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Localization and Quantification of Multiple Damages on One-Dimensional Beam with Sensitive Modal Data and Jensen-Shannon Divergence-Based Artificial Neural Network Regression

Vineet Kumar Vashishtha[1], Dr. Nitin Kumar Jain[2], Dr. Ankur Gupta[3]

[1]Department of Mechanical Engineering, National Institute of Technology Raipur, G.E. Road Raipur, Chhattisgarh, India 492010.
Email: vineet.nitrr.phd@gmail.com
[2]Department of Mechanical Engineering, National Institute of Technology Raipur, G.E. Road Raipur, Chhattisgarh, India 492010.
Email: nkjain.me@nitrr.ac.in
[3]Department of Mechanical Engineering, National Institute of Technology Raipur, G.E. Road Raipur, Chhattisgarh, India 492010.
Email: ankurgupta1729@gmail.com

Abstract

Purpose: This paper introduces a new method to localize and quantify multiple damages in one-dimensional beams by simultaneously minimizing three loss functions in an Artificial Neural Network. It enhances modal amplitude sensitivity by elastically adding small mass, demonstrating that this approach yields more accurate results compared to traditional methods.

Design/methodology/approach: Free vibration dynamic Finite Element Analysis (FEA) is used to generate modal amplitude data for a damaged one-dimensional beam. Three loss functions—Jensen Shannon Divergence, Mean Squared Error, and Mean Absolute Error—are minimized simultaneously. Damaged Finite Element heights are converted into Probability Mass Functions for accurate loss reduction. The method is validated on beams with four boundary conditions: cantilever, simply supported, overhanging, and propped cantilever. Adding a small mass strip enhances input data, improving prediction accuracy over traditional methods.

Findings: This research shows that adding a small mass increases the sensitivity of modal amplitude data. It lowers total training and validation losses, reduces Jensen-Shannon divergences, and improves damage prediction accuracy in all four beam cases compared to no mass increment, demonstrating the effectiveness of this mass-enhanced approach.

Originality/value: The proposed Artificial Neural Network architecture uses three loss functions—Jensen Shannon Divergence, Mean Squared Error, and Mean Absolute Error—simultaneously, which is novel and unreported. Adding a small elastic mass generates extensive training data, enhancing accuracy. It uniquely predicts multiple damages in the 0.1 mm to 0.3 mm range with high precision, making the approach original and innovative.

Keywords: Damage Localization, Damage Quantification, Jensen-Shannon Divergence, Artificial Neural Network Regression, Structural Health Monitoring, Non-Destructive Testing

1. Introduction

Structural Health Monitoring is essential to maintain the reliability and serviceability of mechanical, civil and aerospace engineering structures. Various Condition Based Monitoring System (CBMS) techniques have been developed as early warning systems. New advances in Artificial Intelligence during the last decade provided better prediction models. CBMS checks the health of engineering structures on-line, which is faster than periodic manual inspection.

At large, damage to engineering structure can be defined as the change in dimensions beyond the acceptable limit or a change in material properties. Damage is a chronic problem which may shorten the design life of engineering structures. Non-detectable damage propagates over time, and sophisticated CBMS is required to identify, localize, and quantify the damage. Fine or coarse granularity of damage depends on causes like corrosion, fatigue, environmental conditions, extreme loading, etc. Fine granular damages are undetectable by traditional techniques and propagate over time and shorten the structural serviceability. The current paper proposes an approach to identify, localize, and quantify multiple fine granular damages that may be caused by corrosion, among others.

Various Non-Destructive Testing(NDT) have been developed in recent years like Ultrasonic Testing, Ground Penetrating Radar, Laser Testing Methods, Infrared Thermography, Acoustic Emissions, Radiographic Testing, Magnetic Flux Leakage, Magnetic Particle Testing, Digital Image Correlation, Liquid Penetrant Testing etc. Most of the NDT methods are advantageous in identifying coarse granular damages that could propagate over time. The current paper is focused on free natural vibrations based CBMS as an early warning system to identify, localize and quantify multiple fine granular material loss on the surface from processes like corrosion etc. The proposed CBMS can identify, localize and quantify multiple damages in the range of 0.1 mm to 0.3 mmon small 1-D beams, which are challenging to identify, locate and quantifyby manual inspection.

(Rytter, 1993)proposed four goals for any CBMS

1. Damage Identification
2. Damage Localization
3. Damage Quantification
4. Damage Prognosis

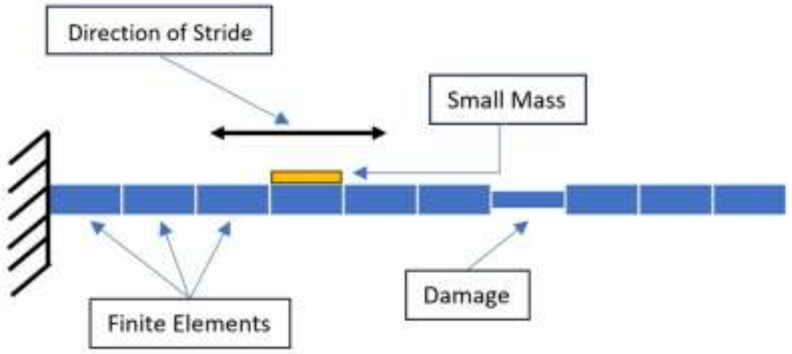


Fig. 1. Cantilever beam with 10 finite elements and striding mass

The current paper addresses the first three goals, and the order of complexity to achieve these goals increases from the first goal to the fourth goal. Damage Prognosis, which evaluates the integrity and serviceability of engineering structures with existing damages, is not addressed in the current paper. Damage Identification is done by Support Vector Machine (SVM), whereas Damage Localization and Damage Quantification are achieved by a triple loss ANN-based Regression model. The presentresearch proposes condition monitoring of1-D beam by its free vibration Modal Amplitude data.

(Dems & Mroz, 2001) proposed that while frequency shift measurements can offer a general evaluation of damage, they often lack sensitivity to specific damage levels, particularly when dealing with localized defects like cracks or holes. To enhance sensitivity, additional parameters were introduced into the structure, such as concentrated elastic or rigid supports, masses elastically or rigidly attached to the structure, boundary constraints, or prestress.

The present work uses a similar approach as adopted by (Dems & Mroz, 2001) but instead of using free vibration natural frequencies the present model uses free vibration modal amplitude data which has global span over engineering structures.

At training phase of the ANN Model;Modal Amplitude data is calculated with each stride of the strip of small material (Fig. 1). Free vibration Modal Amplitude data is calculated with numerical simulation by Dynamic Finite Element Analysis (FEA) of 1-D Beam. This Modal Amplitude data is input totrainthe ANN model. It is established in the current paper that Modal Amplitude data calculated in this way to train ANN model; identify, localize and quantify multiple damages better than without adding a small mass in the form of striding strip.

At testing phase Modal Amplitude data is calculated without stride of the strip of mass and it is used as input data to pretrained ANN model to localize and quantify multiple damages on beam.

Structural Health Monitoring (SHM) is a multi-disciplinary area of research and varies like variations in measured frequencies to baseline frequencies, wavelet transform, variation in curvature of mode shapes, variation in frequency response function, to computational methods like genetic algorithm and fuzzy logic.

Change from baseline frequencies is a direct indication of the presence damage on engineering structure. (Adams et al., 1978) assumed damage located at the axial position of the prismatic bar at an unknown location, and stiffness which represents the damage amount indirectly, is also unknown. Baseline frequency has been used to theoretically measure the direct receptance at either side of damage. Differences in baseline natural frequency and decrease in natural frequency of two modes have been used to plot the sum of direct receptance (at either side of unknown damage location), and two plots intersect at damage location. Click or tap here to enter text. analytically developed a relationship between the change in natural frequencies of the cantilever beam and the crack depth of the weld under the assumption that Young's Modulus of beam material is equal to weld material. An empirical relationship has been developed between crack depth and different natural frequencies. The crack depth is detectable with confidence in order of 10%. The presence of multiple cracks in the cantilever beam has been addressed by (Khiem & Lien, 2004). Dynamic Stiffness Matrix method has been used to form constrained convex optimization problem; they have concluded that measuring more natural frequencies would improve the predictability of their approach to identify the multiple cracks.

Wavelet Transform is an effective method in damage identification because of its capability to detect small perturbations in the deflection profile. (Shahsavari et al., 2017) used Continuous Wavelet Transform on Simply Supported and Fixed Beams for damage detection and localization. To get a good estimate of the wavelet coefficients and to minimize the effects of experimental uncertainties they used Principal Component Analysis (PCA). Their algorithm detects damage at multiple locations with good statistical significance.

Modal shape curvatures are highly sensitive to location and amount of damage.(Wahab & De Roeck, 1999) have been summarized the difference of all mode shape curvature as a single metric to identify and localize the damage. The method was proved by simulation on beams of different boundary conditions and applied to real-life civil engineering structures. (Pandey et al., 1991) applied the fact that change in modal shape curvature increases with the amount of damage. FEA has been used in cantilevers and simply supported beams to calculate Modal Amplitude values. Difference in baseline curvature mode shape and the current value of it has been used to localize the damage.

Frequency response function (FRF) is defined as the Fourier Transform of the time domain response divided by the Fourier transform of the time domain input. (Dackermann et al., 2013) used the difference between baseline FRF and present FRF of a two-storey framed structure. PCA has been used to filter out the noise from the signal. ANN has been used to find joint damage with processed FRF. (Bandara et al., 2014) used PCA to reduce FRF data obtained from FEA of two-storey framed structures. Damage index values have been calculated from FRF and mapped to damage location and severity of damage by ANN.

Genetic Algorithm is a meta-heuristic optimization technique to optimize complex objective functions. (Alves et al., 2020) have used different damage indicators like natural frequencies, vibration mode shapes, modal curvatures and frequency response functions. Their methodology successfully applied to finite element models and real structures to detect, locate and quantify damage.

Fuzzy logic is a logical system which is an extension of multivalued logic.(Allali et al., 2018) developed a fuzzy set of No damage, Slight damage, Moderate damage, Severe damage and Collapse for post-earthquake assessment of building's damage. Rule weights have been optimized with genetic algorithm. Their results showed a high performance with 90% of global accordance.

The above research works vary in their experimental setup. First is a direct measurement of actual engineering structure (Chondros & Dimarogonas, 1980), (Shahsavari et al., 2017), (Allali et al., 2018), second is verification of methodology on actual engineering structure (Adams et al., 1978), third is the FEA model along with experiment on the real model (Wahab & De Roeck, 1999), (Dackermann et al., 2013), (Alves et al., 2020), fourth is only FEA to verify the methodology (Khiem & Lien, 2004), (Pandey et al., 1991), (Bandara et al., 2014).

The current paper verifies a new methodology with Dynamic FEA of 1-D beams along with ANN. ANN is a universal function approximator which can establish a non-linear relationship between input data and targets. Various studies Refs.(Pawar et al., 2007), (Hakim et al., 2015), (Gordan et al., 2020), (Jeyasehar & Sumangala, 2006), (Rosales et al., 2009)have been done on beams to establish non-linear relationships with input data like natural frequencies and Modal Amplitude values and targets like damage identification, damage location and damage amount.

(Pawar et al., 2007) have done dynamic FEA simulation on a fixed-fixed beam with 20 finite elements, 600 mm length and an area of 240 mm^2. A three-layered ANN has been used with Fourier coefficients as input where damaged mode shapes were expanded using a spatial Fourier series. Their work isa case of ANN learning where the damage locations and amount have been predicted. Their proposed methodology has been verified by dynamic FEA of 1-D beams along with ANN.(Hakim et al., 2015)used FEA and ANN in conjunction for an I-Section Beam and simulated with an eight-node linear 3-D Brick finite element. The finite element modaldata was input to ANN of fifteen input neurons where one neuron accepted natural frequency, and fourteen neurons acceptedModal Amplitude values. The three output neurons predictedthe location of two damages and the severity of damages. Dimensions of the I-Section beam was 3200 mm length, flange width 75 mm, section depth 150 mm, flange and width thickness are 7 mm and 5 mm.Hybrid Imperial Competitive Algorithm (ICA) and ANN have been used by (Gordan et al., 2020) to identify damage on a structure consisting of three steel I-beams attached to a slab specimen of 3200 mm length. Total of 25 damage severities were considered with 5 mm width, and 3 mm to 75 mm depth with increment of 3 mm in depthfor each damage scenario. For FEA a 4-node shell homogeneous (S4R) and 8-node solid homogeneous linear brick (C3D8R) have been used for beams and girder deck, respectively. Their ANN architecture consisted of 15 input neurons (one for natural frequency and 14 for mode shapes), and the output of ANN was damage severity (one neuron). Mean Absolute Errorhas been used as a metric of performance, ICA-ANN performed better than simple ANN.(Jeyasehar & Sumangala, 2006) considered prestressed concrete beams of length 4860 mm with a rectangular cross-section of 125 x 250 mm under dynamic response to assess only the severity of damage. Four beams of the same size and same boundary condition have been considered with severity of damage 33.33%, 50%, 66.67% and 83.33%.Inputs to ANN were combination of static and dynamic properties like natural frequency, deflection, crack width, first crack load, ultimate load and outcome was degree of damage. (Rosales et al., 2009) considered cantilever beam of 100 cm length with a rectangular cross section of height of 5 cm and width of 1 cm.A minimum crack depth of 0.01 m (1 cm) has been considered. Theyobtainedthe first three natural frequencies as input data to the ANN. Their ANN testing error was considerably high when both location and amount of damage were tried to be predicted by ANN. Further, to improve their results, damage location was found bythe Power Series Technique and the amount of damage was found by ANN.

The fact overlooked in Refs. (Pawar et al., 2007), (Hakim et al., 2015), (Gordan et al., 2020), (Jeyasehar & Sumangala, 2006), (Rosales et al., 2009)(Gaidhane et al., 2025)is that while localized damages significantly impact local stress and strain, frequencies and Modal Amplitude values, which represent global energy measures, are not sensitive to small and localized variations in stiffness.To address this issue (Raipure , N. et al., 2025) introduced additional parameters in the form of concentrated elastic or rigid support and mass addition to localize a single damage using analytical method.

The following are the gaps in(Dems & Mroz, 2001) approach. First, only one damage has been considered, but the current paper considers multiple damages. Second, only the problem of damage localisation has been solved, but the current paper solves both damage localization and damage quantification. Third, free vibration natural frequencies have been considered to localize the single damage, but the current paper considers free vibration Modal Amplitude values because their span is global to engineering structure hence produces better results. Fourth, analytical approach with FEA has been used to solve the damage localization problem, but current paper incorporates a more sophisticated technique, ANN with triple loss function.

Concluding the literature review, to the best of the author's knowledge, the following research gaps are identified and are addressed in the present work:

1. The current paper uses Modal Amplitude data and aims to find multiple fine granular damages of 0.1 mm to 0.3 mm, which are smaller than those considered in previous research works Ref. (Pawar et al., 2007), (Hakim et al., 2015), (Gordan et al., 2020), (Jeyasehar & Sumangala, 2006), (Rosales et al., 2009).
2. The beam dimensions considered in the current paper are smaller than all previous research works Ref. (Pawar et al., 2007), (Hakim et al., 2015), (Gordan et al., 2020), (Jeyasehar & Sumangala, 2006), (Rosales et al., 2009).
3. To the best of the authors knowledge, no or very limited papers have addressed the problem of multiple damage identification, localization, and quantification altogether. This study aims to fill this gap by introducing a novel ANN-based method for the simultaneous identification, localization, and quantification of multiple damages.
4. Another gap identified in the literature Refs. (Pawar et al., 2007), (Hakim et al., 2015), (Gordan et al., 2020), (Jeyasehar & Sumangala, 2006), (Jagtap , M. et al., 2025), (Rosales et al., 2009) is the exclusive use of Mean Squared Error (MSE) or Mean Absolute Error (MAE) as loss functions for ANN. In contrast, this paper incorporates Jensen-Shannon Divergence along with MSE and MAE as loss functions, enhancing the ability to quantify damage in the range of 0.1 mm to 0.3 mm, which is challenging to detect through human inspection, particularly on smaller beam dimensions.
5. The final gap is that while this paper considers four beams with different boundary conditions (Fig. 2) to verify the proposed methodology, Refs. (Pawar et al., 2007), (Hakim et al., 2015), (Jeyasehar & Sumangala, 2006), (Rosales et al., 2009) only considered one boundary condition in their verification processes.

2. Problem Description

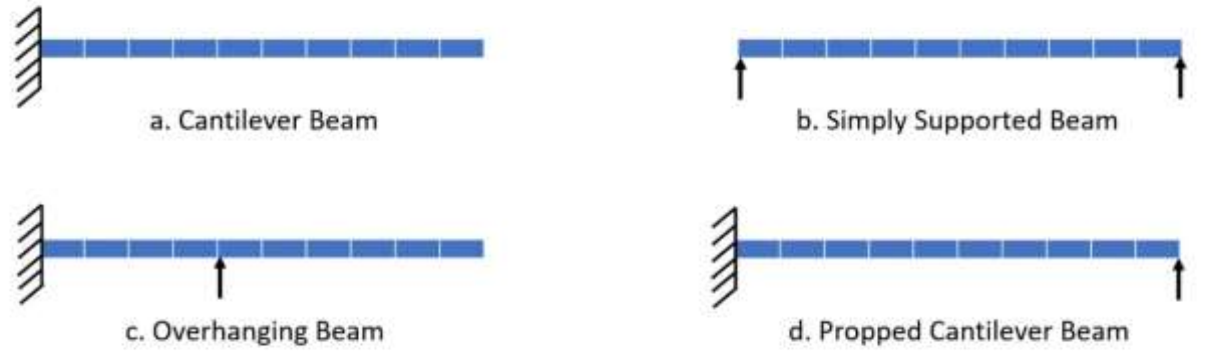
The current paper considers a 1-D Beam,which has a Modulus of elasticity E = 200x10^9 Pa, Density ρ = 7840 kg/m^3,Beam height h=1 cm, width b=1.5 cm, length l=15 cm. The beam has a rectangular cross-section, area A=b× h, moment of inertia $I = \frac{b \times h^3}{12}$.

1-D Beam Finite Element has 2 nodes and each node has two Degrees of Freedom (DOF).Following is the elementary stiffness $'k'$ and mass $'m'$ matrix (Chandrupatla, 2002).

$$k = \frac{EI}{l^3} \times \begin{bmatrix} 12 & 6l & -12 & 6l \\ 6l & 4l^2 & -6l & 2l^2 \\ -12 & -6l & 12 & -6l \\ 6l & 2l^2 & -6l & 4l^2 \end{bmatrix} \qquad m = \frac{\rho A l}{420} \times \begin{bmatrix} 156 & 22l & 54 & -13l \\ 22l & 4l^2 & 13l & -3l^2 \\ 54 & 13l & 156 & -22l \\ -13l & -3l^2 & -22l & 4l^2 \end{bmatrix}$$

Numerical experiments have been done on four 1-D Beams (Fig. 2)

a. Cantilever Beam
b. Simply Supported Beam
c. Overhanging Beam
d. Propped Cantilever Beam



a. Cantilever Beam

b. Simply Supported Beam

c. Overhanging Beam

d. Propped Cantilever Beam

Fig. 2. Boundary conditions of beams under consideration

The number of finite elements in each beam is 10. Damage is introduced by reducing the height of the finite element of the beam (Fig. 1). Dynamic FEA is done by considering three possibilities of damage count, i.e. only one finite element is damaged, only two finite elements are damaged, or three finite elements are damaged. All ${}^{n}C_{r}$ damage combinations have been considered, where n is the total number of finite elements, and r is the number of damaged finite elements (damaged locations). Total damages considered are $\sum_r {}^{n}C_r$ where r = 1, 2, 3 and n = 10.

It has been proved in the current paper that adding a small amount of extra mass elastically (Fig. 1)improves the predictability of ANN. With each stride of strip of elastically added small amount of extra mass, the Modal Amplitude values have been calculated numerically by free vibration Dynamic FEA. For all four beams, only 10 (not all) Modal Amplitude values have been considered as input data to ANN. Modal Amplitude values have been pre-processed before feeding into ANN. The triple loss ANN predicts the location and the amount of multiple damages in the range of 0.1 mm to 0.3 mm.

3. Methodology

The following are core ideas in current research work: -

- Add small mass elastically to finite elements to make Modal Amplitude Data Sensitive
- Produce vast amounts of Modal Amplitude data by striding small mass strip over beam
- Minimize Jensen-Shannon Divergence (JSD), Mean Squared Error (MSE) and Mean Absolute Error (MAE) loss functions simultaneously by ANN Regression
- Convert heights of damaged Finite Elements (FE) into SoftMax Probability Mass Function (PMF), which is used to minimize JSD and MSE
- Damage Identification by Support Vector Machine (SVM)
- Predict Damage Location and Damage Amount by ANN Regression

3.1 Divergence for Probability Mass Function (PMF)

Kullback Leibler Divergence (KLD) – KLD describes how dissimilar two probability distributions are. When KLD is used as a loss function in ANN, it describes the effort required to make predicted probability distribution Q similar to target probability distribution P. If the random variable is X

$$KLD(P \parallel Q) = \sum\nolimits_{x \in X} P(x) \times \log[P(x)/Q(x)]$$

KLD is not symmetric.

$$KLD(P \parallel Q) \neq KLD(Q \parallel P)$$

If two probability distributions are far apart horizontally, then KLD suffers a divide by zero (or divide by a very small number) problem. If distributions P and Q are not overlapping, then for given x where $P(x) \neq 0$ then

$Q(x) = 0$, in that case, $KLD(P \mid\mid Q) = \infty$. If distribution P and Q are slightly overlapping, then for given x, the $Q(x) \sim 0$, then $KLD(P \mid\mid Q) \sim \infty$, it means KLD will be a large number and it will cause explosion of gradient during Backpropagation. If $KLD(P \mid\mid Q) \sim 0$, it means ANN approximated predicted PMF Q to target PMF P.

Jensen Shannon Divergence (JSD) – JSD is a modification over KLD. Like KLD, the JSD describes how dissimilar two probability distributions are.

$$JSD(P \mid\mid Q) = \frac{1}{2}KLD(P \mid\mid M) + \frac{1}{2}KLD(Q \mid\mid M)$$

Where Mixture Distribution $M = \frac{1}{2}\ (P + Q)$

JSD is symmetric, $JSD(P \mid\mid Q) = JSD(Q \mid\mid P)$

When JSD is used as a loss function in ANN, it describes the effort required to make predicted PMF Q similar to target PMF P. JSD, when used as a loss function in ANN, avoids the divide by zero (or divide by very small number) problem; it helps prevent gradient explosion during Backpropagation. This is the reason to use JSD as one of the loss functions for ANN Regression in present work. If $JSD(P \mid\mid Q) \sim 0$, it means ANN approximated predicted PMF Q to target PMF P.

3.2 Damage Amount as PMF

SoftMax (S) is a very common activation function for ANN classification problems, and it is used with Categorical Cross-Entropy loss function usually.

$$S(HD_i) = \frac{e^{HD_i}}{\sum_j e^{HD_j}}$$

$\sum_j S(HD_j) = 1$ and $0 \leq S(HD_i) \leq 1$, is sufficient conditions to consider S as a PMF.

HD_i is the height of ith damaged finite element, and j representsthe total number of damaged finite elements and e is Euler's Number.

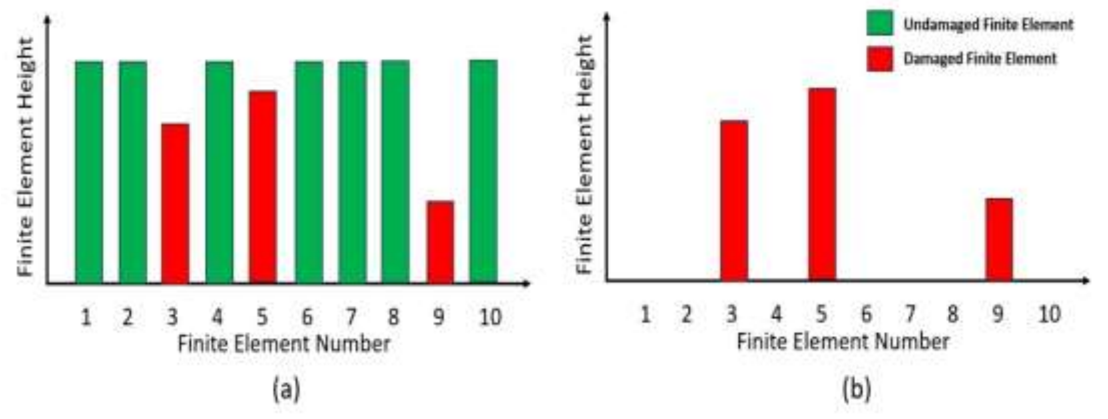


Fig. 3. Damaged FE height to SoftMax probability (a) All FE heights (b) Only damaged FE heights

Current paper minimizes JSD between two PMFs, a target PMF and a PMF predicted by ANN. For target PMF height of only damaged finite elements (HD) are considered (Fig. 3.b) and then converted into SoftMax Distribution $S(HD_i)$ as described above.

When calculating target PMF, we consider the undamaged finite element's height as zero and only consider the heights of damaged finite elements HD_i (Fig. 3.b), because we are interested in the location of damage and the height of the damaged finite element. This approach makes the objective simpler and easy to converge. Since the output layer of ANN (Fig. 4) uses SoftMax activation, the predicted PMF is also SoftMax distribution. Predicted SoftMaxPMF is approximated with target SoftMax PMF by reducing JSD and MSE simultaneously by ANN.

3.3 Data Preprocessing for ANN Regression

1. Mathematically free vibration dynamic FEA is an eigenvalue problem. Eigenvectors are Modal Amplitude values, and these eigenvectors are normalized (it is different than converting input data values between0 and 1, which is often called Normalization).
2. As a part of data preprocessing, normalized Modal Amplitude values are standardized with zero mean and unit standard deviation. This data is input to ANN.
3. The height of undamaged finite elements is considered as zero units, and the heights of damaged finite elements are not changed. The size of the height vector is equal to the number of damaged finite elements. This data of the height vector is converted into SoftMax PMF. This SoftMax PMF, of actual damaged finite element heights, is the target for ANN to minimize JSD and MSE loss functions (Fig. 4).
4. For the physical properties of 1-D Beam, the mass unit is in grams, the length unit is in millimetres, and the time unit is in seconds.
5. Finite Element's height is reduced in the range of 0.1 mm to 0.3 mm to introduce the damage.

Damage Identification is binary classification as damage vs no damage in 1-D Beam, SVM with Gaussian kernel is trained on pre-processed Modal Amplitude values data with two classes (damage Vs no damage). Since there is imbalanced data for damage vs no damage class, noise from the Uniform Distribution has been applied to the no damage class. If data is imbalanced, adding white Gaussian Noise is standard practice (Dackermann et al., 2013). Since Gaussian Kernel is used in SVM, noise from Uniform Distribution is used to avoid correlation. The accuracy of SVM is 99.99% for all four beams considered (Fig. 2).

3.4 ANN Architecture

The height of damaged 1-D Beam's finite elements is indirectly considered one of the targets of Deep ANN. These heights are converted into PMF by applying the SoftMax function. This SoftMax distribution of damaged finite element heights is one of the targets of ANN, and another target is the actual height of damaged finite elements.

ANN (Fig. 4) has three hidden Dense Layers with 1024 neurons and ReLU (rectified linear unit) as activation, and then the computational graph is bifurcated into three hidden Dense Layers with 1024 neurons and ReLU as activation. First of the three output layers has SoftMax Activation. It approximates the predicted SoftMax PMF with the target SoftMax PMF of the height of damaged finite elements by reducing Jensen-Shannon Divergence as a loss function. The second output layer has SoftMax activation and minimizes Mean Squared Error (MSE Loss) between target SoftMax PMF with predicted SoftMax PMF of damaged finite elements height. The third output layer has linear activation and minimizes Mean Absolute Error (MAE Loss) between the actual height of damaged finite elements and the predicted height of damaged finite elements. The number of neurons in all output layers equalsthe total number of finite elements in the beam (damage location), which is 10 in the current paper. Instead of considering all Modal Amplitude values, only 10 are considered; hence, the input layer of ANN has 10 neurons.

These three loss functions work in tandem with one another. If MAE loss is zero, it means the predicted heights of all damaged finite elements of 1-D Beam are the same as target heights, and, in this case, MSE and Jensen-Shannon Divergence losses will also be zero. The same argument is valid if MSE loss or Jensen-Shannon Divergence loss is zero. If one of these three losses goes down, it helps other losses to go down in tandem.

3.5 ANN Hyperparameters

Following are the hyperparameter settings

1. JSD loss and MSE loss are scaled up by a factor of 10, and MAE loss is scaled down by a factor of 0.1.
2. L1 and L2 regularizers are used with a coefficient value of 0.00001 for both.
3. Total loss is the sum of JSD, MAE, and MSE losses along with L1 and L2 regularizers.
4. 140 Epochs are done for training, Batch size is taken as 32.

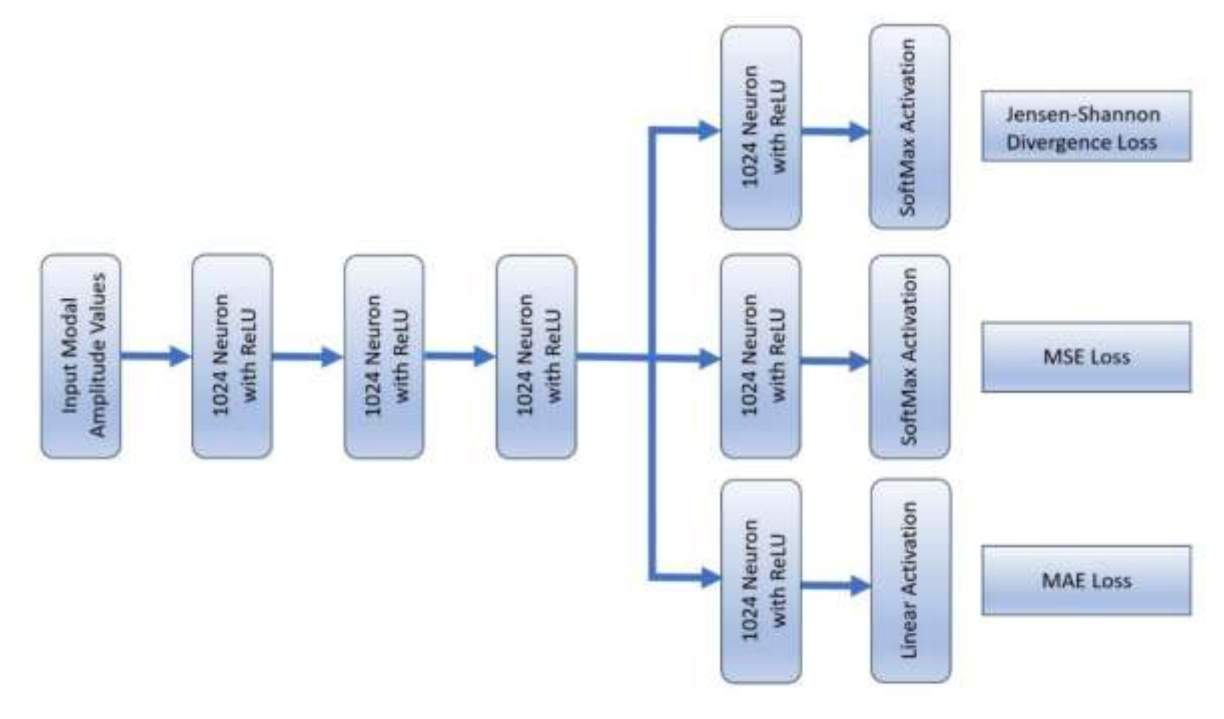


Fig. 4. Artificial neural network architecture

As an optimizer(Kingma & Lei Ba, 2015.), is used and learning rate is reduced stepwise from 0.001 to 0.00000625. Other parameters of Adam optimizer are set to proposed defaults by (Kingma & Lei Ba, 2015).

ANN is trained on sensitive Modal Amplitude data produced by a small striding strip of material, but it is validated and tested on Modal Amplitude data produced without mass increment.It makesthe proposed methodology practical because it is impractical to stride strip over the engineering structure in real life. Best ANN learnable parameters are saved for minimum validation JSD loss on validation data, and the proposed methodology uses MSE loss on test data as a metric to evaluate the ANN regression. This decoupling between saving the ANN learnable parameters and evaluating the performance of the ANN regression model avoids any room for bias that may exist. The MAE loss on test data also works as a metric to find the best value of mass increment that returns the minimum value of MAE.

The learning (total loss) curves (Fig. 6 to Fig. 9), considered for different beams, indicate no overfitting during the learning process and justifythe ANN architecture, hyperparameters and data preprocessing.

The learning (total loss) curves (Fig. 6 to Fig. 9) indicated that total loss during training and total loss on validation data goes down very well for both no mass increment and with mass increment case.

The learning (total loss) curves (Fig. 6 to Fig. 9), also provide information about minimum total loss achieved on both training data and validation data.

3.6 Flowchart for Algorithm

n is the number of finite elements in the beam, in other words, possible locations of damage. Since we are considering a 1-D beam with ten finite elements, n =10

C is the total number of damage combinations. This paper considers one or, two or three damages C = $\sum_r {}^{n}C_r$ where r = 1, 2, 3 and n = 10

L is the total number of damages introduced per finite element

N is the total number of Modal Amplitude Data produced

In the case of striding a small strip of mass, the N = C x n x L

In the traditional approach, when there is no striding strip of mass, The N = C x L

When a striding strip of mass is used, the number of Modal Amplitude Data is ‘n’ time more than the traditional approach

D is the dimensionality of data; since only 10 Modal Amplitudes have been considered, D = 10

Fig. 5 is a flowchart that produces Modal Amplitude Data as an N x D dimensional matrix, where a striding strip of small mass is present. This N x D matrix is input to ANN.

The flowchart will change slightly in the traditional approach (no striding strip). The loop to stride mass strip will not be there;the rest of the flowchart will remain the same

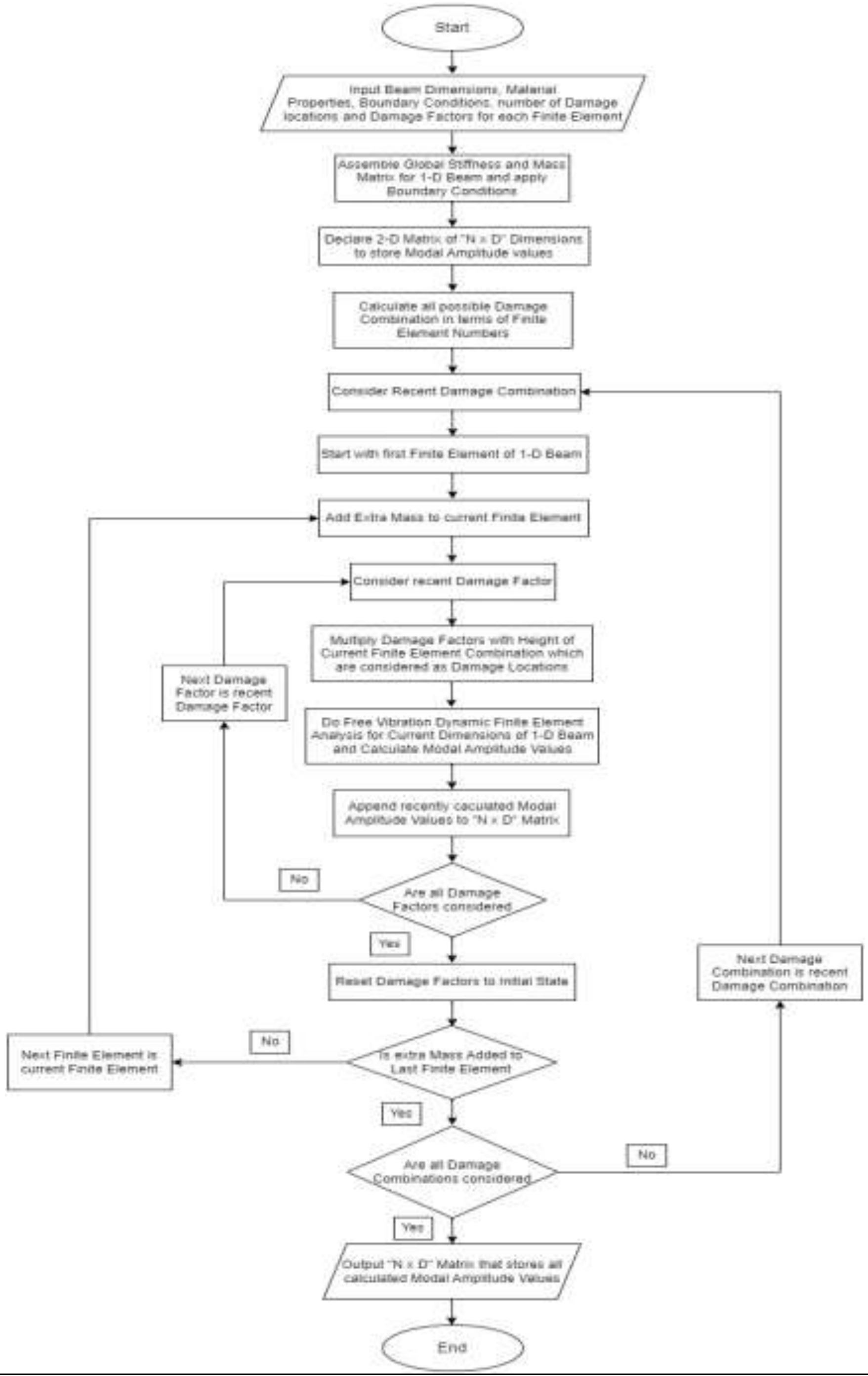


Fig. 5. Flowchart to find Modal Amplitude data with Striding Strip of material

4. Results and Discussions

The results are presented for 1-D Isotropic beams made of steel. MAE between actual damaged finite element (FE) heights and predicted heights of damaged FE on test data is considered as a metric to prove the core idea that the sensitivity of Modal Amplitude data increases with small amount of mass addition elastically. Extra mass is added to FE elastically by incrementing its density between 0.08% and 20%, which is basically the mass increment.

Table 1: MAE for different mass increments

MAE of Damaged FE Heights					
Beam Type		**Cantilever**	**Simply Supported**	**Overhanging**	**Propped Cantilever**
Percentage Increment in FE Mass	**0**	0.013624	0.003685	0.009278	0.008442
	0.08	0.005717	0.000342	0.001312	0.001147
	0.09	0.002767	0.000376	0.001250	0.001325
	0.1	0.001556	0.000312	0.001420	0.001703
	0.5	0.005391	0.000315	0.001745	0.001068
	1	0.006285	0.000413	0.001400	0.001358
	2	0.012702	0.000359	0.001445	0.001749
	3	0.012181	0.000249	0.001313	0.002296
	4	0.014891	0.000339	0.001968	0.002890
	5	0.020652	0.000244	0.001130	0.004366
	10	0.059705	0.000306	0.006957	0.005900
	20	0.060475	0.000407	0.010220	0.208612

It can be seen (Table 1) that for all four beams the MAE,between actual and predicted damaged FE heights, is higher when there is no mass (0%) increment, and MAE starts decreasing when the FE mass is incremented by 0.08 % for all the beams. However, when the mass increment reaches 20%, the MAE is more than that at 0% increment except for Simply Supported Beam.

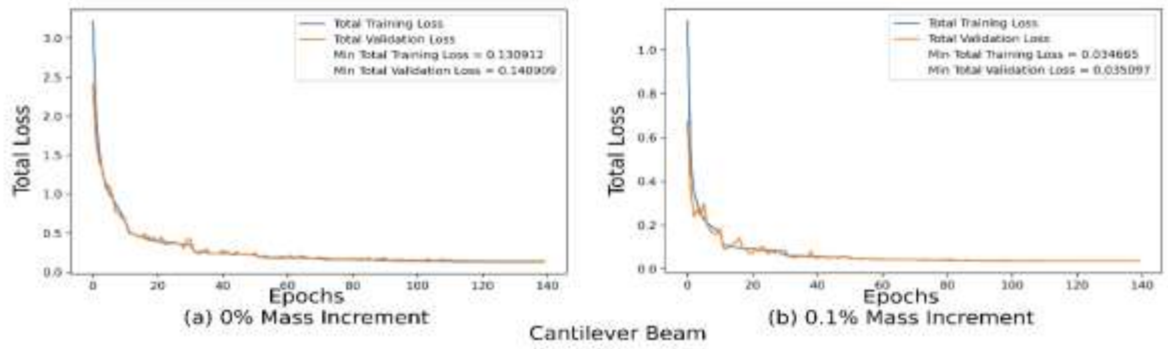
For the Cantilever Beam,MAE reduces for FE mass increment between 0.08 % and 3%, whereas MAE increases for higher values of FE mass increment (4% to 20 %)compared to 0% mass increment.

For Overhanging Beam, and Propped Cantilever Beam, only at 20% mass increment the MAE is higher than the MAE of 0% mass increment; from 0.08% to 10% mass increment, all MAEs are less than the MAE of 0% mass increment. For Simply Supported Beam the MAEs from 0.08% to 20% mass increment are less than the MAE of 0% mass increment.It is clear from MAE data (Table 1) that small amount of mass increment of FE elastically reduces the MAE,between actual and predicted damaged FE heights, on test data for ANN.

The minimum value of MAE for

1. Cantilever Beam is at 0.1% mass increment.
2. Simply Supported Beam is at a 5% mass increment.
3. Overhanging Beam is at 5% mass increment.
4. Propped Cantilever Beam is at 0.5% mass increment.

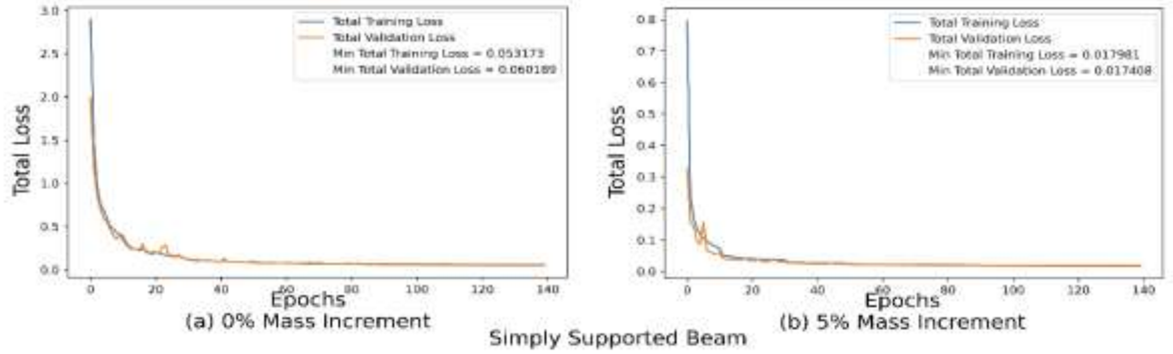
ANN trained on these mass increments for minimum MAEs is used to predict damage location and damage amount. The reason is that for minimum MAE, the ANN predictions are better. Learning curves (Total Loss) for these mass increment values are shown from Fig. 6 to Fig. 9.



(a) 0% Mass Increment (b) 0.1% Mass Increment

Cantilever Beam

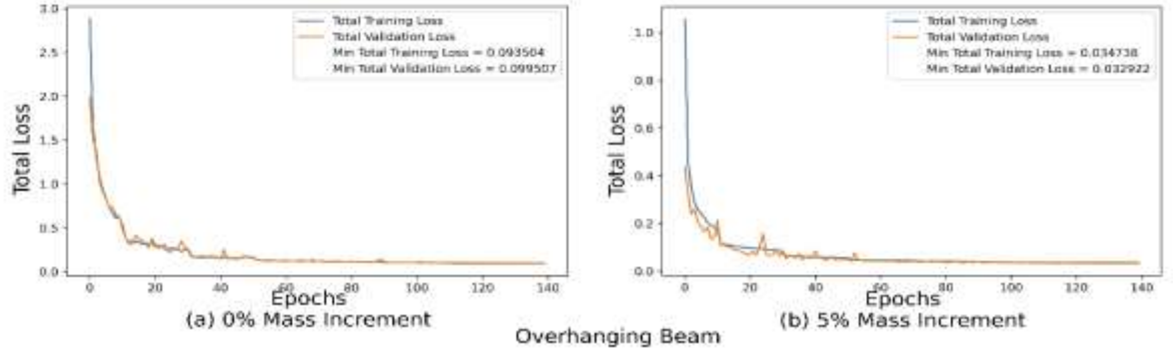
Fig. 6. Learning curves (a) 0% mass increment (b) 0.1% mass increment



(a) 0% Mass Increment (b) 5% Mass Increment

Simply Supported Beam

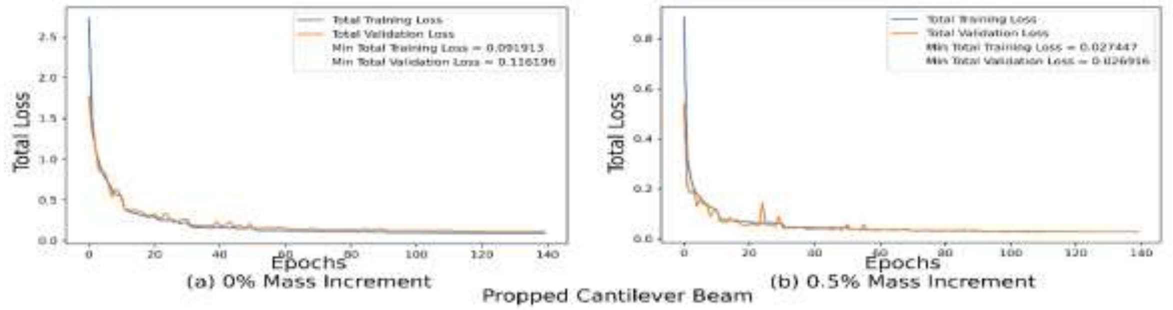
Fig. 7. Learning curves (a) 0% mass increment (b) 5% mass increment



(a) 0% Mass Increment (b) 5% Mass Increment

Overhanging Beam

Fig. 8. Learning curves (a) 0% mass increment (b) 5% mass increment



(a) 0% Mass Increment (b) 0.5% Mass Increment

Propped Cantilever Beam

Fig. 9. Learning curves (a) 0% mass increment (b) 0.5% mass increment

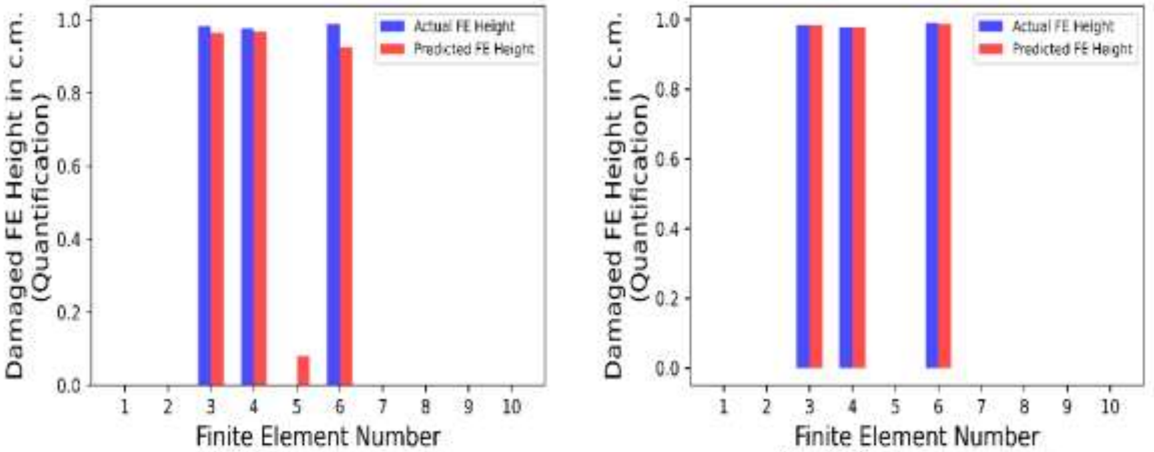
It is clear from the learning curves (Fig. 6 to Fig. 9) that Total Training and Validation losses are higher when there is no mass increment than in the case of mass increment. This is the first numerical evidence that incrementinga small amount of mass helps train ANN better; in other words, it increases the sensitivity of Modal Amplitude data, which is the input data for ANN.

There are three output layers in the proposed ANN Architecture. The first output layer predicts SoftMax probabilities of damaged FE heights, approximated by minimizing JSD loss with target SoftMax probabilities of actual damaged FE heights. Thenumber of neurons in all three output layers equals the number of FE in the beam, which is 10 in the current paper. High values of predicted SoftMax probabilities in these 10 output neurons of the first output layer indicate the location of damages. If there are three damages present, then there should beprecisely three spikes in the activation of output neurons of the first output layer. The lower value of JSD during testing is the metric of Damage Localization. In the case of a small amount of mass increment, there are better values of JSD than in the case of no mass addition; this is the second numerical evidence that incrementinga small amount of mass helps the ANN to better localize the damage. In other words, it increases the sensitivity of Modal Amplitude data, which is the input data for ANN.

The third output layer of the proposed ANN minimizes the MAE between the actual heights of damaged FE and predicted heights of damaged FE. The lower the MAE, the better the damage quantification. In the case of a small amount of mass increment,there are better values of MAE as compared with no mass addition case; this is the third numerical evidence that incrementing a small amount of mass helps the ANN toquantify the damages better, in other words, increases the sensitivity of Modal Amplitude data which isinput data for ANN.

Along with Fig.10 to Fig. 17 the values of JSD and MAE are compared for no mass increment and with mass increment case for all four beams to support the second and third numerical evidence discussed above.

Fig. 10 to Fig. 17 show the SoftMax probability and damaged FE height for all four boundary conditions. It can be seen that, Fig. 10 to Fig. 17 inferthatANN accurately predicts the location and quantity of the damage better when there is a small amount of mass addition.



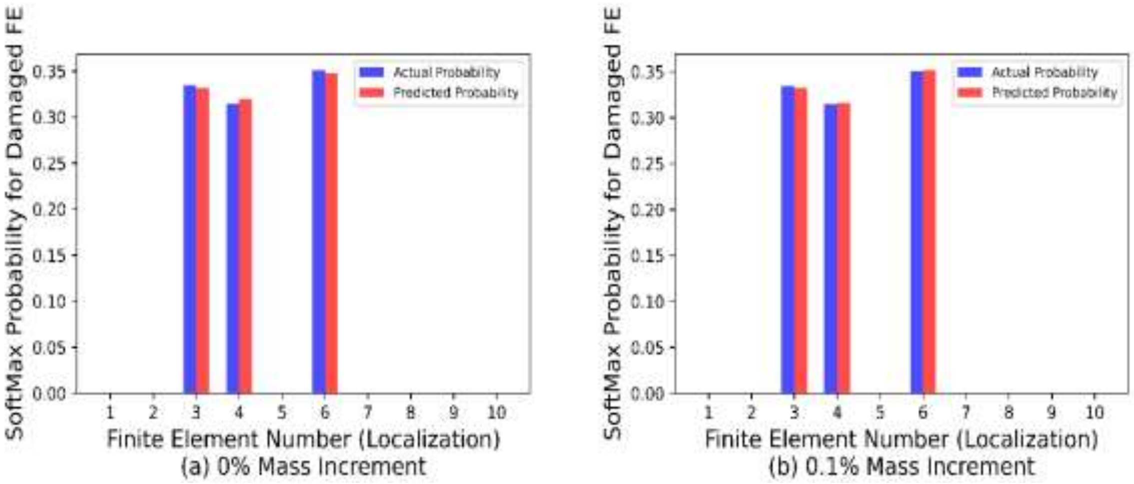
(a) 0% Mass Increment

(b) 0.1% Mass Increment

Cantilever Beam

Fig. 10. SoftMax probabilities(a) 0% mass increment (b) 0.1% mass increment

Cantilever Beam



Cantilever Beam

Fig. 11. Damaged FE heights (a) 0% mass increment (b) 0.1% mass increment

For Cantilever Beam (Fig. 10 and Fig. 11) FE 3, 4 and 6 are damaged and FE heights are 0.98426,0.97814and 0. 98908 cm. In the case of 0% mass increment, there is a JSD of 0.000438, and in the case of 0.1% mass increment, there is a lower value of JSD, which is 0.000045, it supports the second numerical evidence stated previously. Predicted FE heights in case of 0% mass increment are 0.96593, 0.96731 and 0.92488 cm. In the case of 0.1% mass increment, predicted heights are 0.98342, 0.97760 and 0.98829 cm, which is better. In the case of 0% mass increment, the MAE is 0.017354, but the 0.1% mass increment case has a much lower MAE of 0.000225, which supports the third numerical evidence stated previously. In the 0% mass increment case (Fig. 11.a), there is a wrong prediction at 5th FE, but in the case (Fig. 11.b) of 0.1% mass increment, there is a correct prediction; this is another evidence that a small increment of massmakes the Modal Amplitude data sensitive.

Simply Supported Beam

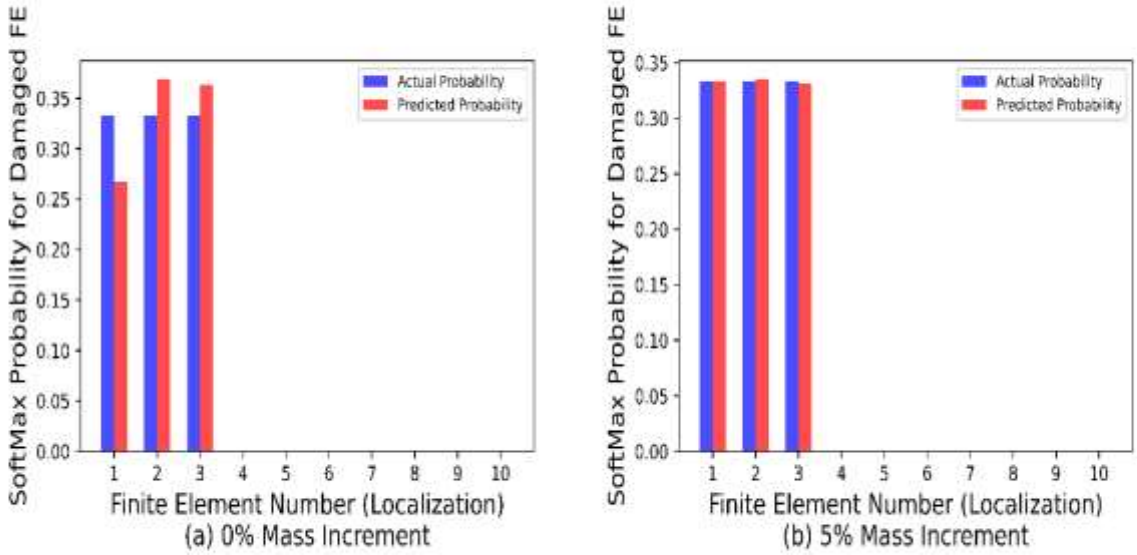


Fig. 12. SoftMax probabilities(a) 0% mass increment (b) 5% mass increment

Simply Supported Beam

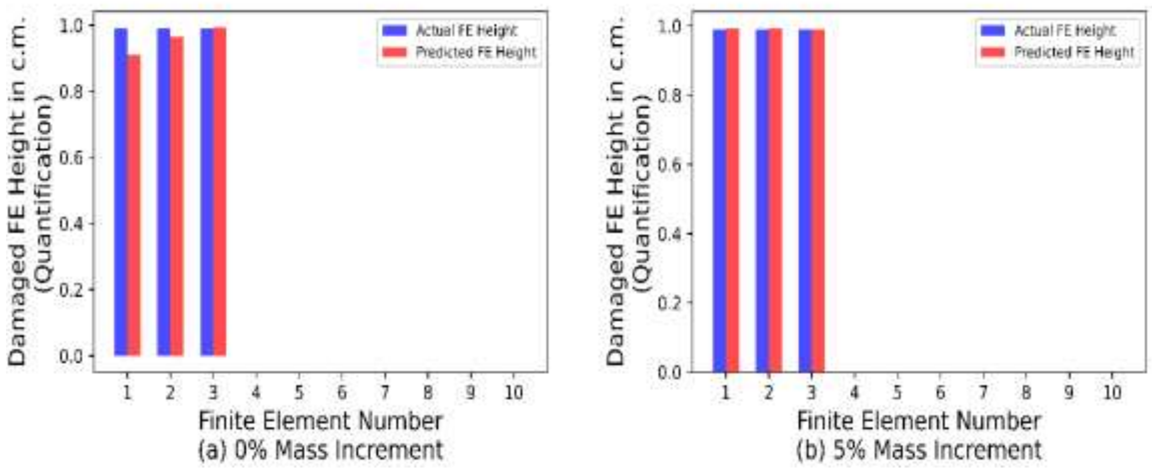


Fig. 13. Damaged FE heights (a) 0% mass increment (b) 5% mass increment

For Simply Supported Beam (Fig. 12 and Fig. 13) FE 1, 2 and 3 are damaged, and FE heights are 0.99, 0.99 and 0.99 cm. In the case of a 0% mass increment, there is a JSD of 0.003765, and in the case of a 5% mass increment, there is a lower JSD of 0.000019, which supports the second numerical evidence stated previously. Predicted FE heights in case of 0% mass increment are 0.90977, 0.96396 and 0.99225 cm. In the case of 5% mass increment, predicted heights are 0.99129, 0.99237 and 0.99031 cm, which are better. In the case of 0% mass increment, the MAE is 0.010855, but 5% mass increment case has a much lower MAE of 0.000401, which supports the third numerical evidence stated previously. This example is a demonstration of the present methodology's prediction capability of 0.1 mm damage in all three FE with MAE of only 0.000401. Another scenario is that the three damaged FE are side by side and near boundary conditions, which makes a very small change in Modal Amplitude values, and the proposed ANN architecture localizes and quantifies damages with high accuracy.

Overhanging Beam

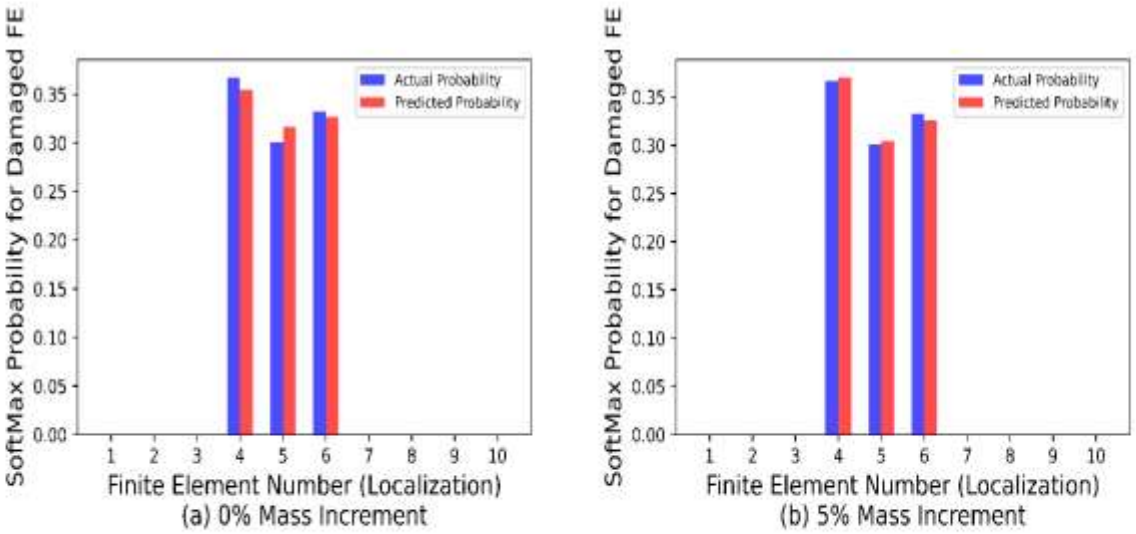


Fig. 14. SoftMax probabilities(a) 0% mass increment (b) 5% mass increment

Overhanging Beam

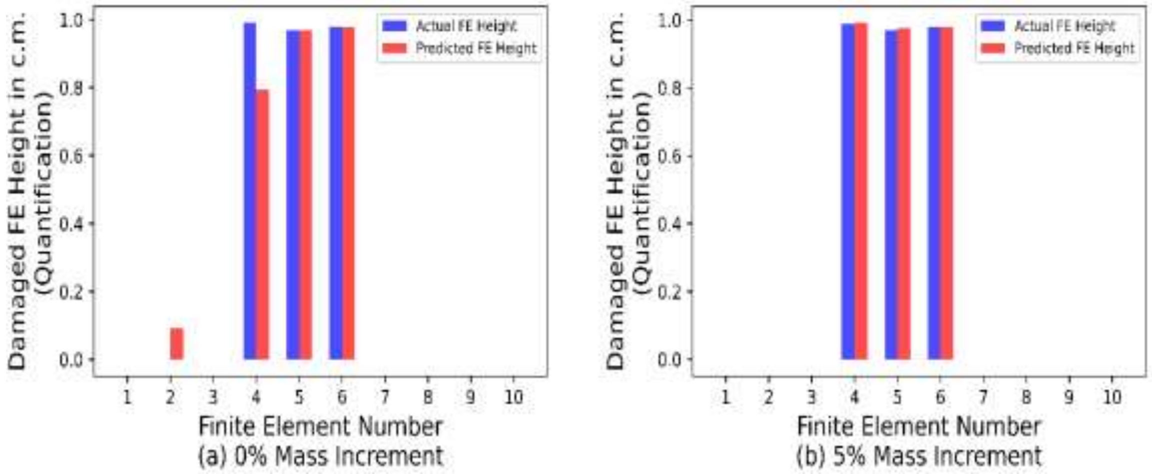


Fig. 15. Damaged FE heights (a) 0% mass increment (b) 5% mass increment

For Overhanging Beam (Fig. 14 and Fig. 15) FE 4, 5 and 6 are damaged and FE heights are 0.99, 0.97 and 0.98 cm. In the case of 0% mass increment, there is a JSD of 0.000501, and in the case of 5% mass increment, there is a lower JSD of 0.000067, which supports the second numerical evidence stated previously. Predicted FE heights in case of 0% mass increment are 0.79449, 0.96904 and 0.97915 cm. In the case of 5% mass increment, predicted heights are 0.99111, 0.97488 and 0.97952 cm, which are better. In the case of 0% mass increment, the MAE is 0.028874, but the 5% mass increment case has a much lower MAE of 0.000681, supporting the third numerical evidence. The 4th FE actual height is 0.99 cm, which is poorly predicted as 0.79449 cm in the 0% mass increment case, but the 5% mass increment case has a very accurate value of 0.99111 cm which corrects up to two decimal places. Another thing is that the 0% mass increment has a wrong prediction at the 2nd FE (Fig. 15.a), which is not present inthe 5% mass addition case (Fig. 15.b). This example demonstrates the present methodology's capability to predict damage in the 0.1 mm to 0.3 mm range. There is damage of 0.1 mm in 4th FE, 0.3 in 5th FE. In this example, damage of 0.1 mm, 0.3 mm and 0.2 mm are side by side, which makes minimal change in Modal Amplitude values, and the proposed ANN architecture predicts damage with high accuracy.

Propped Cantilever Beam

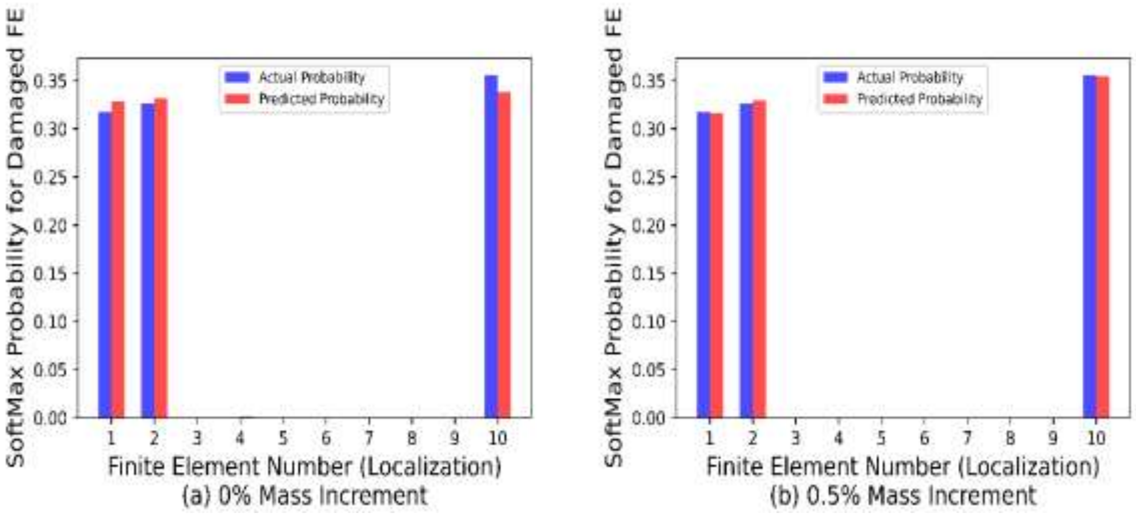


Fig. 16. SoftMax probabilities(a) 0% mass increment (b) 0.5% mass increment

Propped Cantilever Beam

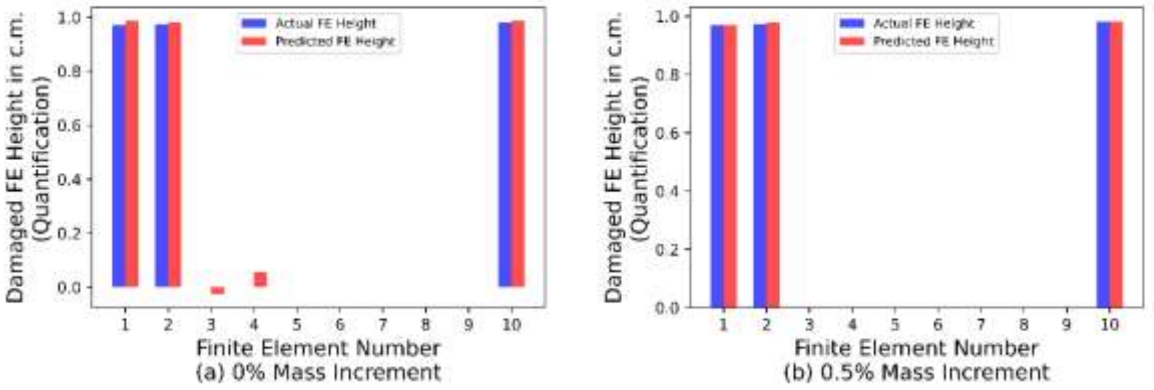


Fig. 17. Damaged FE heights (a) 0% mass increment (b) 0.5% mass increment

For Propped Cantilever Beam (Fig. 16 and Fig. 17) FE 1, 2 and 10 are damaged, and FE heights are 0.97014, 0.97286 and 0.98139 cm. In the case of 0% mass increment, there is a JSD of 0.000966, and in the case of 0.5% mass increment, there is a lower JSD of 0.000043, which supports the second numerical evidence stated previously. Predicted FE heights in case of 0% mass increment are 0.98620, 0.98151 and 0.98622 cm. In the case of 0.5% mass increment, predicted heights are 0.97042, 0.97761 and 0.98149 cm, which are better. In the case of 0% mass increment, the MAE is 0.011032, but the 0.5% mass increment case has a much lower MAE of 0.000516, which supports the third numerical evidence stated previously. In the case of 0% mass increment, there is wrong damage prediction (Fig. 17.a) at 3rd and 4th FE, which is not therein the case of 0.5% mass increment (Fig. 17.b).

The above results establish that a small mass incrementenhances the predictability of the proposed ANN architecture to localize and quantify multiple damages. In other words, it increases the sensitivity of Modal Amplitude data.

5. Conclusions

The current research presents three numerical evidences demonstrating that the sensitivity of modal amplitude data increases with a slight increase in mass. In all four beams considered,

1. Total training and total validation losses are lower in the case of a small amount of mass increment as compared to no mass increment case.
2. Jensen-Shannon divergences are lower with a small mass increment compared to the case with no mass increment.
3. The Mean Absolute Errors between actual damaged finite element heights and predicted damaged finite element heights are lower with a small mass increment as compared to the case with no mass increment.

The proposed ANN architecture, along with consistent hyperparameters and data preprocessing across all four beams, effectively prevents overfitting during training. During testing, it accurately performs both Damage Localization and Damage Quantification. The methodology is validated on four beams with identical dimensions and material properties but different boundary conditions, ensuring its robustness.

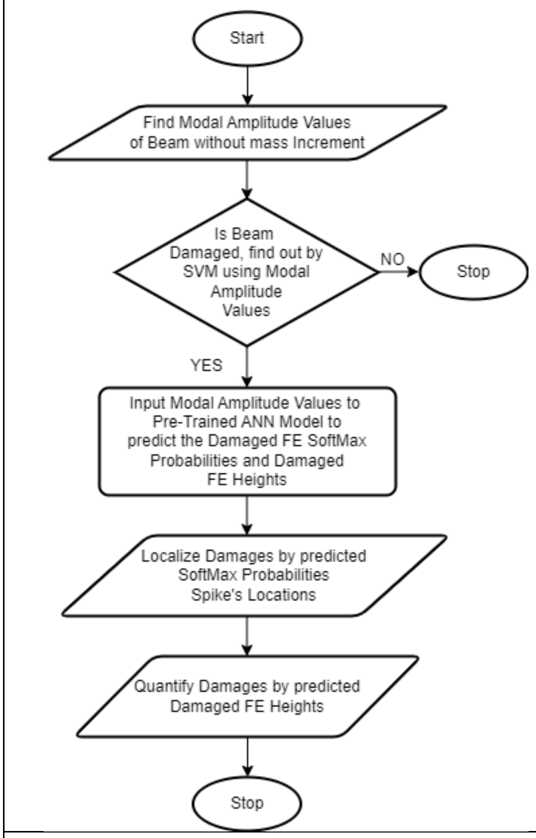


Fig. 18. Flowchart for CBMS

The proposed methodology can function as a Condition-Based Monitoring System (Fig. 18), utilizing Modal Amplitude data from the beam without mass increment. A Support Vector Machine can detect the presence of damage using this data. The ANN, pre-trained on extensive Modal Amplitude data generated through mass increment, can then accurately localize and quantify damage using data from the beam without mass increment.

Future Scope

The present work can be extended to beam, plate, and shell structures with internal cracks, enabling accurate identification of hidden damage. Incorporating damping effects can further improve the accuracy of Finite Element models. Laboratory experiments on scaled-down models of actual engineering structures can help fine-tune the Finite Element model and determine the optimal mass increment. The refined methodology can then be applied to real-world engineering structures, ensuring reliable detection and quantification of internal cracks, which is crucial for structural safety and maintenance.

Conflict of Interest

There is no conflict of interest among authors.

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