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RESEARCH ARTICLE

Automated damage assessment in truss structures via FE model updating and teaching-learning-based optimization

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Abstract

While numerous methodologies for identifying structural damages through finite element (FE) model updating and optimization algorithms have been developed and validated for accuracy, certain unresolved issues necessitate further investigation. The establishment of a numerical model is imperative for damage assessment through model updating, particularly for complex engineering structures with numerous elements, such as trusses, which demand substantial effort. Utilizing commercial software can offer significant convenience in this context. To cope with this challenge, we propose a FE model update strategy employing the SAP2000 Open Application Programming Interface (OAPI) and Teaching-Learning-Based Optimization (TLBO) for evaluating damages in complex truss structures. The FE model of the monitored structure is, first, constituted via SAP2000 software. Subsequently, the damage assessment of the structure is formulated as an unconstrained optimization problem. An objective function is defined as a weighted linear combination of three modal parameters: frequency, Coordinate Modal Assurance Criterion (COMAC), and flexibility. For the identification and quantification of stiffness degradation induced by damage, the optimization problem is addressed through TLBO. The iterative optimization process is automated by establishing a linkage between MATLAB and SAP2000 through the OAPI feature of SAP2000. The efficacy of the proposed approach is demonstrated through two numerical test examples, accounting for measurement noise and sparse measured data.

1. Introduction

Engineering structures may be subject to various types and levels of damage throughout their service lives. If these damages are not early diagnosed, they may develop over time and lead to catastrophic failure of the structure to fulfill its function or even its complete collapse. Therefore, effective monitoring of structures is essential to ensure their integrity and safety. In this regard, a considerable amount of research has been devoted to the development of structural damage detection techniques which have played an essential role in structural health monitoring (SHM) in recent years. Among them, vibration-based damage identification techniques have become more popular [1]. They have been first developed and applied in aerospace, mechanical, and civil engineering communities since the early 1980s [2]. The fundamental principle behind

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vibration-based damage detection is that the presence of damage will change the physical properties of a structure such as mass, stiffness, and damping, which causes changes in the modal parameters such as frequencies and mode shapes [3]. Tracking these changes provides information about the damage to the structure.

Vibration-based methodologies for detecting structural damage can be broadly classified into two categories: (i) non-model-based or data-driven methods and (ii) model-based methods. Model-based techniques have attracted increased attention and preference owing to their high precision in identifying structural damage. These approaches necessitate the formulation of a numerical model corresponding to the structure under investigation. For numerical modeling, the finite element (FE) method has been generally preferred along with model updating strategies [4].

FE model updating provides an effective manner of structural damage detection [4–11]. In this strategy, the numerical model of the structure is updated by gradually adjusting its parameters and assumptions to ensure a good match between the parameters of the damaged structure. Once the agreement is achieved, the local modification of the FE model indicates the damage [1, 4, 12].

The process of damage identification through finite element (FE) model updating can be conceptualized as an optimization problem, where the design variables correspond to the damaged elements. In comparison to numerous alternative approaches, there is a noticeable trend towards the growing utilization of metaheuristic optimization methods in the FE model updating. [4, 13]. Over the past decade, researchers have used various metaheuristic optimization methods to solve the damage detection problem by FE model updating and have achieved quite successful results. Genetic algorithm (GA) [14–17], harmony search (HS) algorithm [18, 19], particle swarm optimization (PSO) algorithm [20–23], teaching–learning-based optimization (TLBO) algorithm [24–27], Jaya algorithm [28–30], lightning attachment procedure optimization (LAPO) algorithm [31], and further improved/ hybrid optimization algorithms [32–39] are representative examples successfully applied by researchers in solving the problem.

Recent scientific investigations have been prominently directed towards the development of hybrid methodologies, wherein the integration of commercial software packages with MATLAB is employed to elevate the sophistication of FE modeling and speed up structural damage identification. The cohesive incorporation of commercial software packages with MATLAB demonstrates substantial potential in refining and advancing FE model updating techniques for structural damage identification. These hybrid methodologies capitalize on the distinctive strengths inherent in both software platforms, effectively harnessing advanced optimization algorithms embedded in MATLAB and leveraging the formidable simulation capabilities intrinsic to commercial software. Numerous scholarly contributions have advocated and proposed the adoption of such hybrid methodologies within the scientific community. Sanayei and Rohela [40] introduced the Parameter Identification System (PARIS) program, an Optimization Toolbox available in MATLAB. This program interfaces with the Finite Element (FE) analysis solver of SAP2000 software through the Open Application Programming Interface (OAPI) to autonomously update FE models for full-scale structures. In a separate study, Nozari et al. [41] proposed a framework for FE model updating, combining a gradient-based least-squares optimization approach with SAP2000 software for modal identification and damage detection in a 10-story building using ambient vibration measurements. Recently, Dinh-Cong et al. [42] introduced an FE model updating approach utilizing the SAP2000-OAPI and an enhanced symbiotic organism's search (ESOS) algorithm for assessing damages in full-scale structures. Their study involved the analysis of an industrial steel frame and a 3D two-story full-scale building, considering various hypothetical damage scenarios for numerical investigation.

While numerous methodologies for identifying structural damage through finite element (FE) model updating and optimization algorithms have been developed and validated for accuracy, there is still limited research on damage identification and quantification in large complex engineering structures with numerous elements, such as trusses. Since establishing a numerical model is imperative for damage assessment in such structures, utilizing commercial software can offer significant convenience in this context. Inspired by this need, an FE model update strategy is proposed for evaluating damages in complex truss structures. The technique uses the commercial software SAP2000 Open Application Programming Interface (OAPI) and the TLBO algorithm. In the damage detection strategy, the SAP2000 FE models of the considered trusses are, first, constructed to extract the natural frequencies and mode shapes. The TLBO algorithm is, then, used to minimize a novel objective function dependent on frequency, flexibility matrix, and coordinate modal assurance criterion (COMAC). TLBO algorithm is executed using MATLAB and establishes communication with SAP2000 via OAPI for bidirectional data exchange. The efficacy of the proposed method is assessed through experimentation on two numerical examples: a plane truss and a space truss structure, each subjected to diverse damage scenarios. Furthermore, the study delves into the examination of the influence of measurement noise and sparse data on the performance of the proposed technique.

2. Methods

2.1. Iterative improved reduction system (IIRS)

One of the practical challenges of model-based techniques is the limited number of sensors available for collecting measurement information. To overcome this challenge, previous studies have proposed using modal expansion or reduction techniques [43, 44]. The simplest method for the latter was proposed by Guyan [45], which ignores the inertia effects, and it is reliable only at zero frequency. According to the Guyan method (or static reduction), the static transformation between the full state vector and the master coordinates can be expressed as

$$\mathbf{x} = \mathbf{T}_G \mathbf{x}_m \tag{1}$$

where

$$\mathbf{x} = \begin{Bmatrix} \mathbf{x}_m \\ \mathbf{x}_s \end{Bmatrix}, \quad \mathbf{T}_G = \begin{bmatrix} \boldsymbol{I} \\ -\mathbf{K}_{ss}^{-1} \end{bmatrix} \tag{2}$$

The reduced mass and stiffness matrices are then given by

$$\mathbf{M}_R = \mathbf{T}_G^T \mathbf{M} \mathbf{T}_G, \quad \mathbf{K}_R = \mathbf{T}_G^T \mathbf{K} \mathbf{T}_G \tag{3}$$

In the above expressions, $\mathbf{x}$ denotes the state vector, $\mathbf{M}$ and $\mathbf{K}$ are the mass and stiffness matrices, respectively. Subscripts m and s denote master and slave DOFs, respectively.

O'Callahan [46] introduced inertia terms as pseudo-static forces to eliminate the drawback of static reduction. This technique is known as the Improved Reduced System (IRS) method. The IRS transformation may be conveniently written as

$$\mathbf{T}_{IRS} = \mathbf{T}_G + \mathbf{S}\mathbf{M}\mathbf{T}_G \mathbf{M}_R^{-1} \mathbf{K}_R \tag{4}$$

where

$$\mathbf{S} = \begin{bmatrix} \mathbf{0} & \mathbf{0} \\ \mathbf{0} & \mathbf{K}_{ss}^{-1} \end{bmatrix} \tag{5}$$

and the reduced mass and stiffness matrices are represented by

$$\mathbf{M}_{IRS} = \mathbf{T}_{IRS}^T \mathbf{M} \mathbf{T}_{IRS}, \quad \mathbf{K}_{IRS} = \mathbf{T}_{IRS}^T \mathbf{K} \mathbf{T}_{IRS} \tag{6}$$

The IRS method has a significant error in calculating higher-order frequencies. Friswell [47] improved the precision of the IRS through an iterative process called the iterative improved reduced system (IIRS), which aims to create a simplified version of a complex dynamic system while retaining its essential characteristics. The IIRS method starts by developing an initial reduced-order model, which is then iteratively improved by incorporating additional information from the full-order model. The first iteration of the IIRS is computed by Eq. (4), and the subsequent iterations are given by

$$\mathbf{T}_{IRS,i+1} = \mathbf{T}_G + \mathbf{SMT}_{IRS,i}\mathbf{M}_{IRS,i}^{-1}\mathbf{K}_{IRS,i} \qquad i = 2,3,\ldots \tag{7}$$

This iterative process results in a reduced model that captures the dynamic behavior of the original system while requiring significantly fewer computational resources. In the present study, the number of iterations is set to ten for all examples considered.

2.2. Teaching-learning-based optimization (TLBO)

Teaching-Learning-Based Optimization (TLBO), initially proposed by Rao et al. [48], is a population-based metaheuristic algorithm designed for solving optimization problems. This algorithm draws inspiration from the dynamics of the teaching and learning process observed in a classroom setting. Functioning as a nature-inspired approach, TLBO simulates the exchange of knowledge and skills within a collective of individuals, where each individual signifies a prospective solution to the given optimization problem. This collective is bifurcated into two distinct groups: the teachers and the learners.

During the teaching phase, the preeminent individuals, denoted as the teachers, extend assistance to the less proficient individuals, identified as the learners, to enhance their respective solutions. The spatial configuration of the learner in the ith iteration, characterized by D number of decision variables, is denoted as $\boldsymbol{x}_i = (x_i^1, x_i^2, \ldots, x_i^D)$. The mean of the class with NP number of learners (population) in the ith iteration is $\boldsymbol{x}_{mean} = \frac{1}{NP}\sum_{i=1}^{NP}\boldsymbol{x}_i$. The learner with the optimal solution within the population is chosen as the teacher, denoted as $\boldsymbol{x}_{teacher}$ for the ith iteration. The positions of each learner are then updated based on the following criteria:

$$\boldsymbol{x}_{i,new} = \boldsymbol{x}_{i,old} + \mathrm{rand}(0,1)(\boldsymbol{x}_{teacher} - T_F \cdot \boldsymbol{x}_{mean}) \tag{8}$$

$$T_F = \mathrm{round}[1 + \mathrm{rand}(0,1)\{2-1\}] \tag{9}$$

where the teaching factor T_F takes on a value of either 1 or 2 for each iteration, and " rand" represents a random number between 0 and 1. If the newly computed solution $\boldsymbol{x}_{i,new}$ yields a lower objective function value than the previous solution $\boldsymbol{x}_{i,old}$, the individual's old position is replaced with the new position. This updated position is then utilized as input in the subsequent learner phase.

In the learning phase, individuals designated as learners' endeavor to acquire knowledge from one another, aiming to enhance their respective solutions. Here, another learner $\boldsymbol{x}_j$ different from $\boldsymbol{x}_i$ is randomly selected, and the following criterion is applied:

$$\boldsymbol{x}_{i,new} = \begin{cases} \boldsymbol{x}_{i,old} + \mathrm{rand}(0,1)(\mathbf{x}_i - \boldsymbol{x}_j), & \text{if } f(\mathbf{x}_i) \le f(\boldsymbol{x}_j) \\ \boldsymbol{x}_{i,old} + \mathrm{rand}(0,1)(\mathbf{x}_j - \boldsymbol{x}_i), & \text{if } f(\mathbf{x}_i) > f(\boldsymbol{x}_j) \end{cases} \tag{10}$$

If the newly computed learner $\boldsymbol{x}_{i,new}$ exhibits a lower objective function value compared to the existing learner $\boldsymbol{x}_{i,old}$, the new learner supplants the old one. Conversely, if the objective function value of the new learner is not superior to the old learner, the position of the learner remains unchanged.

3. Damage detection strategy

3.1. Modeling damage

Damage is modeled by assigning a stiffness loss parameter (or damage index) αe ranging from the value of zero to one to any element of the structure. To do this, for the ith-damaged element, Young's modulus is assumed as

$$E_i^d = (1 - \alpha_i)E_i^u \quad (0 \leq \alpha_i \leq 1) \; (i = 1,2,\cdots,ne) \tag{11}$$

where the superscripts d and u denote damaged and undamaged states, respectively, and ne is the number of elements in the FE model. In this assumption, the mass of the structure remains unchanged [49]. The boundaries of the parameter α_i represent two limiting cases such as a fully damaged element and an intact element. By considering the damage condition of each element, it is possible to update their respective stiffness matrices. These updated stiffness matrices are then combined globally to form the overall stiffness matrix of the structure.

3.2. Modeling noise

Noise is an inevitable component in experimental modal testing due to various factors, reflecting real-life situations. Therefore, it is crucial to evaluate the effectiveness of the proposed approach using noisy data. To simulate real-world scenarios, the frequencies and mode shapes acquired through numerical analysis from the FE model are intentionally contaminated with noise. The addition of noise to the frequencies and mode shapes are, respectively, accomplished by the following expressions [49]:

$$\begin{aligned} f_i^{noise} &= \left(1 + \frac{\eta}{100} \times randn\right) f_i \\ \phi_{ij}^{noise} &= \left(1 + \frac{\eta}{100} \times randn\right) \phi_{ij} \end{aligned} \tag{12}$$

where, f_i is the ith frequency, ϕ_{ij} is the jth component of the ith mode shape vector, the superscript noise is the related value contaminated by noise, η is the noise level in percentage, and randn is a random scalar drawn from the standard normal distribution. Given that frequencies are generally less susceptible to measurement noise and can be measured with greater accuracy in comparison to mode shapes; unless explicitly mentioned otherwise, standard errors of ±0.15% and ±3% are assumed for the frequencies and mode shapes, respectively.

3.3. Optimization-based damage detection

The endeavor to detect damage through FE model updating is cast as an unconstrained optimization problem, wherein the identification of the location and extent of structural damage constitutes unknown parameters to be ascertained. This problem is mathematically formulated as follows:

$$\begin{aligned} &\text{Find } \mathbf{x} = \{\alpha_1, \alpha_2, \alpha_3, \ldots, \alpha_{ne}\} \\ &\text{minimize } f(\mathbf{x}) \\ &\text{subject to } 0 \leq \alpha_i \leq 1 \; (i = 1,2, \ldots, ne) \end{aligned} \tag{13}$$

where $f(\mathbf{x})$ is the objective function, and $\mathbf{x}$ is the design variable vector including the stiffness loss parameters of each element.

A novel objective function is considered in this study, which is a weighted linear combination of residuals depending on vibration parameters (frequencies, mode shapes, and modal flexibility), as in the following:

$$f(\mathbf{x}) = w_1 \sqrt{\frac{1}{nm}\sum_{i=1}^{nm}\left(\frac{f_i^E - f_i^C}{f_i^E}\right)^2} + w_2 \sqrt{\sum_{i=1}^{nm}[1 - \text{COMAC}(i)]^2} + w_3 \frac{\|\mathbf{F}^E - \mathbf{F}^C(\mathbf{x})\|_{Fro}}{\|\mathbf{F}^C\|_{Fro}} \tag{14}$$

where f_i is the ith frequency (in Hz), $\text{COMAC}(i)$ is the Coordinate Modal Assurance Criterion, $\mathbf{F}$ is the flexibility matrix, and the notation $\| \quad \|_{Fro}$ denotes the Frobenius norm of a matrix. The Coordinate Modal Assurance Criterion is given by [50]

$$\text{COMAC}(i) = \frac{\sum_{j=1}^{np}\left|\left(\phi_{ij}^E\right)^T \phi_{ij}^C\right|^2}{\sum_{j=1}^{np}\left(\phi_{ij}^E\right)^2 \sum_{j=1}^{np}\left(\phi_{ij}^C\right)^2} \quad (i = 1,2,\dots,nm) \tag{15}$$

and the flexibility matrix of a structure is defined as [51]

$$\mathbf{F} = \sum_{i=1}^{nm} \frac{1}{\omega_i^2}\mathbf{\Phi}_i\mathbf{\Phi}_i^T \tag{16}$$

In Eqs. (14-16), nm is the number of modes considered, np is the number of locations where the measurements are taken, $\omega_i$is the ith natural frequency (in rad/sec), $\mathbf{\Phi}_i = \{\phi_{11} \ \phi_{12} \ \cdots \ \phi_{1np}\}$ is the ith mode shape vector, w_1, w_2 and w_3 are the weighting coefficients, and the superscripts T, E, and C denote the transpose of a matrix, the measured and calculated values of the related quantity, respectively. The weighting coefficients signify the relative significance of each residual in the objective function as defined in Eq. (14), and their values are established through trial-and-error and/or engineering judgment. For the current investigation, based on a trial-and-error study, these coefficients are unity for which the best results are obtained.

In the optimization process, the set of stiffness loss parameters (design variables), denoted by $\mathbf{x}$ that minimizes the objective function $f(\mathbf{x})$, i.e., $f(\mathbf{x}) = 0$ theoretically, represents the sought-after damage status of the structure. In each iteration of updating the vector $\mathbf{x}$, a SAP2000 model of the monitored structure functions as a slave program for FE analyses. Through the OAPI feature, a connection is established between MATLAB and SAP2000, facilitating two-way data exchange. This seamless integration enables the automated execution of the iterative optimization process. The flowchart illustrating the proposed methodology is presented in Fig. 1.

4. Test examples and numerical results

In this section, the proposed methodology is utilized for damage assessment of truss structures. Two numerical examples compromising a 31-bar planar truss and a 52-bar space truss are chosen to demonstrate the effectiveness of the proposed method as shown in Fig. 2. Various possible damage scenarios are considered for each example under noise-free and noisy conditions. As mentioned earlier, structural damage is designated as a reduction in the Young's modulus of the relevant truss members. The assumption is made that the structures under consideration exhibit linear elastic behavior both before and after the occurrence of damage. Given the stochastic nature of the optimization process, five independent runs are conducted for each damage scenario. The best results from these runs are subsequently presented for damage assessment. Unless otherwise stated, the optimization parameters of the TLBO algorithm are assumed as follows: the population size $N_p = 35$ for the 31-bar truss and $N_p = 60$ for the space truss, respectively, the maximum number of iterations $maxIter = 100$, and the stop criterion $tol = 1 \times 10^{-4}$.

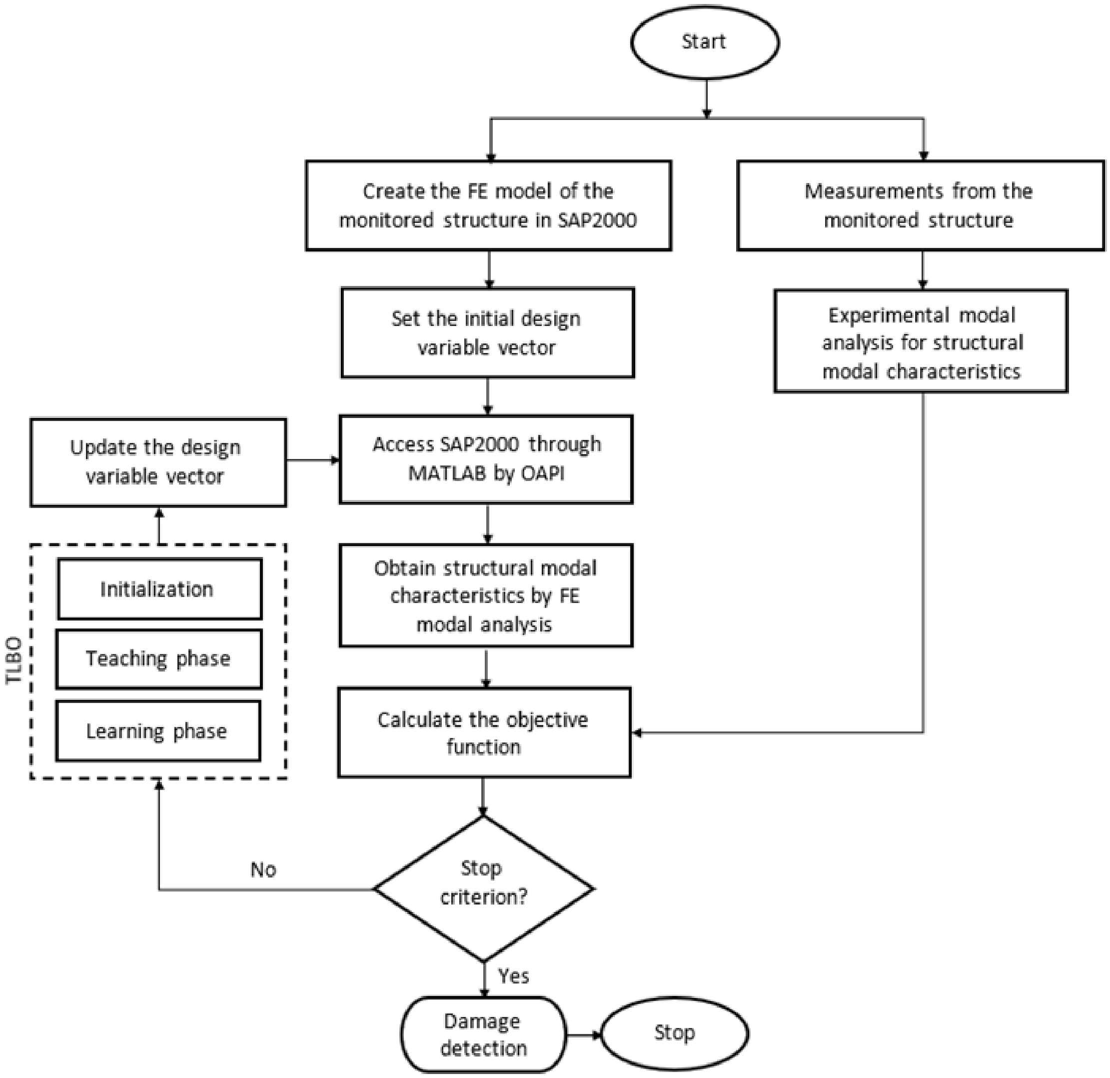
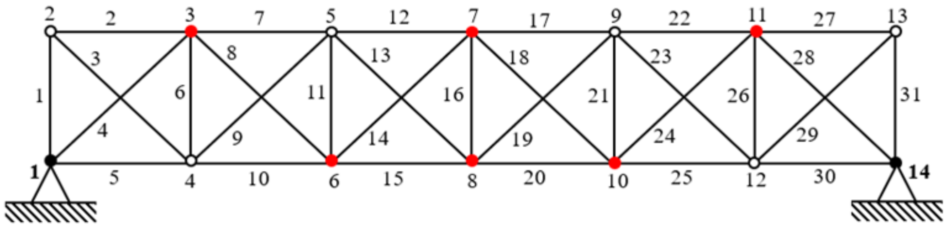


Fig. 1. The flowchart of the proposed damage detection methodology

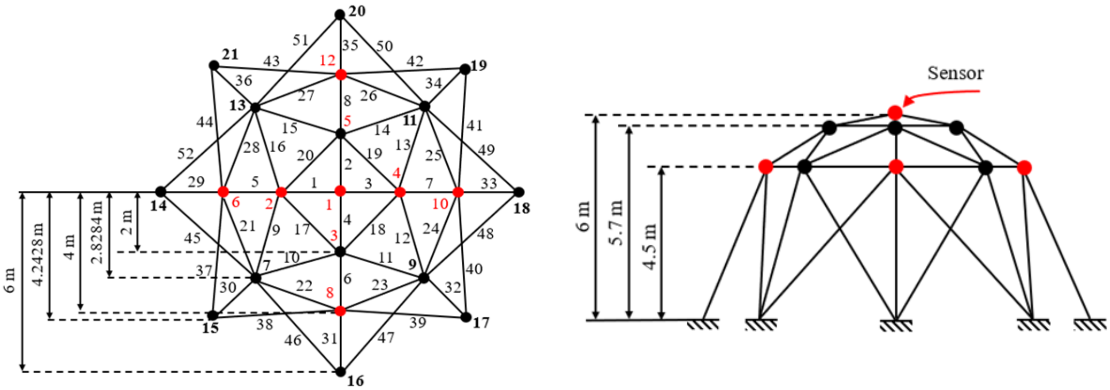
4.1. 31-bar planar truss

The first example is a 31-bar planar truss [27, 49]. The geometry of the structure and the sensor locations are shown in Fig. 2. In SAP2000, the finite element model is constituted of 31 planar bar elements, 14 nodes, and 28 DOFs. The length of horizontal and vertical bars is 1.52 m. For each truss member, Young's modulus $E = 70$ GPa, Poisson's ratio $\nu = 0.2$, and material density $\rho = 2770$ kg/m^3 are assumed. All truss members have a hollow section with an outer diameter of 150 mm and a wall thickness of 5.5 mm. In numerical simulations, three damage scenarios given in Table 1 are assumed.

For damage detection, the data from the six sensor locations corresponding to node numbers 3, 6, 7, 8, 10, and 11 are considered (see Fig. 2). Note that the sensors are installed on the same nodes as Das and Dhang [49] for comparison. Since each sensor measures the response of two DOFs of the corresponding node, the six installed sensors can measure the response of 12 DOFs, representing around 42% of the total DOFs of the system. The suitability of the installed sensor positions was confirmed by Das and Dhang [49] in which the IIRS method was used for model reduction.



a) 31-bar planar truss



Plan Elevation

b) 52-bar space truss

Fig. 2. Truss models considered in the study (red solid circles show the sensor locations)

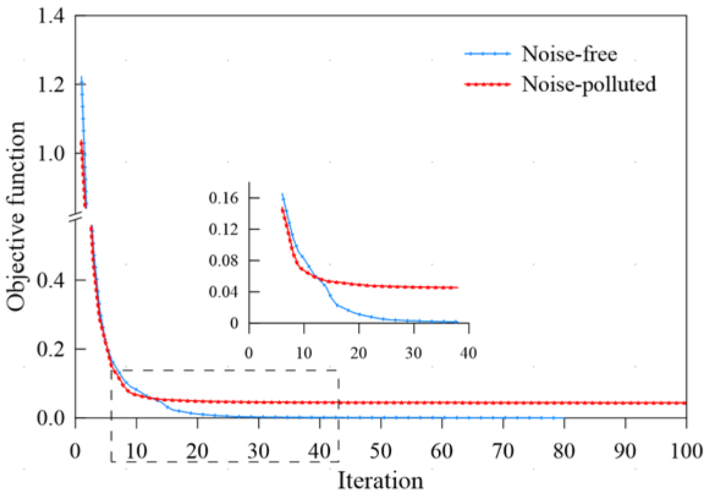


Fig. 3. Convergence history for scenario 2 of 31-bar planar truss

Table 1. Damage scenarios for 31-bar planar truss example [49]

Damage scenario	1		2	3	
Damaged element	11	25	16	1	2
Damage severity	0.25	0.15	0.30	0.30	0.20

Table 2. Statistical results of five independent runs for each scenario of Example 1

Scenario	Actual	Run 1	Run 2	Run 3	Run 4	Run 5	Average	Std. dev.
Noise-free case								
1	$\alpha_{11} = 0.25$	0.249856	0.249656	0.238522	0.24955	0.249608	0.2474384	0.004459
	$\alpha_{25} = 0.15$	0.149498	0.149714	0.121565	0.149349	0.149914	0.144008	0.011223
2	$\alpha_{16} = 0.30$	0.299692	0.299789	0.299897	0.299982	0.299793	0.2998306	0.000099
3	$\alpha_1 = 0.30$	0.298936	0.299753	0.29929	0.298883	0.300379	0.2994482	0.000559
	$\alpha_2 = 0.20$	0.20099	0.199861	0.199971	0.201092	0.197521	0.199887	0.001286
Noisy case								
1	$\alpha_{11} = 0.25$	0.250781	0.251368	0.243945	0.248879	0.248651	0.248725	0.002611
	$\alpha_{25} = 0.15$	0.150297	0.144805	0.132958	0.127051	0.14744	0.14051	0.008949
2	$\alpha_{16} = 0.30$	0.296641	0.290905	0.312839	0.302089	0.300403	0.300575	0.007235
3	$\alpha_1 = 0.30$	0.299372	0.307091	0.297657	0.295844	0.299577	0.299908	0.003836
	$\alpha_2 = 0.20$	0.172589	0.178869	0.138696	0.086822	0.182632	0.151922	0.036081

In Fig. 3, the convergence history of the proposed method for the 31-bar planar truss example with damage scenario 2 is shown. In the figure, the variations of the average of the best cost values for all runs with iteration numbers are given under noisy and noise-free cases. According to the figure, the algorithm quickly converges for both cases. In the noise-free case, the curve reaches a value in the order of 10^{-5} at 80 iterations, however, the same cannot be seen when the noise is considered. In the noisy case, the curve converges to a value in the order of 10^{-2}. The value of the average best cost for the noise-free case is smaller than that of the noisy case.

Table 2 presents the statistical results of five independent runs for each scenario of Example 1 with and without noise, respectively. As seen, damage indices are, in general, determined with small errors, i.e., within the range of 1-5%. Further, standard deviations for the damage detection results are relatively small, which shows the robustness of the present method. Note that some exceptions have also appeared. For multiple damages, the errors in damage indices, as well as standard deviations, are slightly increasing. Due to the obtained results being very close to the actual values, it appears possible to further reduce these errors by increasing the number of independent runs. However, due to the small error rates, it was not considered necessary to increase the number of independent runs in this study.

Fig. 4 shows the damage detection results for the 31-bar planar truss under three considered damage scenarios with and without noise. These figures showcase the best results obtained from the five runs conducted during the damage detection process. An overall analysis reveals that the proposed method accurately detects damages for all the scenarios considered. In the presence of noise, it is observed that false alarm elements are slightly more pronounced for damage scenarios 2 and 3. However, these false alarms have negligible magnitudes and do not significantly affect the correctness of the proposed method.

Table 3 compares the damage identification results of the present method and those of Das and Dang [49] who obtained their results by four well-established optimization algorithms, e.g., GA, PSO, Jaya, and TLBO, with a self-controlled multi-stage strategy (SCMS) for the 31-bar planar truss with and without noise. In the work by Das and Dang [49], cross-over percentage = 0.7, mutation percentage = 0.3, roulette wheel selection, and selection pressure = 0.8 for GA and $c_1 = c_2 = 2.05$, $w_{max} = 1.1$, and $w_{min} = 0.1$ for PSO were assumed as the specific control parameters, respectively. The population size was selected as 35 for all algorithms. In the tables, the performance of the algorithms is evaluated by comparing their mean damage indices (α_{mean}), the standard deviation of the damage indices, and the average number of structural analyses (MNSA).

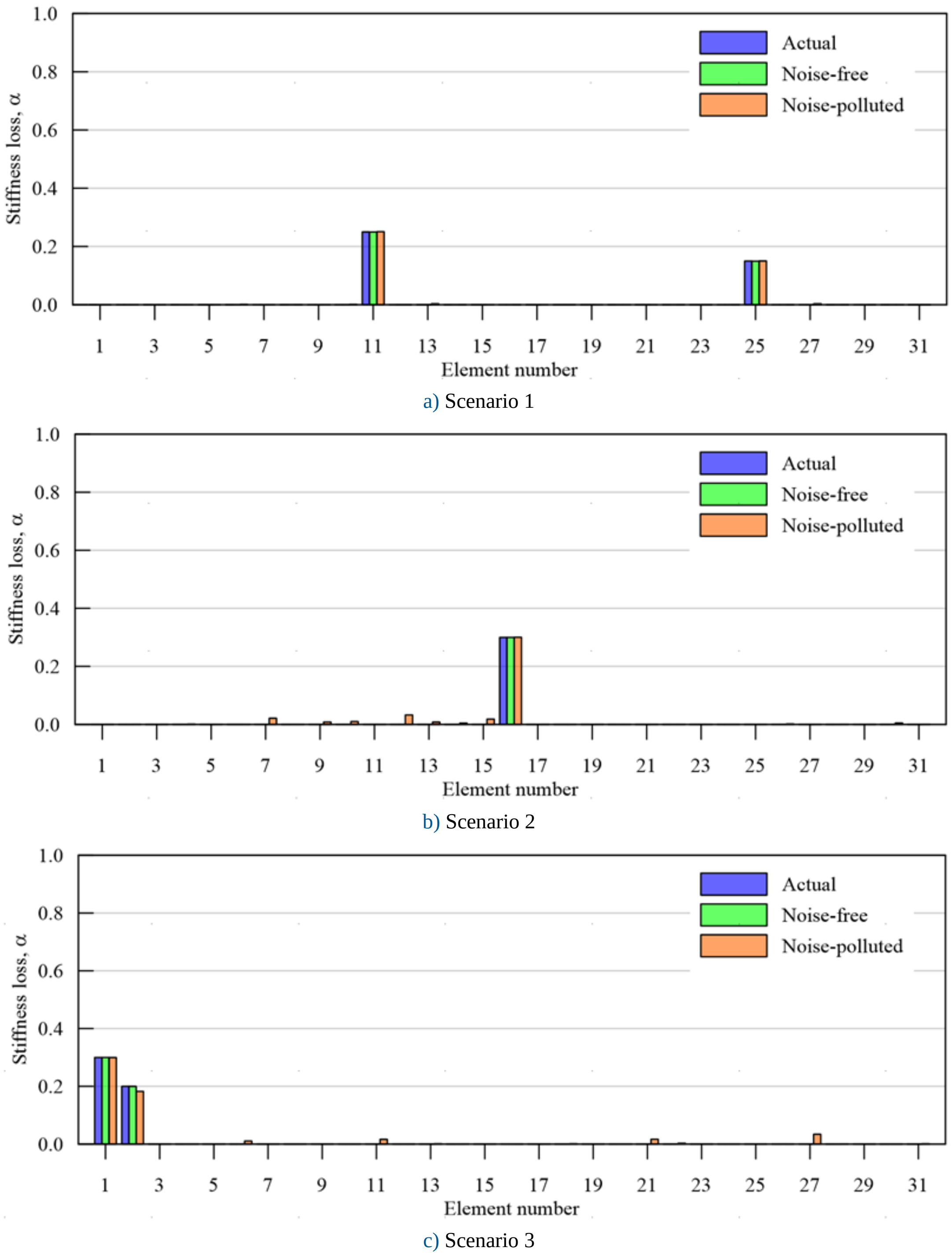


Fig. 4. Damage detection results for 31-bar planar truss under the scenarios considered

Table 3. Comparison of the present method for the 31-bar planar truss with different optimization algorithms using the multi-stage strategy of Ref. [49]

Scenario	GA			PSO			Jaya			TLBO			Present		
	α_{mean}	Std. dev.	MNSA	α_{mean}	Std. dev.	MNSA	α_{mean}	Std. dev.	MNSA	α_{mean}	Std. dev.	MNSA	α_{mean}	Std. dev.	MNSA
Noise-free case															
1	0.2501	8.4×10^{-5}	27,600	0.2500	0.0	6685	0.2500	3.7×10^{-5}	14,785	0.2500	6.4×10^{-5}	6000	0.2474	4.46×10^{-3}	6587
	0.1491	1.4×10^{-3}		0.1500	0.0		0.1500	4.0×10^{-4}		0.1500	8.0×10^{-4}		0.1440	1.12×10^{-2}	
2	0.3005	1.5×10^{-3}	12,120	0.3000	0.0	7780	0.2999	9.12×10^{-5}	2150	0.3000	4.0×10^{-5}	1585	0.2998	9.90×10^{-5}	5243
3	0.3000	4.6×10^{-4}	9650	0.3000	0.0	8260	0.3001	6.3×10^{-4}	5015	0.3000	1.0×10^{-4}	5160	0.2994	5.59×10^{-4}	6083
	0.1998	7.0×10^{-4}		0.2000	0.0		0.2001	1.5×10^{-5}		0.2000	2.0×10^{-4}		0.1999	1.29×10^{-3}	
Noisy case															
1	0.2506	7.4×10^{-4}	35,900	0.2633	3.16×10^{-2}	12,135	0.2500	6.8×10^{-4}	45,025	0.2500	8.2×10^{-4}	8665	0.2487	2.61×10^{-3}	7035
	0.1512	5.9×10^{-3}		0.1447	1.41×10^{-2}		0.1464	1.1×10^{-2}		0.1516	6.2×10^{-3}		0.1405	8.95×10^{-3}	
2	0.3006	1.3×10^{-3}	27,985	0.3214	2.84×10^{-2}	15,840	0.2996	8.1×10^{-4}	29,120	0.2996	7.9×10^{-4}	3960	0.3006	7.24×10^{-3}	7035
3	0.3007	2.4×10^{-3}	19,180	0.2988	4.83×10^{-3}	11,750	0.3016	2.5×10^{-3}	18,395	0.3017	2.3×10^{-3}	4715	0.2999	3.84×10^{-3}	7035
	0.1994	2.9×10^{-3}		0.2024	8.76×10^{-3}		0.1980	2.5×10^{-3}		0.1979	3.1×10^{-3}		0.1519	3.61×10^{-2}	

MNSA: Mean number of structural analyses

Considering the results without noise, despite being a single-stage strategy, the present method appears to perform relatively close to Jaya, while achieving results with fewer structural analyses than GA and PSO. In scenarios 1, 2, and 3, the present method required 76.13%, 56.74%, and 36.96% fewer MNSA than GA, respectively. Similarly, the present method needed 1.47%, 32.61%, and 26.36% fewer MNSA than PSO for scenarios 1, 2, and 3, respectively. The present method exhibited slightly worse performance than TLBO with SCMS in terms of MNSA. In terms of the error and standard deviation of the results, the present method exhibits similar performance with the other algorithms.

Regarding the results in the presence of noise, notably, the present method exhibited superior performance compared to the other algorithms in the noisy case except TLBO with SCMS. In terms of MNSA, the present method required 80.40%, 74.86%, and 63.32% fewer MNSA than GA, 42.03%, 55.59%, and 40.12% fewer MNSA than PSO, and 84.38%, 75.84%, and 61.76% fewer MNSA than Jaya algorithm for scenarios 1 to 3, respectively. As mentioned above, it is seen that the present method had a slightly worse performance than TLBO with SCMS in terms of MNSA. Moreover, the error in damage prediction and the standard deviation of the results exhibited similar patterns across all algorithms and remained within an acceptable range.

4.2. 52-bar planar truss

In the second example, a 52-bar space truss is considered [27]. The geometry of the structure is given in Fig. 2. The FE model consists of 52 3D-bar elements, 21 nodes, and 63 DOFs. The material properties of each truss member are Young's modulus $E = 210$ GPa, Poisson's ratio $\nu = 0.3$, and material density $\rho = 7800$ kg/m3. Again hollow-sectioned truss members with an outer diameter of 109.1 mm and a wall thickness of 3 mm are used in modeling. Three damage scenarios are assumed for numerical simulations as given in Table 4. Only seven sensors located at nodes 1, 2, 4, 6, 8, 10, and 12 are employed for obtaining the modal data. The sensor locations are the same as the work by Dinh-Cong et al. [27]. As a result, the FE model of the structure is reduced to a model with 21 DOFs for seven installed sensors, which represents about 33% of the total DOFs.

In Fig. 5, the convergence history of the proposed method for the 52-bar space truss example with damage scenario 2 is given. In the figure, the average of the best costs for all runs are given for noise-free and noise-polluted cases. As seen, the algorithm quickly converges for both cases. Without noise, the curve reaches a value in the order of 10-3 at 100 iterations, while it converges to a value in the order of 10-2 with noise. As in Example 1, the noise-free case more quickly converges than the noisy case.

In Table 5, the statistical results of five independent runs for each scenario of Example 2 are presented for both noise-free and noisy cases. As observed, the present method accurately identifies the damaged elements with only small errors in severity, specifically average errors of 2.5% in the noise-free case and 3.5% in the noisy case, respectively. These results indicate the method's robustness, as evidenced by the relatively small standard deviations. Although scenario 3 shows a slight increase in errors for the damage indices, they remain within acceptable limits.

Table 4. Damage scenarios for 52-bar space truss example [27]

Damage scenario	1	2		3		
Damaged element	9	10	51	9	10	49
Damage severity	0.25	0.20	0.30	0.20	0.30	0.30

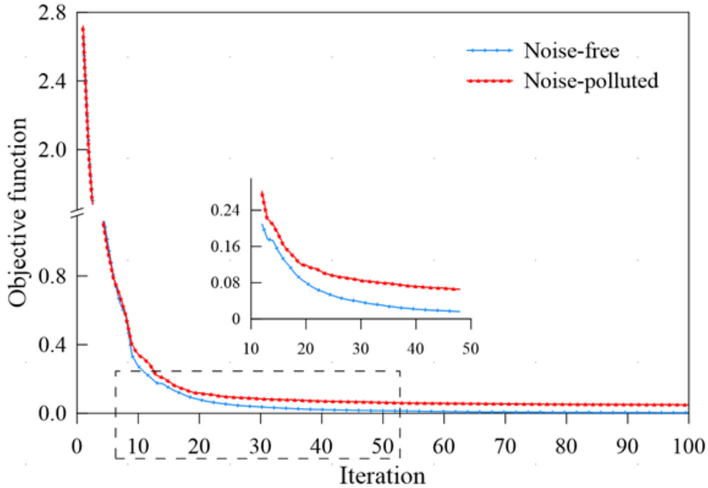
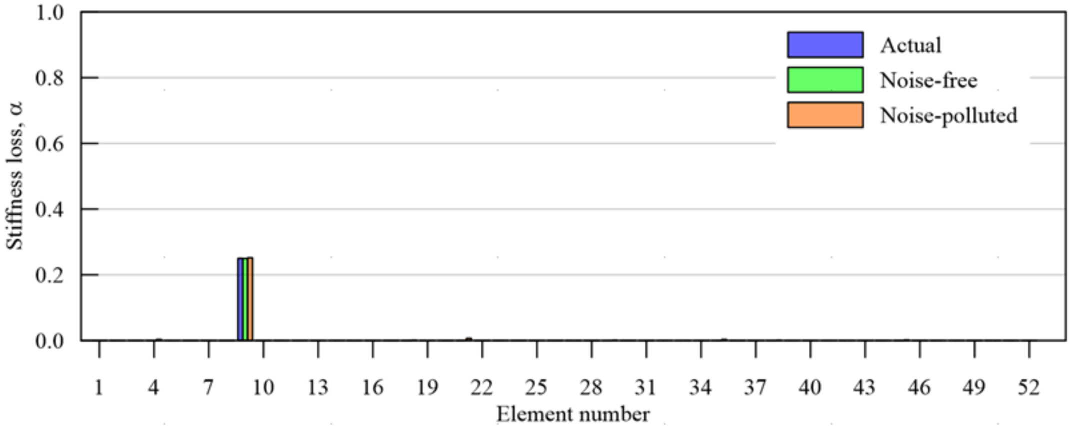


Fig. 5. Convergence history for scenario 2 of Example 2

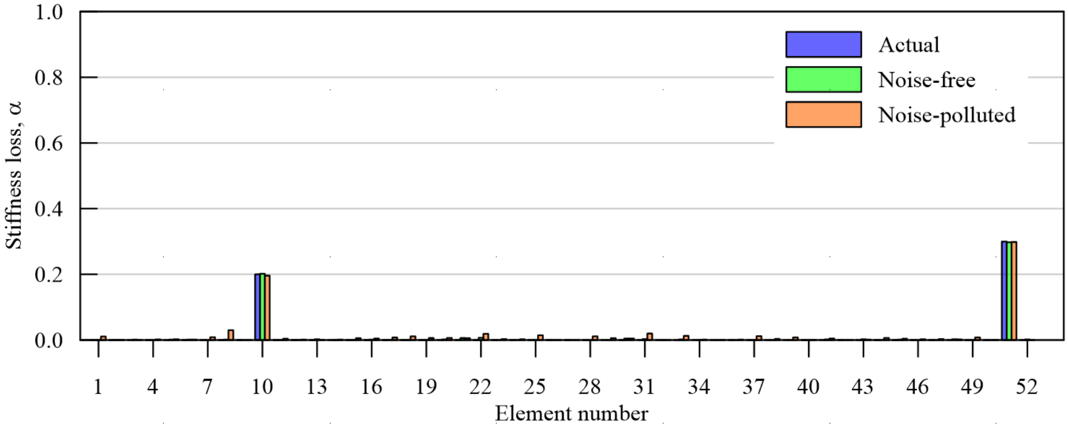
Table 5. Statistical results of five independent runs for each scenario of Example 2

Scenario	Actual	Run 1	Run 2	Run 3	Run 4	Run 5	Average	Std. dev.
Noise-free case								
1	$\alpha_9 = 0.25$	0.249709	0.249814	0.249902	0.247851	0.249938	0.249443	0.0008
2	$\alpha_{10} = 0.20$	0.195096	0.202012	0.197932	0.195885	0.19355	0.196895	0.002922
	$\alpha_{51} = 0.30$	0.278426	0.297855	0.299438	0.294443	0.294486	0.29293	0.007506
3	$\alpha_9 = 0.20$	0.179972	0.188175	0.192325	0.196821	0.192325	0.189924	0.005678
	$\alpha_{10} = 0.30$	0.289009	0.278039	0.287848	0.290622	0.287848	0.286673	0.004435
Noisy case								
1	$\alpha_9 = 0.25$	0.25	0.242156	0.253588	0.251853	0.237915	0.244667	0.005895
2	$\alpha_{10} = 0.20$	0.196009	0.192942	0.19578	0.191524	0.23068	0.201387	0.014745
	$\alpha_{51} = 0.30$	0.298515	0.273155	0.293699	0.316857	0.255885	0.287622	0.021104
3	$\alpha_9 = 0.20$	0.190387	0.188724	0.199436	0.1445	0.175856	0.179781	0.019178
	$\alpha_{10} = 0.30$	0.272378	0.293193	0.288663	0.268326	0.287413	0.281995	0.009783

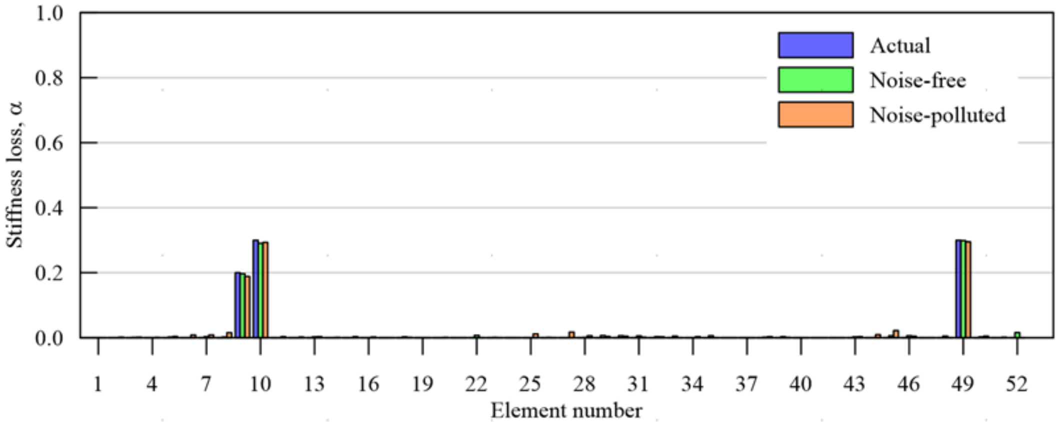
Fig. 6 illustrates the results of damage detection for the 52-bar planar truss across three specific damage scenarios, both with and without noise. These figures display the most favorable results achieved from the five runs conducted. It is evident that the proposed method successfully identifies damages for all the considered scenarios. In the presence of noise, it is noticeable that false alarms are slightly more prominent in damage scenarios 2 and 3. Nevertheless, these false alarms are of negligible magnitude and do not substantially impact the accuracy of the proposed method.



a) Scenario 1



b) Scenario 2



c) Scenario 3

Fig. 6. Damage detection results for 52-bar planar truss under the scenarios considered

4.3. Performance of the proposed method

In this section, we employ the following formulas, originally presented by Hoseini Vaez and Fallah [52] to further illustrate the performance of the current method:

Table 6. The error indices I_1 and I_2 calculated for each example in noise-free and noisy conditions

Structure	Scenario	Noise-free case			Noisy case		
		I_1	I_2	RMSE*	I_1	I_2	RMSE
31-bar planar truss	1	5.019307	0.046224	2.60×10^{-3}	6.836613	0.047632	3.02×10^{-3}
	2	0.056467	0.003076	1.36×10^{-4}	0.1918	0.234604	1.25×10^{-2}
	3	0.240433	0.002919	1.72×10^{-4}	24.0698	0.158867	1.13×10^{-2}
52-bar space truss	1	0.22288	0.005113	$1,55\times10^{-4}$	1.58568	0.06783	1.91×10^{-3}
	2	3.9093	0.113356	3.31×10^{-3}	4.819433	0.726136	1.72×10^{-2}
	3	10.74127	0.362242	9.84×10^{-3}	24.50623	0.675553	1.80×10^{-2}

$$RMSE = \sqrt{\sum_{i=1}^{n} \frac{(\alpha_i - \hat{\alpha}_i)^2}{n}}$$

$$I_1 = \sum_{i=1}^{m} \left| \frac{\alpha_i - \hat{\alpha}_i}{\alpha_i} \right| \times 100 \tag{17}$$

$$I_2 = \sum_{i=1}^{n-m} \hat{\alpha}_{i,mis} \tag{18}$$

where α_i represents the actual damage of the ith damaged element, $\hat{\alpha}_i$ denotes the estimated damage of the same element using the algorithm, and $\hat{\alpha}_{i,mis}$ is the estimated damage of the ith undamaged element. The variables m and n correspond to the number of damaged elements and the total number of elements in the structure, respectively. The error-index I_1 quantifies the absolute percent of error in the damaged elements, while the index I_2 represents the sum of the values of misidentified elements in each scenario. Therefore, smaller values of these indices indicate the more efficient the algorithm.

Table 6 shows I_1 and I_2 indices calculated for each example in noise-free and noisy conditions. In the table, it is also seen the root-mean-square error (RMSE) for each case as a separate column. Note that the calculations were made using the average of five independent runs for damage identification results of each scenario. Based on the table, both the I_2 error index and RMSE exhibit reasonable values close to zero across all damage scenarios in both considered examples. However, the I_1 error index sometimes shows unreasonably large values. Nevertheless, as mentioned in the reference study [52], since this index alone cannot provide a definitive assessment of the algorithm's performance, it can be concluded that the proposed method in the study demonstrates an exceptionally high level of performance when evaluated in conjunction with the other two error indices.

5. Conclusions

This investigation introduces a novel optimization-based procedure for FE modal updating, integrated with a commercial software package, to detect damage in intricate truss structures with limited modal data. The approach leverages SAP2000 as a slave program for FE analysis and employs TLBO as the optimization solver to address the FE model updating challenges. Implemented in MATLAB, the TLBO algorithm is seamlessly integrated with the SAP2000 OAPI feature, facilitating two-way data exchange throughout the optimization process. The efficacy of the proposed methodology is validated through the application of two numerical examples: a 31-bar planar truss and a 52-bar space truss, each subjected to various hypothetical damage scenarios. The outcomes from these examples lead to the following conclusions:

1. When compared to established algorithms like Genetic Algorithm (GA), Particle Swarm Optimization (PSO), Jaya, and Teaching-Learning-Based Optimization (TLBO), which employ multi-stage search strategies, the single-stage TLBO method introduced in this study presents a computationally efficient alternative. This efficiency is attributed to its utilization of a reduced number of structural analyses.
2. The damage detection technique proposed in this study, integrating a novel three-term objective function that includes frequency change, mode shape correlation, and flexibility, consistently identifies accurate damage locations, and reliably predicts damage magnitudes. This holds even when confronted with spatially incomplete measurements and relatively elevated levels of noise. Across the tested damage scenarios, minimal misidentification of elements with negligible damage severity was observed, and no damaged elements were overlooked.
3. The proposed strategy adeptly combines commercial FE modeling software with custom research software, enabling the integration of advanced technology for damage assessment in full-scale structures. This approach demonstrates promise for continued refinement and application in practical structural health monitoring systems. However, it is imperative to acknowledge that under real-world conditions, operational and environmental variables, including temperature, wind, and humidity, may exert adverse effects on the proposed technique's performance. Therefore, a comprehensive assessment of its efficacy under the diverse influences of these factors is essential before deploying the technique in real-world structural applications.

Conflict of interests

The author(s) declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

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Data availability statement

Data generated during the current study are available from the corresponding author upon reasonable request.

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