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RESEARCH PAPER

Optimal sensor placement for modal identification of large truss structures using the Circle-Inspired Optimization Algorithm

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Abstract

Determining the optimal placement of a fixed number of sensors in a structure to assess its structural integrity remains an open challenge, primarily due to the need to define an appropriate optimization algorithm and select a suitable quality metric. This study evaluates the performance of the recently developed Circle-Inspired Optimization Algorithm (CIOA) for sensor placement in truss structures. CIOA has demonstrated strong performance in structural design optimization and is therefore a promising candidate for addressing the sensor placement problem. Regarding quality metrics, several objective functions are considered to evaluate sensor configurations, including the Fisher Information Matrix and Modal Kinetic Energy. To assess the robustness and scalability of the proposed approach, five large trusses with varying levels of complexity are analyzed. The results show that sensor distributions are strongly influenced by the chosen criterion, with the Effective Independence-based objective function generally yielding more spatially distributed configurations. Moreover, the findings indicate that the search space contains numerous local optima, underscoring the need for additional performance criteria to compare sensor arrays generated using CIOA. Comparative analyses with well-known metaheuristic algorithms further demonstrate CIOA's effectiveness. A sensitivity analysis of the two CIOA parameters is conducted, revealing that using the values recommended by the CIOA authors ensures efficient and accurate convergence. Therefore, the approach proposed in this paper proved to be a useful tool for optimal sensor placement.

Keywords Optimal location of sensors · Modal identification of structures · Metaheuristic algorithms · Truss structures

1 Introduction

Over the last few decades, technological advancements in civil infrastructure have enabled the design and construction of highly complex structures in terms of both materials and geometry. Such complexity requires structural engineers to create structures with longer lifespans, capable of withstanding severe conditions while ensuring user comfort and safety [1]. Consequently, experimental procedures are necessary to determine modal properties from operational measurements, such as the Stochastic Subspace Identification (SSI) method [2]. Additionally, modern structural designs face vibration concerns as structures become slender. For example, Periyasamy et al. [3] assess the comfort level of a slender structure through ambient vibration tests, developing a regression model to predict wind pressure at various points on the structure based on wind velocity. Undesired vibrations can be mitigated using passive or active vibration control devices, whose effectiveness depends on the modal properties of the current structure. It is also possible

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to assess the structural integrity of a damaged structure by observing changes in its modal parameters, as, for example, in Fadel Miguel et al. [4–9] and Monteiro et al. [10, 11]. In principle, this concept is straightforward: Any changes in the stiffness or mass matrices will result in a modification of the structure's dynamic parameters. Sun et al. [12] provide a review of methodologies that use vibration principles to detect damage in structures, presenting a conceptual framework that classifies the analyzed methodologies. The key question now is how to experimentally determine the modal properties of the structure.

Structural Health Monitoring (SHM) is a field for developing strategies and technology to determine the state of different structural systems from the information measured in the field. Worden et al. [13] established seven axioms regarding the damage detection process, one of which emphasizes the impossibility of directly measuring damage. Therefore, it is necessary to detect damage through further analysis of field-measured information, such as strains, accelerations, and temperatures, among others [14]. Acceleration measurements are used to derive the dynamic parameters of structures using modal identification techniques. However, engineers face the challenge of determining the type, number, and positioning of devices on the structure. While it is theoretically possible to instrument the entire structure, technical and economic constraints generally limit the number of sensors used and the positions where they can be placed. It is worth mentioning that several authors discuss the impact of limited measurements on the damage detection process, including [15]. Thus, it is crucial to install the available sensors at strategic points on the structure to ensure the most effective monitoring process [16]. A mathematical optimization problem can be formulated, where the design variables correspond to the placement of a set of available sensors, and the objective function is based on the quality of the subsequent modal identification process. Typically, a finite element model of the structure is used to determine sensor locations. Additionally, uncertainties arising from measured data and errors in the finite element model can also be considered [17]. One of the main concerns is the choice of the numerical algorithm to solve the optimization problem, given the specific characteristics of the studied problem.

The optimal sensor placement (OSP) problem has been widely investigated in the literature across a variety of structures such as beams [18], TV towers [19], frame buildings [20], trusses, bridges [21], dome trusses [22], transmission towers [23], arch dam [24], laminated composite plates [25], wind turbine tower [26], engine-generator set [27], aircraft [28] and space solar power satellite [29]. The problem has been approached from both deterministic and stochastic perspectives [30] to solve the mathematical formulation. However, the possibility of having discrete design variables (binary or integer types) makes metaheuristic algorithms well-suited for the OSP problem. Several metaheuristic algorithms have been applied to solve the OSP problem, including Ant Colony Optimization [31], Genetic Algorithms [32], Particle Swarm Optimization [33], Firefly Algorithm, Simulated Annealing [34], Monkey Optimization Algorithm [35], and Wolf Optimization Algorithm [36]. Nonetheless, it is possible to continue exploring new algorithms in search of the most suitable one. This is particularly true as the number of new metaheuristic algorithms grows each year, with more than 500 nature-inspired algorithms already published [37]. One such algorithm is the Circle-Inspired Optimization Algorithm (CIOA), recently developed by one of the authors of the present paper (De Souza and Miguel, 2022 [38]), which has been successfully applied to structural engineering problems. Another possibility corresponds to the monitored convergence curve [39], which proved good performance in structural optimization of steel frames [40]. It is also worth mentioning that a more complex solution coding, using graph theory, has been applied as well. Such implementations require modifications to the metaheuristic, as seen in [41]. The constraints of the problem are primarily related to the number of degrees of freedom available for sensor placement. Tan and Zhang [42] present a literature review on the OSP problem in the context of SHM, including a comparison table that outlines the advantages, disadvantages, and applications of various approaches.

Regarding the objective function, it is essential to establish a criterion for determining the quality of a specific sensor array for modal identification. The Fisher Matrix Information (FIM) is one of the main criteria used in the literature as the basis for the objective function. In 1993, Yao et al. [43] were among the first to work in maximizing the determinant of the FIM for a given set of sensors and their positions. From this, it is possible to find applications of the FIM criterion for the identification of a plate [44], a box girder bridge [45], historical masonry structures [46], and a planar truss [47]. The Modal Assurance Criterion (MAC) has also been used to account for the orthogonality between two modes. The Modal Strain Criterion (MSC) helps to increase the signal-to-noise ratio in the information obtained for a spatial lattice structure [48]. The concept of entropy is considered in [49] to assess the quality of a sensor configuration based on the identified model of a transmission tower structure. Zhao et al. [50] formulated an objective function based on the maximization of the observability of shape modes under noise conditions. It is also possible to combine the OSP problem with the damage detection problem to ensure a reliable process. Cobb and Liebst [51] used an eigenvector sensitivity analysis to identify the best sensor positions that contribute to the damage detection process in a 104-bar truss structure. Some studies have formulated a multi-objective problem, where one objective corresponds to minimizing the number of sensors on the structure [52]. It is worth mentioning that there is no final consensus in the literature on which objective function is the best, and further research is needed on the topic.

Steel truss structures are important components in civil construction, used in applications such as bridges, transmission towers, and roofs. Most studies focus on steel truss optimization under static loads; however, Azad [53] addressed the simultaneous size and geometry optimization problem of steel truss structures subjected to dynamic excitations. Dynamic loads, such as wind or traffic, can damage the structure, and the material properties may degrade over the structure's lifetime. For this reason, it is crucial to rely on structural health monitoring systems to assess the current condition of the trusses [54]. In the specific case of trusses, it is possible to find an application of direct OSP methods in references such as [55]. However, it is also possible to implement an optimization problem as in [47, 48]. Classical binary and integer values are used to represent the variables for the sensor positions at the various degrees of freedom (DoFs) at each node in the structure. This representation can lead to a very large number of possibilities. For example, assuming five sensors and a finite element model with 500 DoFs, the number of possible sensor placements would be 3.06E13. This might explain why the trusses tested in the literature typically have fewer than 300 DoFs [48, 50, 55–58]. However, Kaveh et al. [22] were the first to explore sensor positioning in a large 1180-bar truss dome using both a metaheuristic and a reinforcement learning algorithm. Thus, further assessment of metaheuristic algorithms for larger structures is necessary.

In this context, this research develops a Circle-Inspired Optimization Algorithm (CIOA) to determine the optimal positions of a predefined number of sensors for modal identification. CIOA is a metaheuristic algorithm inspired by the geometric properties of circular motion, which enables a balanced exploration and exploitation of the search space. A set of five large three-dimensional and planar trusses is used to demonstrate the performance of the proposed methodology. Eight objective functions, based on the modal parameters of the structure, are considered, taking into account the physical solution of the sensor array for each analyzed truss. Convergence curves are presented to illustrate the optimization process. The results obtained using the CIOA are compared with those obtained using four other metaheuristics. Thus, this research is important for the following reasons:

- It presents the use of CIOA in solving the sensor location optimization problem in large trusses. The CIOA, proposed by Souza and Miguel [38], i.e., by one of the authors of the present paper, was selected as the optimization algorithm due to its demonstrated efficiency, simplicity, and robustness when applied to a wide variety of complex engineering problems [59, 60]. Furthermore, Souza and Miguel [38] tested CIOA on a broad set of benchmark problems and engineering applications, reporting consistent and competitive results.
- It compares the impact of the chosen objective function to determine the quality of the set of sensor locations. These functions include criteria related to effective independence, modal strain energy, and driving point residue, among others.
- It uses large trusses to demonstrate the impact of the search space size on the performance of the proposed methodology. This includes assessing the impact of the CIOA parameters on its performance.

2 Location of sensors in structures as an optimization problem

2.1 Description of the problem

Imagine a truss bridge structure crossing a river, as shown in Fig. 1, for which it is necessary to identify its modal parameters. Then, a protocol must be defined to instrument the structure with a reduced number of accelerometers that need to be located. To illustrate the complexity of this task, Fig. 1 shows four different arrays of sensors (represented by black squares) that could be placed on the bridge, assuming that the truss nodes are the possible positions. The four arrays show the possibility of defining the number of sensors (1–3 in the figure) and the position through the structure (left-center-right). However, the number of feasible combinations is high for this small structure, with a total of 35,904 if three sensors are available. In a structure with a high number of degrees of freedom, locating a few sensors is a challenge due to the number of possibilities. Thus, there are several questions that the engineer in charge must answer. Some of these include: How should the engineer decide the position and degrees of freedom (DoFs) to place the available sensors? What is the appropriate number of sensors to ensure reliable modal information? What is the noise tolerance of the measured data? What modal information from all the DoFs of the structure can be obtained using a limited number of sensors?

The problem of locating a predefined number of uniaxial sensors can be formulated as an optimization problem. Generally, a finite element model is required to represent the structure. The DoFs of the model represent the possible positions for placing the sensors. The size of the design variable vector corresponds to the number of available sensors,

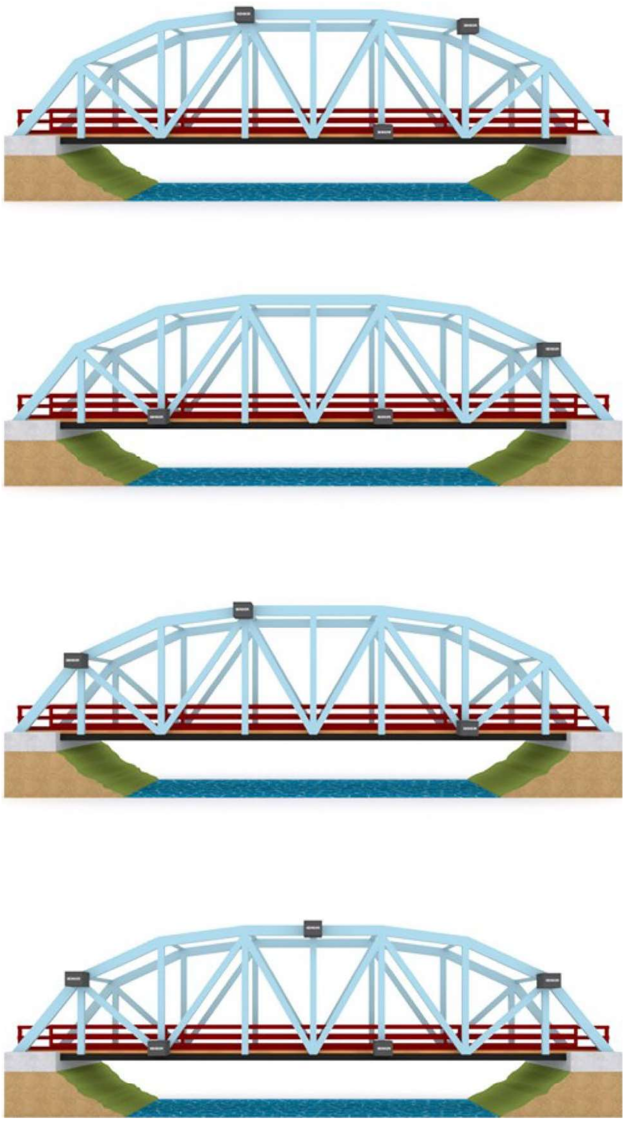

Fig. 1 Examples of sensor positions (black squares) on a truss bridge for modal identification

and the range of values is determined by the number of DoFs. Each sensor array will have a quality measure related to the modal identification process. Section 2.2 describes a series of possible objective functions for modal identification, which use the modal information obtained from the finite element model. In its simplest form, the problem does not have constraints; however, DoFs that are forbidden due to technical limitations can be excluded. The main limitations of this research relate to the assumptions of no uncertainty in finite element models and the non-availability of experimental data for validation.

2.2 Definition of the objective function

In this research, sensor placement (SP) criteria were adapted to align with a minimization-based optimization goal. This approach was taken to allow for the configuration of a single optimization algorithm, thereby eliminating the need for modification if the optimization problem was a maximization one. A total of eight traditional criteria were employed to evaluate their impact on sensor placement. This raises the following question: How can an engineer distinguish the quality of two solutions generated by different SP criteria? The criteria themselves quantify the contribution of each degree of freedom (DoF) to the modal information, yielding results in the form of a vector with strictly positive values. To adapt these methods for optimization, the objective function was modified to return the negative sum of the contributions across all DoFs. This adaptation ensures that the optimization process minimizes the total contribution, effectively identifying the optimal sensor positions while preserving the fundamental characteristics of the original methods.

To effectively apply SP criteria, the first step involves using the finite element model of the structure to determine its natural frequencies and the corresponding mode shapes. The number of mode shapes must be defined in advance by the user based on the experimental test. The second step involves defining a specific sensor array, known as the target modal matrix Φ_t, which serves as the basis for subsequent operations. The matrix Φ_t has dimension N_d x N_t, where N_d represents the number of preselected DoFs and N_t is the number of vibration modes chosen for analysis. The matrix Φ_t is composed by the vectors $\overrightarrow{\phi_m}$ for $m = 1, 2, 3, ..., N_d$. The original method produces a vector of length N_d, where each element represents the quantified contribution of a specific DoF. For each of the following criteria, the objective function is modified to be a sum of all the contributions of each DoF. In this case, modal damping is not considered for the study. As will be observed, the main advantage of these functions is their ease of computation. It is worth noting that the original maximization problem had to be reformulated as a minimization problem in order to simplify the calculations. Since all the objective functions presented below (Eqs. 1–8) yield positive values, this transformation can be achieved by simply taking their negative values. This procedure was applied consistently to all the objective functions considered in this study.

2.2.1 Effective independence—EFI

The EFI method [61] optimizes sensor placement by maximizing the independence of modal information captured by sensors. The first objective function f_1 uses the Fisher Information Matrix as follows:

$$minf_1 = -EFI = -\sum_{l=1}^{N_d}\sum_{m=1}^{N_t}[\Phi_t\Psi] \otimes [\Phi_t\Psi]\,\Lambda^{-1} \tag{1}$$

where Ψ and Λ are the solution of an additional eigenvalue problem that involves the matrix $\Phi_t^T\Phi_t$. Such problem is formulated as $\left[\Phi_t^T\Phi_t - \lambda I\right]\psi = 0$, where solving this problem, the method identifies how identifiable the modal partitions are when observed along the corresponding axes.

2.2.2 Eigenvalue vector product—EVP

The EVP method [62] combines modal amplitudes and eigenvalues to assess the contribution of each mode to the structural energy. The presence of zero coordinates in a mode will result in a value of zero for the contribution of the corresponding DoF. The second objective function f_2 is given by:

$$minf_2 = -EVP = -\sum_{l=1}^{N_d}\prod_{m=1}^{N_t}\left|\overrightarrow{\Phi_m}\right| \tag{2}$$

2.2.3 Modal kinetic energy—MKE

The MKE method [44] begins by calculating the kinetic energy of the system, which represents the vibration-associated energy of the structure. Similarly to the *EFI* metric, the contribution of each degree of freedom to the kinetic energy of the system is quantified in the objective function f_3:

$$minf_3 = -MKE = -\sum_{l=1}^{N_d}\sum_{m=1}^{N_t}[\mathrm{C}\Phi_t\Psi] \otimes [\mathrm{C}\Phi_t\Psi]\,\Lambda^{-1} \tag{3}$$

where $\mathrm{C} = U\Phi_t$ and $\mathrm{M} = LU$, M represents the mass matrix of the DoF selected. L and U are the lower and upper triangular matrices, respectively, derived from the Cholesky factorization.

2.2.4 Modal strain energy—MSE

The MSE method [63] focuses on the distribution of strain energy to consider the effect on the structure. The Modal Strain Energy method leverages a comparable framework, substituting the mass matrix M with the stiffness matrix K. The MSE quantifies the strain energy within the vibrational modes. Thus, the objective function f_4 would be:

$$minf_4 = -MSE = -\sum_{l=1}^{N_d}\sum_{m=1}^{N_t}[\mathrm{C}\Phi_t\Psi] \otimes [\mathrm{C}\Phi_t\Psi]\,\Lambda^{-1} \tag{4}$$

2.2.5 Mode shape summation plot—MSSP

The MSSP method [64] evaluates the significance of each degree of freedom in contributing to the system's overall dynamic response. The use of the absolute mathematical symbol ensures that the DoFs contribute independently of their position relative to the original position. This method enhances sensor placement by prioritizing locations that maximize observable modal effects. In that sense, the objective function f_5 is

$$minf_5 = -MSSP = -\sum_{l=1}^{N_d}\sum_{m=1}^{N_t}\left|\overrightarrow{\phi_k}\right| \tag{5}$$

2.2.6 Non-optimal driving point—NODP

The NODP [65] method is an energy-based approach designed to identify optimal positions by minimizing displacement. The criterion can be forced to avoid a specific DoF as it uses the minimum value of the corresponding DoF. It is possible to propose an objective function f_6 as follows:

$$minf_6 = -NODP = -\sum_{l=1}^{N_d} min_t\left|\overrightarrow{\phi_k}\right| \tag{6}$$

2.2.7 Driving point residue—DPR

The DPR method [65] determines the placement of the sensor by evaluating the susceptibility to excitation and response. It is worth mentioning that it is possible to have one or multiple excitations in traditional modal analysis. The objective function f_7 based on the DPR criteria is:

$$minf_7 = -DPR = -\sum_{l=1}^{N_d}\sum_{m=1}^{N_t}\Phi_t \otimes \Phi_t\Lambda^{-1} \tag{7}$$

2.2.8 EFI-DPR

As highlighted in [66], the combination of the DPR method with the EFI method can enhance the positioning accuracy. The authors point out that a limitation of the EFI method lies in its disregard for the energy associated with the degrees of freedom. Therefore, it is advisable to weigh the EFI results with the DPR method. This combination enables the