Structural Damage Detection in Beam Structures Using the Pathfinder Algorithm

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Abstract- This paper presents an approach to structural health monitoring (SHM) using the Pathfinder Algorithm (PFA), a metaheuristic method for detecting damage in beam-type structures. The damage identification task is formulated as an unconstrained optimization problem that estimates both the location and severity of damage by maximizing the correlation between simulated and measured modal data. The Multiple Damage Location Assurance Criterion (MDLAC) is employed as the objective function. A 15-element cantilever beam model is analyzed under different damage scenarios. The performance of PFA is compared with that of the Genetic Algorithm (GA). Results show that PFA identifies damage locations and severities more accurately and efficiently, with improved convergence speed and robustness.

Keywords: Structural health monitoring, damage detection, cantilever beam, pathfinder algorithm, metaheuristic optimization.

Table 1. List of acronyms

Acronym	Full Term	Description
SHM	Structural Health Monitoring	Monitoring of structural integrity over time
PFA	Pathfinder Algorithm	A swarm-based metaheuristic inspired by leader-follower dynamics
GA	Genetic Algorithm	Evolution-based optimization algorithm
MDLAC	Multiple Damage Location Assurance Criterion	Objective function for comparing simulated vs. actual modal data
FEM	Finite Element Method	Numerical method for structural modelling
AI	Artificial Intelligence	Techniques that simulate intelligent behaviour
PSO	Particle Swarm Optimization	Swarm-based optimization method
FRF	Frequency Response Function	Dynamic response characteristic used in modal analysis
SVM	Support Vector Machine	Machine learning algorithm used in some comparative studies
CNN	Convolutional Neural Network	AI-based method for data interpretation (mentioned in references)
DLAC	Damage Location Assurance Criterion	Related to MDLAC, used in early damage detection methods

1. Introduction

Structural Health Monitoring (SHM) has become an essential discipline in civil engineering, providing tools for early damage detection, reducing maintenance demands, and extending the service life of infrastructure systems. This is particularly important for bridges, which are exposed to dynamic loading, harsh environments, and aging effects. Timely detection of damage can prevent abnormal structural failures, which is critical for transportation infrastructure under daily use.

Among the many SHM approaches, modal data-based methods—which rely on natural frequencies and mode shapes to detect structural changes—are among the most widely used. These techniques are attractive because they are non-invasive and sensitive to damage. However, identifying damage in complex structures such as flexible bridges remain challenging due to their high flexibility and complex dynamic responses.

Modal-based methods date back to the late 1970s, when Cawley and Adams [1] first utilized shifts in natural frequencies to locate structural damage. Reviews in the 1990s, notably by Doebling et al. [2], laid the foundation for modern SHM. Messina et al. [3] introduced the DLAC and MDLAC methods, applying frequency correlations and sensitivity analysis to identify multiple damage sites. In the early 2000s, Kim and Stubbs [4] integrated frequency and mode shape data to improve localization accuracy. Koh and Dyke [5] later extended MDLAC by incorporating Genetic Algorithms (GA) for multi-damage detection in a 15-element cantilever beam and the Bill Emerson Memorial Bridge, though their approach remained sensitive to noise and mode selection.

During the 2010s, metaheuristic optimization algorithms such as GA, PSO, ABC, and GWO became popular for handling the nonlinearities of damage detection. Seyedpoor (2011) [6] proposed a two-step PSO method based on modal strain energy, achieving accurate results in fixed beams. Na and Lee [7] applied neural networks with an electromechanical impedance approach to locate damage in composite plates. Cherrier et al. [8] introduced damage localization maps for thin composite plates using impedance spectrums and interpolation methods, improving detection in complex materials. Di Sante [9] reviewed SHM applications in aircraft composites, highlighting the benefits of multi-sensor techniques such as vibration, strain, and acoustic monitoring for reliability and accuracy.

Nonn et al. [10] employed Electrical Impedance Tomography (EIT) to detect small defects such as 5-mm holes in CFRP materials. This non-invasive method, based on conductivity changes, showed potential for routine monitoring of aerospace composites. Ultrasonic guided waves have also been widely used to detect surface defects such as cracks and corrosion in large metallic structures. This high-frequency technique has been successfully applied to bridges, pipelines, and industrial plants [11]. CCawley [12] highlighted the gap between SHM research and industrial deployment, noting challenges such as high costs, data processing complexity, and system integration. The study emphasized the need for common protocols to enable large-scale adoption. Inspired by leader–follower dynamics, Yapici and Cetinkaya [13] introduced the Pathfinder Algorithm (PFA) in 2019 as a novel metaheuristic optimizer for unconstrained optimization problems.

Hoult and Glisic [14] demonstrated the effectiveness of SHM in the Mackinac and Buna bridges using fiber optic sensors, acoustic emission, and digital image correlation. The Mackinac Bridge case validated long-term monitoring, while the Buna Bridge advanced concrete monitoring for safety improvements. More recently, multi-sensor data fusion approaches have been proposed, combining information from strain, vibration, and acoustic sensors to improve accuracy and reliability in complex structures [15].

Since 2020, SHM has increasingly incorporated smart, data-driven techniques. Avci et al. [16] reviewed the impact of machine learning and deep learning, emphasizing Bayesian models and CNNs for structural response analysis. Guo et al. [17] applied the Lion Optimization Algorithm (LOA) for beam damage detection, showing superior performance under noisy conditions compared to PSO. Zhang et al. [18] integrated Shuffled Frog Leaping Algorithm with Support Vector Machines (SFLA–SVM) to identify damage in bending beams. More recently, Alkadhim et al. [19] proposed a hybrid Harris Hawks Optimization (HHO) model for bridge damage detection, demonstrating improved accuracy even with incomplete modal data.

Motivated by these developments, this paper proposes a new approach for damage identification in beam-like structures using the Pathfinder Algorithm (PFA). The problem is formulated as an unconstrained optimization task with MDLAC as the objective function. The algorithm is tested under different damage scenarios and compared against the Genetic Algorithm (GA), demonstrating that PFA improves both accuracy and computational efficiency. As a modern AI-based search method inspired by leader–follower dynamics, PFA can efficiently explore complex, non-convex solution spaces and adapt to uncertainties in data. This robustness and balance between exploration and exploitation make PFA particularly suitable for inverse problems such as structural damage detection, where traditional optimization techniques often fall short.

2. Structural Damage Identification

2.1. Modal Analysis and Problem Formulation

Dynamic approaches based on natural frequency shifts are widely used in damage detection because they are globally sensitive and non-destructive. The undamped free-vibration equation of a discrete system is given as:

$$M \quad \ddot{u}(t) + K \quad u(t) = 0 \tag{1}$$

Assuming harmonic motion $u(t) = e\Phi^{iwt}$ the eigenvalue problem becomes:

$$(K - \omega_i^2 M) \quad \Phi_i = 0 \tag{2}$$

where M is the mass matrix, K is the stiffness matrix, ω are natural circular frequencies and Φ_i are mode shapes.

The Multiple Damage Location Assurance Criterion (MDLAC) measures the correlation between measured and computed modal responses [5]:

$$MDLAC(X) = \frac{|(\Delta F)^T \delta F(X)|^2}{((\Delta F)^T \Delta F.(\delta F(X))^T \delta F(X))} \quad (3)$$

where: $\Delta F = \frac{(F_H - F_D)}{F_H}$, the normalized frequency difference between healthy F_H and damaged F_D states. $\delta F(X) = \frac{(F_H - F_x)}{F_H}$, the normalized frequency change for a trial damage vector X.

MDLAC approaches 1 when the model matches experimental data. The objective function is:

$$\omega(X) = -MDLAC(X) \quad (4)$$

2.2. Damage Representation and Optimization Variables

Damage in element *i* is modeled as a reduction in the element stiffness (or Young's modulus). Let $\alpha_i \in [0,1]$ be the damage index for element *i*, then:

$$E_i^{damaged} = (1-\alpha_i)E_i^{\text{healthy}} \quad (5)$$

or equivalently the element stiffness

$$K_i^{damaged} = (1-\alpha_i)K_i^{\text{healthy}}$$

Here $\alpha_i = 0$ denotes no damage and $\alpha_i = 1$ denotes complete stiffness loss.

The damage vector is $X = \{x_1, x_2, .., x_n\}$ with x_i representing the damage intensity in element *i*. The optimization problem is:

$$\begin{gathered} find: X^T = \{x_1, x_2, .., x_n\} \\ minimize: w(X) = -MDLAC(X) \\ subject-to: x_l \le x_i \le x_u \end{gathered} \quad (6)$$

3. The Proposed Optimization Algorithm

The optimization method adopted in this study is the Pathfinder Algorithm (PFA), a swarm-based metaheuristic inspired by leader–follower dynamics [13]. PFA maintains a balance between exploration and exploitation through a hierarchical structure in which a leader directs the search, while followers move in stochastic patterns. Each agent represents a candidate damage vector X. Initialization: agents are randomly initialized within $X_i \in [0,1]$.

Followers update their positions based on three contributions: (I) attraction to a randomly selected neighbour, (II) attraction to the current pathfinder (best-so-far solution), and (III) a small random vibration term to enhance diversity. The pathfinder itself performs a guided exploration governed by an adaptive fluctuation term. At each iteration, agents are evaluated by the MDLAC objective and the best agent is selected as the pathfinder.

The algorithm parameters (population size N, maximum iterations maxLoop, vibration amplitude ε, fluctuation magnitude A) were tuned empirically — see Table 3 for chosen values. Stopping criteria were either reaching MDLAC ≥ 0.999 or exhausting the maximum number of iterations.

Each individual is a candidate solution. The position of follower $x_i^{(k+1)}$ at iteration k+1 is updated as:

$$x_i^{(k+1)} = x_i^k + R_1.(x_j^k - x_i^k) + R_2.(x_p^k - x_i^k) + \varepsilon \quad (7)$$

where:

x_j^k : position of a randomly selected neighbor

x_p^k : pathfinder's position

$R_1 = \alpha r_1, R_2 = \beta r_2$: random scaling vectors $(r_1, r_2 \in [0,1])$

ε: vibration vector for diversity.

The pathfinder's position is updated as:

$$x_p^{(k+1)} = x_p^k + 2r_3.(x_p^k - x_p^{(k-1)}) + A \quad (8)$$

where:

$r_3 \in [0,1]$: random vector.

A: fluctuation vector.

The vibration and fluctuation vectors are:

$$\varepsilon = \left(1 - \frac{k}{k_{\max}}\right) u_1.D_{ij}, A = u_2 e^{(-2k/k_{max})} \quad (9)$$

With $D_{ij} = \| x_i - x_j \|$ and $u_1, u_2 \in [-1,1]$.

- x_k^i: Position vector of follower agent *i* at iteration *k*.
- x_r: Position vector of a randomly selected neighbouring agent.
- x_p: Position vector of the current pathfinder (best) agent.
- *r*: Random vector in [0,1], controlling neighbour influence.
- *v_k*: Random scaling factor (or vector) in [0,1], balancing exploration vs. exploitation.
- ε: Vibration vector that introduces diversity and helps avoid local optima.
- *A*: Fluctuation vector for fine-tuning of pathfinder's movement.
- x_{k+1}^p: Updated position of the pathfinder at iteration *k+1*.

The pathfinder is selected based on fitness evaluation, ensuring that the best solution guides the search process. The adaptive parameters of PFA allow fast exploration of various search spaces with strong guarantees against falling into local optima. In contrast to PSO or GA, PFA directly update positions in the search space and introduce the leader model, as a result, reducing complexity in the proposed algorithm.

This paper uses PFA for minimizing the objective function of MDLAC to update damage indicators to solve the structural damage identification problem. For clarity, the main steps of the proposed PFA are summarized in a flowchart, as shown in Figure 1. The flowchart illustrates the initialization of agents, pathfinder selection, follower and pathfinder position updates, fitness evaluation using MDLAC, and termination criteria.

The Pathfinder Algorithm (PFA) was implemented using MATLAB R2021b. All simulations were performed on a personal computer equipped with an Intel Core i7 CPU (2.6 GHz), 16 GB of RAM, and Windows 10 OS. The optimization was carried out over 200 and 400 iterations for different cases, using a population size of 20 agents. The algorithm terminates either when the objective function value reaches below 10^{-3} or when the maximum number of iterations is reached. Random initialization was employed for each agent within the damage index bounds [0, 1]. To improve statistical reliability, all results were averaged over 20 independent runs.

4. The Proposed Optimization Algorithm

To verify the accuracy of the proposed technique, a 15-element cantilever beam is used as the benchmark model [5], as shown in Figure 2. The geometric parameters, node arrangement, element connectivity, and structural layout are directly obtained from the figure.

The cross-section of the beam is defined as:

- Width (b): 0.076 m
- Height (h): 0.00635 m
- Total length (L): 2.74 m

The material properties are:

- Density: 7860 kg/m^3
- Young's modulus: 210 GPa

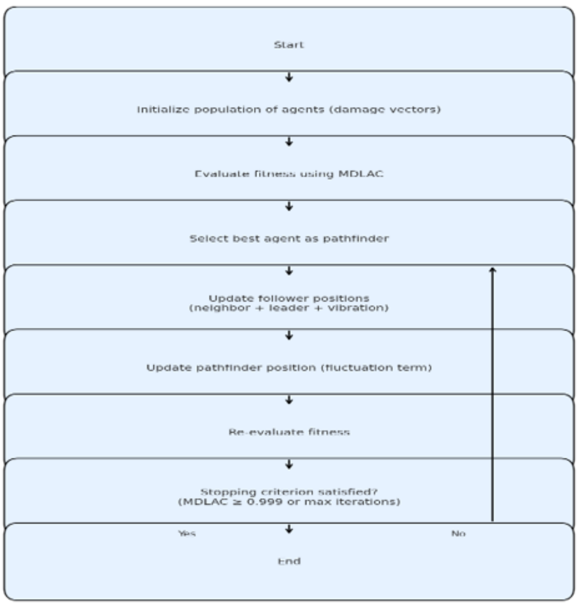

Fig. 1. Flowchart of the PFA for structural damage detection.

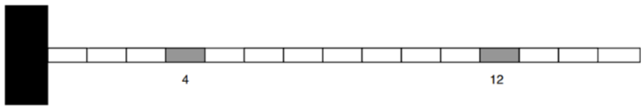

Fig. 2. A cantilevered beam having 15 elements.

Several types of damage scenarios were defined and are summarized in Table 2. Damage is modelled as a reduction in Young's modulus for the affected elements. The parameters of the proposed algorithm are listed in Table 3. The 15-element discretization was chosen to allow comparison with previous studies (e.g., Koh and Dyke, 2007). This balance ensures computational simplicity while maintaining sufficient resolution for structural analysis.

Table 2. Damage pattern

Scenario 1		Scenario 2	
Element	Damage	Element	Damage
4	0.30	4	0.30
-	-	12	0.30

Table 3. The parameters of PFA

Parameters		Value
Number of search agents	N	20
Maximum number of iterations	maxLoop	200,400
Fluctuation magnitude	A	0.1
Vibration amplitude	ε	0.01
Stopping criterion		MDLAC ≥ 0.999 or maxLoop

The damage scenarios consist of 30% stiffness reduction in selected elements, representing both single and multiple damage cases. Element 4 represents a mid-span location, while element 12 is near the free end, allowing the evaluation of sensitivity to local and distributed damage. These cases provide a basis for assessing localization accuracy, severity estimation, and convergence behavior.

Figures 3 to 6 illustrate the predicted damage locations and convergence histories for different scenarios and numbers of modes. In Scenario 1, increasing the number of modes improves localization accuracy.

In Scenario 2, the proposed PFA method outperforms Koh and Dyke's GA-based approach, showing superior accuracy in both location and severity estimation. The convergence plots confirm that the objective function approaches its optimum value (≈ –1) within fewer iterations, demonstrating stable and reliable performance.

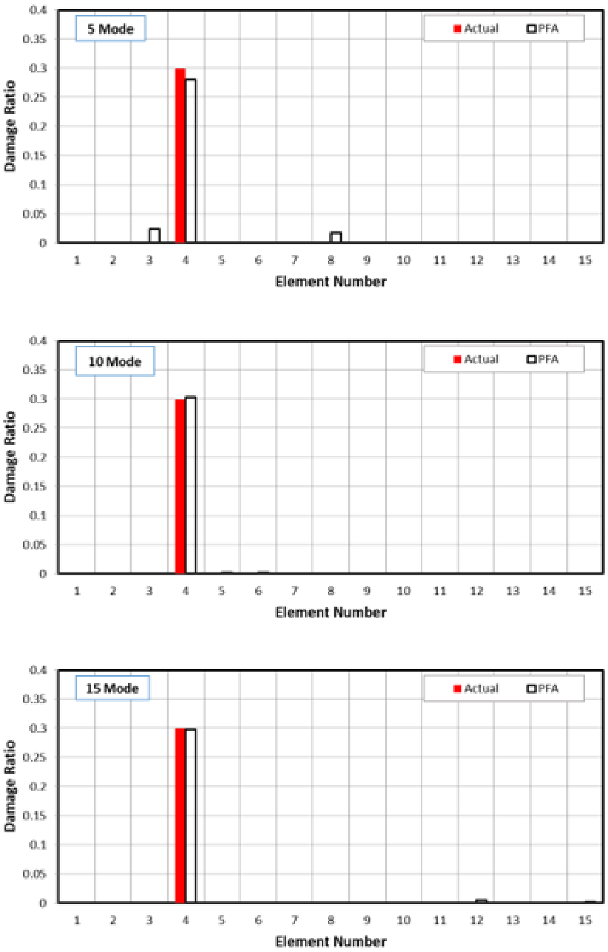

Fig. 3. Scenario 1: Damage prediction of the 15-element cantilever beam for scenario1- 5, 10, and 15 modes.

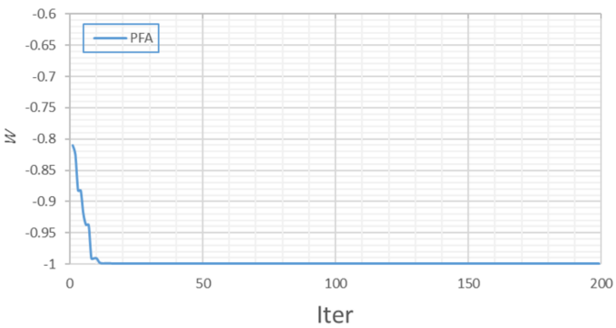

Fig. 4. The convergence histories of optimization of the beam for damage scenario 1.

To quantify the advantages of PFA, Table 4 provides a comparative evaluation against GA. Metrics include localization and severity accuracy, convergence speed, reproducibility, robustness, and sensitivity to parameter tuning. Results are averaged over 20 independent runs. Overall, PFA achieves lower localization error and RMS severity error, converges faster, and shows higher robustness and reproducibility compared to GA.

First to third states: The first three states are seen in figures (2) to (5) in the convergence diagram for the damage and the 15-element beam algorithm, respectively.

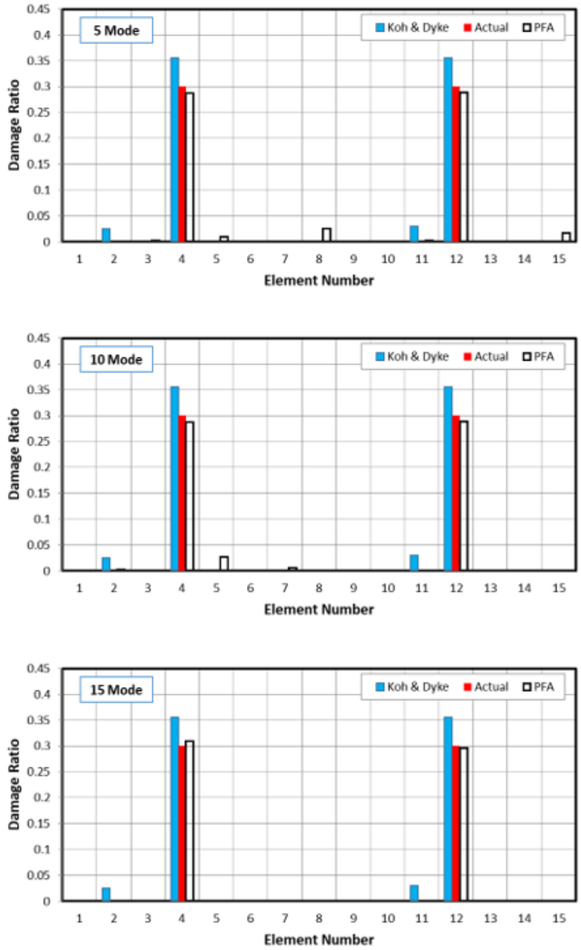

Fig. 5. Scenario 2: Damage prediction of the 15-element cantilever beam for scenario2- 5, 10 and 15 modes.

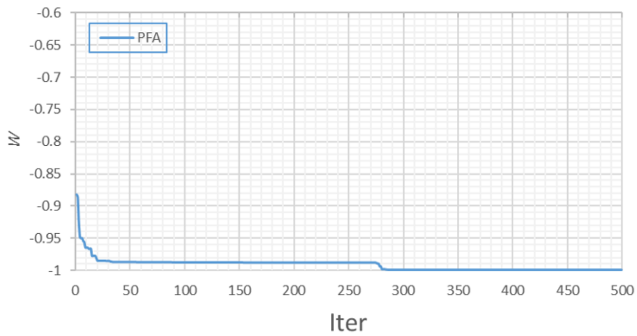

Fig. 6. The convergence histories of optimization of the beam for damage scenario 2.

As observed in Scenario 1, the accuracy of damage location detection improves with an increase in the number of modes. The performance of objective function for the first state, according to 200 repetitions with a favourable slope, is inclined towards the number -1, which is the optimal value of the objective function, and the condition for algorithm to be broken in both cases has been estimated. It is seen from the comparison between the method proposed in this study and the method by Koh, the accuracy and the location in the damage size estimation are superior by PFA algorithm than genetic algorithm used by Koh's method. Thus, we managed to locate and assess the sensitivity of the defect very accurately.

Table 4. Comparative performance between GA and PFA

Criterion	GA	PFA
Localization Accuracy (avg err)	10–15%	≤ 5%
Severity Estimation (RMS error)	0.062	0.028
Convergence Speed (iterations)	400–600	200–400
Reproducibility (variance over 20 runs)	Medium	High
Noise Robustness	Moderate	High
Parameter Tuning Sensitivity	High	Low–Moderate

The value of the objective function for the third state after 500 runs of the with the favourable slope tends to value -1(optimum value of the objective function). An upper bound on the requirement for the particular algorithms to break in both of the cases has been calculated.

As shown in Figures 2 and 4, the proposed technique accurately identified both the location and severity of damage. Thus, the results in severity of single and multiple dam ages showed that the efficiency of the proposed approach is pretty high. The convergence strategy of the Pathfinder optimization method, illustrating its good convergency characteristics, is also presented in Figure 3 and Figure 5. To quantify the advantages of the proposed PFA method, Table 4 presents a comparative evaluation against the Genetic Algorithm (GA). The metrics include localization and severity accuracy, convergence behaviour, and robustness across multiple runs.

Values are averaged over 20 independent runs. The results indicate that PFA achieves lower localization error and RMS severity error while converging faster and showing higher reproducibility and noise robustness compared to GA.

5. Conclusion

This study applied the Pathfinder Algorithm (PFA) to structural damage detection in beam structures, using modal frequency shifts and the Multiple Damage Location Assurance Criterion (MDLAC) as the objective function. Damage was modeled as localized stiffness reductions, and the inverse identification problem was solved through metaheuristic optimization.

The numerical results demonstrate that PFA provides superior localization accuracy, more precise severity estimation, faster convergence, and greater reproducibility compared to a conventional Genetic Algorithm (GA). Statistical analysis confirmed the robustness of PFA to noise and its lower sensitivity to parameter tuning, making it suitable for practical damage-identification tasks.

Beyond numerical performance, this work contributes methodologically by:

- demonstrating the effectiveness of MDLAC combined with PFA for multi-damage detection,
- clarifying the role of algorithmic parameters and stopping criteria, and
- establishing a reproducible evaluation protocol based on multiple runs and statistical reporting.

Nevertheless, some limitations remain. The validation was carried out using numerical models and synthetic data, and further experimental studies are required to confirm real-world applicability. Moreover, relying solely on modal frequency changes may limit detection in lightly damaged or complex structures; integrating additional information such as mode shapes or time-domain responses could improve accuracy. Finally, scalability to larger structural models requires further study, potentially through hybrid or parallel implementations. These findings suggest that PFA-based damage detection has strong potential for integration into real-world SHM systems, particularly for bridges and beam-type infrastructures.

For future work, we suggest three directions:

- Experimental validation on laboratory and field data to assess robustness in real conditions.
- Multi-source data fusion, incorporating additional modal and time-domain information for improved identifiability.
- Scalability and hybridization, combining PFA with local refinement techniques or parallel computation to enhance efficiency in large-scale problems.

In conclusion, the Pathfinder Algorithm, coupled with the MDLAC objective, offers an efficient and reliable strategy for structural damage detection in beam-type structures. The encouraging results provide a strong foundation for experimental extensions and methodological refinements toward robust, scalable, and practical SHM solutions.

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