Structural Damage Detection Through Finite Element Model Updating Using Evolutionary Algorithm

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ABSTRACT

Structural damage can be caused by a variety of factors, which include internal factors such as design flaws, construction errors, material deficiencies, and external factors such as earthquakes, overloading, environmental factors, and terms of service violations. As such damage can compromise the safety, functionality, and financial viability of a structure, it is essential to identify and address any issues quickly. The engineering community, including civil, mechanical, and aerospace engineers, is greatly interested in structural damage identification. Numerous methods, such as experiential and simulation-based techniques, have been developed to achieve this goal. However, accurately modeling a structure and developing a robust inverse algorithm for damage detection is a significant challenge. Finite element modeling is one of the widely used methods for detecting structural damage. Here, Model updating is a crucial process that involves adjusting a structural model to improve its accuracy and reliability. Various methods for updating Finite Element Models have been proposed, including sensitivity-based, direct, statistical, probabilistic, and iterative methods. However, traditional methods can be complex and time-consuming, leading researchers to explore the use of evolutionary algorithms to streamline the process. Evolutionary algorithms are a type of computational optimization technique that mimics the process of natural selection to find the best solution to a given problem. In the context of model updating, evolutionary algorithms can identify the optimal combination of model parameters that best matches measured data. There has been a growing interest in using evolutionary algorithms to update Finite Element Models for structural damage identification in recent years. This paper presents a case study on damage identification, specifically sectional loss and boundary condition rigidity, as an optimization problem. It demonstrates the use of an evolutionary algorithm to update a Finite Element model for structural damage detection and discusses the advantages of using this algorithm over traditional methods. The abstract also highlights some of the key challenges associated with using evolutionary algorithms for model updating, including the need for accurate and reliable data and the need to carefully tune algorithm parameters.

INTRODUCTION

Identification of structural damage is a very important part of engineering to ensure the functionality and safety of structures. Due to which the financial viability of a structure can be impacted by a number of internal and external factors resulting in structural damage. There have been several methods proposed to detect structural damage,

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including experiential and simulation-based ones. In this context Finite element (FE) model updating is an essential component of numerical simulations in structural engineering particularly in Structural Health Monitoring (SHM) [1]. Sophisticated and modern finite-element (FE) procedures have been developed for analysis of structures. However, practical application often reveals significant discrepancies among analytical predictions and experimental outcomes. To address this issue, it is necessary to modify the modeling assumptions and parameters until the analytical predictions and experimental results align with practical requirements. Various techniques aim to minimize these discrepancies by adjusting structural parameters and minimizing an error function that compares measured and numerical responses [2]. The effectiveness of these methodologies relies on several factors, including the definition of a meaningful error function, the use of an appropriate numerical model, accurate identification of experimental parameters, and the application of an effective optimization algorithm capable of finding the global minimum of this function [3].

The parameters of a finite element model are updated to best match the experimental data. Numerous approaches, such as sensitivity-based [4, 5], vibrational [6], direct [7], statistical [8], probabilistic [9], and iterative ones [10], have been proposed before. These conventional methods are difficult to use and time-consuming, hence, researchers are now looking into using Evolutionary Algorithms (EAs). The main flaw in traditional methods is that it cannot handle complex, nonlinear systems with many parameters whereas EAs can [11]. They are robust in the presence of noise and uncertainties and can quickly explore the solution space and converge to the best solution. These algorithms mimic the evolution of natural selection in order to find the best answer to a problem. However, there are drawbacks to using EAs, one of which is the requirement for precise and trustworthy data and the need for careful algorithm parameter tuning. The use of computational techniques such as EAs to update finite element models for the detection of structural damage has recently gained more attention. This paper presents a case study on damage detection using a fitness function between stiffness and Young's modulus, focusing on sectional loss and boundary condition rigidity. In the case study included in this paper, the suggested approach of using EAs for model updating is successful in identifying structural damage. To perform modal updating for finite element modelling, the method specifically used a fitness function between stiffness and Young's modulus, and the genetic algorithm is used, iteratively tries to converge to the experimental result of a particular frequency value. The algorithm displays the Young's modulus and stiffness for which it matches the experimental frequency, revealing the ideal set of model parameters that most closely matches the data. The study demonstrated that by detecting changes in stiffness and Young's modulus, can be used to detect damage in a beam. The proposed method proved to be more practical for updating models in the field of structural engineering as it achieved the experimental outcome in a shorter timeframe and with a reduced number of iterations. Overall, the results show how well EAs work for updating models and how this method might be used to solve other structural damage identification issues. Additional study is required to examine the algorithm's robustness in the presence of noise and uncertainties and to validate the suggested method for use with other types of structural damage.

PROPOSED ALGORITHM

In this paper, the utilization of the optimization technique, specifically the genetic algorithm, for updating the finite element model in structural damage detection is discussed in detail. The aim is to optimize the modal parameters to match the experimental frequency, with the focus divided into two major cases that will be further explored. To achieve a more versatile and effective solution, the proposed approach combines the strengths of individual optimization techniques, integrating the genetic algorithm with other methods. Before proceeding, the importance of the fitness function, a critical step in model updating, is emphasized. Two fitness functions are presented in this study, relating to either the stiffness or Young's modulus of the beam to its frequency. The fitness function employed in this research is based on the frequency characteristics of the beam. Specifically, the frequency of a beam can be expressed in terms of its stiffness and Young's modulus using the following equations:

Case 1:

$$F = ((1.875^2) * sqrt((stiffness)/(3 * mass * length)))/(2 * pi) \tag{1}$$

Case 2:

$$F = ((1.875^2) * (sqrt((E * I)/(density * area)))/(2 * pi)) \tag{2}$$

Where F is the frequency of the beam, 'E' is the Young's modulus, 'I' is the second moment of area, 'L' is the length of the beam, and 'm' is the mass per unit length of the beam. The stiffness of the beam is given by $k = EI/L^3$. The fitness function used in this study is the difference between the calculated frequency and the experimental frequency of the beam. The fitness function is given by-

$fitness = |f_{calculated} - f_{experimental}|$

The fitness function used in this study, $|f_{calculated} - f_{experimental}|$, represents the difference between the calculated frequency and the experimental frequency. By taking the absolute value of this difference, we ensure that the fitness function always returns a non-negative value.

In order to find the stiffness and Young's modulus that give the frequency of the beam closest to the experimental value of frequency, we use the fitness function. The fitness function is used to evaluate the performance of each member of the generated population of solutions. Where each member of the population is the combination of a stiffness value and a Young's modulus value. On the evaluation of each member of the population, we try to find the best member, i.e., the combination of stiffness and Young's modulus value that holds the least fitness in the population.

Now that the fitness function has been defined, the working of the algorithm can be investigated. Firstly, the experimentally calculated frequency value is provided as input. In this study, a genetic algorithm is used to optimize the stiffness and Young's modulus of the beam in order to match the experimental frequency. The flow chart of the process is shown in Figure 1. The genetic algorithm initiates by creating a population consisting of randomly generated values for stiffness and Young's modulus. The fitness function is then computed for each member of the population (assessing the difference between the calculated frequency and the experimental frequency of the beam). Subsequently,

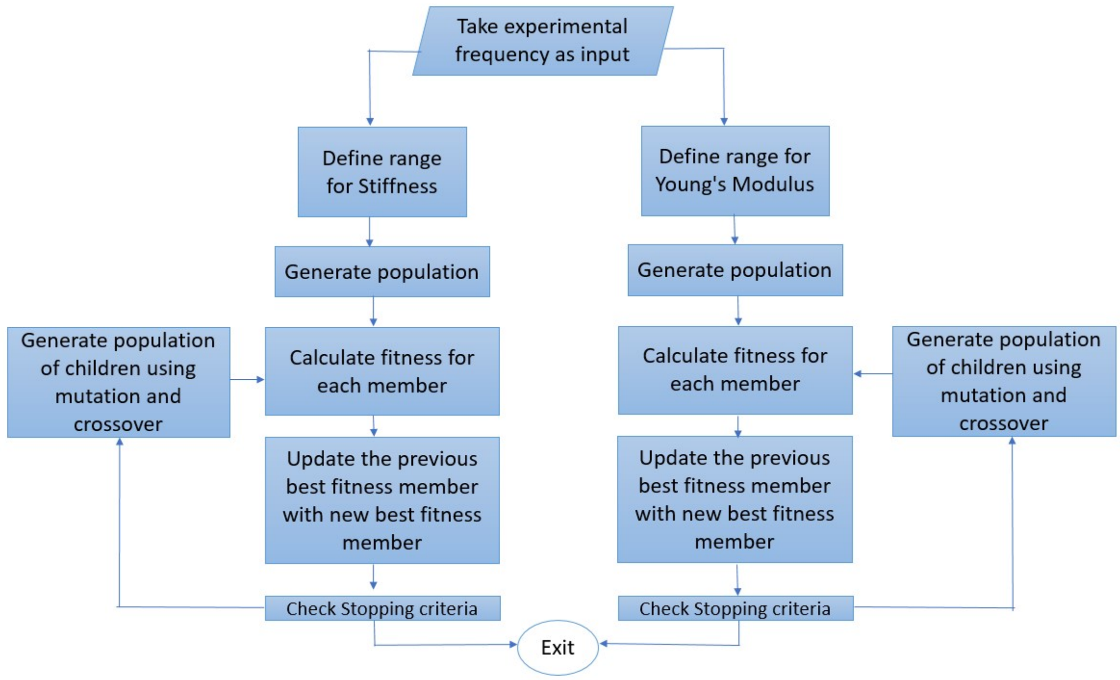


Figure 1. Flow Chart of EA for finding Stiffness and Young's modulus for damage detection.

individuals with the most favorable fitness values are chosen as parents to form subsequent generations of children. The children are produced through a process known as crossover, where the genetic material of two parents is combined to generate offspring. Additionally, a mutation operation introduces slight random alterations in the genetic material, based on a specified mutation rate that can be adjusted. The newly generated children are evaluated using the fitness function, and the weakest members of the population are replaced with the most promising offspring. This iterative process continues for multiple generations, usually with a predetermined number of iterations or until convergence is achieved i.e. after satisfying a specific threshold for fitness. In conclusion, The genetic algorithm endeavors to optimize the stiffness and Young's modulus values by iteratively evolving the population based on their fitness values. The ultimate goal is to converge towards the frequency that best aligns with the experimental frequency of the beam.

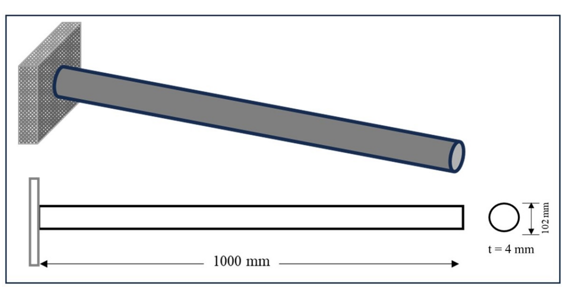


Figure 2. Geometrical properties of the cantilever beam.

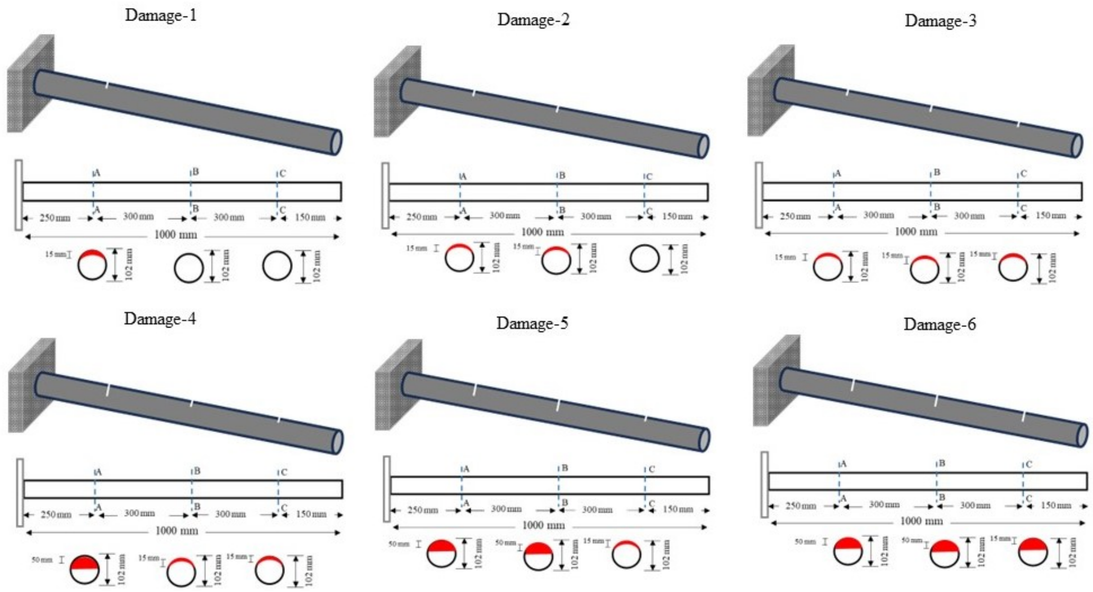
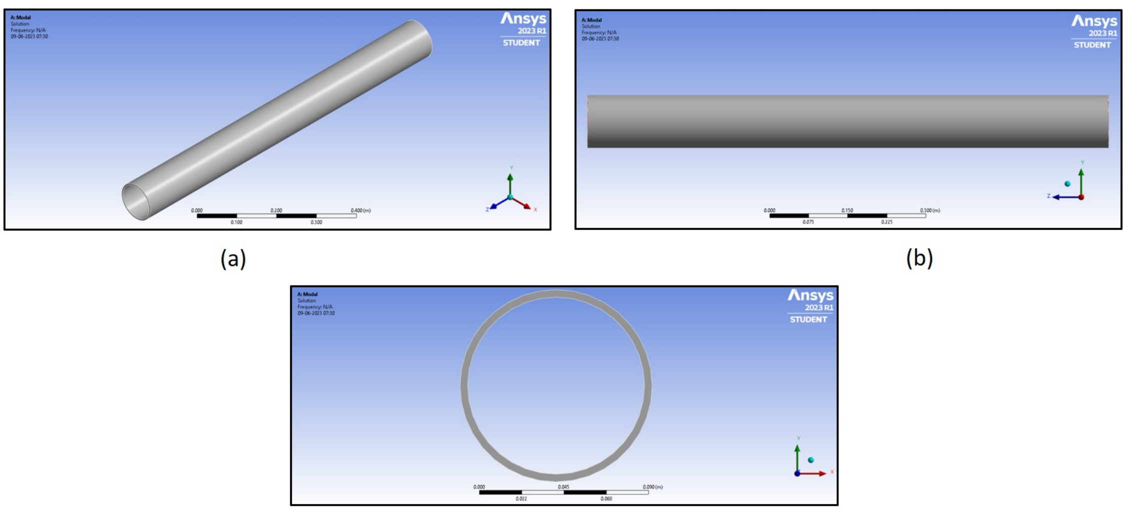


Figure 3. Deferment damage scenarios for a circular hollow sectional beam [12].



(a) (b)

(c)

Figure 4. 3D Numerical model of Cantilever beam.

NUMERICAL MODELING

For the validation of the study, a three-dimensional steel cantilever beam has been developed as shown in figure 2. Material properties considered for this study are $E = 206GPa$, $\rho = 7850\ kg/m^3$, and $\mu = 0.3$. Numerical models induced with damage in terms of the loss of cross-section at a distance of 0.25L, 0.55L and 0.85L respectively. And the same is carried for single damage location and multiple damage locations as shown in figure 3. Cross-sectional and numerical model with different views are shown in figure 4.

RESULTS AND DISCUSSION

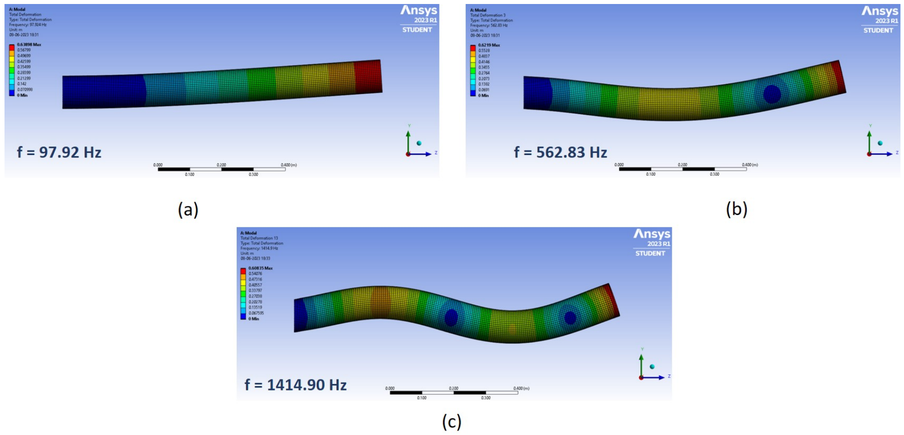


Figure 5. First three Natural frequencies(Hz) of the Cantilever beam.

To demonstrate the efficacy of the proposed technique for damage detection, an application scenario is considered. Specifically, an experimental cantilever beam made of CFRP (carbon fiber reinforced polymer) composite with aluminum connectors is examined. The use of composite materials has gained popularity in industries such as aerospace, aviation, and automotive. Understanding the brittle fracture behavior of composites under impact and their overall damage behavior is a complex research area. In some cases, damage within the material, such as delamination, may not be easily detectable through visual inspection. Additionally, locating damage becomes even more challenging in complex multi-part structures. Composite materials are characterized by non-homogeneity and non-isotropic behavior.

TABLE I. FIRST THREE NATURAL FREQUENCIES OF DEFERMENT DAMAGE SCENARIOS FOR A CIRCULAR HOLLOW SECTIONAL BEAM USING NUMERICAL MODAL ANALYSIS

Details	UD	D-1	D-2	D-3	D-4	D-5	D-6
F1 (Hz)	97.92	92.26	89.99	85.97	61.06	55.98	58.28
F2 (Hz)	562.83	557.9	519.87	503.91	495.52	348.89	341.44
F3 (Hz)	1414.9	1367.9	1324.7	1274.7	1266.7	907.06	891.1

where UD represents undamaged, D1-D6 represents six damage scenarios shown in fig3.

To evaluate the proposed method's capabilities in this type of material, a benchmark experimental setup is selected. The setup consists of a circular hollow section CFRP composite beam with a length of 1 meter, a wall thickness of approximately 4 mm, and a cross-section diameter of 102 mm. The natural frequency of the cantilever beam is measured and validated. The frequencies corresponding to various states of the beam, ranging from undamaged to six levels of damage, are provided in a table I obtained from numerical modal analysis and respective figures are shown in figure 5, figure 6, figure 7 and figure 8. Proposed algorithm is tested on these values, dividing the experiment into two cases considering frequency as the reference point.

Case 1: FEM to detect damage using the change in Young's modulus.

Case 2: FEM to detect damage using the change in stiffness.

The following table shows the results of both cases for evaluation if the beam has

TABLE II. ESTIMATION OF YOUNG'S MODULUS FOR DIFFERENT DAMAGES ARE PRESENT ON BEAM

	Stiffness Constant			
	A1	A2	E (Young's Modulus)$10^2 Gpa$	diff (%)
Undamaged	99.64	99.38	2.06	0.015
Damage 1	93.74	93.75	1.83	11.01
Damage 2	92.72	92.72	1.79	12.97
Damage 3	92.79	92.77	1.79	12.87
Damage 4	71.67	71.69	1.075	47.96
Damage 5	69.08	69.08	0.99	51.68
Damage 6	69.08	69.08	0.99	51.69

where A1 and A2 are calculates using Analytical equations.

damage. Table II the values of Young's Modulus of Beam calculated for Experimental frequency(Actual Frequency) of the beam by maintaining stiffness as constant using an EA. The table also shows the percentage difference between the calculated Young's Modulus with Actual Young's modulus. Results obtain indicate the challenge of knowing the damage accurately, when the system has multiple damages. And similar phenomenon is also observed in calculating the frequencies as shown in table III. Table III shows

TABLE III. ESTIMATION OF STIFFNESS AT DIFFERENT DAMAGES ARE PRESENT ON BEAM

	Young's modulus Constant			
	A-1	A-2	Stiffness $N/m(10^5)$	diff $(\%)$
Undamaged	99.64	99.17	9.11	0.45
Damage 1	93.74	93.68	8.13	11.15
Damage 2	92.72	92.74	7.968	12.93
Damage 3	92.79	93.02	8.01	12.41
Damage 4	71.67	71.61	4.75	48.09
Damage 5	69.08	69.73	4.50	50.77
Damage 6	69.08	69.12	4.42	51.63

the values of Stiffness of the beam Calculated for the experimental frequency(Actual Frequency) of the beam by maintaining stiffness as constant using the EA. The table also shows the percentage difference between calculated Stiffness with Actual Stiffness.

The findings suggest several research directions to improve the use of the FE model updating with EAs for structural damage detection. These include expanding the application of EAs to large-scale complex structures, exploring the combination of different dynamic characteristics for objective functions, investigating suitable EAs for accurate and efficient damage identification, conducting comparative studies on reliable algorithms, addressing challenges of noisy measurements and incomplete data through industrial

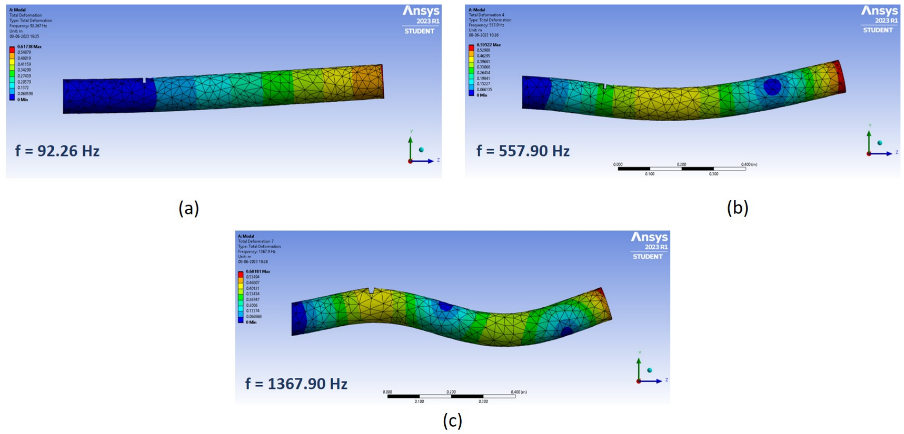


Figure 6. First three Natural frequencies(Hz) of the Damage-1 Cantilever beam.

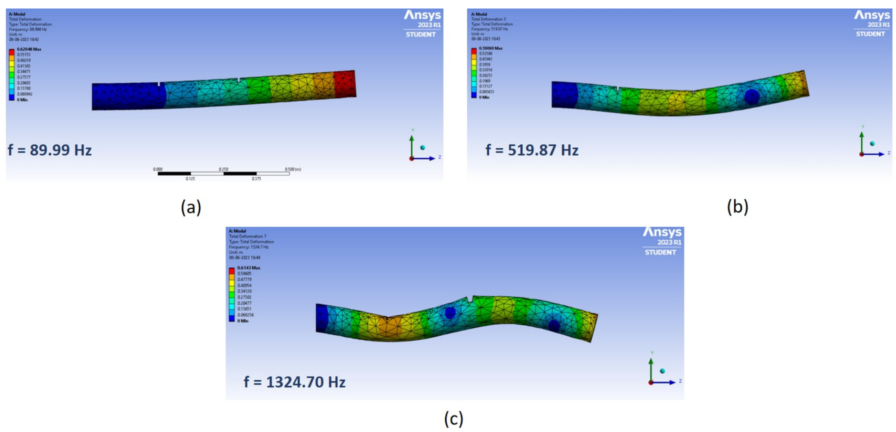


Figure 7. First three Natural frequencies(Hz) of the Damage-2 Cantilever beam.

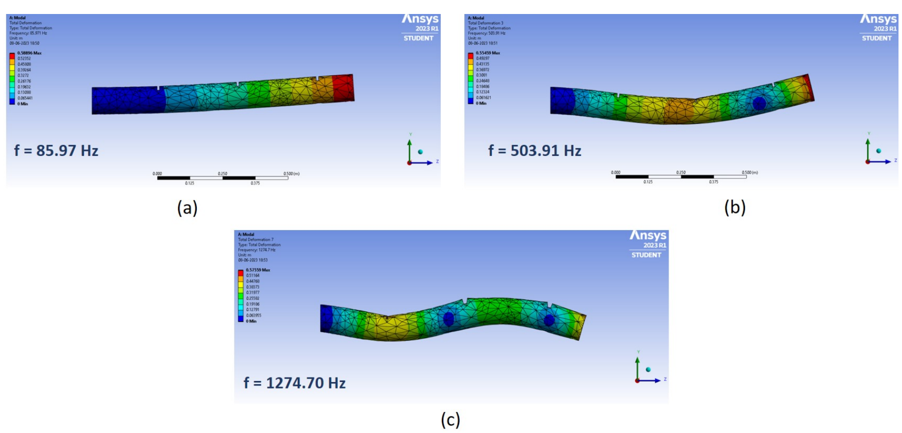


Figure 8. First three Natural frequencies(Hz) of the Damage-3 Cantilever beam.

implementations, and utilizing multi-attribute decision-making techniques for optimal solutions in multi-objective EAs for damage tracking.

Table IV shows the comparative analysis between analytical solutions, numerical solutions and Evolutionary Algorithms. And as discussed previously, EA have shown

TABLE IV. COMPARITIVE ANALYSIS OF ESTIMATED VALUES WITH NUMERICAL VALUES.

	Frequencies (Hz)					ES (N/m) through		
	A-1	A-2	diff (%) (A1-A2)	FEM	diff (%) (A1-FEM)	FEM (10^5)	EAs (10^5)	diff (%)
UD	99.64	99.17	0.47	97.92	1.72	8.97	9.11	1.52
D-1	93.74	93.68	0.06	92.26	1.57	8.51	8.1	4.46
D-2	92.72	92.74	0.02	89.99	2.94	8.10	7.96	1.69
D-3	92.79	93.02	0.25	85.97	7.35	7.97	8.01	0.57
D-4	71.67	71.61	0.08	61.06	14.79	3.64	4.75	30.47
D-5	69.08	69.73	0.94	55.98	18.96	3.08	4.50	45.92
D-6	69.08	69.12	0.06	58.28	15.63	3.05	4.42	44.94

where ES represents Estimated stiffness

very good results for undamaged and single damage scenarios but for multiple damage scenarios the rate of error is increasing. The same can be decreased with more data obtained from both analytical and numerical solutions.

CONCLUSION AND FUTURE WORK

This study offers a thorough analysis of the application of EAs in updating finite element (FE) models for structural damage detection. An illustration is provided using a case study. Even the theoretical foundations of structural damage detection are covered in this paper, which also looks at various methods for FE model updating. The formulation of objective functions using popular dynamic characteristics for damage tracking is given particular focus. Two single-objective EAs are evaluated in order to identify damage through FE model updating. Additionally, a case study using two single-objective functions is presented to show the practical application of the FE model updating-based structural damage detection. The case study emphasizes how effective and useful EAs can be in improving the precision of structural damage detection through FE model Updating.

In summary, the use of EAs for FE model updating has shown potential in identifying structural damage in beams. To evaluate its robustness to noise and uncertainties and to determine its suitability for various types of structural damage, more research is required. To increase the accuracy of the model, future research should consider a wider variety of structures, compare the suggested approach with other approaches and optimization techniques, and take into account conditions like temperature and humidity. This research contributes to the advancement of more efficient and effective techniques for detecting structural damage, offering potential benefits in terms of enhancing structural safety, longevity, and reduction of cost.

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