



Implementation of a control project based on Tuned Liquid Column Dampers optimized by Teaching-Learning Based Optimization

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Abstract. Tuned Liquid Column Dampers (TLCDs) are passive control devices implemented in buildings to reduce the structural response of the controlled system when subjected to dynamic environmental loads. These devices consist of U-shaped tanks containing a liquid, usually water, where the oscillating motion of the fluid in the tank columns is used to generate inertial forces that counteract the motion caused by the excitation, thereby dissipating the incoming energy into the system. These devices have been the focus of research in recent decades and have attracted the attention of the scientific community interested in finding reliable, simple, and economical mechanisms to reduce the effects of dynamic loads on civil structures. Thus, this research aims to develop and evaluate the performance of an optimal control project based on the operation of a TLCD installed on the top floor of a mid-rise building excited by different seismic records. For this purpose, a metaheuristic algorithm known as Teaching-Learning Based Optimization (TLBO) is employed to execute the process of selecting optimal parameters for the control device, maximizing the effectiveness of the controller in reducing the overall response of the controlled building. The results obtained allow to establish that the implementation of TLCD in the structure leads to a significant reduction in the structural response of the building, highlighting the efficiency of the device in mitigating displacements during seismic events.

Keywords: Structural control, Passive devices, tuned liquid column damper, Teaching learning-based optimization, Seismic records.

1. Introduction

Modern structural engineering faces the critical challenge of ensuring the stability of buildings subjected to non-deterministic dynamic events, prioritizing the protection of human life and the integrity of structures. Construction materials have evolved over time, becoming more resistant and lighter, thus increasing their vulnerability to vibrations caused by natural forces such as wind gusts or seismic events. This scenario has romped the development of strategies and devices that help to mitigate the structural response to these types of loads, minimizing risks to occupants and reducing damage to buildings. The concept of structural control is rooted in the pioneering experiments of John Milne in Japan more than a century ago, as noted by Housner [1], which has evolved to address contemporary challenges in civil engineering, with protection against seismic vibrations being the main need that has led to the development of control systems, including passive, active, semi-active and hybrid devices (Datta) [2]. This work will focus on the evaluation of the performance of a passive control system called Tuned Liquid Column Damper (TLCD), being these devices that respond to the movement of the structure, thus working with the inertial forces to dissipate the vibrations of the main structural system. These passive devices do not require the use of external energy sources for their activation, which is their main strength over other types of devices (Gomez et al. [3]). The TLCD is a system consisting of a set of rigid pipes partially filled with liquid,

usually water. This system is integrated into the building, and its operation is based on the dissipation of energy through the movement of the liquid in the tank, caused by the restoring force of the liquid, gravity, and the passage of the liquid through the orifice, generating a significant head loss as defined by Chakraborty [4]. Compared to other vibration reduction devices, TLCDs offer significant advantages such as low installation costs, easy application to new buildings or the possibility of retrofitting structures, and virtually no maintenance requirements. In fact, a TLCD can add no significant cost or weight when used as water supply or fire suppression reservoir (Hochrainer [5]). One of the most effective methods for tuning controllers is the use of metaheuristic optimization algorithms due to their simplicity and flexibility. In order to obtain the optimal design parameters that ensure the best performance of the TLCD. In this research the optimization is performed using the Teaching-Learning Based Optimization (TLBO) algorithm, a novel teaching and learning-based optimization process that can obtain solutions with little computational effort and high numerical consistency, which has allowed a quick and wide acceptance in the scientific community in recent years (Črepinšek et al. [6], Rao et al. [7]). So, in this paper the optimal design parameters of a TLCD are founded to perform a comparative analysis of the response of a medium rise building subjected to different ground motions equipped with and without the optimal TLCD, focusing on the reduction of the peak displacements of the structure as the indicator that most highlight the efficiency of the control system.

2. Theoretical foundation

2.1. Tuned liquid column damper (TLCD)

The Tuned Liquid Column Damper is a control device used in structures, particularly high-rise structures, to reduce the displacements of the structures subjected to dynamic loads as Espinoza et al. indicate [8]. Different geometries for this device have been proposed in the literature, however, the most common is the U-shaped TLCD, which is the original design. This geometry consists of a horizontal tube and two vertical tubes at each end, forming a single tube that is partially filled with liquid, usually water. Its operation is based on the transmission of vibrations from the main structure (building) to the device (TLCD), which dissipates energy through the movement of the liquid inside the tube, which can be increased if hydraulic resistance is created by means of orifices installed in the horizontal part of the device, as shown in Figure 1 (Hochrainer [5]).

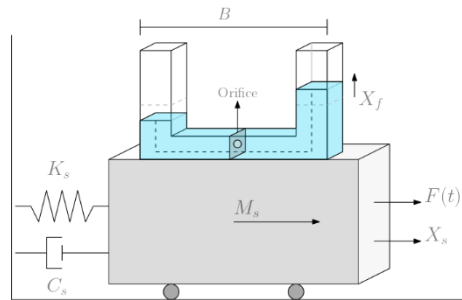


Figure 1. Outline of a TLCD

The variables described in Figure 1 correspond to X_s = Response of the primary system; X_f = Response of the liquid; M_s = Mass of the primary system; K_s = Stiffness of the primary system; C_s = Damping of the primary system; $F(t)$ = Force acting on the system; B = Horizontal length of the liquid column.

The device is an independent substructure of the main system, so the equation of motion of the TLCD is determined before analyzing the coupled system. It is modeled as an SDOF that will have the direction of the motion of the liquid, which in this case is vertical.

2.2. Equation of the TLCD system

The equation of motion of the control device is shown in Eq. (1):

$$\rho AL\ddot{X}_f + \frac{\rho A\xi}{2}|\dot{X}_f|X_f + 2\rho AgX_f = -\rho AB(\ddot{X}_s + \ddot{u}_g). \quad (1)$$

Where ρ = density of water; A = Cross-sectional area; L = water column length; ξ =Damping ratio and g =acceleration of gravity

2.3. Mathematical model of a coupled TLCD controller with a multi-degree-of-freedom system

An outline of an n -degrees-of-freedom frame equipped with a TLCD at the last level is shown in Figure 2. For this system, the relative displacement of the water column of the device is assumed as an additional degree of freedom in the matrices. The stiffness, damping, and floor mass are represented, respectively, as k_i , c_i , and m_i , where i symbolizes the level of the structure.

Eq. (2) corresponds to the dynamic equation of motion of the coupled system in the time domain for the controlled structure shown in Figure. 2, when subjected to the action of ground acceleration produced by an earthquake.

$$\mathbf{M}\ddot{\mathbf{X}}(t) + \mathbf{C}\dot{\mathbf{X}}(t) + \mathbf{K}\mathbf{X}(t) = -\mathbf{M}|\mathbf{I}|\ddot{u}_g(t). \quad (2)$$

Where \mathbf{M} , \mathbf{C} and \mathbf{K} correspond, respectively, to the mass, damping and stiffness matrices of the coupled system. \mathbf{X} , $\dot{\mathbf{X}}$, and $\ddot{\mathbf{X}}$, correspond to the displacement, velocity, and acceleration vectors, respectively. $|\mathbf{I}|$ is the location vector of the external forces, \ddot{u}_g is the earthquake acceleration, and t are the time. Reviewing in more detail the matrices and vectors of Eq. (2), the following expression is obtained:

$$\begin{bmatrix} \mathbf{M}_s + m_d & \alpha.m_d \\ \alpha.m_d & m_d \end{bmatrix} \begin{bmatrix} \ddot{\mathbf{X}}_s \\ \ddot{\mathbf{X}}_f \end{bmatrix} + \begin{bmatrix} \mathbf{C}_s & 0 \\ 0 & c_{eq} \end{bmatrix} \begin{bmatrix} \dot{\mathbf{X}}_s \\ \dot{\mathbf{X}}_f \end{bmatrix} + \begin{bmatrix} \mathbf{K}_s & 0 \\ 0 & k_f \end{bmatrix} \begin{bmatrix} \mathbf{X}_s \\ \mathbf{X}_f \end{bmatrix} = -\mathbf{M}|\mathbf{I}|\ddot{u}_g(t). \quad (3)$$

Where m_d = mass of the liquid column; c_{eq} = equivalent damping of the TLCD; k_f = stiffness of the liquid column and α = length ratio. These parameters are defined in Eq (4).

$$m_d = \rho Al \quad c_{eq} = 2m_d\omega_d\xi \quad k_f = 2\rho Ag \quad \alpha = \frac{B}{l}. \quad (4)$$

Where A = cross-sectional area of the tube; l = length of the liquid column; ω_d = natural frequency of the damper; ξ =damping ratio of the TLCD; and ρ = density of the liquid.

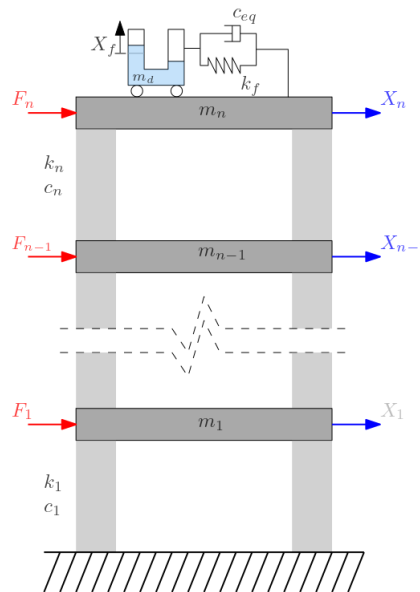


Figure 2. Frame structure with n degrees of freedom equipped with a TLCD

3. Teaching Learning Based Optimization

Teaching Learning Based Optimization (TLBO), proposed by Rao et al. [9] in 2011, is a population-based algorithm originally employed for mathematical and constrained mechanical design optimization problems. It is inspired by learning process in a classroom, where the influence of teachers on students aims to improve mutual learning among its members. (Mortazavi [10]).

Like other algorithms, TLBO uses a set of options to reach the optimal solution, but it is easier to implement because it does not require tuning of algorithm parameters, such as the mutation rate in genetic algorithms or the belief space acceptance rate in cultural algorithm. Through the preliminary applications mentioned above, this algorithm has shown its effectiveness when compared to alternative techniques.

3.1 General aspects of the TLBO implementation.

This algorithm consists of teaching and learning phases. During the teaching phase, each member is evaluated based on its objective function result. The best individual is selected to be the teacher. Following this, all agents redefine their positions based on both the average knowledge of the classroom and the performance of the teacher, which is expected to contribute to the improvement of the learning of the student. This is expressed mathematically as:

$$X_{new,i} = X_i + r(X_{teacher} - TF \cdot X_{mean}). \quad (5)$$

Where TF is the teaching factor and can be either 1 or 2, and r is a random number within the range of 0 to 1. X_i is the existing solution of the student i . If the evaluation of $X_{new,i}$ in the objective function results in an improvement of the previous value, it is accepted; otherwise, it is rejected and X_i is retained. (Baghlani and Makiabadi [11]).

During the learning phase, students aim to improve their performance through the interaction and support from their classmates. Two individuals are randomly selected, a student will only acquire knowledge if the other individual has a higher level of it, meaning that they have better results in the objective function. This can be described mathematically as:

$$\begin{aligned} X_{new,i} &= X_i + r(X_j - X_i) & \text{if } f(X_j) < f(X_i). \\ X_{new,i} &= X_i + r(X_i - X_j) & \text{if } f(X_i) < f(X_j). \end{aligned} \quad (6)$$

Similarly, $X_{new,i}$ is accepted only if evaluating the objective function yields a better result than X_i .

4. Case study

The performance of an optimally designed TLCD using TLBO will be evaluated in a 12-story, 30 m high reinforced concrete building located in the city of Medellin, as shown in Figure (3a). The lateral force resisting system of the structure is constituted of rigid frames and structural walls.

To simplify the analysis, a representative plane frame is selected to study the building. This section is highlighted in red in Figure 3(b). The frame consists of a 0.3 x 0.8 m column (E axis), a 0.3 x 0.9 m column (H axis) and two 0.3 x 1 m columns (K and L axes). The beams used in the analysis have a cross-section of 0.3 x 0.45 m. The material of the columns and beams is reinforced concrete with a compressive strength of 28 MPa. For the analysis of the structure, each level was reduced to one degree of freedom per floor, assuming infinite in-plane stiffness provided by a rigid diaphragm. Considering their low participation in the structural response, the rotational and vertical degrees of freedom are condensed to reduce the problem.



Figure 3 (a) General view of the building; (b) Typical floor plan

4.1 Seismic records

Four seismic records, with different magnitudes, time lengths and frequency content have been selected to be used as input accelerations for the numerical study in question. These records are presented in Table 1.

Table 1 Seismic records used in the study. Taken from: Center for Engineering Strong Motion Data.

Seismic record	Year	Station	Component	Magnitude	PGA [g]	Time [s]
El Centro	1940	El Centro (117)	S90W	6,9	0,348	53,73
Kobe	1995	Kakogawa	90°	6.9	0.345	40.96
Tabas	1933	Tabas	270°	6.2	0.124	27.05
Japan	2011	Tsukidate (MYG004)	N-S	9	2.755	300

5. Results

For this study, two objective functions were analyzed: the reduction of the maximum displacement and the reduction of the RMS value of the maximum displacement. Table 2 summarizes the results obtained for the uncontrolled and controlled structure using different seismic events. This comparison allows for a clear understanding of the effectiveness of the control strategies in reducing the structural responses under different seismic conditions.

Table 2. Structure response using a TLCD optimized with TLBO.

Ground motion	Objective function	η_d	ξ	Maximum displacement (m)	RMS value of the maximum displacement (m)	Maximum interstory drift (m)
El Centro	Uncontrolled			0.1792	0.0628	0.0224
	Min(abs(X_{max}))	0.6428	0.2033	0.1514	0.0539	0.0229
	Min(RMS(X_{max}))	0.8241	0.1240	0.1797	0.0489	0.0239
Kobe	Uncontrolled			0.4091	0.1447	0.0463
	Min(abs(X_{max}))	0.8899	0.0246	0.2379	0.0770	0.0304
	Min(RMS(X_{max}))	0.9341	0.0622	0.2575	0.0629	0.0313
Japan	Uncontrolled			0.3287	0.2306	0.0755
	Min(abs(X_{max}))	0.8684	0.0005	0.2306	0.0616	0.0519
	Min(RMS(X_{max}))	0.8342	0.0853	0.2595	0.0445	0.0548

	Uncontrolled			0.4435	0.1308	0.0638
Tabas	Min(abs(X_{\max}))	0.7246	0.1017	0.3463	0.1206	0.0641
	Min(RMS(X_{\max}))	0.6879	0.0970	0.3585	0.1194	0.0623

Overall, the results presented in Table 2 show that the device optimized for the reduction of the maximum displacement achieves a better performance in terms of structural response than the device optimized for the RMS value of the maximum displacement. However, in both cases, there are significant reductions in the structural response of the controlled building compared to that of the uncontrolled building.

Taking as reference the performance of the structure controlled by a TLCD optimized using the TLBO and the objective function of minimizing the maximum displacement, Figure 4 shows that the controlled structure shows a significant reduction in the peak displacements, especially in the upper stories, confirming the effectiveness of the optimization strategy. This reduction in displacement enhances the overall structural performance and resilience during the different seismic events.

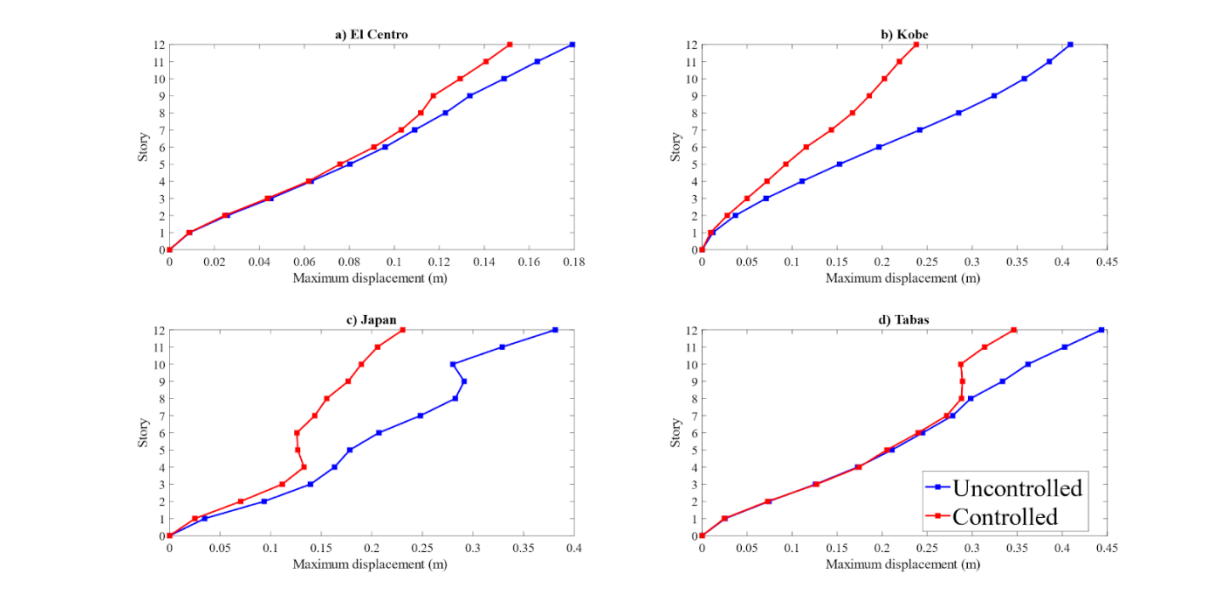


Figure 4. Maximum displacement of each story of the structure: a) El Centro, b) Kobe, c) Japan, d) Tabas.

Figure 5 presents the results obtained for the RMS displacement during each seismic excitation. In this context, the RMS displacement in Japan reveals that although the objective function reduces the maximum peak displacement, it does not smooth out all the peaks. As a result, the RMS displacement values for Japan without control are lower than those with control. However, for the other seismic events, the results are as expected, with the RMS of the maximum displacement being lower for the controlled structure compared to the uncontrolled one.

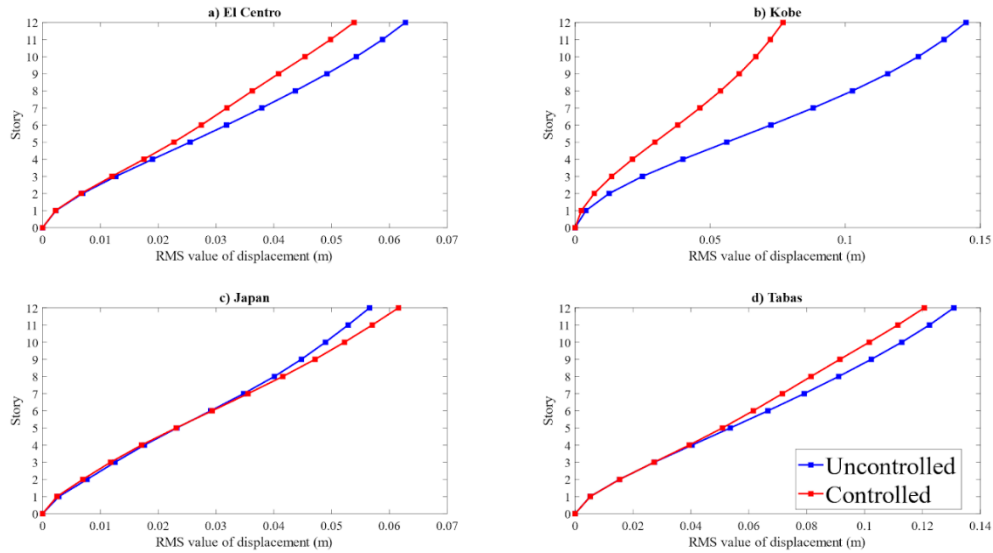


Figure 5. RMS value of displacement of each story: a) El Centro, b) Kobe, c) Japan, d) Tabas.

The interstory drift results are shown in Figure 6. Reducing interstory drift is crucial for limiting structural damage and ensuring occupant safety. In most cases, the data show a significant reduction in interstory drift, demonstrating the effectiveness of the control measures in improving the overall structural performance during seismic events.

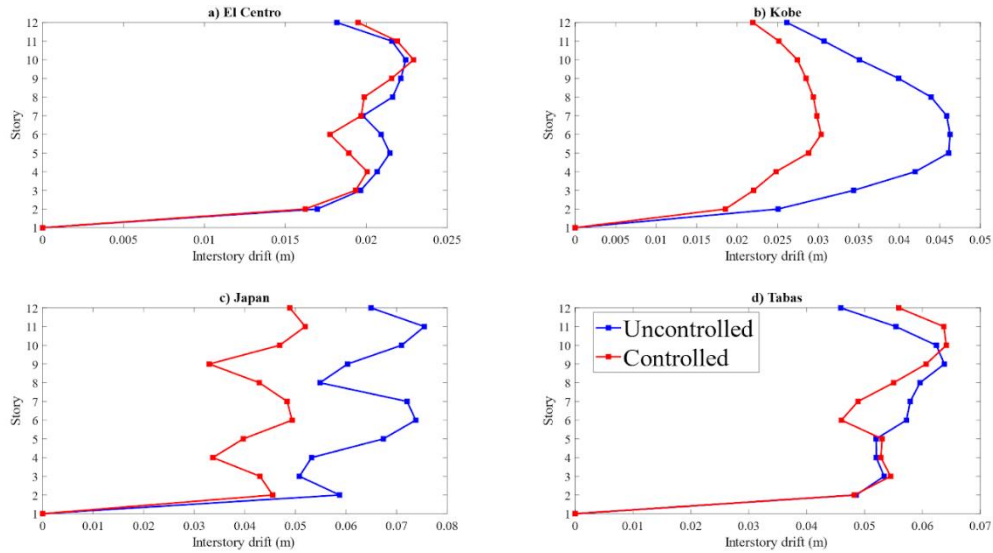


Figure 6. Interstory drift of each story: a) El Centro, b) Kobe, c) Japan, d) Tabas.

6. Conclusions

The use of a TLCD optimized with the TLBO algorithm significantly improves the structural response of a building subjected to seismic excitations. However, the optimization process that minimizes the maximum displacement gives better performance than the one that reduces the RMS values of the maximum displacement. As a result, the controlled structure has reductions in maximum displacements, RMS values, and interstory drifts for all tested ground motions, confirming the robustness and efficiency of the optimized TLCD. By implementing

this type of optimized controller, the seismic performance of structures can be greatly enhanced, resulting in safer and more resilient buildings.

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References

- [1] G. W. Housner, L. A. Bergman, T. K. Caughey, A. G. Chassiakos, R. O. Claus, S. F. Masri and J. T. P. Yao, “Structural Control: Past, Present, and Future”. *Journal of Engineering Mechanics*, vol. 123, n. 9, pp. 897-971, 1997.
- [2] T. K. Datta. “Control of dynamic response of structures”. *Indo-US symposium on emerging trends in vibration and noise engg*, pp. 18–20, 1996.
- [3] D. Gómez, J. Marulanda and P. Thomson, “Sistemas de control para la protección de estructuras civiles sometidas a cargas dinámicas”. *Dyna*, vol. 75, n. 155, pp. 77-89, 2008.
- [4] S. Chakraborty, R. Debbarma and G. C. Marano. “Performance of tuned liquid column dampers considering maximum liquid motion in seismic vibration control of structures”. *Journal of Sound and Vibration*, vol. 331, n. 7, pp. 1519-1531, 2012.
- [5] M. J. Hochrainer, “Tuned liquid column damper for structural control”. *Acta Mechanica*, vol. 175, n. 1-4, pp. 57-76, 2004.
- [6] M. Črepinšek, S-H. Liu; L. Mernik, “A note on teaching-learning-based optimization Algorithm”. 2012.
- [7] R.V. Rao, V. J. Savsani and D. P. Vakharia, “Teaching-learning-based optimization: A novel method for constrained mechanical design optimization problems”. Pp. 303–315. 2011.
- [8] G. Espinoza, C. Quinteros, K. Gajardo, Á. Suazo and S. Quijada, “Eficiencia de un amortiguador de columna de líquido sintonizado considerando una excitación sísmica de bajo contenido de frecuencias e incertidumbre”. *Obras y proyectos*, pp. 54-66, 2021.
- [9] R. V. Rao, V. Savsani and D. P. Vakharia, “Teaching-learning-based optimization: An optimization method for continuous non-linear large scale problems”. *Information Sciences*, vol. 183, 2012.
- [10] A. Mortazavi, “The Performance Comparison of Three Metaheuristic Algorithms on The Size, Layout and Topology Optimization of Truss Structures”. 2019.
- [11] A. Baghlani and M.H. Makiabadi, “Teaching-Learning-Based Optimization Algorithm for Shape and Size Optimization of Truss Structures with Dynamic Frequency Constraints”. *Iranian journal of science and technology*, 2013.