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TLBO algorithm for the optimum sensor placement in barrel structures

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Abstract: In civil engineering, structural health monitoring (SHM) involves observing and analyzing a system over time using periodic measurements of the engineering structures themselves. These measurements are made using sensors. This study aims at reducing the total number of sensors needed and to find the optimal sensor placement. The meta-heuristic method named the Teaching-Learning Based Optimization (TLBO) algorithm is preferred. To get modal properties of the barrel structures, the OAPI properties of the SAP2000 program were used. A computer program coded in MATLAB programming was developed to combine the modal analysis of the structure and the optimization process for sensors.

Keywords: structural health monitoring, TLBO algorithm, sensor placement, SAP2000-OAPI

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Introduction

The steel-braced barrel vault structure is a type of barrel vault structure that is strengthened with steel supports and consists of a sequence of continuous arches generating a semi-cylindrical shape. These structures can cover large spans without the need for internal support columns. Thanks to these features, the steel-braced barrel structure is often preferred in large areas such as airports, shopping malls,

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sports arenas and industrial buildings. Steel-braced barrel vault structures are usually designed based on a double or single-layer geometric curved structure. Double-layer systems are more capable of covering large spans. The installation of sensors in double-layer braced barrel vault (DLBBV) structures for structural health monitoring (SHM) is essential to ensure the safety and service life of these structure. By monitoring the dynamic responses of the structure through sensors, possible structural deterioration can be detected early. Thus, necessary interventions can be made on time and possible loss of life and property can be prevented.

The number and placement of sensors used in SHM systems are critical to obtain accurate vibration data on the structure. Placing the minimum number of sensors in the most suitable locations is addressed by the optimal sensor placement (OSP) problem. The positioning of sensors using OSP methods allows increased accuracy and quality of the data received from the sensors, reduce the evaluation time of the data, and thus save costs. Using an inadequate number of sensors may result in insufficient quality of data and decreases the reliability of the SHM system. Using too many sensors is not cost-effective and leads to an increase in the amount of data to be processed and a longer data evaluation time (Ostachowicz et al., 2019; Tan & Zhang, 2020).

A review of previous studies reveals that there is a lack of studies on the optimal sensor placement for DLBBV structures. However, a limited number of different studies have been carried out for OSP problems of other three-dimensional steel structures. Cruz et al. (2010) used a genetic algorithm (GA) to position sensors on a three-dimensional stadium structure. They compared the results obtained with GA with the results obtained by sensor placement methods such as effective independence and the modal kinetic energy method. They concluded that GA provides a more uniform sensor distribution than other methods. Zhang et al. (2014) used the improved particle swarm optimization (IPSO) algorithm for sensor placement on the lattice shell structure. They concluded that the IPSO algorithm has a better convergence rate than the PSO algorithm. Beygzadeh et al. (2014) used the improved genetic algorithm (IGA) for sensor placement in space structure damage detection. They showed that IGA converges better than GA and provides better sensor layouts. Kaveh et al. (2022) proposed a Q-learning-based water strider algorithm (QWSA) for optimal sensor placement on two different scale dome structures with a large number of candidate locations. They concluded that the proposed algorithm is superior to the binary particle swarm optimization (BPSO), binary Harris hawks optimization (BHHO) and binary gray wolf optimizer (BGWO) and has a better convergence rate. Yin et al. (2019) optimized sensor placement on a truss structure and a rigid-framed arch bridge using a relaxation sequential placement algorithm (SPA). They used the modal assurance criterion (MAC) as the objective function. According to the results, they showed that the proposed method requires fewer sensors and reaches the largest off-diagonal value of the MAC matrix faster than other SPAs, but the computation time increases as the number of sensors increases.

Many optimization algorithms have been considered in OSP problems. However, the teaching-learning based optimization algorithm has been used in a limited number of studies. Mghazli et al. (2023) presented a novel modal assurance criterion

(MAC) based methodology to achieve optimal sensor placement of a 410 m high rise structure with a hybrid metaheuristic algorithm combining teaching-learning based optimization (TLBO), artificial bee colonies (ABC), and stochastic paint optimizer (SPO). They concluded that this methodology provides better fitting without the need for user-defined parameters, avoids local optimum because of higher accuracy, and provides effective results in cost-effective optimization as it requires fewer iterations compared to the other six evolutionary algorithms.

In this study, the aim is to determine the optimum number and location of sensors for a DLBBV structure. For these purposes, a computer program coded in MATLAB (2022) programming language to combine TLBO algorithm and SAP2000 (2016) Open Application Programming Interface (OAPI) features effectively was developed and the optimum sensor placement for structural health monitoring of the DLBBV structure was realized. A similar arrangement (OAPI and SAP200) was used by Atmaca et al. (2020).

1. TLBO algorithm

The teaching-learning based optimization (TLBO) algorithm was developed by Rao et al. (2011; 2012). TLBO is a population-based heuristic stochastic optimization algorithm inspired by the teaching-learning process in a classroom. Population size and number of iterations are the control parameters of the TLBO algorithm. The TLBO algorithm basically consists of teacher and learner phases. In the teacher phase, each individual (learner) uses the best available solution (the teacher) to improve its solution. The best individual in the population is considered as the teacher. Other individuals improve themselves by receiving information from the teacher. In any iteration *i*, assuming M_i is the mean and T_i is the teacher, T_i will try to move the mean M_i towards its own level. Now the new mean will be T_i, designated as M_{new}. The existing solution is updated with the following expression

$$X_{new,i} = X_{old,i} + r_i(M_{new} - T_F M_i) \tag{1}$$

where $X_{old,i}$ is the existing solution and $X_{new,i}$ is the updated solution. The teaching factor T_F determines the mean value to be changed. In the range [0,1], r_i is a random value. T_F = round [1 + rand (0,1) {2 –1}] randomly decided with equal probability and the value of T_F can be 1 or 2.

In the learner phase, individuals try to improve the solution quality by interacting with each other. A learner learns something new from another learner who has more knowledge than the previous learner. The expression for learner modification is as follows:

$$X_{new,i} = \begin{cases} X_{old,i} + r_i(X_i - X_j) & \text{if } f(X_i) < f(X_j) \\ X_{old,i} + r_i(X_j - X_i) & \text{otherwise} \end{cases} \tag{2}$$

Here, the new positions of learner X_i are $X_{new,i}$. X_j is a learner selected at random from the class. The fitness values of learners X_i and X_j are $f(X_i)$ and $f(X_j)$ respectively. A random vector in the range [0, 1] is called r_i.

2. Optimum sensor placement problem

The optimal sensor placement (OSP) as an optimization problem aims at identifying a limited number of locations that allows the record of as much information as possible in terms of modal and vibration characteristics of a given structure. The modal assurance criterion (MAC) has been widely used as the basis of objective functions as it describes the sensor distribution quality based on their mode shapes collinearity

$$MAC_{ij}(\mathrm{v}) = \frac{\left[\varphi_i^T(v)\varphi_j(v)\right]^2}{\left[\varphi_i^T(v)\,\varphi_i(v)\right]\cdot\left[\varphi_j^T(v)\varphi_j(v)\right]} \quad i,j = 1,2,3,\ \ ,p \tag{1}$$

where $\varphi = (\varphi_1, \varphi_2, \dots, \varphi_p)$ is the mode shape matrix calculated based on the finite element model; φ_i and φ_j is the i^{th} and j^{th} mode shape vector, φ_i^T is the transpose vector of φ_i; $\varphi_i(v)$ is the i^{th} mode shape vector, with mode shape values related to the sensor location (v), and p is the considered number of vibration modes. Correlated mode shapes i and j account for a MAC = 1 while the opposite means a MAC = 0. The OSP problem can be formulated in a way to obtain a sensor placement that will realize a minimum MAC value between two different mode shapes $i \neq j$.

Assuming that there are n possible sensor locations (degrees of freedom) in a structure and s sensors $(s < n)$ to be placed in these locations. The number of combinations of sensors is given in the following equation

$$C = \frac{n!}{s!\,(n-s)!} \tag{4}$$

where C denotes the number of all combinations. Since the number of possible combinations of structures with few degrees of freedom is small, the solution of the OSP problems of such structures can be obtained easily. However, as the degree of freedom in the structure increases, the number of combinations increases, and this makes it difficult to find the best solution. The aim is to reach the best solution in the shortest time by using optimization methods for solving the OSP problem of complex structures with many degrees of freedom. In this study, the modal assurance criterion, which specifies the correlation between two mode shape vectors, is used as the objective function in the optimization process to achieve optimum sensor placement in the DLBBV structure. For this purpose, the general equation can be written as follows

$$F_{obj} = \max_{i \neq j}\left\{MAC_{ij}\right\} \tag{5}$$

where F_{obj} represents the objective function. In this equation, i and j represent row and column values respectively. The value of the off-diagonal elements of the MAC matrix varies between 0 and 1. Values close to 1 mean that there is high similarity between mode shape vectors, and they are indistinguishable from each other, while values close to 0 mean that there is little similarity between mode shape vectors, and they are distinguishable from each other.

3. Numerical example

In this study, a 384-bar DLBBV structure was used to test the computer program. The weight optimization of this example was previously performed by Kaveh & Ghazaan (2018) and Dede et al. (2020). The three-dimensional view of the selected DLBBV structure is given in Figure 1a. There are two rectangular nets in this barrel vault structure. Between the top and bottom nets, there is a 5.12 m vertical distance. The bottom nets are symmetrically positioned between the two top barrel nets. The 384 bars of this structure were categorized into 31 groups.

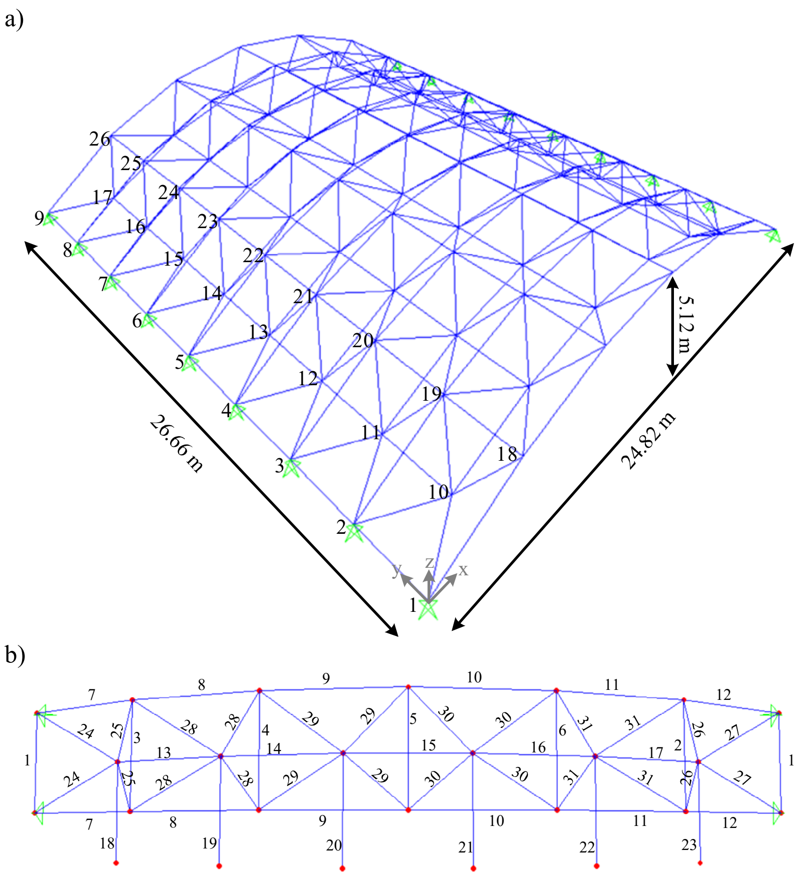

Fig. 1. 384-bar DLBBV: a) 3D view, b) sub-structure grouping details (*own research*)

This grouping can be seen in detail in Figure 1b. The material properties of the elements are; Young's modulus 30,450 ksi (210,000 MPa), and material density 0.288 lb/in^3 (7971.810 kg/m^3). Table 1 shows the cross-sectional areas of the pipe steel sections used in each group for this example, taken from the AISC-LRFD code. In this DLBBV structure, there are 93 nodes (excluding the supports) where the sensors can be placed. Since a single axis sensor will be used, if the degrees of freedom in the x, y, and z directions are considered, there are a total of 279 degrees of freedom in which the sensors can be placed.

Table 1. Cross-sectional areas of the pipe steel sections used in the 384-bar DLBBV structure (*own research*)

Element group	Steel pipe area	Element group	Steel pipe area	Element group	Steel pipe area	Element group	Steel pipe area
1	1.4800	9	15.6000	17	3.6800	25	1.7000
2	0.6690	10	12.8000	18	0.6690	26	0.6690
3	2.2300	11	11.3000	19	0.7990	27	1.4800
4	0.6690	12	11.3000	20	1.0700	28	1.0700
5	0.8810	13	3.0200	21	0.7990	29	0.7990
6	0.8810	14	21.3000	22	1.7000	30	0.7900
7	14.6000	15	2.2500	23	1.0700	31	0.7990
8	15.6000	16	4.0300	24	1.7000		

The finite element model of the 384-bar DLBBV was created using the SAP2000 program and the modal parameters (number of modes, period, modal displacements, modal mass participation) were determined. The modal mass participation rate indicates the percentage participation of the dynamic behavior of a structure and shows the participation rate of the total mass of the structure in each mode. To obtain the modal parameters of the structure accurately, important modes should be considered. It is generally accepted in the literature that the modal effective masses calculated for each mode reach 90 % of the total mass of the structure (Wilson, 2002). Within the scope of this study, the number of relevant modes to be considered in the OSP problem of a 384-bar DLBBV structure was determined by determining the mode in which the modal mass participation rate calculated for each mode reaches 90 % of the total mass of the structure. Since the modal mass participation ratio of the 384-bar DLBBV structure in the y and z directions reaches 90 % in the 27th mode, the first 27 modes were selected as the relevant modes. After determining the number of relevant modes, the number of single-axis sensors to best represent the selected relevant mode was determined. The objective function given in Eq. (5), which tries to minimize the off-diagonal maximum value of the *MAC* matrix, was optimized for different sensor numbers. An off-diagonal maximum value of the *MAC* matrix between 0.20 and 0.25 ensures the independence between the mode shape vectors and means that the number of sensors to represent the relevant mode well is reached

(Carne & Dohrmann, 1995). While determining the number of sensors, the optimization parameters of population size and iteration number were set as 50 and 150, respectively. While determining these values, the best optimization parameters were selected by using different population size. The total number of runs was also considered as 10. At the end of the optimization process, the number of sensors that first reached the acceptable *max-MAC* value between 0.20 and 0.25 was determined as the optimum number of sensors. The change in the *max-MAC* values for different sensor numbers is shown in Figure 2. As can be seen from the graph, 23 sensors were the first to reach the acceptable range. It was observed that the *max-MAC* value reached 0.2494 using a total of 23 sensors.

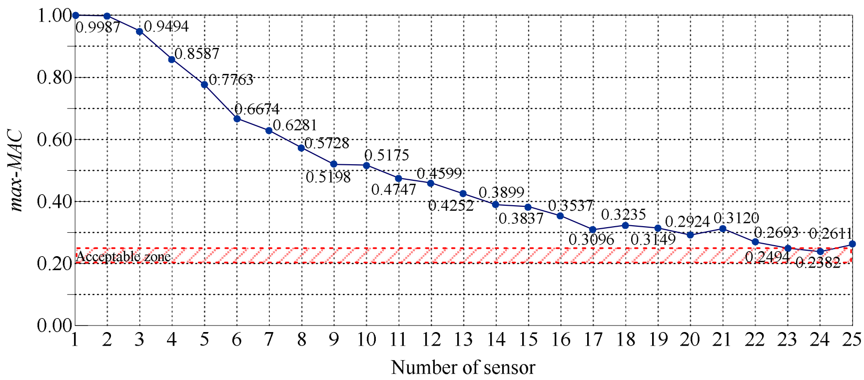

Fig. 2. Determination of the number of sensors (*own research*)

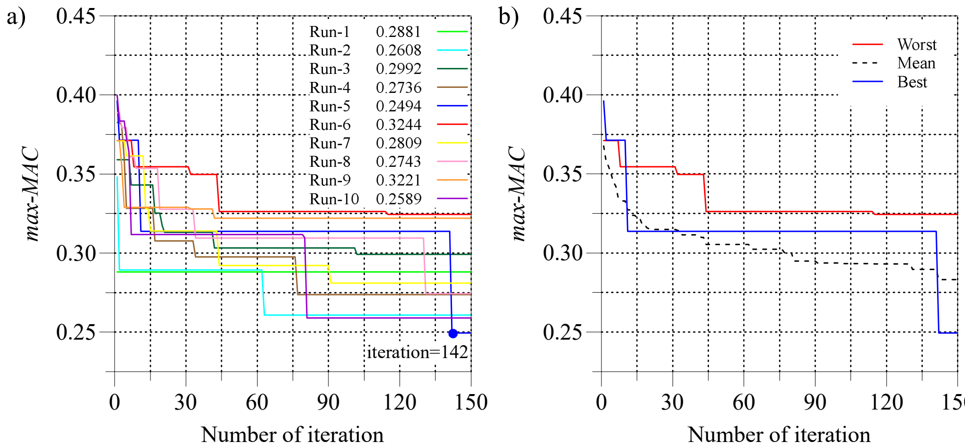

Fig. 3. Convergence graph of *max-MAC*: a) all Runs, b) Run-5 and Run-6 (*own research*)

The convergence graph was then obtained by using the *max-MAC* method as the objective function in the optimization process in order to determine the optimal locations of the sensors and is given in Figure 3a. When this graph is analyzed, it is seen that among the 10 runs, Run-5 is the fastest converging run, reaching the best result at the 142nd iteration. The best run (Run-5), the worst run (Run-6) and the average of all runs are given in Figure 3b.

The optimum sensor locations obtained are shown in Figure 4. The three-dimensional plot of the *max-MAC* matrix is given in Figure 5. The *max-MAC* values obtained in each run, the number of iterations and the number of function evaluations (NFE) are given in Table 2. The optimum sensor locations obtained from Run-5 are given in Table 3.

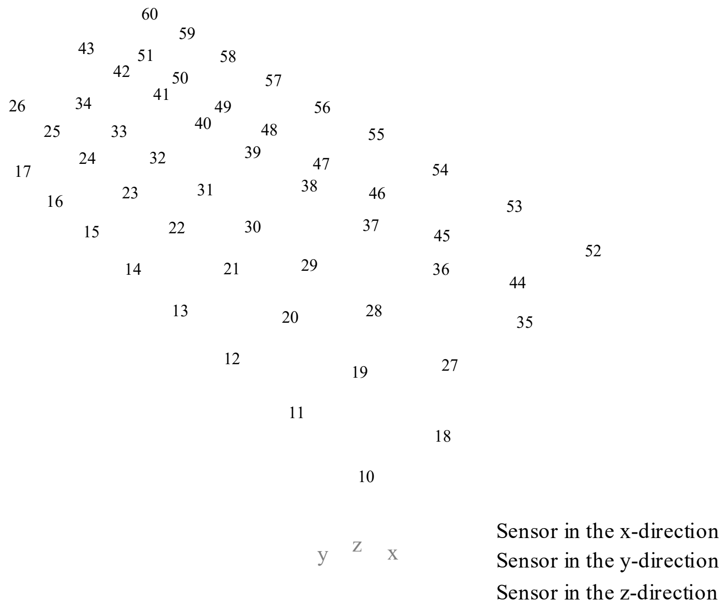

Fig. 4. Optimum sensor locations (*own research*)

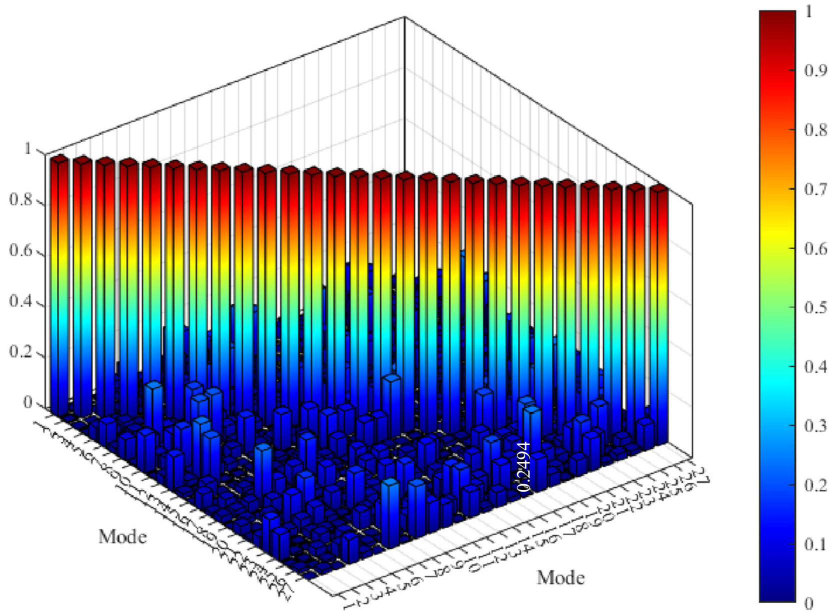

Fig. 5. Optimum *max-MAC* value in DLBBV structure (*own research*)

Table 2. *max-MAC* values obtained as a result of the analysis (*own research*)

Run	*max-MAC*	Iteration	NFE	Run	*max-MAC*	Iteration	NFE
1	0.2881	1	100	6	0.3244	115	5800
2	0.2608	63	3200	7	0.2809	91	4600
3	0.2992	102	5150	8	0.2743	131	6600
4	0.2736	77	3900	9	0.3221	42	2150
5*	**0.2494**	**142**	**7150**	10	0.2589	81	4100

* Best run

Table 3. Optimum sensor locations obtained (*own research*)

Number of relevant modes	Number of sensors	Objective function	Best run	Optimum sensor locations	
27	23	*max-MAC*	Run-5	x	23, 25, 30, 35, 52, 62, 86, 88, 92
				y	52, 59, 71, 72, 78
				z	24, 28, 34, 38, 40, 53, 55, 66, 92

Conclusions

The aim of this study was to determine the optimum number and location of sensors for a DLBBV structure. For these purposes, a computer program coded in MATLAB programming language in order to combine the TLBO algorithm and the SAP2000 with Open Application Programming Interface (OAPI) features effectively was developed and the optimum sensor placement for structural health monitoring of the DLBBV structure was realized.

Since the modal mass participation ratio of the DLBBV structure reaches 90 % in the 27th mode, the first 27 modes were selected as the relevant modes. The fact that the maximum off-diagonal value of the MAC matrix is between 0.20 and 0.25 ensures independence between the mode shape vectors and means that the number of sensors that will best represent the relevant mode has been reached. When the number of sensors that best represent the relevant mode is determined by the optimization of the max-MAC method, the optimum number of sensors is obtained as 23.

When the results obtained from the 10 runs performed for the DLBBV structure are examined, it is seen that Run-5 is the fastest converging study and the best result is reached in the 142nd iteration.

While $2.70 \cdot 10^{33}$ combinations were required to find the best placement of 23 sensors in the 384-bar DLBBV structure, the NFE is 7150 in the developed program.

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