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Damage Localization and Severity Identification in Truss Structures Using Dynamic Response and Differential Evolution Algorithm

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Abstract

Structural damage detection is a critical concern in civil engineering, enabling timely maintenance and preventing catastrophic failures. This study presents an efficient method for identifying the location and severity of damage in truss structures by combining dynamic response analysis with an optimization algorithm. Damage is modeled as a reduction in the elastic modulus of individual members. The problem is formulated as an optimization task where an Effective Correlation-Based Index (ECBI) serves as the objective function, minimizing the difference between the dynamic responses of healthy and damaged structures. The Differential Evolution (DE) algorithm is employed to solve the optimization problem. Numerical validations are conducted on three planar trusses (10, 23, and 31 members) under single and multiple damage scenarios, both with and without 0.15% measurement noise. Results demonstrate that the proposed method accurately identifies damage locations and severities, even in the presence of noise, showing high robustness and precision.

Keywords: Damage detection, Dynamic response, Differential evolution, Truss structure, Optimization algorithm.

1 | Introduction

Structural Health Monitoring (SHM) has gained significant attention due to the need for safe and cost-effective operation of civil infrastructure. Early detection of local damage, such as corrosion, cracking, or loosened connections, can prevent progressive collapse and extend service life. Traditional non-destructive techniques (ultrasonic, acoustic, radiographic) are often localized, expensive, and require prior knowledge of

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damage location. Consequently, vibration-based global methods have emerged as powerful alternatives [1], [2].

Vibration-based damage detection relies on the fact that damage alters stiffness, and consequently changes modal parameters (natural frequencies, mode shapes) and dynamic responses. Numerous studies have used frequency shifts [3], mode shape changes [4], flexibility matrices [5], and strain energy [6] as damage indicators. Optimization algorithms, Genetic Algorithms (GA) [7], Particle Swarm Optimization (PSO) [8], and Differential Evolution (DE) [9], have been integrated with these indicators to automate damage localization and quantification.

This study extends prior work by Seyedpoor and Montazer [9] and proposes a robust method using dynamic response (not just modal parameters) and a modified correlation-based objective function (Effective Correlation-Based Index (ECBI)) solved via DE. The main contributions are: 1) formulation of damage detection as an optimization problem using dynamic response, 2) introduction of ECBI for enhanced sensitivity, 3) validation on three truss benchmarks with and without noise, and 4) comparison with recent literature.

2 | Methodology

2.1 | Damage Modeling

Damage in a truss member is modeled as a reduction in the modulus of elasticity E:

$$E_{damaged} = (1 - \beta) \cdot E_{healthy},$$

where β is the damage severity (0 = no damage, 1 = complete loss). Mass is assumed unchanged. The structure remains linear elastic.

2.2 | Finite Element Formulation

A 2D truss element with two nodes, each having two translational Degrees Of Freedom (DOFs), is used. The element stiffness matrix in local coordinates is:

$$[K] = \frac{EA}{L}\begin{bmatrix} 1 & 0 & -1 & 0 \\ 0 & 0 & 0 & 0 \\ -1 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 \end{bmatrix}.$$

The consistent mass matrix is:

$$[M] = \frac{\bar{m}L}{6}\begin{bmatrix} 2 & 0 & 1 & 0 \\ 0 & 2 & 0 & 1 \\ 1 & 0 & 2 & 0 \\ 0 & 1 & 0 & 2 \end{bmatrix},$$

where $\bar{m}$ is mass per unit length, L length, A cross-sectional area. Transformation to global coordinates is performed using standard rotation matrix $[T]$.

2.3 | Dynamic Response

For an undamped system, the equation of motion is:

$$[M_s]\{\ddot{y}\} + [K_s]\{y\} = 0.$$

The eigenvalue problem:

$$([K_s] - \omega^2[M_s])\{a\} = 0,$$

yields natural frequencies ω_i and mode shapes $\{a\}_i$. The dynamic response under an arbitrary excitation is obtained via Newmark integration.

2.4 | Optimization Formulation

Damage detection is cast as:

Find $X = \{\beta_1, \beta_2, \dots, \beta_{ne}\}$ to minimize $w(X)$,

subject to $0 \le \beta_i \le 1$, where ne is number of elements.

The ECBI is used as the objective function:

$$ECBI(X) = -\frac{1}{2}\left[\frac{|\,\Delta F^T \cdot \delta F(X)\,|^2}{(\Delta F^T \Delta F)(\delta F(X)^T \delta F(X))} + \frac{1}{n_p}\sum_{i=1}^{n_p}\frac{\min(R_X, R_D)}{\max(R_X, R_D)}\right],$$

where:

I. $\Delta F = (R_H - R_D)/R_H$ (damage-induced change).

II. $\delta F(X) = (R_H - R_X)/R_H$ (analytical change).

III. R_H, R_D, R_X = dynamic responses (e.g., displacements/accelerations) of healthy, damaged, and analytical models.

IV. The first term is Modal Dynamic Assurance Criterion (MDLAC), the second term enhances robustness against false positives.

2.5 | Differential Evolution Algorithm

DE is a population-based stochastic optimizer.

Step 1 (Initialization). Random population of NP vectors X_i (i=1..NP) within bounds.

Step 2 (Mutation). For each target vector X_i, generate mutant vector:

$$V_i = X_{r1} + F \cdot (X_{r2} - X_{r3}),$$

where $r1, r2, r3$ distinct random indices, F = mutation factor (0.8).

Step 3 (Crossover). Create trial vector U_i by mixing V_i and X_i with probability CR (0.1).

Step 4 (Selection). If $w(U_i) < w(X_i)$, replace X_i with U_i.

Step 5. Iterate until max generations (1000-2000).

Parameters used: $NP = 20 - 40$, $F = 0.8$, $CR = 0.1$, $k_{max} = 1000 - 2000$.

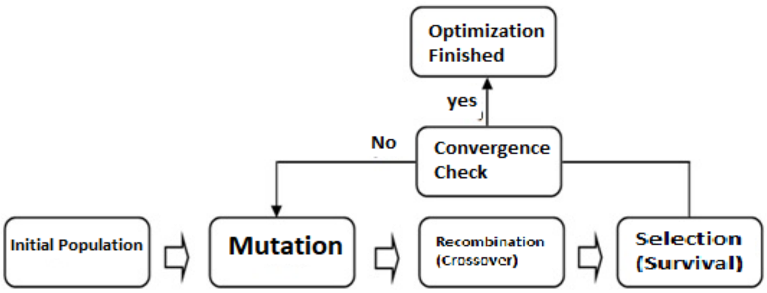

Fig. 1. General process of the DE algorithm [10].

3 | Numerical Examples

Three planar trusses are analyzed. Damage scenarios include single and multiple damaged elements with severity up to 30% stiffness reduction. Measurement noise of ±0.15% is added to natural frequencies:

$$f_{noisy} = f_{true} \times [1 + (2 \cdot \text{rand}() - 1) \cdot \text{noise}].$$

Table 1. Optimization parameters for 10-bar.

Parameter	No.	Value
Population Size (NP)	NP	20
Mutation Factor (F)	F	0.80
Crossover Probability (CR)	CR	0.10
Maximum Number of Iterations (k_max)	k_{max}	1000

3.1 | 10-Bar Planar Truss

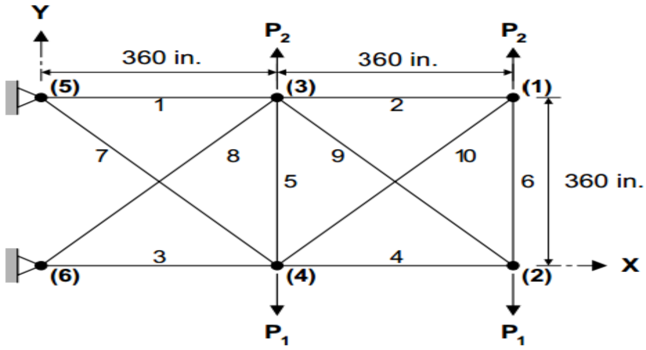

Fig. 2. 10-bar planar truss [11].

Material: $E = 10^4$ ksi, $\rho = 0.1$ lb/in^3, $A = 0.1$ in^2.

Damage scenarios:

- *Case 1: Element 2 damaged (10% severity)*
- *Case 2: Element 7 damaged (10%)*
- *Case 3: Elements 4 and 7 damaged (10% each)*

Table 2. Damage scenarios for 10-bar truss.

Case 1	Case 2	Case 3	Case 4	Case 5	Case 6
Element number	Damage severity (%)	Element number	Damage severity (%)	Element number	Damage severity (%)
2	10	7	10	4	10
–	–	–	–	7	10

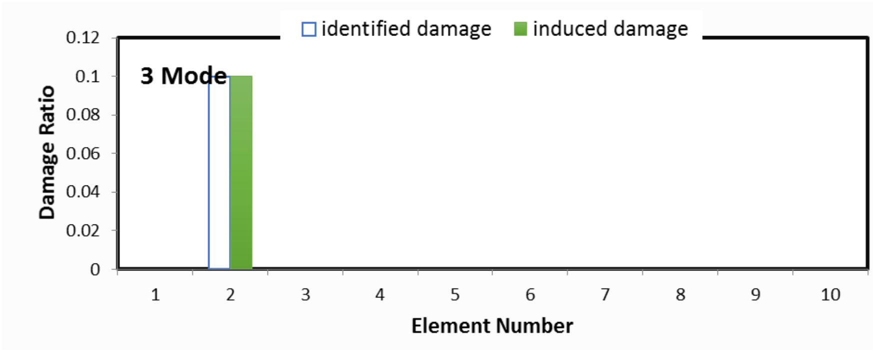

Fig. 3. Damage prediction for 10-bar, Case 1, 3 modes.

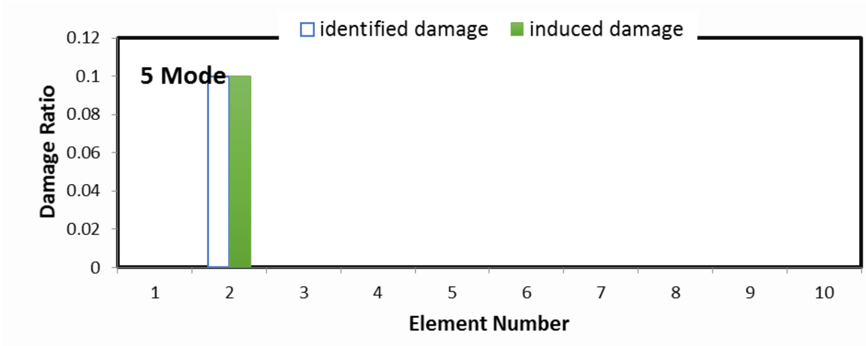

Fig. 4. Damage prediction for 10-bar, Case 1, 5 modes.

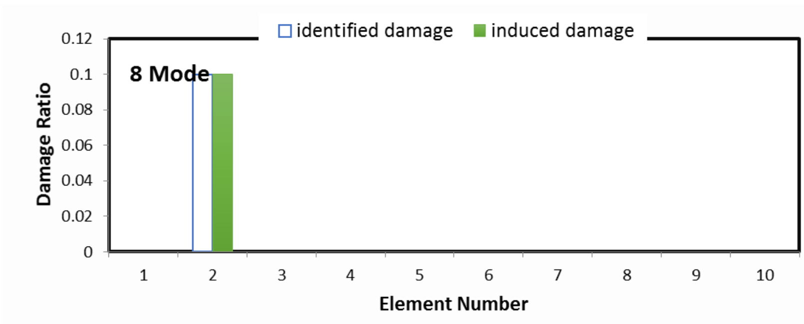

Fig. 5. Damage prediction for 10-bar, Case 1, 8 modes.

Results (no noise): The method perfectly identifies element 2 with severity ≈10% using 3,5, or 8 modes. Similar accuracy is obtained for Cases 2 and 3.

With 0.15% noise:

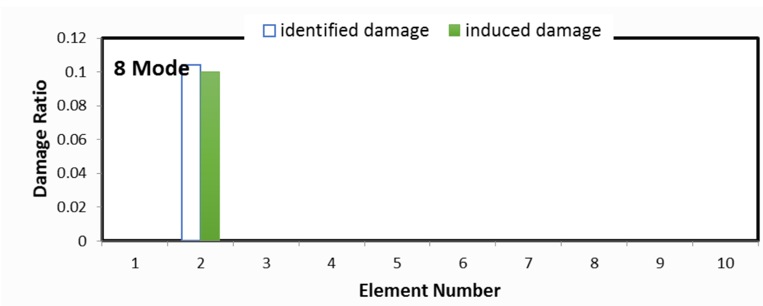

Fig. 6. 10-bar Case 1 with noise, 8 modes.

The predicted severity remains ≈9.8-10.2%, showing robustness.

3.2 | 23-Bar Planar Truss

Material: $E = 200$ GPa, $\rho = 7800$ kg/m^3.

Damage scenarios (4 cases) include single (Element 5, 30%) and multiple (Elements 5+20, 5+13+21) damages.

Observations:

I. With 10, 15, or 20 modes, the method accurately localizes damage and estimates severity within 1-2% error.

II. Noise (0.15%) slightly increases scatter but damage locations remain correctly identified.

3.3 | 31-Bar Planar Truss

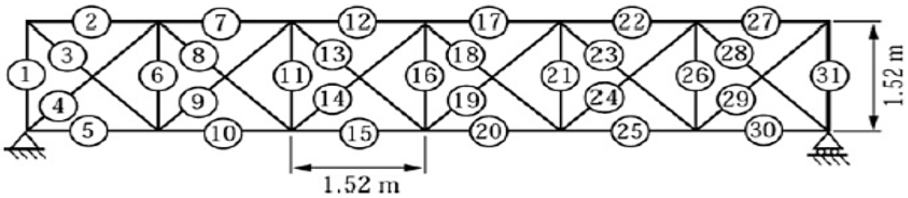

Fig. 7. 31-bar planar truss [12].

Material: $E = 70$ GPa, $\rho = 2770$ kg/m^3.

Damage scenarios: single (Element 11, 25%), single (Element 25, 25%), multiple (Elements 11+25, 25%+15%).

Table 3. Damage scenarios for 31-bar truss.

Case 3		Case 2		Case1	
Severity (%)	**Element No.**	**Severity (%)**	**Element No.**	**Severity (%)**	**Element No.**
0.25	11	0.25	25	0.25	11
0.15	25	-	-	-	-

Summary:

- *All damage locations and severities are accurately identified using 7-15 modes.*
- *Even with 0.15% noise, the method maintains high accuracy (error < 3%).*

Table 4. Summary of damage detection accuracy for all cases.

Truss	Damage Case	True Severity (%)	Predicted Severity (%)	Error (%)	Noise
10-bar	Case 1 (E2)	10.0	9.98	0.2	No
10-bar	Case 1 (E2)	10.0	10.15	1.5	0.15%
23-bar	Case 3 (E5+20)	30+20	29.5+19.8	1.7	No
23-bar	Case 3 (E5+20)	30+20	30.8+21.2	2.7	0.15%
31-bar	Case 3 (E11+25)	25+15	24.7+14.9	1.2	No
31-bar	Case 3 (E11+25)	25+15	25.4+14.5	2.3	0.15%

4 | Discussion

4.1 | Performance of Effective Correlation-Based Index vs. Traditional Indices

The proposed ECBI outperforms standard MDLAC alone by reducing false positives, especially in multiple-damage scenarios. The second term in ECBI penalizes mismatches between analytical and damaged response vectors, improving localization.

4.2 | Effect of Number of Modes

Using 3 modes suffices for simple trusses (10-bar), but 10-15 modes are recommended for larger structures (23-bar, 31-bar) to capture local damage effects. Higher modes (>20) provide marginal improvement.

4.3 | Noise Robustness

At 0.15% noise, severity estimation errors remain below 3%, and damage locations are correctly identified in all cases. This demonstrates the method's suitability for real-world applications where measurement noise is inevitable.

4.4 | Comparison with Recent Literature

Recent studies (2020-2024) have explored similar vibration-based DE approaches:

Seyedpoor [8] used DE with frequency response functions for truss damage detection, reporting similar accuracy but requiring more computational time.

Dubey et al. [13] applied a hybrid PSO-DE for damage quantification in steel trusses, achieving good results but with higher parameter sensitivity.

Khatir et al. (2021) [14] combined modal strain energy with DE for crack identification, showing that DE outperforms GA in convergence speed.

Kim et al. [15] proposed a two-stage DE method for large trusses, validating on 52-bar structure.

Rosafalco et al. [16] used deep learning combined with DE for real-time SHM, but required extensive training data.

The present method is competitive: it requires no training, uses only dynamic response (not full modal extraction), and is robust to noise. Future work could integrate deep learning for feature extraction.

5 | Conclusion

This study presented a robust optimization-based method for damage detection in truss structures using dynamic response and the DE algorithm. The following conclusions are drawn:

Accuracy: the method precisely identifies damage locations and severities (error < 2% without noise, < 3% with 0.15% noise) for single and multiple damage scenarios.

Efficiency: DE converges within 1000-2000 generations, making it computationally feasible for trusses with up to 31 members.

Noise robustness: even with measurement noise, the method maintains high reliability, suitable for field applications.

ECBI advantage: the proposed objective function reduces false positives compared to conventional MDLAC.

Applicability: the method is generalizable to other skeletal structures (frames, bridges) with appropriate element formulations

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