 10^{-8}.

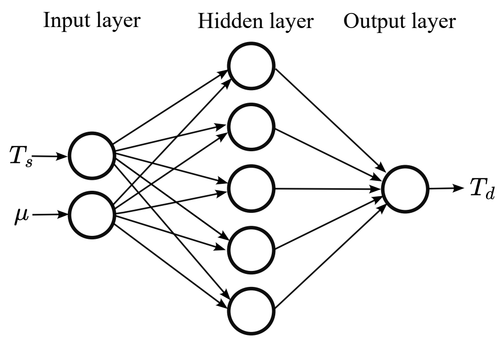

Figure 4. Artificial neural network architecture

5 ANN model and verification

For the artificial neural network generation, 95 optimum results for SDOF systems were used. The training was performed using 19 different natural periods of the structures (T_s = 0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, 0.9, 1, 2, 3, 4, 5, 6, 7, 8, 9, 10) and 5 different mass ratios (μ = 0.02, 0.025,0.03, 0.035, 0.04). These values of natural periods and mass ratios were chosen within the usual parameters for civil structures. All structures had 5% inherent damping. Then, the ANN was verified through five examples with T_s and μ intermediate values shown in Table 1.

Table 1. Verification of the ANN model

	Input parameters		CIOA	ANN	Difference (%)
	T_s (s)	μ	T_d (s)	T_d (s)	
1	0.500	0.027	0.502	0.501	0.10
2	0.800	0.022	0.803	0.803	-0.05
3	1.500	0.022	1.508	1.501	0.44
4	2.600	0.027	2.618	2.603	0.58
5	9.200	0.033	10.117	9.618	4.93

The biggest prediction difference occurred in case 5, as the training dataset did not include intermediate natural periods for values higher than $1s$. However, the five cases presented a maximum difference of less than 5%, validating the ANN model.

6 Application of the ANN model in shear-buildings

Five shear-building structures were studied to test the ANN model in the MDOF structure (Table 2), with the stiffness and mass values based on the studies presented in [16–18] .Inherent damping of 5% was arbitrated for all systems. Each structure was assembled according to its story number following the scheme presented in Figure 5. It was considered that all the structural systems were under seismic excitation, which was defined by Kanai-Tajimi [14, 15]. The ground acceleration PSD has as input the ground natural frequency $\omega_g = 8\pi$ rad/s and the ground damping factor $\zeta_g = 0.6$. The peak ground acceleration of the signal was $0.5g$.

Table 2. Shear-buildings properties

Story number	m (tons)	k (kN/m)	T_s (s)	μ	T_d (s)
10	100	175×10^3	1.003	0.040	1.080
20	100	175×10^3	1.958	0.040	2.138
30	100	175×10^3	2.912	0.040	3.102
40	100	1580×10^3	1.289	0.040	1.399
50	100	1580×10^3	1.607	0.040	1.747

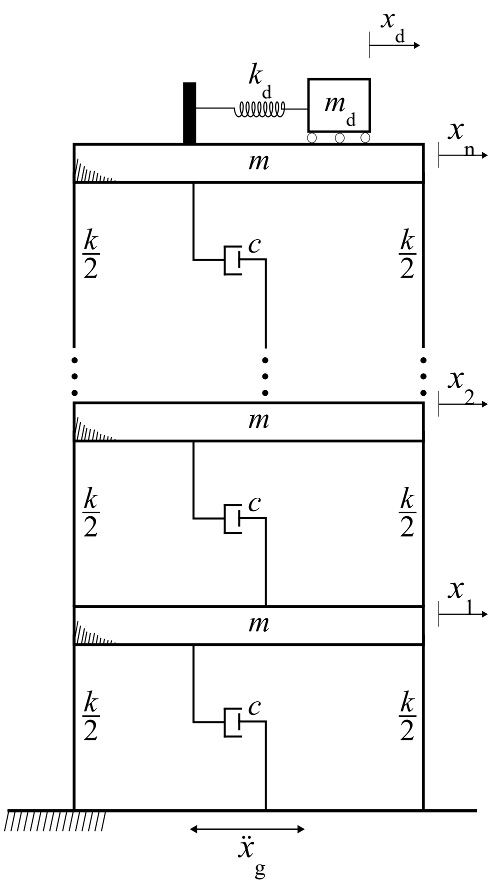

Figure 5. Schematic of a multi-story shear building

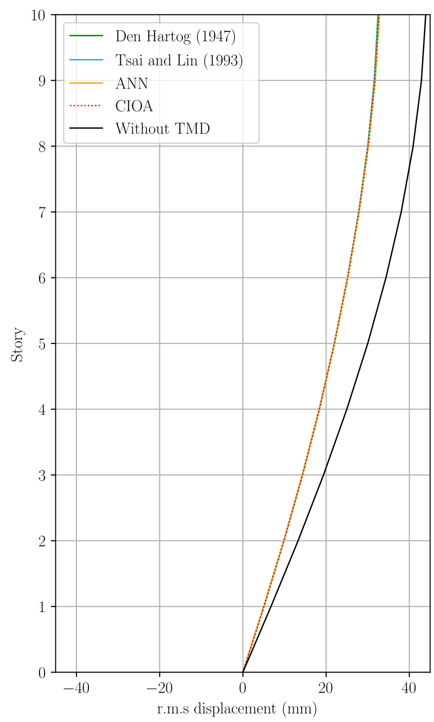

Figure 6. RMS displacement along the 10-story shear building

The predicted natural periods of the TMDs for all the structures are shown in Table 3, in comparison with the CIOA results and the values obtained by the analytical formulations of [6] and [8]. Figure 6 and Table 4 present the r.m.s displacements of the 10-story shear-building. While the results predicted by the ANN are close to the ideal values generated by CIOA, the processing time of the neural network can be significantly lower, representing less than 0.15% of the processing time of the metaheuristic algorithm, as shown in Table 5 (0.02% for 50 stories or 0.13% for 10 stories). The power spectrum density presented in Figure 7 confirms that the periods obtained are near, showing a significant reduction in displacement when compared to the system without the TMD.

Table 3. Results for shear-buildings

Story number	Input parameters		CIOA	ANN	Den Hartog [6]	Tsai & Lin [8]
	T_s (s)	μ	T_d (s)	T_d (s)	T_d (s)	T_d (s)
10	1.003	0.04	1.080	1.007	1.043	1.082
20	1.958	0.04	2.138	1.964	2.036	2.112
30	2.912	0.04	3.102	2.929	3.028	3.140
40	1.289	0.04	1.399	1.292	1.341	1.390
50	1.607	0.04	1.747	1.611	1.671	1.733

Table 4. R.M.S displacement: 10-story shear-building

U_rms	Without TMD	CIOA	ANN	Den Hartog [6]	Tsai & Lin [8]
1^{st} story (mm)	6.7483	5.0553	5.0418	5.0385	5.0558
10^{th} story (mm)	42.6061	32.4429	32.8036	32.6373	32.4419

Table 5. Processing time of the shear-buildings

Methodology	Story number				
	10	20	30	40	50
CIOA	30.70 s	64.07 s	96.64 s	166.53 s	178.41 s
ANN	0.04 s	0.04 s	0.04 s	0.04 s	0.04 s

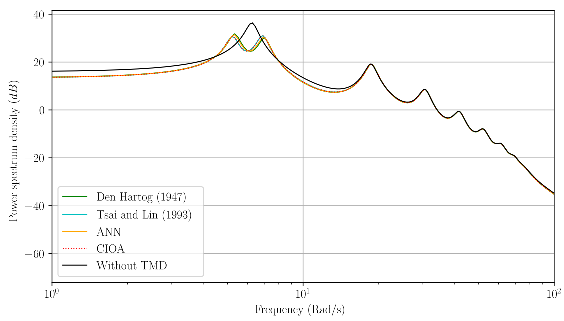

Figure 7. Power spectrum density: 10-story shear-building (10^{st} story)

7 Concluding Remarks

This paper pursued the objective of investigating and optimizing the performance of buildings equipped with absorbers as Tuned Mass Damper, when subject to earthquake loadings. Methods based on Metaheuristic algorithms and Artificial Neural Networks were applied seeking to minimize the structural responses generated by seismic excitation. In the study, shear-building structures with different story numbers were analyzed to assess the efficiency of the methodologies in comparison with analytical formulations.

It is observed that the optimization methods presented similar and close damper periods to the buildings studied. While the metaheuristic algorithms are great tools to solve MDOF problems, the ANNs can show similar performance with less than 0.15% of the processing time. However, it is noteworthy that processing time using the CIOA was already low because of the frequency domain analysis. Therefore, the difference between ANN and CIOA processing time could be even greater in a time domain analysis.

In this sense, it is important to emphasize that closed formulas can be an excellent solution for this building model subjected to artificially generated PSD. It can produce optimal values close to those obtained through ANN and CIOA. Therefore, it is essential to analyze whether in situations with more strongly random earthquakes the result would be similar.

Future works using neural networks and other Machine Learning techniques are suggested to assess the capacity of these tools for non-linear structures and more complex systems, such as MDOF plane and space frame structures. The training dataset can include multi degrees of freedom cases in addition to the data presented in this paper.

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