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Research Article

Damage Diagnosis in 3D Structures Using a Novel Hybrid Multiobjective Optimization and FE Model Updating Framework

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Structural damage detection is a well-known engineering inverse problem in which the extracting of damage information from the dynamic responses of the structure is considered a complex problem. Within that area, the damage tracking in 3D structures is evaluated as a more complex and difficult task. Swarm intelligence and evolutionary algorithms (EAs) can be well adapted for solving the problem. For this purpose, a hybrid elitist-guided search combining a multiobjective particle swarm optimization (MOPSO), Lévy flights (LFs), and the technique for the order of preference by similarity to ideal solution (TOPSIS) is evolved in this work. Modal characteristics are employed to develop the objective function by considering two subobjectives, namely, modal strain energy (MSTE) and mode shape (MS) subobjectives. The proposed framework is tested using a well-known benchmark model. The overall strong performance of the suggested method is maintained even under noisy conditions and in the case of incomplete mode shapes.

1. Introduction

Structural health monitoring (SHM) and failure diagnosis have recently witnessed increasing attention because of its importance for guaranteeing the integrity and service perfection of a structure. One of the main research foci of SHM is damage detection in structures under service, in which a preliminary assessment of damage is conducted to ensure the reliability and persistent performance of the structure. The evolution of structural damage detection techniques has been mainly inspired by the invention of accurate sensors and transducers in addition to improvements in signal processing techniques, which in combination were applied to nondestructive vibrational testing that reveals the dynamic characteristics of a structure. Those dynamic characteristics carry the changes in real structural parameters that in turn illustrate the existence and rate of structural damage [1–3].

Structural damage could be defined as variations between the FE model of a structure and the structure in-service that brings the concept of FE model updating into a picture [4]. FE model updating can provide an efficient way of tracking damage in structures under service. For a structural damage identification problem, the structural parameters related to the FE model of a structure are slightly and gradually regulated and dynamic responses are registered. Thereafter, distortions between the model's and measured dynamic responses are minimized until a relative consistency is reached. During that process, such local modifications can indicate damage in the studied structure. The minimization task can be thought through by utilizing efficient optimization algorithms [5–7].

In order to integrate the FE model updating into a structural damage tracking procedure, the basic task is to establish the dynamic characteristic subobjectives. The developed subobjectives are milestones in formulating the objective function that addresses the optimization problem of damage characterization. Modal analysis can provide an effective manner for gathering dynamic features. Mode shapes (MSs) are fundamental characteristics that can give general information about the alterations that have occurred in a structure due to damage. For that reason, MS subobjective can be developed by using some correlation paradigms such as the

modal assurance criterion (MAC) [8, 9]. Another modal property with great damage sensitivity, modal strain energy (MSTE), has been used by various researchers [10–14]. It performs efficiently when utilized for tackling damage problems in complex structures experiencing damage. Furthermore, MSTE is applicable in three-dimensional structures [14, 15]. Hence, both mode shape-based and MSTE-based subobjectives are more than sufficient to be employed in this research.

Computational intelligence has been implemented for solving complex prediction, diagnosis, and detection problems in various fields such as mechanical engineering [16–18], computer science [19, 20], biomedical engineering [21, 22], and electrical engineering [23]. As major disciplines of computational intelligence, swarm intelligence and EAs are powerful stochastic optimization techniques that have been implemented for solving various engineering problems in recent years. Single-objective EAs have been widely and successfully utilized for damage localization in structures. Research has shown the efficacy of genetic algorithms (GAs), the most common form of EA [24–27]. Other representative research can be found in [28, 29]. Swarm intelligent algorithms have also been implemented for the same purpose. Ding et al. [30] developed a hybrid swarm for damage identification using modal properties with pleasing results. Qian et al. [31] implemented a hybrid PSO simplex method for delamination detection in laminated beams using a delamination parameter-based objective function with robustness and efficient performance. Kang et al. [32] as well as Gökdağ and Yildiz [33] proposed two different PSO versions to track damage with successful performance. Zhu et al. [34] developed a bird mating optimizer (BMO) in the time-frequency domain for damage detection in 2D structures. Other techniques have been used efficiently, as in the work of Seyedpoor et al. [35, 36]. From the above survey, it is seen that single-objective EAs have performed well in solving structural damage detection problems. Nevertheless, most applications were 1D or 2D problems.

Multiobjective EAs (MOEAs) have also been implemented by various researchers for damage localization in structures. Cha and Buyukozturk [14, 15] developed a MOEA for damage prognostic in three-dimensional structures. Their research outcomes showed the robustness of the proposed method even under noisy environments. Liu et al. [37] used natural frequency and MS subobjectives with the successful incorporation of the weighted sum method and a GA to perform a multiobjective optimization for damage identification. Jung et al. [38] utilized the NSGAII for damage identification in truss structures, concluding that further enhancements were needed for the proposed method to be recommended for damage deduction. NSGAII was also implemented successfully by Shabbir and Omenzetter [39]. Other representative research into the application of NSGAII for damage detection can be found in [40, 41]. Farokhzad et al. [42] compared multiobjective GA (MOGA) and modified multiobjective GA (MMOGA) for damage localization in Timoshenko beams, with remarkable results obtained from MMOGA. MOGA was also successfully employed for damage detection in truss by Jung et al. [43].

Other MOEAs have been implemented for structural damage identification, as in [44, 45].

A literature survey of the implementation of MOEAs showed that relevant research has rarely addressed the problem of structural damage in complex structures. Hence, further research is important to explore the effectiveness of MOEAs and swarm intelligence in structural damage localization. Moreover, it is essential to introduce more powerful algorithms that can efficiently and accurately solve the problem of damage identification in 3D structures. For those reasons, a novel multiobjective optimization algorithm combines the multiobjective particle swarm optimization (MOPSO), Lévy flights (LFs), and the technique for the order of preference by similarity to ideal solution (TOPSIS) with a FE model updating framework is proposed for solving the problem of damage estimation in complex 3D structures. The coherence of the proposed algorithm can be measured by the combination between the global and local search of MOPSO and LFs. Furthermore, the integration of TOPSIS inside the algorithm to iteratively select a leader solution can provide an efficient paradigm that improves the overall performance of the algorithm.

This work illustrates the application of the novel multiobjective optimization algorithm called MOLFPSO/TOPSIS applied on FE model updating for structural damage localization. Two dynamic characteristic-based subobjectives, namely, MS- and MSTE-based subobjectives, are embodied in an objective function. The proposed technique is applied on a 4-story benchmark building model. In order to examine the performance of the developed technique, two damage scenarios are studied. Furthermore, the algorithm is tested under noisy conditions in correspondence to the two damage scenarios. Also, the incomplete mode shape problem is evaluated. At last, a detailed discussion of the performance of the suggested method is presented.

2. The Objective Function

It has been observed that in structural damage tracking combined with the FE model updating, the most critical key point is the proper selection of dynamic characteristics that includes the changes in structural parameters due to the occurrence of structural damage. On that basis, the subobjectives of errors between the dynamic features of the FE model of the intact structure and those measured from the damaged structure are developed. By the formulation of those subobjectives, they can be merged in such a way that an objective function for the damage detection optimization problem can be established. In the current research, both MS- and MSTE-based subobjectives are employed and engrafted into the objective function to be solved for the damage localization.

To develop the MS subobjective, a correlation technique should be employed [8]. One of the most commonly used correlation techniques is the MAC [46]. The MAC measures the uniformity between two vectors, one of which being a reference MS and the other a measured MS. The MAC matrix can be stated as

$$\text{MAC}(\{\varphi_I\}, \{\varphi_D\}) = \frac{\left|\{\varphi_I^*\}^T \{\varphi_D\}\right|^2}{\{\varphi_I^*\}^T \{\varphi_I\}\{\varphi_D^*\}^T \{\varphi_D\}}, \tag{1}$$

where $\{\varphi\}$ is the MS, I and D represent the undamaged and the damaged structures, respectively, and T and $*$ are the transpose and the conjugate. It is defined that full correlation is observed when MAC is one and no correlation is deduced when MAC is zero.

The MS subobjective can be expressed as

$$F_1(\varphi^I, \varphi^D) = \sum_{i=1}^{M} (1 - \text{diag}\,(\text{MAC}_i(\{\varphi_i^I\}, \{\varphi_i^D\}))), \tag{2}$$

where $F_1(\varphi^I, \varphi^D)$ is the MS subobjective, i is the MS number, and M is the total number of MSs diag is the diagonal element of MAC.

MSTE can serve as a sensitive indicator of structural damage. In a large-scale complex structure, MSTE can hold better information about the existence and position of minor damage than other modal characteristics. One of the most commonly occurring types of structural damage can be thought of as a stiffness lessening [47]. In spite of the reality that stiffness alterations cannot reflect all sorts of structural damage, it can be adopted in this research to simulate linearly structural damage. Consequently, by handling the MSs of the structure and the stiffness matrix $\mathbf{K}$ of the model, the MSTEs corresponding to healthy and damaged structures can be defined as

$$\text{MSTE}_i^I(\varphi_i^I, K) = \frac{1}{2} \varphi_i^{I^T} K \varphi_i^I,$$
$$\text{MSTE}_i^D(\varphi_i^D, K) = \frac{1}{2} \varphi_i^{D^T} K \varphi_i^D, \tag{3}$$

where MTTE_i^I and MSTE_i^D are the MSTEs of the robust and deteriorated structures for the ith MS, respectively. The global MSTE subobjective can be written as

$$F_2(\varphi^I, \varphi^D, K) = \sum_{i=1}^{M} \left(1 - \frac{\varphi_i^{I^T} K \varphi_i^I}{\varphi_i^{D^T} K \varphi_i^D}\right)^2, \tag{4}$$

where F_2 is the MSTE subobjective. Based on the above description, the overall hybrid objective function is built as

$$\text{Min}\,(F_1, F_2) = \text{Min}\,\left(\sum_{i=1}^{M}(1 - \text{diag}\,(\text{MAC}_i(\{\varphi_i^I\}, \{\varphi_i^D\}))),\right.$$
$$\left.\sum_{i=1}^{M}\left(1 - \frac{\varphi_i^{I^T} K \varphi_i^I}{\varphi_i^{D^T} K \varphi_i^D}\right)^2\right). \tag{5}$$

Damage causes changes in the mechanical parameters of a structure [48]. The parametric changes can be directly used to track damage by performing a FE model updating framework [8, 14]. Commonly, to select the appropriate updating parameters that can be used as damage indicators, the possible damage patterns must be defined depending on the structure under consideration and loading conditions. Some

recommendations can be followed before choosing the updating parameters. First, greater importance should be assigned to the positions where structural damage is more likely to exist. Then, dynamic characteristics that are more damage-sensitive must be considered. Finally, efforts should be made to reduce the size of the updating parameter set so that the overall complexity of the problem can be tackled, by ignoring structural parameters that do not illustrate possible existing damage scenarios [49, 50].

One of the most widely used parameterization methods is to adopt the material and geometrical properties directly [51]. Material properties can be chosen as damage indexes for tracking structural damage, because the stiffness and mass matrices are proportional to material properties. A useful strategy is to develop a vector of damage indexes for all elements (el) as $\Theta = [\theta_1, \theta_2, \dots, \theta_{el}]$, where $\theta \,\epsilon\, [0, 1]$. If we choose a damage conductor as v, Θ is utilized to reflect the variations between the FE model parameter v^I and the parameter v^U related to damage simulation. The damage parameter can be defined as

$$v_i^U = v_i^I(1 - \theta_i), \tag{6}$$

and the changes in model's elemental matrixes $\mathbf{M}$ and $\mathbf{K}$ can be written as

$$M_i^U = M_i^I + \Delta M_i,$$
$$K_i^U = K_i^I + \Delta K_i,$$
$$\Delta M_i = v_i^U . M_i^I,$$
$$\Delta K_i = v_i^U . K_i^I, \tag{7}$$

where ΔM_i and ΔK_i are the deviations in model's matrixes.

To examine the performance of the proposed MOLFPSO/TOPSIS, the structural damage is presumed to be a reduction of some elements' moduli of elasticity (E). It is important to mention that reductions in E cannot mimic all sorts of structural damage, but it can be used to simulate damage to check the performance and robustness of the proposed technique.

3. Structural Damage Localization Framework

To tackle the structural damage estimation problem, it is essential to organize the optimization problem into two main divisions: the single-objective EAs and the MOEAs. The key points to understand the differences between the two divisions can be shown in [52, 53].

Structural damage tracking using MOEAs and FE model updating is shown in Figure 1. We summarize the framework as follows: initially, a FE model of the robust structure is evolved and the damage indicators are selected. Then, the framework is partitioned into two subprocesses. The former is the damage simulation process where the damage-simulated MSTE and MS subobjectives can be deduced. The second subprocess is to perform the minimization task applied on the objective function. The detailed overall framework can be well observed in [52].
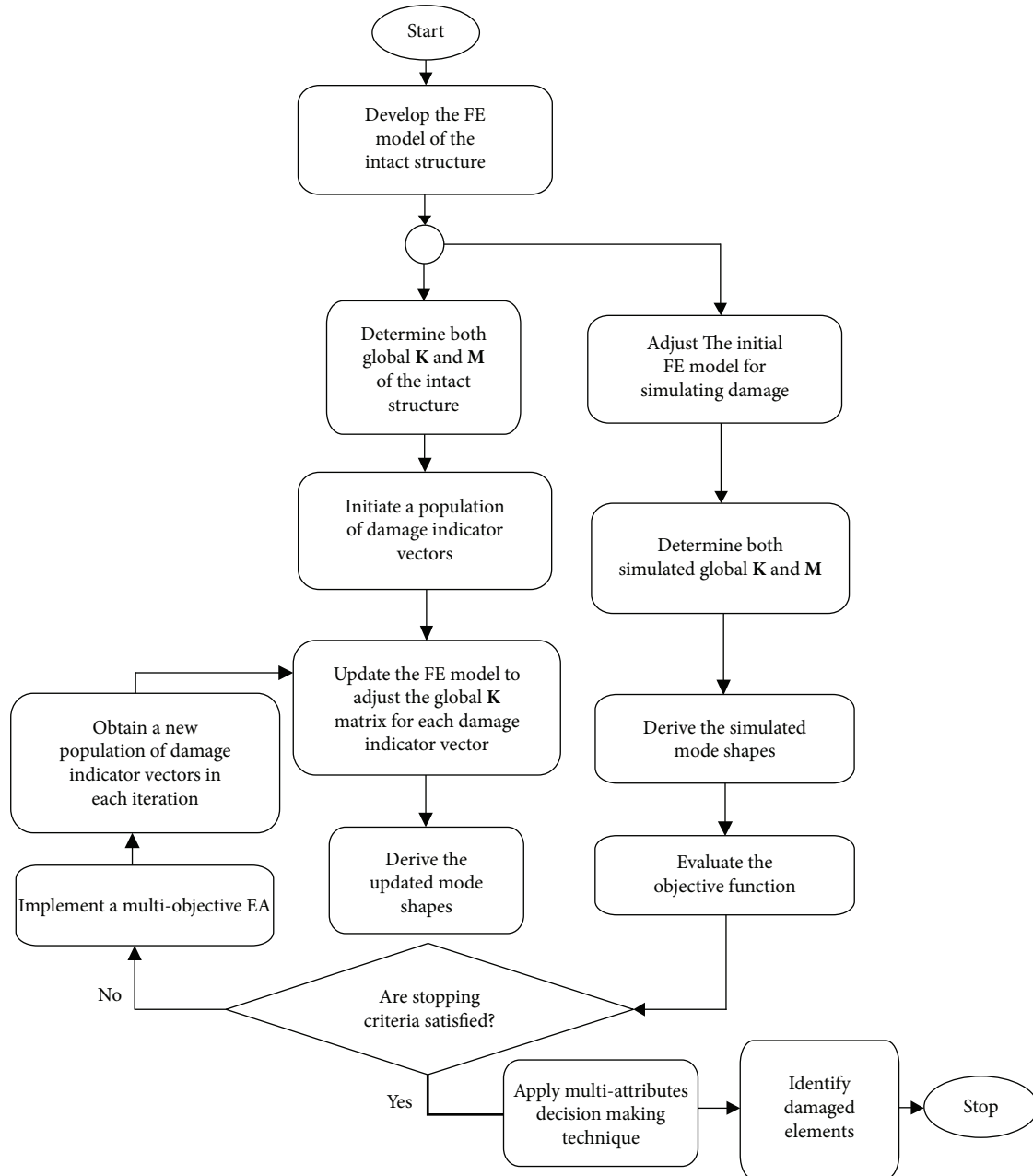
FIGURE 1: Damage prognostic paradigm using the MOEAs and FE model updating.

4. The MOLFPSO/TOPSIS

By following back to the excellent research conducted by Cha and Buyukozturk [14, 15], it is observed that one dynamic characteristic has been used inside the multiobjective optimization problem by dividing the MSTE-based objective function into two subobjectives. In the current research, an improvement is suggested by adding an extra subobjective that relies on the MSs. The use of independent mode shape subobjective can study the alterations in the structure independent from the stiffness matrix utilized in MSTE and without losing the benefit of damage detectability when only MSTE is utilized. This can help

to improve the overall ability of the damage identification procedure when noisy conditions exist as well as when the complete MSs cannot be obtained. Moreover, because MSTE can describe only the linear type of structural damage, adding the mode shape term can enhance the damage deducibility of other types.

The MOLFPSO/TOPSIS algorithm combines various paradigms and concepts to perform a strong and reliable multiobjective optimization framework to solve complex problems comprising the problem of damage tracking in structures with FE model updating. To provide a comprehensive elucidation of the developed method, some preliminary concepts and techniques must be explained. Firstly, Lévy

1. Create a population of random solutions *Pop* and corresponding speeds *Vel*.
2. Initialize an external archive *Ac* and define a memory of flight experience for each individual, i.e. *Pbest*.
3. Evaluate *Pop* using the multi-objective functions.
4. Find the non-dominated solutions and store them in *Ac*.
5. Develop hypercubes of the search space and distribute the individuals within the hypercubes using the multi-objective function values.
6. Apply TOPSIS on *Ac* to determine the leader solution or the global best individual *Gbest*.
7. **While** stopping criteria are not satisfied **do**:
   a) Generate a new population *A* by using LFs using a modified version of Eq. (9) as:
   $$s = a_0(Gbest - x_{G,i}) \oplus \text{Lévy}(\lambda) \sim 0.01(u/|v|^{1/\lambda})(Gbest - X_{G,i})$$
   $$\overline{P_{i+1}} = P_i + s$$
   b) Evaluate all particles in *A*, compare *A* with *Pop* using the non-domination criterion and update *Pop*.
   c) Generate a new population *B* by using PSO as:
   $$V_i^{t+1} = W \times V_i^t + r_1 \times (Pbest_i - P_i) + r_2 \times (Gbest - P_i),$$
   $$P_{i+1} = P_i + v_i^{t+1},$$
   where p_i is the current particle; v_i is the particle's velocity; w is the inertia factor; r_1 and r_2 are acceleration coefficients; r_1 and r_2 imply random numbers $\in [0, 1]$; t is the current generation number.
   d) Evaluate all particles in *B*, compare *B* with *Pop* using the non-domination criterion and update *Pop*.
   e) Remove the non-dominated solutions and fill the empty positions with randomly created solutions as:
   $$In_i = randper(P_{new,i}),$$
   $$\overline{P_{new,i}} = rnd(0, 1) + P_{new}(In_i),$$
   where *randper* is a Gaussian random permutation operator; $P_{new,i}$ is the ith removed dominated solution; *rnd* is a random number $\in [0, 1]$.
   f) Evaluate all particles in *Pop* and insert the non-dominated solution into *Ac*.
   g) Update the hybercubes in the current *Ac*.
   h) Remove the extra individuals in *Ac* by eliminating the crowded individuals within the corresponding hypercubes.
   i) Apply TOPSIS on *Ac* to determine the global best individual *Gbest*.
   j) Update *Pbest* for all individuals.
8 **End.**

ALGORITHM 1

flights (LFs) can be defined as random permutations that are capable of mimicking the random movements of creatures seeking food, reproduction, or other activities [54]. LFs can be implemented efficiently to expose unknown search space for optimization purposes. Moreover, LFs can perform both global and local searches around promising solutions that can be referred to as the exploration and exploitation of the global search space. To generate a new solution X_i^{t+1} by LF, (8) can be used:

$$X_i^{t+1} = X_i^t + s, \tag{8}$$

where *s* is the step size, proposed by Yang and Deb [55]:

$$s = a_0(x_{G,j} - x_{G,i}) \oplus \text{Lévy}(\lambda) \sim 0.01 \frac{u}{|v|^{1/\lambda}} (X_{G,j} - X_{G,i}), \tag{9}$$

where a_0 is a constant, $X_{G,j}$ and $X_{G,i}$ are two random solutions, and *u* and *v* can be defined as

$$\begin{aligned} u &= N(0, \sigma_u^2), \\ v &= N(0, \sigma_v^2), \end{aligned} \tag{10}$$

where $\sigma_u = [\Gamma(1 + \lambda) \sin(\pi\lambda/2)/\Gamma[(1 + \lambda)/2]\lambda 2^{(\lambda-1)/2}]^{1/\beta}$ with $1 \le \lambda \le 2$ is an index, Γ is a gamma function, and $\sigma_v = 1$.

TOPSIS is a MCDM technique that was proposed by Hwang and Yoon [56]. From any decision matrix with *m* number of alternatives and *n* number of attributes, it chooses two sets of solutions known as the positive (X^+) and negative (X^-) ideal solutions. The solution with the best data from all the alternatives is called the positive ideal solution; similarly, the negative ideal solution has the worst data from all the alternatives. TOPSIS calculates the Euclidean distance of all points (alternatives) from two positive and negative solutions and compares them. The point that has the least Euclidean
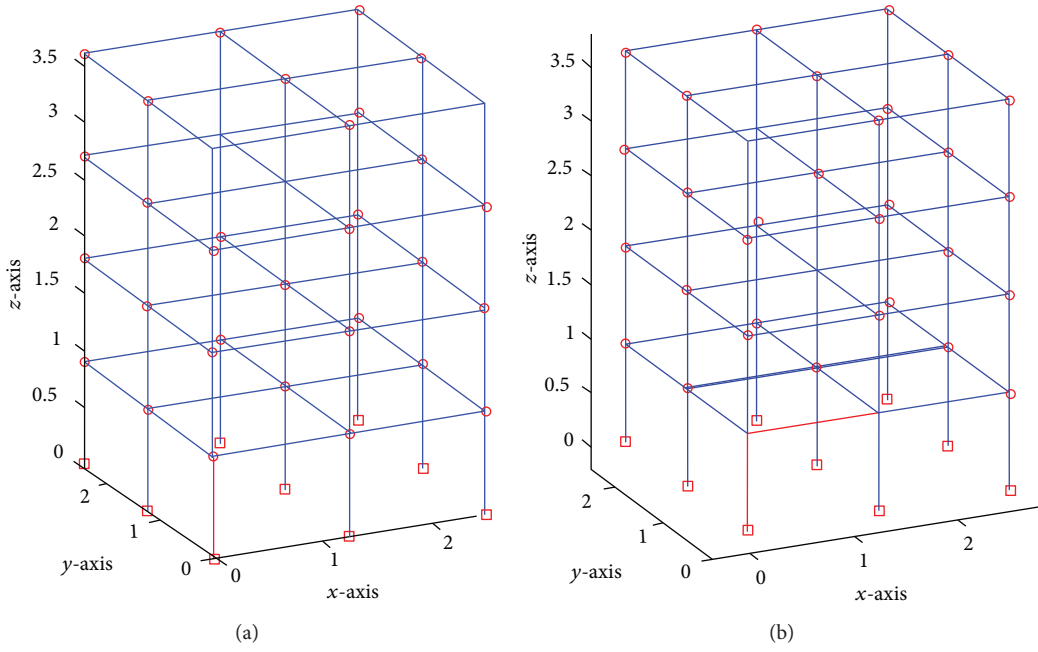
(a)

(b)

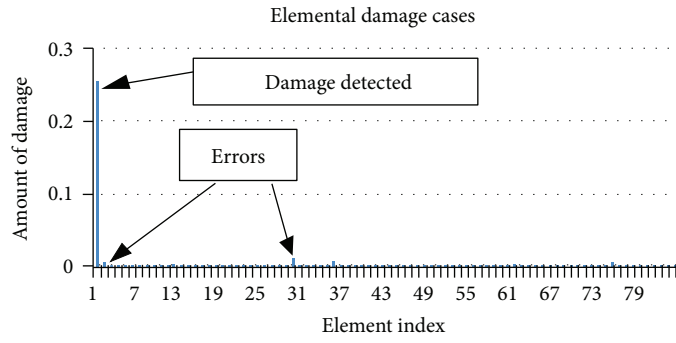FIGURE 2: Damage scenarios: (a) scenario 1 and (b) scenario 2.
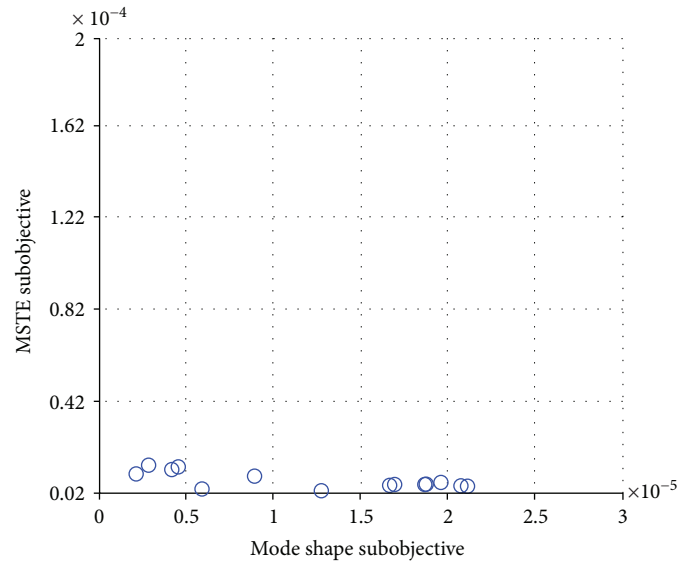

FIGURE 3: Damage locations in damage scenario 1.

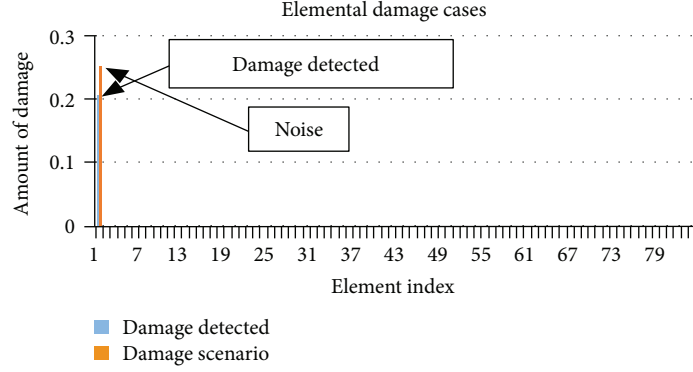FIGURE 4: Optimal front obtained from MOLFPSO/TOPSIS in damage scenario 1.

FIGURE 5: Damage positions in damage scenario 1 with noisy MSs.

distance from (X^+) and the greatest distance from (X^-) is considered the best. The steps of applying TOPSIS are as follows:

Step 1. The input **x** matrix contains $m \times n$ elements (the elements of **x** matrix are the Pareto solutions).

Step 2. To convert the dimensional problem into a nondimensional problem, a normalized decision matrix is performed from the **x** matrix.

$$\bar{x}_{ij} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^{m} x_{ij}^2}}, \tag{11}$$

where $i = 1, \ldots, m$ and $j = 1, \ldots, n$, $(m = 100 \text{ and } n = 5)$.

Step 3. By assuming a set of weights for each attribute w_j for $j = 1, \ldots n$, we can find the weighted normalized decision matrix **v**.

$$v_{ij} = w_j \bar{x}_{ij}, \tag{12}$$

where $\sum_{j=1}^{n} w_j = 1$.

Step 4. Determine the positive and negative ideal solutions.

$$\begin{aligned} X^+ &= \{v_1^+, \ldots, v_n^+\}, \\ X^- &= \{v_1^-, \ldots, v_n^-\}, \end{aligned} \tag{13}$$

where $v_j^+ = \{\max_i v_{ij} | j \in J, \min_i v_{ij} | j \in J'\}$ and $v_j^- = \{\min_i v_{ij} | j \in J, \max_i v_{ij} | j \in J'\}$, where J is the set of benefit attributes and J' is the set of cost attributes.

Step 5. Calculate the distances d_i^+ and d_i^- from the positive ideal and negative ideal solution, respectively.

$$\begin{aligned} d_i^+ &= \sqrt{\sum_{j=1}^{n} \left(v_j^+ - v_{ij}\right)^2}, \\ d_i^- &= \sqrt{\sum_{j=1}^{n} \left(v_j^- - v_{ij}\right)^2}, \end{aligned} \tag{14}$$
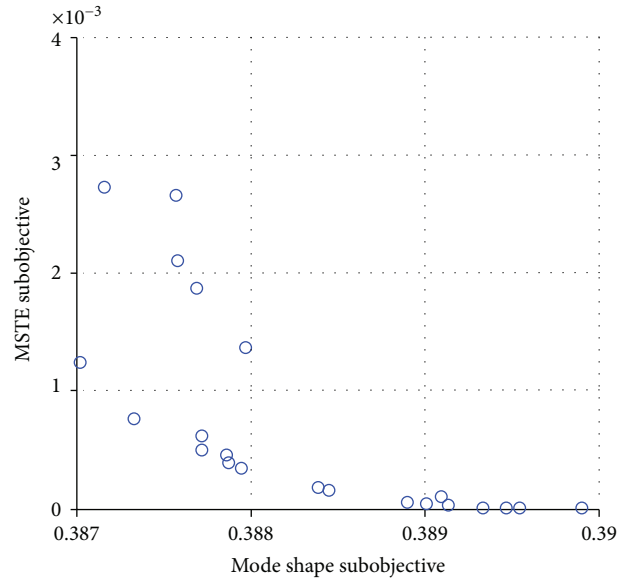

FIGURE 6: Optimal front obtained from MOLFPSO/TOPSIS in damage scenario 1 under noisy conditions.

Step 6. Determine the relative closeness of alternatives to the ideal solution.

$$C_i^+ = \frac{d_i^-}{d_i^- + d_i^+}, \tag{15}$$

where $0 \leq C_i^+ \leq 1$ and the best solutions have relative closeness C_i^+ closest to 1.

MOPSO was originally proposed by Coello and Lechuga [57] and further explained by Coello and Reyes-Sierra [58]. They extended the PSO algorithm into MOPSO by employing the Pareto ranking scheme as well as initializing an archive or repository to register the superior performance of any individual in each generation by means of sets of nondominated solutions. The archive is exploited to choose a global best solution that leads the swarm to reach the Pareto front. In each generation, the archive should be updated by a spatially or geographically based process where the search space is partitioned into a set of hypercubes using multiobjective function rates.
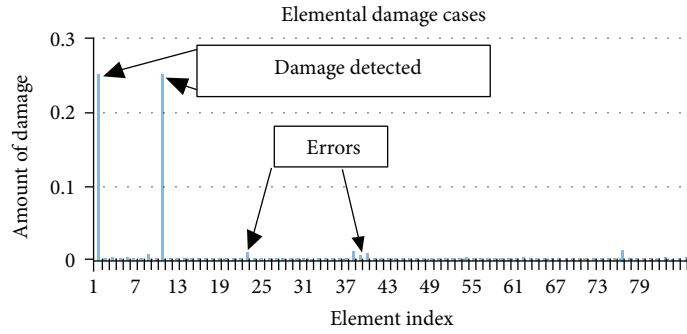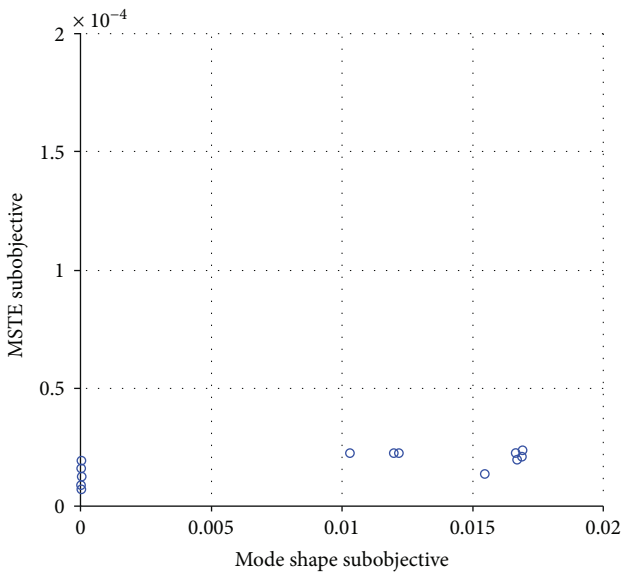
Figure 7: Damage locations in damage scenario 2.

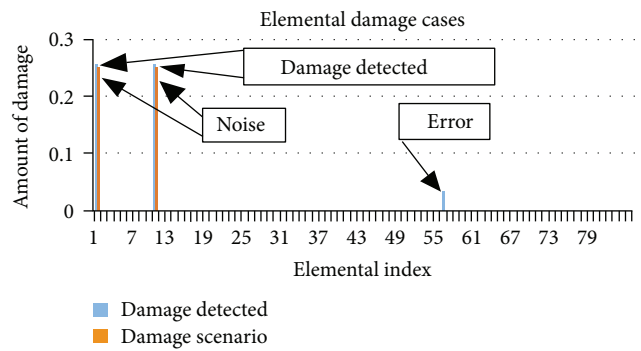Figure 8: Optimal front obtained from MOLFPSO/TOPSIS in damage scenario 2.

Figure 9: Damage positions in damage scenario 2 with noisy MSs.
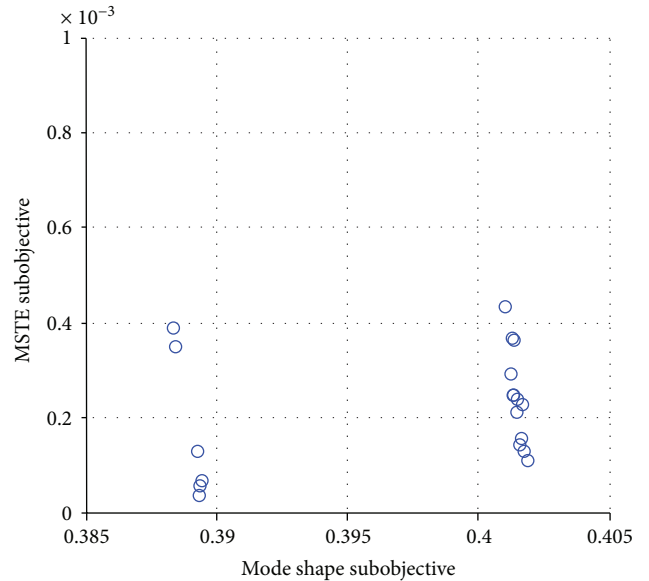
Figure 10: Optimal front obtained from MOLFPSO/TOPSIS in damage scenario 2 under noisy conditions.

The proposed MOLFPSO/TOPSIS is designed using the above-mentioned concepts. The key point in the proposed method is to use TOPSIS to rank all solutions in the archive and to sort them to choose the leading best solution in each generation. That helps to reduce the complexity of the problem because there is no need for a MCDM at the end of the structural damage detection process when the leader solution is chosen in each generation by TOPSIS. Another advantage is that both LFs and PSO are utilized within the algorithm in such a way that there is no need for a large population size and exploration and exploitation are well performed in each generation, reducing the computational time and improving the overall efficiency and reliability. The spatial representation in MOPSO is still employed in MOLFPSO/TOPSIS for removing crowded solutions among the archive. The MOLFPSO/TOPSIS algorithm can be summarized as follows:

Although multiobjective genetic algorithms have shown a prominent performance when applied by Cha and Buyukozturk [14] for structural damage tracking and also

when implemented for active control device optimal placement by Cha et al. [59], it is important to develop a stronger multiobjective optimization approach able to overcome more complexity in the structure and can not only detect but also

TABLE 1: Numerical evaluation of the MOLFPSO/TOPSIS with FE model updating.

		Min	Mean	Max
Case 1	MS subobjective	$2.18E-06$	$1.45E-05$	$2.11E-05$
	MSTE subobjective	$2.975E-06$	$6.99E-06$	$1.364E-05$
	Computational time		2551.97823 seconds	
Case 2	MS subobjective	$3.08E-06$	0.012812	0.017029
	MSTE subobjective	$7.33E-06$	$2.09E-05$	$2.56E-05$
	Computational time		4783.06526 seconds	
Case 1 with ±5% white noise	MS subobjective	0.387019	0.388337	0.390032
	MSTE subobjective	$1.74E-06$	0.00066	0.002721
	Computational time		4912.28630 seconds	
Case 2 with ±5% white noise	MS subobjective	0.388335	0.398434	0.401908
	MSTE subobjective	$7.33E-06$	$2.09E-05$	$2.56E-05$
	Computational time		7523.17741 seconds	

determine the accurate severity of structural damage. The MOLFPSO/TOPSIS algorithm can combine the well-known global optimization feature of PSO when used for FE model updating [60] with the local search ability of LFs. Such combination can serve better when damage detection accuracy is required and complex structures are under investigation. Furthermore, the guided elitist search feature provided by TOPSIS can help to reduce the computational cost and provide better convergence towards the optimal Pareto front. Also, it makes the MCDM determine the best compromise solution unnecessary.

5. Case Study: 3D Modular Structure

After benchmarking the algorithm and evaluating the performance of the proposed MOLFPSO/TOPSIS algorithm, a three-dimensional model is built similar to the benchmark model [61, 62] as shown in Figure 2. The model's dimensions are $2.5\,m \times 2.5\,m \times 3.6\,m$. The model's beams and columns are Euler–Bernoulli beams built of hot rolled grade 300 W steel with 300 MPa nominal yield stress. The material properties of the structure are given in [62]. The model is composed of 84 elements and 45 nodes with 270 DOFs. To examine the efficiency of the developed MOLFPSO/TOPSIS technique, two damage scenarios are taken into account as in Figure 2. Damage is simulated by reducing 25% of the modulus of elasticity.

In testing the application of MOLFPSO/TOPSIS to identify damage in 3D structures, first, the previously mentioned objective function is utilized and the first 12 MSs are employed. Then, after several trials, MOLFPSO/TOPSIS is implemented using 50 particles and $W = 0.5$. The number of hypercubes in set to 7 and repository size is 25. In LFs, the parameters λ and β are set to 1.5 [54, 55]. The weighting factors in (12) are set to 0.5; that is, both subobjectives will have similar significance. The framework is executed 20 times, and results are recorded. In damage case 1, the algorithm is proved to be able to locate the damage with very minor errors, as shown in Figure 3. The optimal front

achieved by the MOLFPSO/TOPSIS is presented in Figure 4. Also, when the simulated MSs are contaminated with ±5% white noise, the MOLFPSO/TOPSIS successfully tracks the damage with very few significant errors, as observed in Figure 5. The optimal front in damage case 1 with noise is illustrated in Figure 6. It is obvious that the MOLFPSO/TOPSIS can detect and locate damage in the studied structure accurately and efficiently, even under noisy conditions.

In damage case 2, which is the more difficult case, the proposed technique shows excellent performance in tracking the structural damage with insignificant errors, as shown in Figure 7. The optimal front resulting from the MOLFPSO/ TOPSIS is highlighted in Figure 8. Moreover, when ±5% Gaussian noise contaminates the simulated MSs, the developed methodology shows good ability to determine damage with acceptable errors, as shown in Figure 9. For damage case 2 with noise, the optimal front is exhibited in Figure 10. It is clear from the figures that the MOLFPSO/TOPSIS combined with FE model updating can serve as a powerful and reliable framework for identifying and diagnosing damage in the 3D structures, even within noise-polluted environments.

To fulfill the evaluation of the overall paradigm, all result outcomes are tabulated in Table 1. All minimum, mean, and maximum values of both MS-based and MSTE-based subobjectives (subobjectives) corresponding to all Pareto solutions as well as the computational time and number of successful runs are all given in Table 1. It can be seen that the multiobjective values almost match the target zero values of the dynamic subobjectives in damage cases 1 and 2. Moreover, even in noisy environments, the increase in multiobjective values due to noise has not affected the overall performance and ability to localize structural damage. Over and above these virtues, the computational time is convenient in all cases. Only in damage case 2 with noise is the number of successful runs lower, due to difficulty in inferring damage when two damaged beams are connected perpendicularly.

Another important factor to judge the overall performance is to evaluate the problem of incomplete MSs. Two
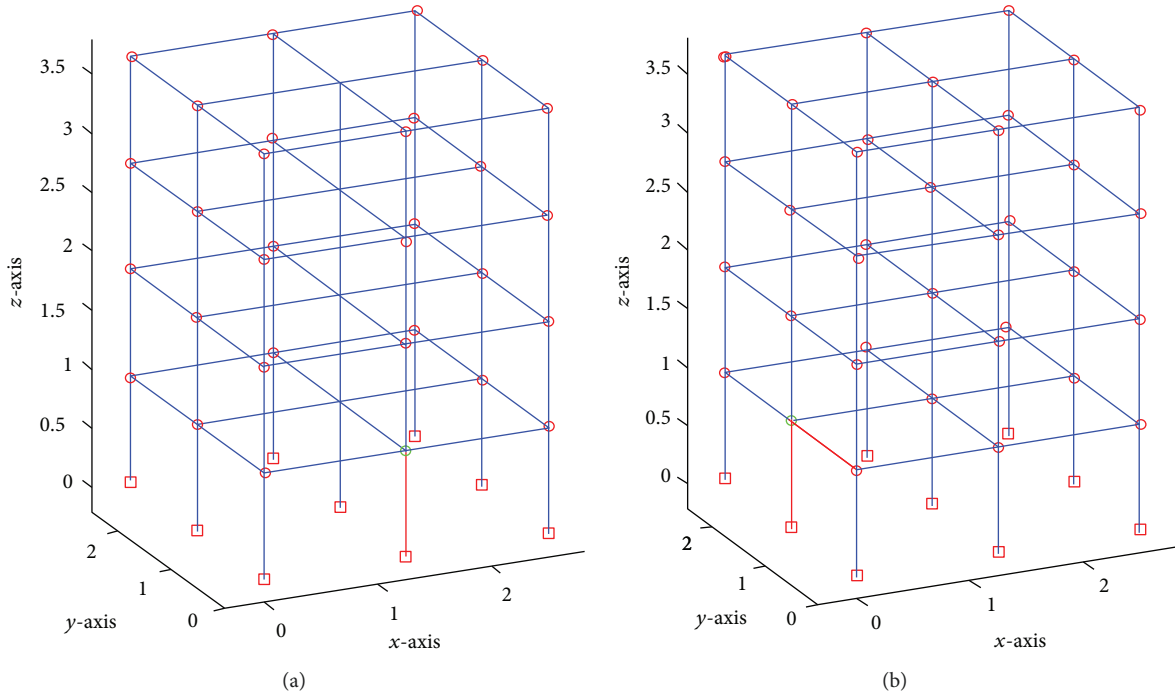
Figure 11: Incomplete MSs damage scenarios: (a) scenario 3 and (b) scenario 4.
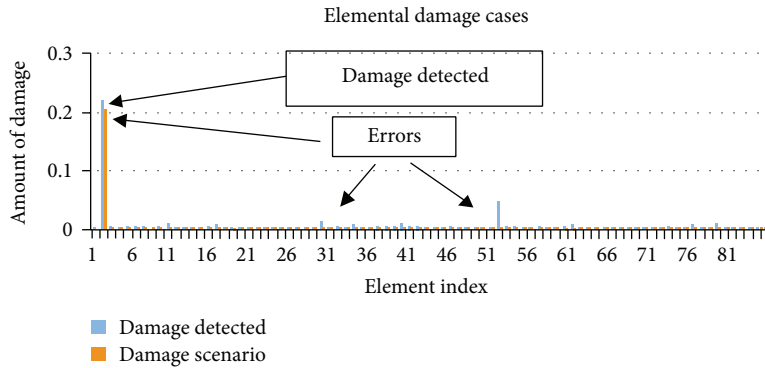

Figure 12: Damage locations in damage scenario 3.

damage scenarios are considered to study the incomplete MSs problem. Scenario 3 in which 20% damage is assigned to element 2 (red beam) and MS information are unknown at node 12 (green dot) as well as scenario 4 in which 20% damage is assigned to elements 4 and 16 (red beam) and MS information are missing at node 13 (green dot), as they are observed in Figure 11. Considering the use of the first three mode shapes, the results of damage tracking when complete MSs cannot be defined are shown in Figures 12 and 13. The results show that the proposed algorithm has proven good ability in detecting structural damage even when applied with unavailability of complete MSs. Nevertheless, it has shown inconsistent performance when executed for several times and needed almost the double computational time.

Finally, it is clear that the proposed framework has evidenced good performance when applied to damage identification in 3D structures. Moreover, its accuracy and relative consistency, together with its the ability to track superior solutions in a single run, make the suggested MOLFPSO/TOPSIS with FE model updating paradigm suitable and reliable when damage localization in 3D structures is needed.

6. Conclusion

In this research, the problem of damage prognostic in three-dimensional structures implementing a novel MOEA incorporated with FE model updating was investigated. The novel algorithm called MOLFPSO/TOPSIS was designed to provide an efficient and reliable structural damage localization framework. The methodology included the use of TOPSIS as a MCDM technique to select a leading solution in each iteration within the multiobjective optimization, that is, the MOLFPSO. Proper selection of such a leader solution can highly and positively influence convergence to the Pareto
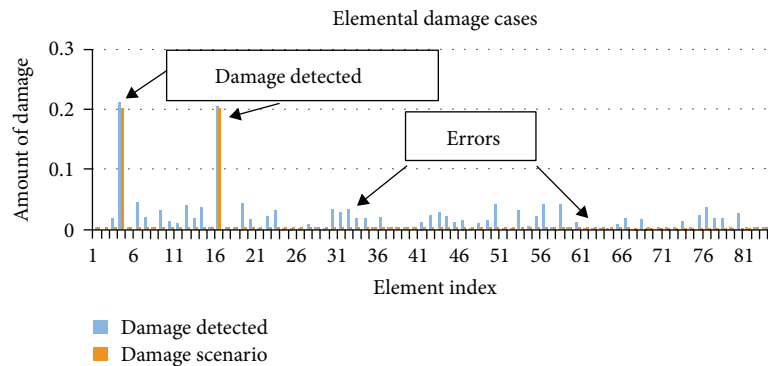
Figure 13: Damage locations in damage scenario 4.

front as well as saving postprocessing time when a best-compromised solution is required. To evaluate the performance of the proposed paradigm, a three-dimensional model was deemed a case study with two simulated damage scenarios. Furthermore, in each scenario, Gaussian noise was added to contaminate the simulated MSs to examine the reliability of the developed technique under polluted conditions. Finally, the incomplete MSs problem has been evaluated with relatively good performance. The proposed technique accomplished effective damage diagnosis in 3D structures with accuracy, reliability, and low computational time, even when tested under a noisy environment and with the absence of complete mode shapes.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

Acknowledgments

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