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A comparative analysis for crack identification in structural health monitoring: a focus on experimental crack length prediction with YUKI and POD-RBF

Analyse comparative de l'identification des fissures dans le cadre de la surveillance de la santé des structures : Prédiction expérimentale de la longueur des fissures avec YUKI et POD-RBF

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Abstract. In recent years, substantial investments in structural construction underscore the paramount importance of ensuring structural integrity for safety and dependability. Structural Health Monitoring (SHM) has emerged as a pivotal tool for assessing structural health, with an emphasis on damage detection, localisation, and quantification, particularly through vibration-based methods that exploit variations in modal properties as precursors to structural damage. This study presents an innovative methodology that synergistically combines Proper Orthogonal Decomposition and Radial Basis Function interpolation for predicting structural responses based on crack parameters. Additionally, the YUKI algorithm, leveraging population clustering for optimisation, is introduced. The approach is rigorously assessed through experimental analysis of two distinct beams (Beam I and Beam II) exhibiting varying crack depths. The results demonstrate the effectiveness of the POD-RBF-YUKI approach, indicating a notable level of accuracy and consistency. Comparative

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evaluations with conventional optimisation algorithms, namely Cuckoo, Bat, and Particle Swarm Optimisation, reveal similar Mean Percentage Error values but with increased result variability, whereas Deep Artificial Neural Network models with varied hidden layer sizes.

Résumé. Ces dernières années, des investissements substantiels dans la construction structurelle ont mis en évidence l'importance primordiale de l'intégrité structurelle pour la sécurité et la fiabilité. La surveillance de la santé des structures (SHM) est devenue un outil essentiel pour évaluer la santé des structures, en mettant l'accent sur la détection, la localisation et la quantification des dommages, en particulier grâce à des méthodes basées sur les vibrations qui exploitent les variations des propriétés modales en tant que précurseurs des dommages structurels. Cette étude présente une méthodologie innovante qui combine de manière synergique la décomposition orthogonale appropriée (POD) et l'interpolation de la fonction de base radiale (RBF) pour prédire les réponses structurelles basées sur les paramètres des fissures. En outre, l'algorithme YUKI, qui tire parti du regroupement de populations pour l'optimisation, est présenté. L'approche est rigoureusement évaluée par l'analyse expérimentale de deux poutres distinctes (poutre I et poutre II) présentant différentes profondeurs de fissures. Les résultats démontrent l'efficacité de l'approche POD-RBF-YUKI, indiquant un niveau notable de précision et de cohérence. Les évaluations comparatives avec les algorithmes d'optimisation conventionnels, à savoir Cuckoo, Bat et Particle Swarm Optimisation, révèlent des valeurs d'erreur moyenne similaires mais avec une variabilité accrue des résultats, tandis que les modèles de réseaux neuronaux artificiels profonds (ANN) avec des tailles de couches cachées variées.

Keywords. Crack identification, Model reduction, Experimental modal analysis, Inverse analysis, YUKI algorithm.

Mots-clés. Identification des fissures, Réduction du modèle, Analyse modale expérimentale, Analyse inverse, Algorithme YUKI.

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1. Introduction

In recent years, substantial budgets have been invested in developing and building structures in different areas, including the oil and gas industry, as well as civil and aerospace engineering. Therefore, ensuring the integrity of these structures during their predicted life span is crucial for safe and reliable performance. In the last decade, a great deal of attention has been directed toward preventing sudden structural failure, which can lead to extensive casualties and property damage. Structural Health Monitoring (SHM) has emerged as a powerful tool for assessing and monitoring structural health in this context. This technique, which considers damage detection a crucial concern, involves four main stages: damage detection, damage localisation, damage quantification, and damage extent [1]. However, in the literature, the first three stages receive the most attention in the assessment of structural integrity [2].

There has been a considerable and continuously growing body of research dedicated to the examination of Structural Health Monitoring systems, where numerous formulations and methods have been proposed [3–8]. In this vein, Nondestructive evaluation (NDE) is one of the most frequently stated problems in the SHM [9–11]. Vibration-based structural integrity approaches have gained new prominence as they offer an efficient tool in practical applications [12–14]. This concept is grounded in the principle that alterations in physical characteristics can lead to variations in modal properties, encompassing mode shapes, frequencies, and modal damping. These variations can function as indicators for evaluating the structural integrity [15, 16]. Vibration-centric methodologies can be expressed within either the temporal or frequency realms. Nevertheless, it has been observed that the stability of frequency domain characteristics surpasses that of the temporal and time-frequency domains [15].

A pioneering study by Adams *et al.* [17] used vibration measurements to evaluate the defect's location and magnitude. Numerous papers have since summarised and reviewed early vibration-based damage detection techniques [2, 6, 18, 19]. Similarly, based on modal parameters, Fan and

Qiao reviewed and compared different damage identification algorithms for plate and beam-type structures [16]. Essentially, their research covered four primary categories, which included investigations into curvature mode shape, natural frequency, mode shape, and mode shape-frequency techniques. As an alternative to natural frequencies, the measured amplitudes of Frequency Response Functions (FRFs) are often used to identify damage. The FRF-based damage detection method provides enhanced insight into structural response dynamics by focusing on a restricted set of modal data within precise frequency bands proximate to resonance frequencies [20]. Furthermore, recent academic review articles, have been written to address the theoretical aspect of this research domain [15, 21].

Machine Learning (ML) algorithms are fast becoming a key instrument in engineering applications due to the huge development in computational capabilities and data availability. These techniques enable computers to solve complex problems based on examples and experience provided through data input [22]. In the field of structural engineering, ML methods have found applications in various domains. Nonetheless, research in ML within this domain is typically categorized into the following areas: Structural Health Monitoring, identification of structural systems, control of structural vibrations, structural design, and predictive applications [23–25]. Vibration-based damage detection methods based on ML techniques can be either parametric or non-parametric [26].

Artificial Neural Networks (ANNs), being efficient pattern recognition tools, have been employed by many researchers to determine damage location and severity [27]. Lee *et al.* [28] introduced a damage detection approach that integrates artificial neural networks (AN) while considering the modelling error within the initial finite element model utilised for training pattern generation. This method relies on a back-propagation neural network for its implementation. Mehrjoo *et al.* [29] introduced an approach to assessing the severity of damage in truss bridge joints. Furthermore, Avci Onur *et al.* [26] Offered an extensive examination of the recently introduced methods in machine learning and deep learning applied to structural health monitoring through vibration analysis.

Tran-Ngoc *et al.* [9] introduced an innovative machine-learning methodology that draws inspiration from the evolutionary algorithm known as Cuckoo Search (CS). This approach effectively addresses the challenge of local minima in ML. In the training phase, their algorithm operates concurrently with ML techniques. Given that local minima can detrimentally impact the precision of ML models, numerous research endeavours have been dedicated to surmounting this particular constraint. Khatir *et al.* [30] demonstrated a solution to this issue by utilising a combination of Particle Swarm Optimisation (PSO) and Teaching Learning Based Optimisation (TLBO) in order to determine the initial training parameters for the ANN. Working along similar lines, Tran-Ngoc *et al.* [31] applied the CS algorithm to determine the most suitable initial step. Their findings demonstrated improved accuracy in comparison to traditional machine learning techniques. In the research conducted by Zenzen *et al.* [32] they employed FRF data in conjunction with genetic and bat algorithms to assess the detection and assessment of damage in both beam-like and truss structures. Additionally [33] investigated composite laminated beams and plates, utilising a damage assessment approach centred around transmissibility and mode shape.

Model order eduction methods such as proper orthogonal decomposition (POD), have pinpointed dependable and efficient strategies for damage identification [34]. The POD technique is exploited for processing substantial volumes of high-dimensional data, facilitating computational analysis to anticipate the future dynamics of the system [35]. Shane and Ratneshwar [36] introduced a novel algorithm rooted in POD, incorporating proper orthogonal modes (POM) as dynamical invariants. This comprehensive approach has been specifically applied to composite beams, underscoring the algorithm's potential and relevance in damage detection across diverse scenarios. In their groundbreaking work, Eftekhar *et al.* [37] proposed an innovative supervised learning method that integrates artificial neural networks and POD. This approach was designed to differentiate alterations in proper orthogonal modes attributed to structural damage while isolating them from variations induced by varying applied load conditions. The efficacy of this proposed methodology was demonstrated through a series of simulated experiments. In a noteworthy study, Khatir *et al.* [38] integrated the radial basis functions with their method, referred to as POD-RBF, to identify the positions, dimensions, and depths of cracks in composite structures made of carbon fibre-reinforced polymer (CFRP). Their results underscore the efficacy of the POD-RBF technique in combination with the Cuckoo search algorithm. Subsequent research efforts have also delved into this specific domain [39–42].

1.1. *POD-based radial basis functions*

Proper orthogonal decomposition (POD) is a powerful technique for dimensionality reduction, widely employed in various data analysis fields. Its fundamental principle lies in capturing the most essential patterns or structures within high-dimensional datasets, thereby enabling a more efficient representation while preserving critical information.

The system represents different points data snapshots, organised into a data matrix $\boldsymbol{U}$. Each column of this matrix represents an individual snapshot, while each row corresponds to a distinct variable or data point. Where $\boldsymbol{U}$ is a $\boldsymbol{n} \times \boldsymbol{s}$ matrix, where $\boldsymbol{n}$ denotes the number of variables and s signifies the number of collected snapshots.

To extract the underlying modes that constitute the predominant variability in the dataset, we employ Singular Value Decomposition on the centred data of U matrix. The singular values in $\boldsymbol{\Sigma}$ are ordered in descending fashion, representing the significance of the modes. By selecting the first few singular vectors (modes) associated with the largest singular values, the primary patterns within the data are captured. These modes encapsulate the essential information for subsequent reduction. Radial basis functions (RBFs) are a type of mathematical function used in this study for multivariable interpolation for they are particularly advantageous with scattered data points. RBFs are centred around a set of control points, and their values at any given point in space are determined by their distance from these centre points [39].

In this research, the analysis utilises a combination of the POD approach and the RBF interpolation methodology to deduce the structural reaction in the framework of an inverse problem. The description of the structural response relies on empirical information contained within the $\boldsymbol{U}$ matrix.

$$\boldsymbol{U} = \begin{bmatrix} u_1^1 & u_1^2 & \cdots & u_1^{\mathrm{S}} \\ u_2^1 & u_2^2 & & u_2^{\mathrm{S}} \\ \vdots & \vdots & \ddots & \vdots \\ u_{\mathrm{N}}^1 & u_{\mathrm{N}}^2 & \cdots & u_{\mathrm{N}}^{\mathrm{S}} \end{bmatrix} \tag{1}$$

In this context, the dataset denoted as $\boldsymbol{U}$ comprises a collection of $\boldsymbol{N}$ snapshots, each characterised by a snapshot vector of size $\boldsymbol{S}$. The primary focus of this research is to analyse the dimensions of the structural response dataset. Additionally, matrix $\boldsymbol{P}$ is employed to store information pertaining to crack parameters. Following this, a set of orthogonal vectors denoted as Φ is extracted. These vectors serve as the basis for projecting the measurement data matrix $\boldsymbol{U}$, ultimately yielding the amplitude matrix $\boldsymbol{A}$:

$$\boldsymbol{A} = \boldsymbol{\Phi}^T \cdot \boldsymbol{U} \tag{2}$$

The matrix denoted as $\boldsymbol{A}$ offers an estimation of the structural response data. It's worth mentioning that $\boldsymbol{\Phi}$ is determined via the POD process, which encompasses the derivation of eigenvectors from the covariance matrix $C = U \cdot U^T$ using singular value decomposition. Subsequently, a dimensionality reduction step is performed to decrease the basis vectors within $\mathbf{\Phi}$, resulting in a lower-rank variant $\widehat{\mathbf{\Phi}}$ obtained by retaining only the initial k (where k ≪ S) columns associated with the largest eigenvalues. As a result, a modified amplitude matrix, referred to as $\widehat{\boldsymbol{A}}$, is introduced as follows:

$$\widehat{\boldsymbol{A}} = \widehat{\mathbf{\Phi}}^T \cdot \boldsymbol{U} \tag{3}$$

In the following stages, we create a connection between structural response information and crack characteristics using Radial Basis Function interpolation. This process entails the utilisation of coefficient matrix $\mathbf{B}$ and interpolation matrix $\boldsymbol{G}$ to define $\widehat{\boldsymbol{A}}$ as the product of $\mathbf{B}$ and $\boldsymbol{G}$. $\boldsymbol{G}$ is determined to be non-singular, the expression can be formulated as follows:

$$\mathbf{B} = \widehat{\boldsymbol{A}} \cdot \boldsymbol{G}^{-1} \tag{4}$$

where $G(S)$ in this study, consider the normalised paramters values, and represent the RBF distances of each sample point from all the other points. M is the number of sample points.

$$G = \begin{bmatrix} g_1(\|p^1 - p^1\|) & \cdots & g_1(\|p^j - p^1\|) & \dots & g_1(\|p^M - p^1\|) \\ \vdots & & \vdots & & \vdots \\ g_1(\|p^1 - p^i\|) & \cdots & g_1(\|p^j - p^i\|) & \cdots & g_1(\|p^M - p^i\|) \\ \vdots & & \vdots & & \vdots \\ g_1(\|p^1 - p^M\|) & \cdots & g_1(\|p^j - p^M\|) & \cdots & g_1(\|p^M - p^M\|) \end{bmatrix} \tag{5}$$

In this context, we evaluate the function, $\boldsymbol{g_i}(p)$ for every parameter within the matrix $\boldsymbol{G}$. Each parameter, denoted as p_i, corresponds to $\boldsymbol{U_i}$ (where i ranges from 1 to N). The magnitude of the difference $|p - p_i|$ signifies the input argument for the ith Radial Basis Function, where $\boldsymbol{p}$ represents the current parameters, and $\boldsymbol{p_i}$ denotes the reference parameters. Following this, once the coefficient matrix $\mathbf{B}$ has been computed, we introduce a reduced-dimensional model in vector format:

$$\mathbf{a}(\mathbf{p_{new}}) = \mathbf{B} \cdot \mathbf{g}(\mathbf{p_{new}}) \tag{6}$$

Using this method, an estimation of the structural reaction associated with novel crack characteristics, denoted as $\mathbf{p_{new}}$, is determined:

$$\mathbf{u}(\mathbf{p_{new}}) = \widehat{\mathbf{\Phi}} \cdot \mathbf{a}(\mathbf{p_{new}}) \tag{7}$$

Hence, the POD-RBF model can replicate unknown structural responses for various crack parameter sets $\mathbf{p}$. A summary of the POD-RBF construction is depicted in Figure 1.

1.2. *Problem formulation based on optimisation algorithms*

1.2.1. *The bat algorithm*

The Bat Algorithm, a nature-inspired optimisation algorithm, derives its principles from the echolocation behaviour observed in bats [43]. This algorithm emulates the hunting strategies of bats, employing their echolocation capabilities for prey localisation. The Cuckoo Search Algorithm, another nature-inspired optimisation algorithm, is grounded in the reproductive conduct of cuckoo birds [44]. It replicates the parasitic tendencies of certain cuckoo species, specifically those that deposit their eggs in the nests of other bird species. Within the algorithmic framework, optimisation problem solutions are analogously represented as nests, and the egg-laying strategy of cuckoos symbolises the exploration and exploitation of the search space. The algorithm integrates random walk and Levy flight steps to update candidate solutions iteratively, with the overarching goal of identifying optimal or near-optimal solutions for diverse optimization problems.

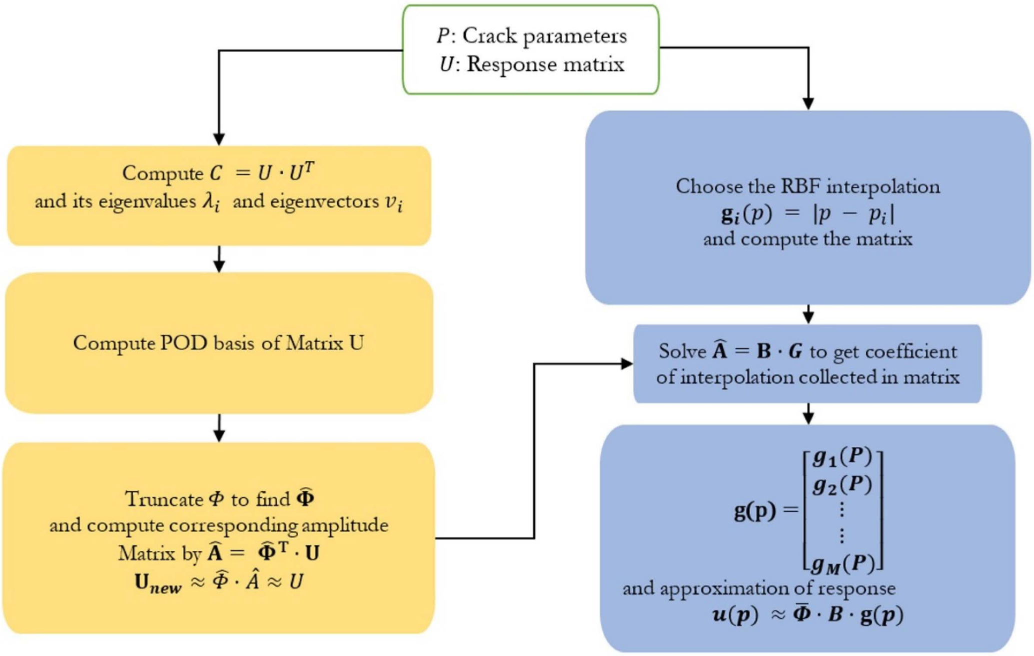


Figure 1. POD-RBF algorithm.

1.2.2. *Particle swarm optimisation (PSO)*

Particle Swarm Optimisation (PSO), a computational optimization technique, takes inspiration from the social behaviour observed in animal flocks [45]. It involves a population of particles navigating through a defined search space, adjusting their positions based on both individual and collective experiences to ascertain optimal solutions for a given problem. Communication and information sharing among particles facilitate the guidance of the search towards regions within the solution space where more favourable solutions are anticipated.

1.2.3. *YUKI algorithm*

This algorithm introduces an innovative approach to population clustering, resulting in the formation of two distinct clusters. One cluster is dedicated to extensive exploration, while the other focuses on the exploration of the best regions so far. YUKI algorithm guides this strategy by setting a consistent ratio across iterations, determined by a user-defined parameter termed the exploration rate (EXP), ranging from 0 to 1. The EXP parameter dictates the proportion of the population dedicated to exploration [40].

The algorithm establishes a local search area centred around the current optimal solution, referred to as $\mathbf{X_{best}}$. The size of this area is determined by the distance between this solution and the ***MeanBest*** point, which serves as the centroid of the cluster containing optimal points. The algorithm calculates the local boundaries, denoted as $\boldsymbol{LT}$ and $\boldsymbol{LB}$, using the following equations:

$$\boldsymbol{D} = \mathbf{X_{best}} - \mathbf{X_{MeanBest}} \tag{8}$$

$$\boldsymbol{LT} = \mathbf{X_{best}} + \boldsymbol{D} \tag{9}$$

$$\boldsymbol{LB} = \mathbf{X_{best}} - \boldsymbol{D} \tag{10}$$

The exploration approach promotes diversification in the search for a solution by expanding beyond the confines of the local search region. This approach is mathematically represented as follows: In this equation, $\boldsymbol{X}^{\boldsymbol{i}}_{\mathbf{loc}}$ represents the local solution chosen for exploration, while $\boldsymbol{X}^{\boldsymbol{i}}_{\mathbf{best}}$ refers to the optimal historical position associated with this specific location.

$$\boldsymbol{E}^{\boldsymbol{i}} = \boldsymbol{X}^{\boldsymbol{i}}_{\mathbf{loc}} - \boldsymbol{X}^{\boldsymbol{i}}_{\mathbf{best}} \tag{11}$$

The value denoted as $\boldsymbol{E}^{\boldsymbol{i}}$ plays a crucial role in defining the extent of the exploration range applicable to the specific point under consideration. To derive fresh solutions, we employ the subsequent equation:

$$\boldsymbol{X}^{\boldsymbol{i}}_{\mathbf{new}} = \boldsymbol{X}^{\boldsymbol{i}}_{\mathbf{loc}} + \boldsymbol{E}^{\boldsymbol{i}} \tag{12}$$

The method guides other solutions to explore the vicinity of the search centre by employing the subsequent equation. In this equation, $\boldsymbol{F}^{\boldsymbol{i}}$ represents the distance from the chosen local point to the optimal solution, and "rand" is a random value ranging from 0 to 1, which is applied uniformly across all design variables.

$$\boldsymbol{F}^{\boldsymbol{i}} = \boldsymbol{X}^{\boldsymbol{i}}_{\mathbf{loc}} - \boldsymbol{X}_{\mathbf{best}} \tag{13}$$

$$\boldsymbol{X}^{\boldsymbol{i}}_{\mathbf{new}} = \boldsymbol{X}^{\boldsymbol{i}}_{\mathbf{loc}} + \mathbf{rand} \times \boldsymbol{F}^{\boldsymbol{i}} \tag{14}$$

The algorithm pseudocode is written as follows:

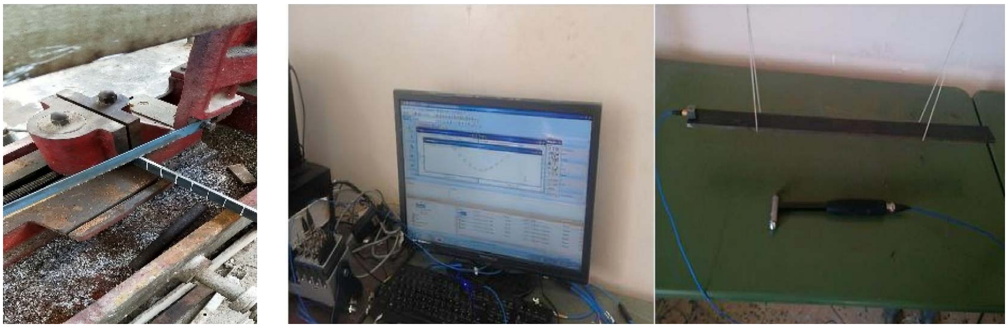
```
Load search parameters
Initialize population X
  Evaluate fitness
       Calculate X_MeanBest and X_best
       for K = 1 to K_max
       Calculate local boundaries
       Generate random local population
If rand < EXP (EXP = 0.7)
   Calculate exploration solutions
    Else
   Calculate focus solutions
  End
    Update X_MeanBest
    Update X_best if better solutions found
End
    Return X_best
```

1.2.4. *Objective function*

Natural frequencies are key parameters characterising the dynamic behaviour of structural systems under external disturbances. These frequencies depend on various factors, including material properties, geometric configurations, and boundary conditions specific to the beam structure. In an intact state, a beam's natural frequencies are determined by its structural integrity. However, the presence of damage alters these frequencies due to changes in stiffness and mass distribution within the beam.

Typically, damage leads to a reduction in stiffness and potential shifts in mass distribution, resulting in observable changes in the beam's natural frequencies. Modal analysis techniques are commonly employed to detect these deviations, involving either experimental measurements or computational simulations to identify the altered natural frequencies.

The utilisation of natural frequency changes for structural damage identification is a well-established approach in structural health monitoring. By comparing measured or computed



(a) (b)

Figure 2. (a) Cutting saw, and (b) Experimental setup.

natural frequencies with those of an undamaged reference state, researchers can pinpoint the location, extent, and severity of structural damage.

The change of natural frequency is used as an objective function as presented in the following equation:

$$OF = \sum_{i}^{n} \left[\left(\omega_i^r - \omega_i^c\right)^2 / \left(\omega_i^r\right)^2 \right] \tag{15}$$

where, n is the number of modes, ω_i^r are the frequencies calculated by the optimisation algorithm–POD, and ω_i^c are the measured frequencies.

2. Experimental analysis

The purpose of this study is to develop a novel approach that combines proper orthogonal decomposition (POD) and radial basis function (RBF) interpolation for predicting structural responses based on crack parameters while introducing the YUKI algorithm to optimise the process and assess its accuracy in real-world crack length estimation as presented in Figure 2.

In this paper, two beams are considred to predict notch and double notch length based on modal analysis. An excitation hammer (Impact PCB Hammer Type 086C03) with a force sensor whose sensitivity is 2:5 mv, a PCB M352C66, Type ICP, sensitivity 96.9 mV/g accelerometer composed of a mass, a data acquisition system and a PC were used. The notches created using cutting saw as presented in Figure 2a and experimental setup is showed in Figure 2b.

In the initial investigation, a beam marked as "beam I" featuring paired notches were introduced at the centre of the latter, encompassing 25 distinct depths. These notches ranged from 1 mm to 25 mm in extension length. Remarkably, a 1 mm deep crack was intentionally introduced both at the upper and lower sections of the beam. Tabulation of the mechanical attributes of the beam can be found in Table 1, while Figure 3 provides details regarding the frequencies observed during the experimental analysis of both the unaltered and double-notched beam.

In the second instance, denoted as "beam II", a series of 20 crack depths were intentionally induced within the central section of the structure. These cracks were incrementally extended from 2 mm to 32 mm, each step measuring 1 mm. The frequencies corresponding to each mode shape resulting from these crack configurations have been compiled and can be found in Figure 4. Additionally, the mechanical properties of beam II are detailed in Table 2.

3. Results and discussions

In this section, we proposed a comparison between the results using Bat algorithms, cuckoo search and YUKI and the results found in [46], where the ANN is used to predict the damage

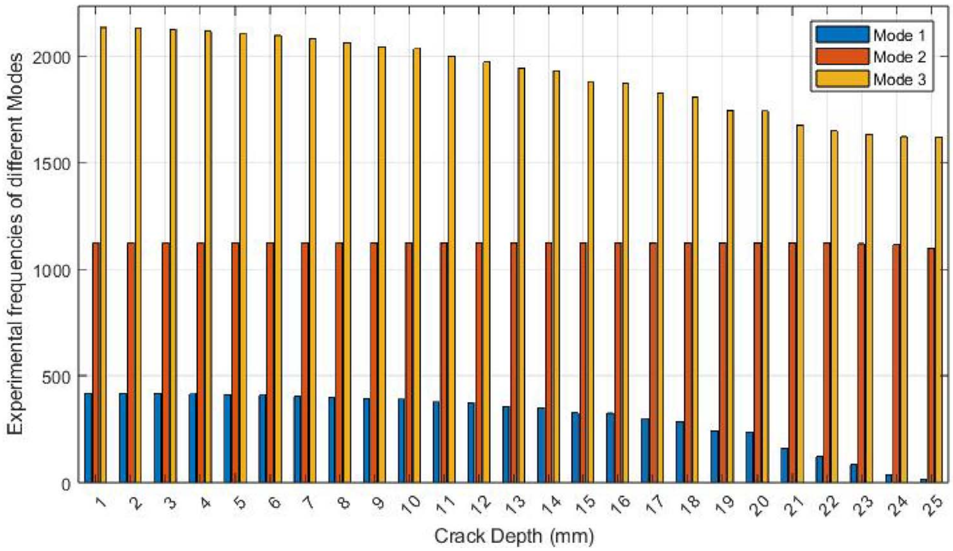


Figure 3. Numerical frequencies of different crack depths (beam I).

Table 1. Dimensions and material characteristics of the beam I

Item	Value
Length (mm)	800
Width (mm)	15
Height (mm)	50
Density (kg/m^3)	7850
Poisson ratio (/)	0.3
Young modulus (GPa)	2.1×10^{11}

Table 2. Dimensions and material characteristics of the beam II

Item	Value
Length (mm)	1000
Width (mm)	10
Height (mm)	40
Density (kg/m^3)	7850
Poisson ratio (/)	0.3
Young modulus (GPa)	2.1×10^{11}

size in two beams (Beam I and Beam II) and using different hidden layer sizes (HLS), and the results indicate that the best regression is achieved with HLS = 8 for Beam I and HLS = 10 for Beam II. In their research, Seguini *et al.* used the frequencies as an input and the damage size as an output. Tables 3 and 4 compare their results with results of the suggested approach for Beam I and Beam II respectively.

Examination is made on the training points, Figure 5 shows the absolute Errors for Different Methods (beam I). The discussion involves a thorough examination of errors in identifying cracks, as presented in Figure 6. That includes two important measures: Mean Error and Standard Deviation, which are used to evaluate the accuracy and consistency of various methods used for

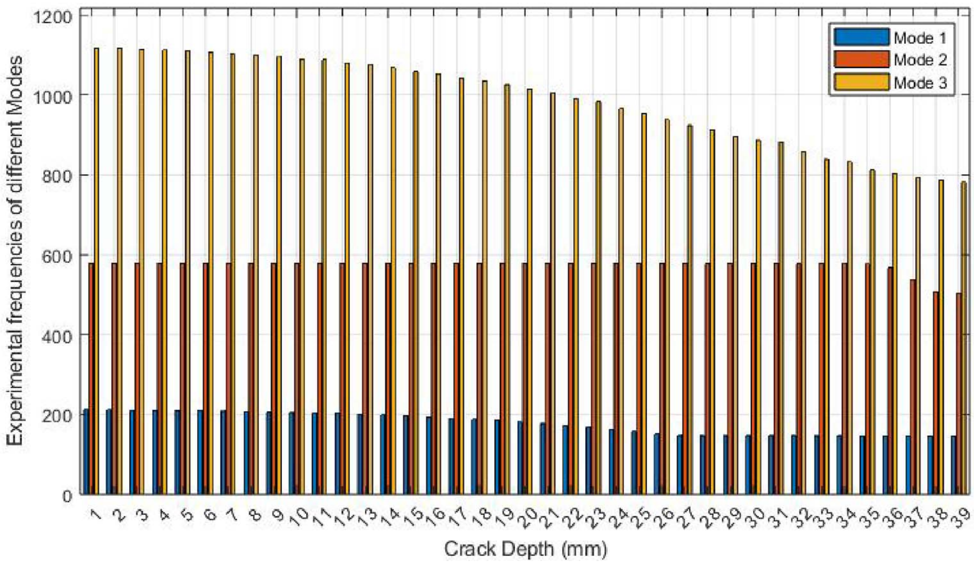


Figure 4. Numerical frequencies of different crack depths (beam II).

Table 3. Exact and estimated results using different optimisation methods (beam I)

Cases	Actual crack length (mm)	Cuckoo	Bat	PSO	YUKI	ANN NHLS = 8 [46]	ANN NHLS = 10 [46]	ANN NHLS = 12 [46]
1	4	3.8815	3.8815	3.8815	3.882	3.80911	3.614833	3.84674
2	10	9.4677	9.4677	9.4677	9.4781	9.54634	9.710795	9.66756
3	20	19.1019	19.1019	19.1019	19.1166	19.86071	19.53756	19.848808

Table 4. Exact and estimated results using different optimisation methods (beam II)

Cases	Actual crack length (mm)	Cuckoo	Bat	PSO	YUKI	ANN NHLS = 8 [46]	ANN NHLS = 10 [46]	ANN NHLS = 12 [46]
1	8	7.9389	7.9388	7.9388	7.9383	7.807456	8.18362	8.93587
2	15	15.2842	15.2840	15.2840	15.2848	15.32850	15.22022	15.47560
3	25	24.9308	24.9308	24.9308	24.9353	24.90070	25.19147	25.11821

crack identification. Mean Error represents the average difference between predicted and actual values. In the context of crack identification, a lower Mean Error indicates better accuracy. On the other hand, a lower Standard Deviation suggests more consistent and predictable results.

When examining the data presented in the table, several noteworthy observations can be made. To begin with, three methods—Cuckoo, Bat, and PSO—display nearly identical Mean Percentage Error and Standard Deviation values. Their Mean Percentage Error stands at approximately 4.26%, indicating an average crack identification accuracy slightly above 50%. However, their Standard Deviation is relatively high, at about 1.20, signifying significant variability in individual results. The YUKI algorithm, on the other hand, demonstrates a slightly better performance, with a Mean Percentage Error of 4.19, still falling within the 50% accuracy range.

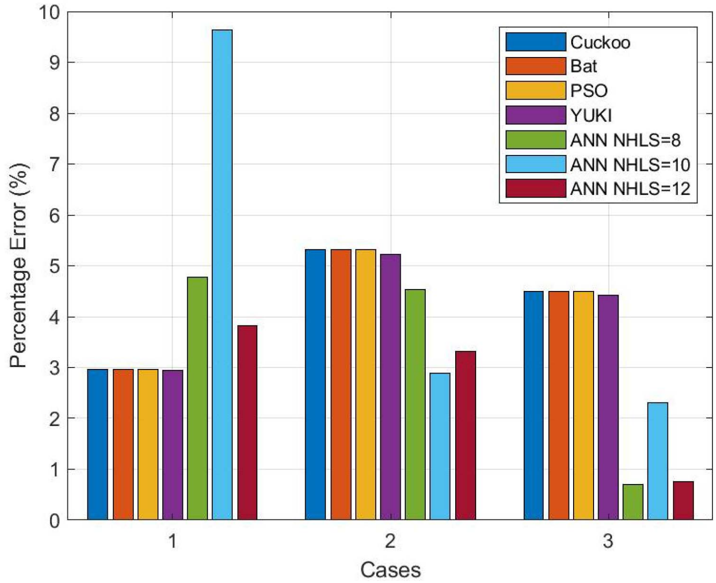


Figure 5. Absolute errors for different methods (beam I).

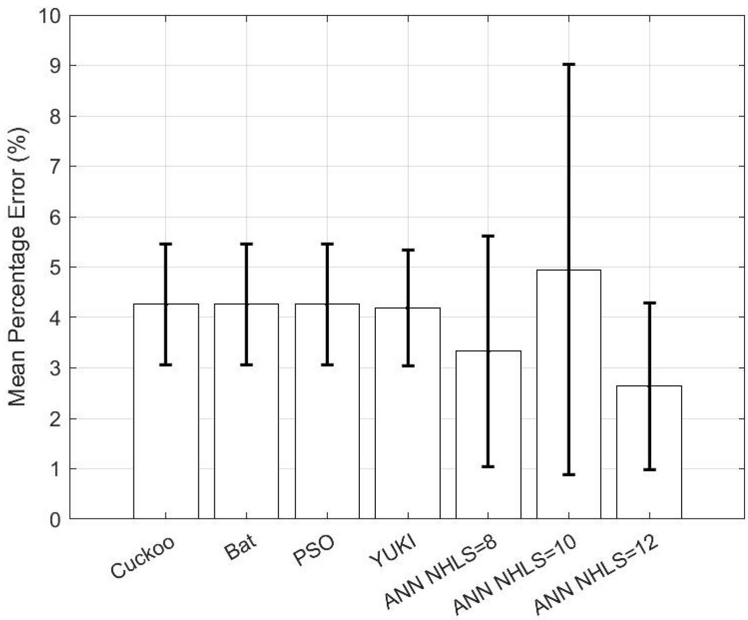


Figure 6. Mean error with standard deviations for different methods (beam I).

Its Standard Deviation is approximately 1.15, suggesting a moderate level of consistency in its predictions.

Moving on to the Artificial Neural Network model with NHLS = 8, it exhibits a noticeable improvement with a Mean Percentage Error of 3.34. This suggests enhanced accuracy compared to the earlier methods. Additionally, its Standard Deviation is lower, at around 2.29, indicating

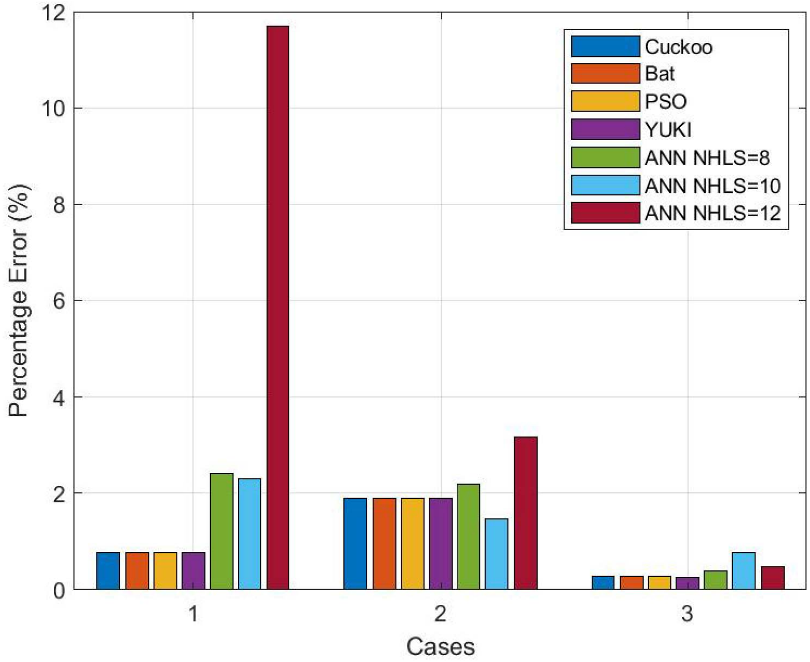


Figure 7. Absolute errors for different methods (beam II).

increased consistency in its predictions. The ANN model with NHLS = 10, while having a higher Mean Error than the NHLS = 8 model (4.94%), compensates with an exceptionally low Standard Deviation of 4.07, implying highly consistent results. Lastly, the ANN model with NHLS = 12 performs the best, boasting a Mean Percentage Error of 2.64 and an impressively low Standard Deviation of 1.65. These values collectively indicate both high accuracy and exceptional consistency in its predictions.

When analysing the errors depicted in Figures 7 and 8, it becomes evident that the three methods, namely Cuckoo, Bat, and PSO, demonstrate very similar Mean Error and Standard Deviation values, all hovering around 0.98 and 0.83, respectively. This suggests that, on average, these methods achieve a relatively high level of accuracy in crack identification, with a minimal degree of variability in their results. While the YUKI algorithm performs slightly better, indicating a marginally improved accuracy, it still falls within a similar range as the previous methods, suggesting moderate consistency in its predictions.

The Artificial Neural Network (ANN) model with NHLS = 8 exhibits a Mean Error of 1.66%, indicating a slightly lower level of accuracy compared to the previous methods. However, its Standard Deviation of 1.10 suggests a reasonable level of consistency in its predictions.

For NHLS = 10, the Mean Error improves to 1.51%, indicating enhanced accuracy compared to the NHLS = 8 model. What's more, it's remarkably low Standard Deviation of 0.77 suggests a high degree of consistency and predictability in its crack identification results. NHLS = 12 stands out with a substantially higher Mean Error of 5.11%, signifying relatively lower accuracy compared to other methods. Furthermore, its Standard Deviation of 5.86 is notably higher, indicating significant variability in its predictions and rendering it less reliable compared to other methods.

In the evaluation of crack identification methods for both Beam I and Beam II, we can observe certain similarities and differences between the approaches. Firstly, when considering the Mean

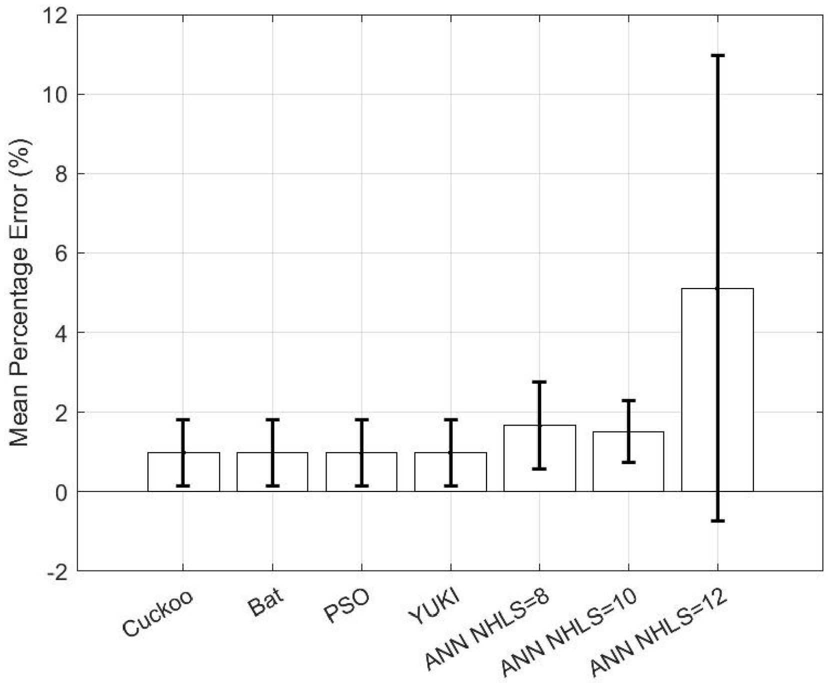


Figure 8. Mean error with standard deviations for different methods (beam II).

Percentage Error values, the Cuckoo, Bat, and PSO methods exhibit comparable performance. In Beam I, they have an average error of approximately 4.26%, while in Beam II, this value drops to around 0.98. This suggests that these methods achieve a moderate to high level of accuracy. However, it's important to note that these methods also display significant variability in their results, as indicated by their relatively high Standard Deviation values. In particular, Beam I show a higher level of result variability for these methods with a Standard Deviation of about 1.20, whereas Beam II exhibits a lower Standard Deviation of approximately 0.83 for the same methods.

On the other hand, the YUKI algorithm outperforms the Cuckoo, Bat, and PSO methods in terms of Mean Percentage Error in both Beam I and Beam II, with an average error of around 4.20% in Beam I and 0.98% in Beam II. While it demonstrates slightly better accuracy, it still falls within the same range. Furthermore, the Standard Deviation values for the YUKI algorithm are relatively consistent in both Beam I and Beam II, indicating a degree of stability in its predictions. Thus, the YUKI algorithm consistently delivers reliable results.

4. Conclusion

In this research paper, a comprehensive exploration of structural health monitoring (SHM) techniques, particularly focused on vibration-based damage detection methods, has been presented. The study investigated the integration of nondestructive evaluation techniques with vibration-based methodologies, aided by advanced machine learning tools, to assess and monitor structural integrity. The research emphasised the critical importance of ensuring structural stability and safety across various industrial sectors, aiming to prevent catastrophic failures. Key methodologies employed in this investigation include artificial neural networks, proper orthogonal decomposition (POD), radial basis functions (RBF), and the innovative YUKI algorithm, which introduces a population clustering approach to crack length prediction.

The study's findings have highlighted the potential of these methodologies in effectively detecting and localising structural damage. Notably, the YUKI algorithm has shown promise in achieving highly accurate predictions of crack lengths. However, it is essential to acknowledge the inherent variability in predictive outcomes across different scenarios and use cases, necessitating further comprehensive investigations and rigorous validation procedures. Overall, this research has contributed valuable insights into the application of SHM techniques and their potential for enhancing structural safety. Future research endeavours should focus on refining these methods and assessing their suitability for real-world structural health monitoring scenarios.

Declaration of interests

The authors do not work for, advise, own shares in, or receive funds from any organization that could benefit from this article, and have declared no affiliations other than their research organizations.

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