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Vibration Based Damage Detection using Localized Crack-type Damage Models and ANN

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Abstract: *By combining finite element modelling and artificial neural network, this paper proposes a novel approach using ANN for single stage prediction of severity and location of damage in structures. The study utilizes FEM for simulating crack type damage of varying severity at various critically stressed locations of the structure. Various modal response data such as vibration frequencies, mode-shapes and frequency response functions, corresponding to the considered damage scenarios are synthetically generated from the FE model and used for training the Artificial Neural Network model.*
Recent studies on damage detection utilizing machine learning algorithms and modal response data of structures, justify the use of frequencies and mode shapes as good damage indicators. However, traditional literature in SHM remarks frequencies and mode shapes to be less sensitive damage features. Utilizing the proposed model, the paper first takes a relook into this issue. The paper further explores the use of various other modal properties of the structure such as frequencies, mode-shapes,mode shape curvatures and frequency response functions as potential damage indicators for training and testing of ANN. Model regression coefficient (R) was seen to be less effective in assessing model accuracy in prediction of damage severity and location. Hence the paper proposes two additional matrices for assessing ANN model performance in damage detection.
Data scarcity resulting from the deployment of a limited number of sensors over a structural member is seen to affect the performance of data driven models such as ANN. The study addresses this issue through use of appropriate computing techniques such as Lagrange based function approximation over modal response measurements from discrete sensor locations and k-fold cross validation based resampling technique.The potential of the resampling technique to improve the damage sensitivity of noise-contaminated vibration signatures is also demonstrated. Early damages of the order of 5% severity, could be detected with an error less than 2% using algorithms devised in this paper.

***Key Word**: Vibration-based damage detection; k-fold cross-validation; frequency response function; mode shape curvatures; artificial neural networks; machine learning.*

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I. Introduction

The era of vibration-based damage detection began when natural frequencies and mode shapes became competent vibration signatures, expecting them to project the location of damages in structures (Farrar *et al*. (2001), Worden *et al.* (2000), Ruocci*et al.* (2011)). Later, these indicators were deemed less sensitive to damages (Farrar et al. (2013)) which led to the exploration of more vibration signatures such as Frequency Response Functions (FRFs). Artificial Neural Networks (ANN) is a major subfield of Machine Learning that can handle nonlinear interactions and complex behaviour among input and output parameters in a system without any prior knowledge about the system and the same has been extensively used in solution of engineering problems including damage detection in the past. For a data driven model such as ANN, to predict both damage severity and location of damage, requires sufficient quantity of structure response data corresponding to damages of various severity at various locations of structure for training the model. A recent review on ANN based damage detection is presented by Alain and Ponciano (2022).

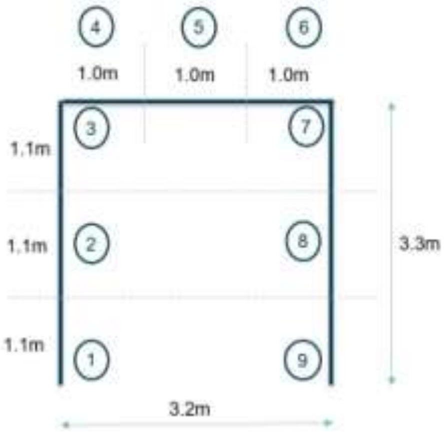
In the absence of field data, vibration responses of a structure corresponding to various damage scenarios are either obtained through numerical simulations or experimentations. Subsequently, a suitable machine learning model, say, ANN, is trained and tested using the data and is subsequently used to predict the possible location and severity of any damage in the structure. Recently, there seems to be a renewed interest in using frequencies and mode shapes, with many authors reporting successful employment of these two damage indicators for training learning algorithms (Bakhary (2008)). However, such studies were based on simulated data with a discrete spring-mass idealization of structures**,** with damages modelled as a uniform reduction in stiffness over an element length.

The first part of this paper takes a relook into the problem by using modal data from a more refined structure and damage models. The paper proceeds further by utilizing mode shape curvatures and FRFs as training inputs for ANN models for damage prediction. In the process, the paper addresses two critical issues associated with using vibration data in ANN-based damage detection. They are (i) the requirement of a large input layer for ANN when FRF is used as training data and (ii) sensor deficiency resulting in the shortage of a sufficient number of mode shape ordinates.

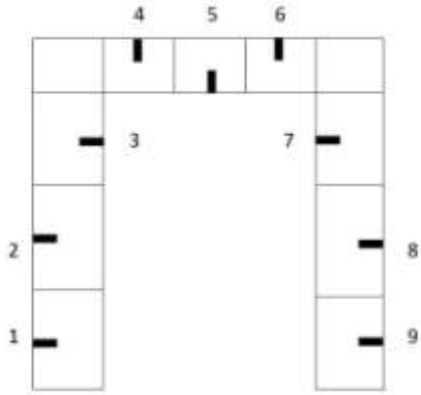
II. Methodology

Structure model and damage simulation

A portal frame structure (Fig. 1(a)) having predominant flexure vibration modes is selected for the study. All frame members are 150 mm x 200 mm in cross-section and of concrete material having elastic properties E = 25,000 MPa and ν = 0.2. FE model of the structure is created in ABAQUS 2017. The entire structure is discretized using 8-noded brick elements of size 25mm. Each member in the structure ispartitioned into suitable segments (3 in this case), as shown in Fig. 1(a), to assist damage localization. In all these segments, single localized cracks are simulated at critically stressed faces of the beam and columns. All degrees of freedom on the nodes at the base of two columns are arrested, simulating clamped boundary conditions.



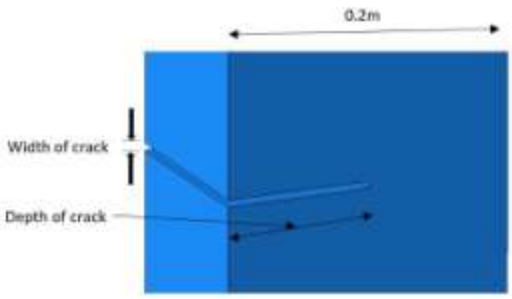
(a) Division of the portal frame into 9 segments



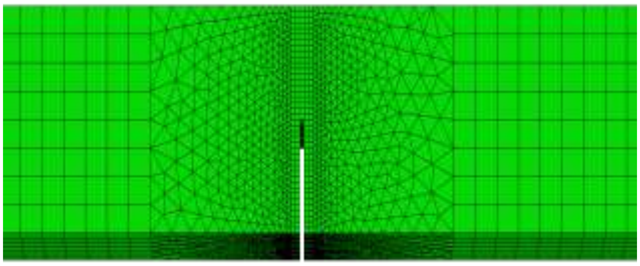
(b) Location of single cracks in each of nine segments in various damage scenarios

Fig. 1 The structure model

Each crack is 3 mm wide and 100mm deep in the initial stage (Fig. 2(a)). The depth of crack is varied, keeping the width constant to simulate different extents of damage for each damage location. Fig. 1(b) shows the location of cracks simulated in various damage scenarios. In all, 90 damage instances (9 damage locations and 10 damage extents at each location) are considered. Responses of the structure were captured for each of the damage instances.



(a) Typical crack on one column of the portal frame



(b) Special meshing scheme adopted for crack zone

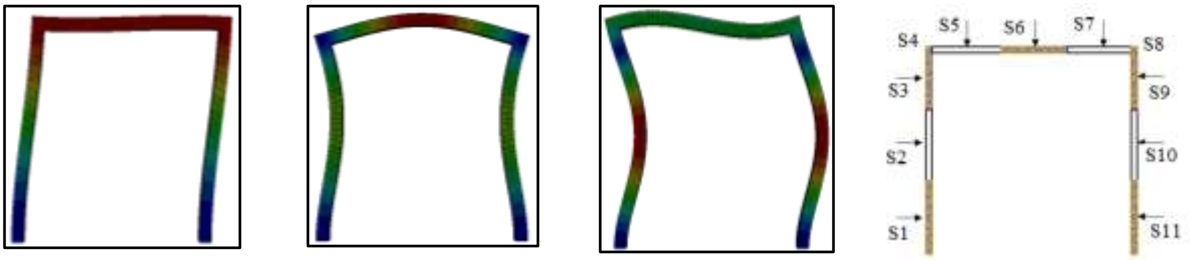
Fig. 2 Damage simulation

An improper FE mesh can affect the stiffness of the structure model and mask the frequency changes resulting from damage. Hence special care is exercised during the meshing stage to develop a mesh-independent structure model. For this, each damage zone is sub-partitioned into three, with the zone adjacent to the crack being fine-meshed using 5 mm size 8-noded brick elements and the segment farther from the crack zone being meshed using a coarser mesh of 25 mm size. Finally, the zone in between was meshed using tetrahedral elements, as shown in Fig. 2(b).

Data generation for damage detection

Frequencies and mode shapes

Frequencies and mode shapes corresponding to the first 10 vibration modes of the structure model were used in ANN models for training and testing (Fig.3).To simulate the condition of data scarcity in field investigations, the present study utilized modal ordinates from midpoint nodes of each segment of the FE model(S1 to S11 in Fig. 3(d)). These nodes possibly denote the potential sensor locations in the case of an experimental study.



(a) Mode 1 (b) Mode 2 (c) Mode 3 (d) modal ordinate extraction locations (S1 to S11)

Fig.3. First three vibration modes of portal frame and locations from where mode shape ordinates were extracted

FRF-based damage indicators

FRF- based ANN models have been utilized in the past for the damage assessment of structures (Jayasundara*et al*. (2020), Maia *et al*. (2002), Bandara (2013)). FRF as a vibration signature can be easily captured with the aid of a couple of sensors, and the same can also be simulated in an appropriate FE modelling environment. However, the heavily populated FRF data demands a huge configuration for the ANN input layer, leading to iteration divergence while training and testing, along with computational inefficiency (Bandara (2013)). Hence, mathematically intensive techniques like Principal Component Analysis (PCA) are employed for the dimensionality reduction of massive FRF data when used for training ANN (Abdeljaber*et al*. (2016)). But, as the structure being monitored becomes more and more complex, the size of FRF data will also increase, resulting in the ineffectiveness of PCA due to the loss of valuable damage information. Padil*et al*. (2020) addressed this issue using a non-probabilistic ANN model and conducting an interval analysis to root out the uncertainties after PCA application. Alternatively, this paper proposes the use of local peaks in FRF data for network training, thus reducing the massiveness of FRF data.

Frequency Response Functions corresponding to all simulated damage scenarios were generated by performing a mode-based steady-state analysis of the structure model. The local extrema of FRF data were identified using the 'find peaks' function in signal processing toolbox of MATLAB. Fig. 4 shows the distinct peaks (indicated in red and yellow at appropriate locations) identified from a typical FRF signal (indicated as a green line). The peaks thus consolidated were considered as inputs for network training.

Mode shape curvature-based damage indicators

A variety of modal data pre-processing techniques were proposed in previous vibration-based damage detection studies to enhance the damage predictability of mode shapes. This includes defining damage indices based on mode shapes (Maia *et al*. (2002)), estimation of curvatures and squared curvatures (Nguyen *et al.* (2021), Rucevskis and Wesolowski (2010)), etc. Notably, numerical estimation of mode shape derivatives for central difference scheme-based curvature estimation demands responses to be captured from a sufficiently large number of locations/sensors to reduce errors in estimation of curvatures. For structures with multiple members, this increased demand makes the procedure expensive and computationally intensive.

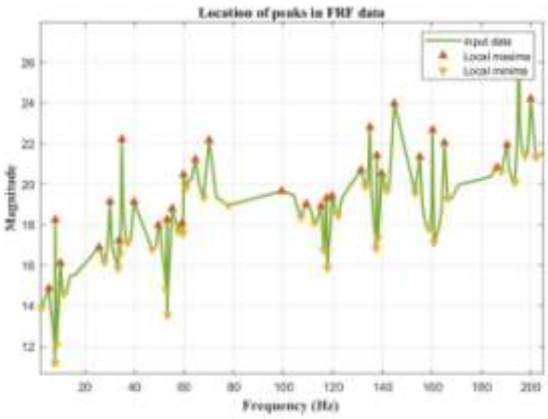


Fig.4. Peaks identified from a typical FRF signal

To overcome this, the present study utilized a curve-fitting approach with a Lagrange polynomial fit made over the modal coordinate data from discrete locations resembling sensor locations in a field test(Fig.3(d)). Subsequently, symbolic differentiation of the polynomial was carried out using MATLAB to obtain the modal curvatures. The Lagrangian polynomial approximation, for the j^{th} vibration mode $\emptyset_j$ using n modal coordinates, is represented as:

$$\emptyset_j = \sum_{i=1}^{n} N_i \emptyset_{i,j} \qquad (1)$$

with the Lagrange shape function corresponding to the i^{th} location N_i is given by:

$$N_i = \frac{(x-x_1)(x-x_2)\dots(x-x_{i-1})(x-x_{i+1})\dots(x-x_n)}{(x_i-x_1)(x_i-x_2)\dots(x_i-x_{i-1})(x_i-x_{i+1})..(x_i-x_n)} \qquad (2)$$

Where, $x_1, x_2, ..x_n$ denote the location of modal coordinate data i.e., sensor position in field investigations, $\emptyset_{i,j}$ denotes the j^{th} modal ordinates at i^{th} location.

After Lagrangian polynomial fit over the mode shape coordinates, the mode shape curvatures were estimated using the symbolic differentiation (MATLAB). This helps in addressing the error in numerical differentiation due to lack of sufficient number of modal coordinate data. Alternatively, additional modal data could be generated from the Lagrangian polynomial fit to various mode shapes coordinates made over each member and utilize the same for numerical differentiation using the following central difference approximation given by

$$\frac{\partial^2 \emptyset}{\partial x^2} = \frac{\emptyset_{i+1,j} - 2*\emptyset_{i,j} + \emptyset_{i-1,j}}{h^2} \qquad (3)$$

where i denotes the node number, j denotes the mode number and h the uniform spacing of nodes.

The whole procedure of Lagrange interpolation and estimation of mode shape curvatures was implemented in the MALTAB environment. The absolute difference between the curvature in each damage instance and mode shape curvature in the undamaged state was considered as the input for ANN model. Ability to evaluate the curvature function at any number of locations for better accuracy is the major advantage of this refined strategy.

Noise contaminated FRFs as damage indicators

A major issue concerning the damage sensitivity of vibration signatures in field investigations is the interference of measurement noise. Hence the damage detection efficiency of developed algorithms using noisy data needs to be investigated. Various studies have been conducted to analyse the effect of variable noise levels in structural responses (Cao *et al.* (2014)) and hence are not revisited here. This paper intends to project the ability of resampling techniques to surpass the poor damage sensitivity of noise-contaminated vibration signatures, specifically FRFs. Noise-free FRFs obtained from simulations were contaminated by adding Gaussian White Noise with a signal-to-noise ratio (SNR) fixed at 10 dB. The local peaks identified from these noise-contaminated FRFs were considered for ANN training and testing.

ANN architecture

Previous studies on damage detection using structure models with multiple members, attempted to subdivide the structure into various segments and employ distinct ANN models for each segment for better accuracy in damage detection (Abdeljaber*et al*. (2016), Jayasundara*et al*. (2020)). Researchers thus have attempted to handle the problem of localization and quantification of damage extent as a two-stage process. Instead, this paper proposes a single-stage ANN model capable of simultaneous localization and quantification of damages in the entire structure.

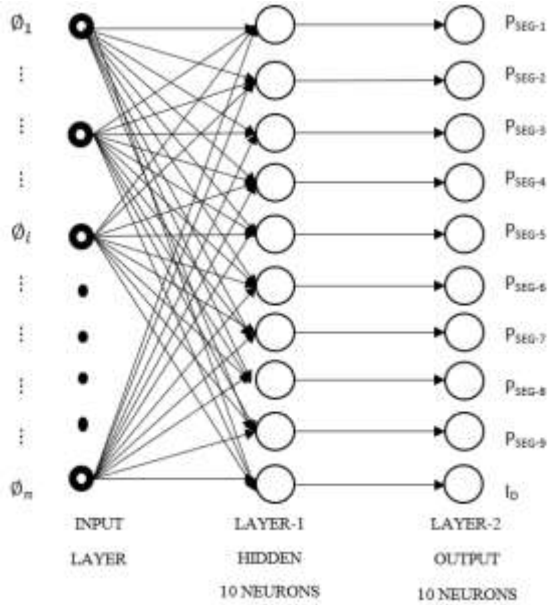


Fig.5 Optimal ANN architecture used in the study

A two-layer feedforward neural network (for addressing regression problems), using Levenberg Marquardt algorithm for regularization (More (1977)), was employed for training and testing. The optimal network configuration- 10 neurons in a single hidden layer- was obtained based on a trial-and-error process. Fig. 5 depicts the optimal ANN architecture used in this study. The input vector $[\emptyset]$ presents the training inputs corresponding to each damage indicator. Generally, $\emptyset_i$ represents input corresponding to the i^{th} input neuron where,i varies from 1 to n (number of training samples representing a damage instance). Though the damage indicators used to feed the ANN models vary, the basic ANN architecture remains the same throughout the paper. The output vector was carefully defined to return two types of neurons: one to support damage localization for each of the segments (9 segments in this case) and the second to support damage quantification (one for the damaged segment only) of the problem. Hence the neurons P_{SEG-1} to P_{SEG-9} were assigned for damage localization and the tenth neuron (I_D) was assigned for damage quantification. From the available training dataset, 70% of the samples were employed for training, 15% for validation, and 15% for testing purposes.

The ANN model performance was evaluated based on the correlation coefficient (R value) obtained from regression plots after training and testing. As a measure of model performance, R values were found to be misleading (Li (2017)). Hence, two additional metrices were also considered in this paper to evaluate the damage sensitivity of various ANN models.

Damage sensitivity measures

The damage sensitivity of each damage indicator was assessed using the following three performance metrics:

(1) **Accuracy in terms of correlation coefficient (R-value) in both training and testing**: The correlation coefficient between two variables is a measure of their dependence for which a value of unity indicates a good correlation.

(2) **Sensitivity of the damage indicator in terms of localization of damaged zone or segment:** This metric was accounted for in terms of the Normalised Damage Modulus (NDM) for each zone or segment of a structural member, defined as:

$$Normalised\ Damage\ Modulus\ (NDM) = \left|\frac{P_{SEG-i}}{P_{SEG(max)}}\right| \ ;\ 0 \leq NDM \leq 1 \quad (4)$$

Here, P_{SEG-i} denotes the output of the i^{th} output neuron from the ANN model or the possibility of damage in the i^{th} segment, where *i* varies from 1 to number of segments (9 in this study), and $P_{SEG(max)}$ is the maximum value among P_{SEG-1} to P_{SEG-9} obtained in a particular training operation. NDM =1 indicates the presence of a damage in the segment and NDM = 0 indicates absence of damage.

(3) **Sensitivity of the damage indicator in terms of the minimum extent of damage that can be quantified**: This metric is recorded in terms of percentage error in predicting the damage extent in each of the zones or segments of the structural member, defined by:

$$Percentage\ error\ (E) = \frac{I_D^{'} - I_D}{I_D} \times 100 \qquad (4)$$

Where, $I_D^{'}$ is the damage severity predicted by the network (output of the 10^{th} neuron) and I_D is the damage severity originally simulated in the FE model (or damage severity from a known location in case of experimental data).

Implementation of k-fold Cross-validation

Researchers have recommended the use of resampling techniques to enhance the generalization ability of data-driven models when they are fed with datasets of a limited population (Almustafa and Nehdi (2020)). k-fold cross-validation is a popularly adopted resampling technique in a variety of machine learning problems.(Almustafa and Nehdi (2020), Huang and Burton (2019), Mangalathu and Jeon (2019), Marcot and Hanea (2020)). The same was used as the resampling technique in the present damage detection study using modal data.

K-fold cross-validation (CV) involves randomly dividing the dataset into *k* folds or groups of samples of nearly equal size. The first fold is treated as the test set, and the remaining folds will be treated as training sets upon which the model is fit. The procedure will be repeated *k* times, wherein a different fold is treated as the test set in each iteration. The optimal value of *k* was established as 5 in a sensitivity analysis using variable values of *k*. The optimal value of *k* was arrived at considering trainingaccuracy (R-value), the standard deviation of accuracy, and normalized CPU computation time. Repeated *k*-fold cross-validation was performed (10 times) and the mean and standard deviation of observations were estimated to ensure if consistent model performance is achieved.

III. Resultsand Discussions

Performance of ANN models before the implementation of k-fold CV

To quantify the significance of resampling especially in the context of scarce data, typical of structural health monitoring of civil engineering structures, and also to signify the efficacy of k-fold CV as a potential resampling tool in context of vibration data, a comparison of the results from developed models with and without k-fold cross validation was made.

ANN models based on frequencies and mode shapes

The ANN model based on frequencies achieved a training accuracy of 0.9986 (R value) and a testing accuracy of 0.9936 (Fig. 6). The ANN model based on mode shapes achieved a training accuracy of 0.7894 and a testing accuracy of 0.7957. Moreover, mode shape dataset being smaller in the number of samples and larger in the number of input neurons, exhibited an overfitting tendency.

With respect to R-value, though the performance of frequency-based ANN seems to be better than mode shape-based ANN, both failed to predict the location of damage accurately in most of the damage instances. Fig. 7(a) shows the plot of Normalised Damage Moduli (NDM) for various segments corresponding to simulated damage of severity 50% in segment 3. A closer look into the values of NDM reveals that the frequency-based ANN failed to predict the correct location and gave a false peak at segment 7. For the same scenario, the mode shape-based ANN model too gave a false peak at segment 5 (Fig. 7(b)).

The direct use of frequencies and mode shapes as good damage indicators for the training and testing of learning algorithms hence seems questionable. The designation of frequencies and mode shapes as good indicators in many literature could be attributed to the fact that the same were derived from discrete spring-mass structural idealizations, with damages modelled as reduction in stiffness for a single element. However, derived from the more realistic structure and damage models using FEM, frequencies and mode shapes do not qualify as good indicators.

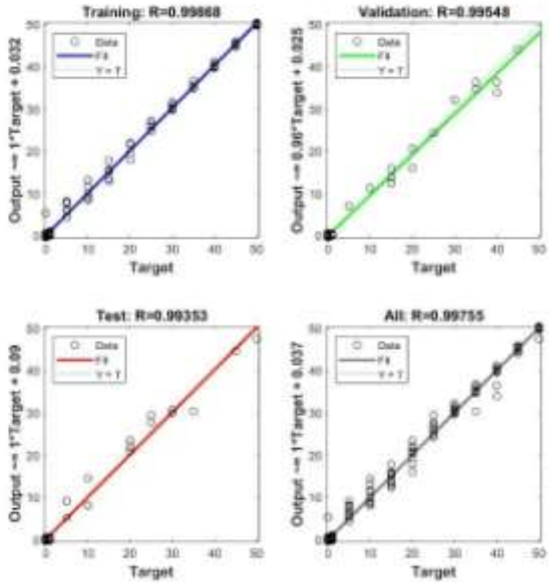
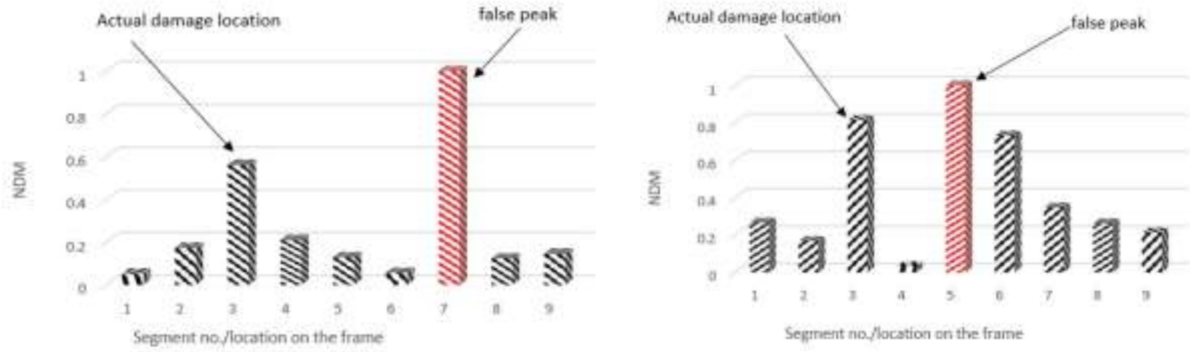


Fig. 6Regression plots obtained in training from frequency-based ANN model for the case of damage severity 50% in segment 3.



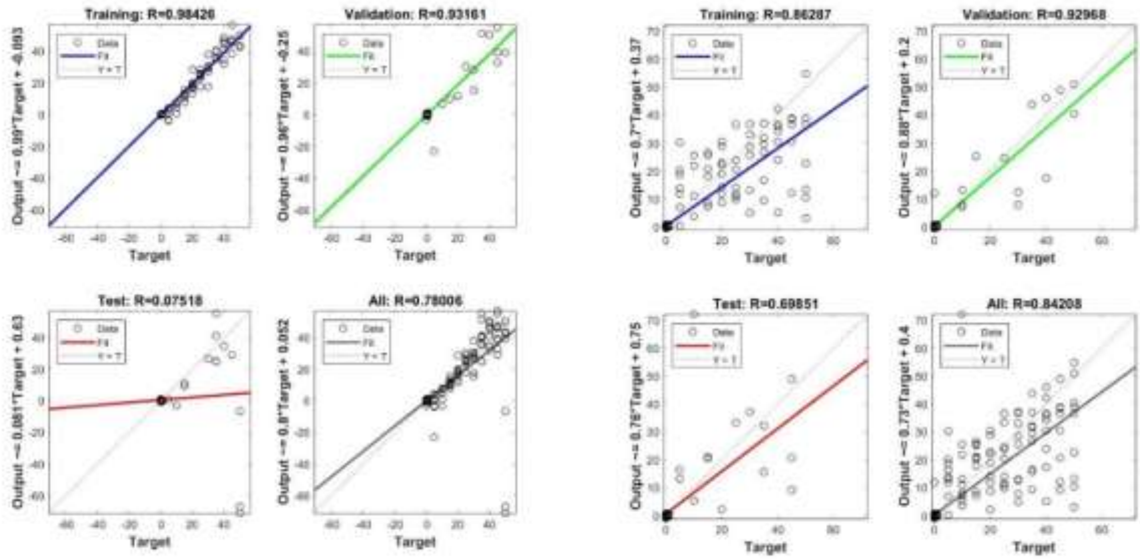
(a) frequencies (b) mode shapes

Fig. 7Prediction of damage locationfrom frequency-based and mode shape based ANN models for the case of damage severity 50% in segment 3

Hence the possibility of using Frequency response functions (FRFs) and mode shape curvatures as damage indicators for network training is explored next.

ANN models based on FRFs and mode shape curvatures

Training and testing of ANN model based on FRFs, achieved a training accuracy of 0.9842 (R value) and a low testing accuracy of 0.0751 (Fig. 8(a)) where as the one based on absolute curvatures achieved an accuracy of 0.8628 in training and 0.6985 in testing (Fig. 8(b)).

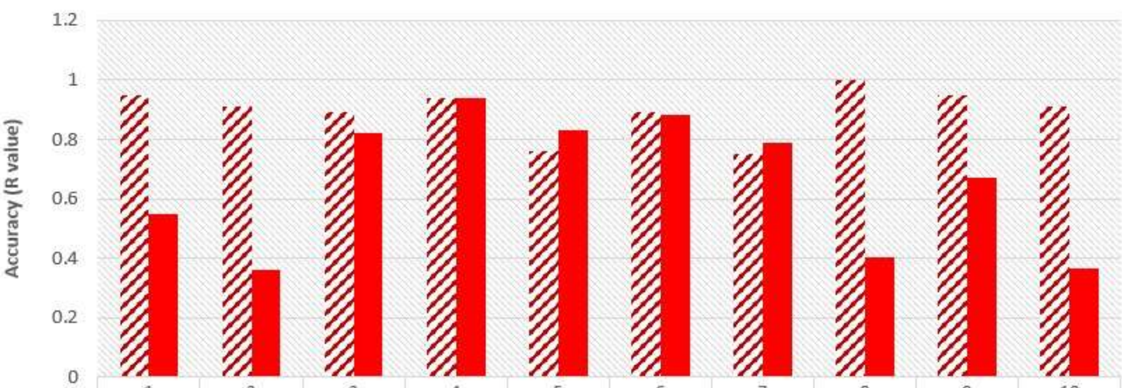


(a) ANN model based on FRFs

(b) ANN model based on mode shape curvatures

Fig. 8Regression plots obtained in model training & testing

However, a randomness was noted in testing accuracy when training was repeated. Fig. 9 shows the variability of testing R values in 10 subsequent trials when the ANN model based on FRF was subjected to training and testing.



	1	2	3	4	5	6	7	8	9	10
Training	0.95	0.91	0.89	0.94	0.76	0.89	0.75	1	0.95	0.91
Testing	0.55	0.36	0.82	0.94	0.83	0.88	0.79	0.40	0.67	0.37

Fig. 9 Variation in training & testing accuracies of ANN model based on FRFs in 10 subsequent trials

Though the training accuracy was almost consistent, the testing accuracy was very low in the 2nd, 8th and 10th trials, which indicates a poor correlation. The testing set has overestimated the model performance in 5th and 7th trials, in which training accuracy is relatively low. The coefficient of variation (CoV) associated with testing accuracies in these 10 trials was estimated and it was as high as 9.24% and 7.604% respectively, for the ANN model based on FRFs and mode shape curvatures. This throws light into a major issue faced by almost all data-driven models like ANN with a limited number of training data. The process of learning in an ANN model involves the division of the input dataset into training and testing sets. In datasets with a limited number of samples, the least populated test set need not represent the entire dataset, which can affect the generalization ability of the entire ANN model. This is usually reflected in either of the following ways:

(1) A variability in testing R values obtained in subsequent training trials
(2) Very low value of testing accuracy
(3) Overestimation of testing R-value compared to training R-value

Due to these issues, many false peaks occurred in the NDM plots in Fig. 10, which shows the damage location prediction by the FRF-based ANN model for 9 damage locations and ten distinct damage scenarios for each location corresponding to damage extents in the range 5 to 50 percent.

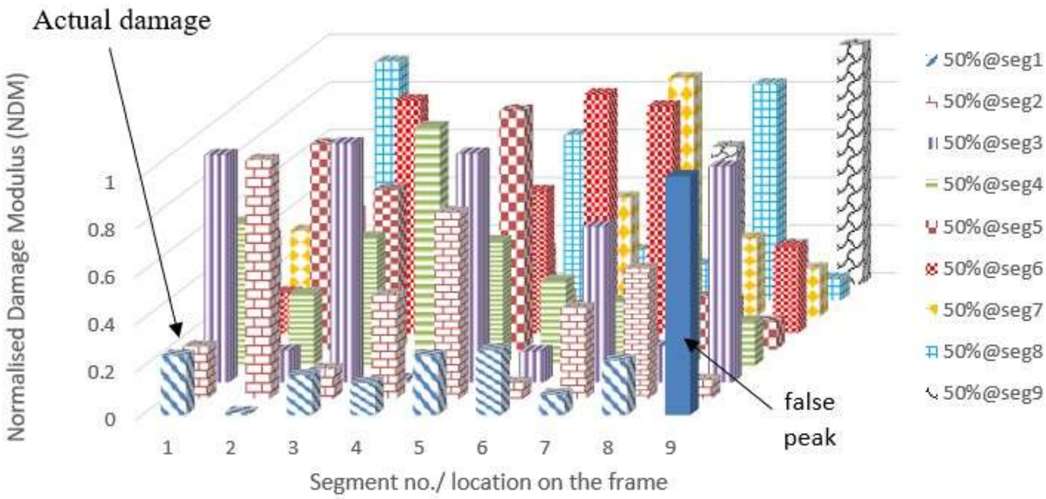


Fig. 10 Prediction of damage location using FRF-based ANN model prior to application of k-fold CV(actual damage in segment 1).

Data scarcity is typical of civil engineering problems, and solving it without increasing the dataset size is a challenge to researchers. Though transitioning to deeper networks with enhanced learning abilities might solve this issue, this paper attempts to improve the scenario using a resampling technique.

Performance of ANN models after the implementation of k-fold CV

Thus far, the choice of training and testing samples in this paper was random. The resulting performance of ANN models were inferior as the models were deficient in generalization. *k*-fold CV was performed in this study to assess the generalization ability of ANN models and to obtain a consistent model performance. Table.1 shows the performance of ANN models in training and testing before and after k-fold application. Frequency-based ANN achieved an average overall accuracy of 0.446 with a standard deviation of 0.1516 after applying k-fold. The mode shape-based ANN achieved an average accuracy of 0.740 with a standard deviation of 0.1957, after applying *k*-fold CV.

R value obtained for frequency-based and mode shape-based ANNs prior to *k*-fold application were comparatively higher. However, those models failed in damage prediction, proving that the R values might be overestimated.

Table 1: Results of ANN training & testing before & after k-fold application

	Before k-fold CV application		After k-fold CV application	
Damage indicator	Training accuracy (R value)	Testing accuracy (R value)	Mean model accuracy in 10 trials	Standard deviation of model accuracy
Frequencies	0.9986	0.9935	0.4460	0.1516
Mode shapes	0.7894	0.7957	0.740	0.1957
FRF	0.9842	0.0752	0.920	0.0160
Mode shape Curvatures	0.8628	0.6985	0.980	0.017

Even though *k*-fold CV does not completely eliminate overfitting in an ANN model, the low R value obtained for frequency-based ANN model is a more realistic estimate of the model performance. The damage sensitivity of these ANN models, discussed in subsequent sections better explains this.

ANN models based on FRFs and mode shape curvatures exhibited overall accuracies of 0.8092 and 0.8690 prior to *k*-fold application. This improved to 0.92 and 0.98, respectively, post *k*-fold application. Mode shape curvature-based ANN model achieved an overall accuracy comparable to that of FRFs in training and testing. Consistent R values achieved through *k*-fold application are appreciable, as observed from the low standard deviation in each case. The performance of mode shape curvature-based ANN is promising since mode-based techniques were less preferred than FRFs in previous works, as they were time-consuming and less sensitive (Maia *et al*. (2002)). The damage sensitivity of various ANN models used in this study are discussed next.

Sensitivity of various ANN models

The sensitivity of a damage indicator to damage is an essential measure of its reliability. The present study quantifies sensitivity as the minimum depth of crack or the minimum damage extent (in terms of percentage of the depth of a member) that the damage indicator can locate and predict through the proposed ANN models.

Damage sensitivity of frequency-based ANN model

Sensitivity in terms of damage localization is demonstrated with the help of 3D bar graphs (Fig. 11). Each row represents a particular damage instanceand columns represents the damage location in terms of segment number. The bar height represents the Normalized Damage Moduli (NDM).

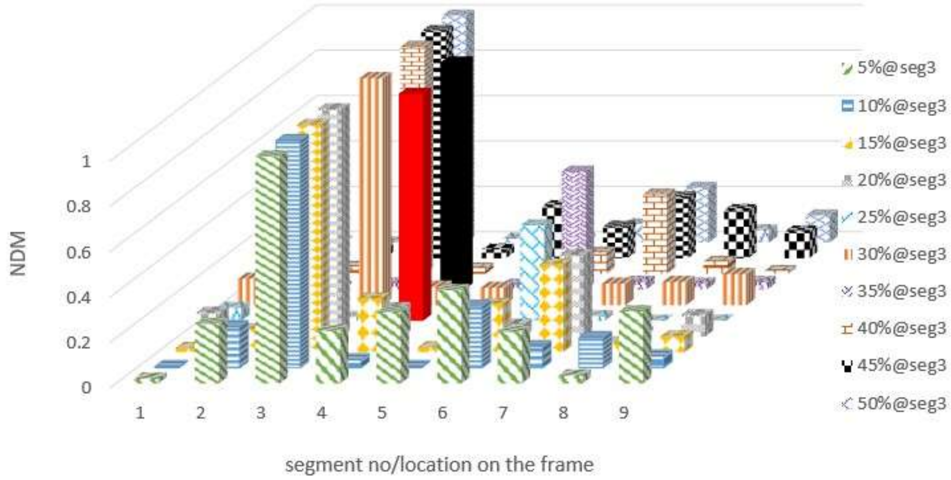


Fig. 11 Prediction of damage location using frequency-based ANN model after application of k-fold cross validation (actual damage simulated at segment 3

The damage location remains the same in all damage instances, with its severity varying from 5 to 50 percent. The segment with the peak value of NDM (unity) indicates the true damage location. The prediction of damage location by a resampled frequency-based ANN model, with the actual damage being simulated at segment 3, is shown in Fig. 11. A false prediction of damage location in segment 4 (red bar) is seen in fifth row. A similar false peak is also seen in the 7th row (black bar). The severity of damage in these cases were 25% and 35% respectively. Among the damage cases studied, the minimum damage that could accurately be located by frequency-based ANN is only 40%.

A comparison of actual damage severity and the model prediction for various damage cases corresponding to resampled frequency-based ANN model is shown in Fig. 12. The firm (red) line denotes the percentage error in predicting a particular damage extent. Error in predicting minor damages can be seen as a serious drawback of frequency-based ANN model. In Fig. 11, it can be seen that a damage of the order of 50% was predicted by the model with an error as high as 11.13%.

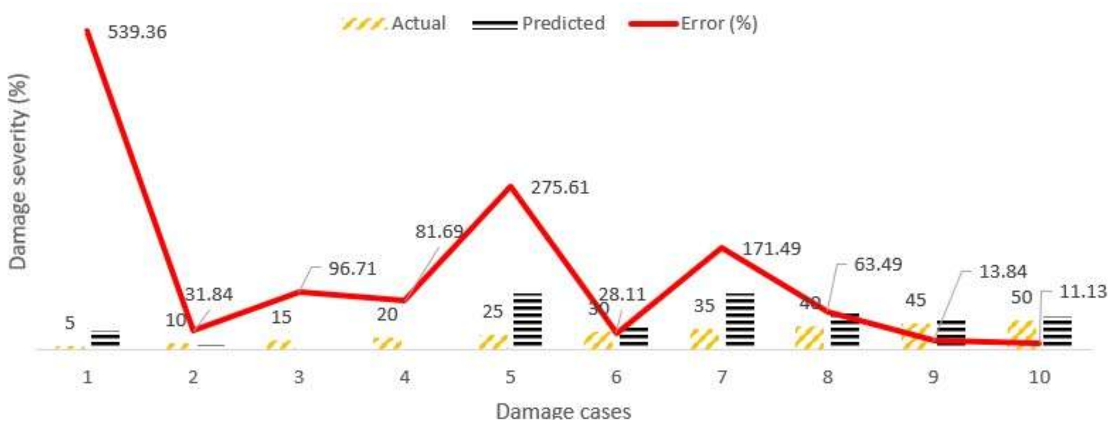


Fig. 12Test for sensitivity: error in damage severity prediction by ANN model using resampled frequencies as damage indicators, each damage case representing a damage extent in segment 3

The above result substantiates that, a higher R value for the model need not mean better model performance. The accuracy of frequency-based ANN given by *k*-fold CV emphasises its low sensitivity to minor damages as observed in the above figures.

Damage sensitivity of mode shape-based ANN model

Appreciable improvement in the damage sensitivity of mode shape-based ANN model after k-fold CV applicationcan be observed in Fig. 13. NDM values were obtained as unity at the exact locations of damage itself, i.e., at segment 4. Mode shape-based ANN exhibited better sensitivity compared to frequencies, with the minimum damage predicted being 35%, with an error of 1.81% (Fig. 14).

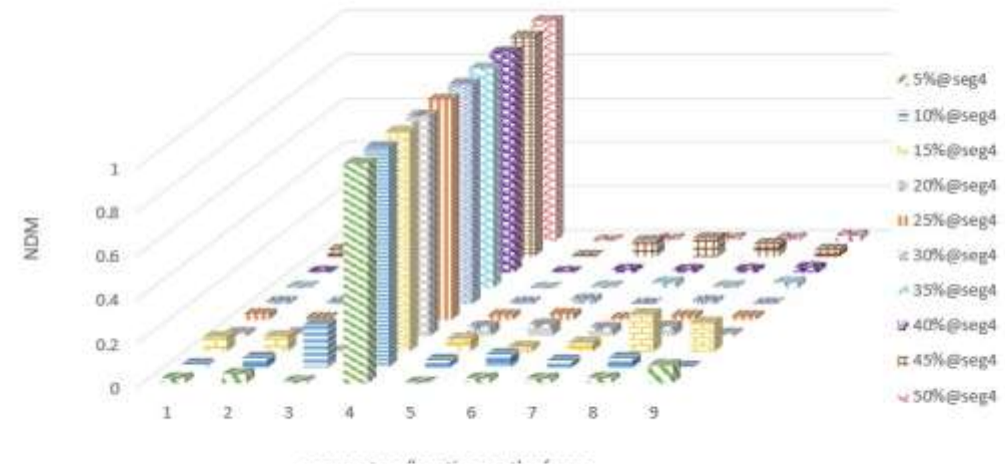


Fig. 13Prediction of damage location using ANN model based on resampled mode shapes (actual damage at seg.4)

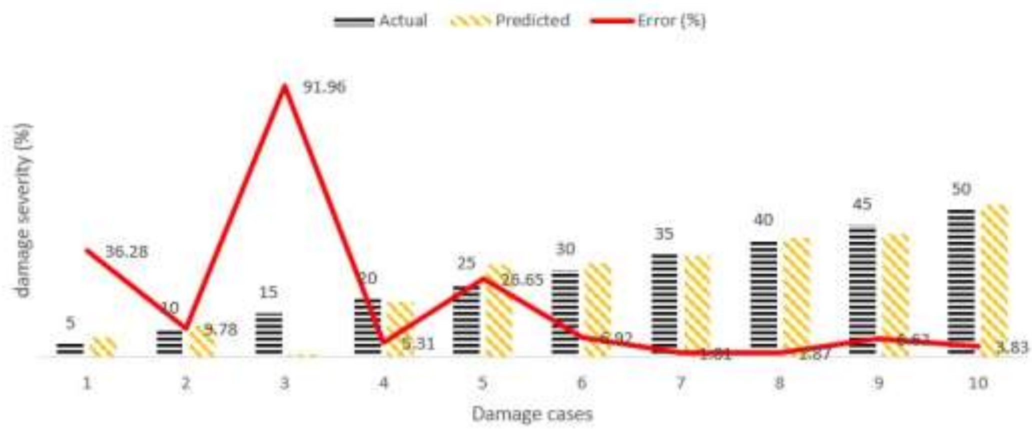


Fig. 14 Test for sensitivity: error in damage severity prediction by ANN model using resampled mode shapes as damage indicators, each damage case representing a damage extent in segment 4.

Damage sensitivity of FRF-based ANN model

Fig. 15 presents the prediction of damage location by a resampled FRF-based ANN model, with the actual damage being simulated at segment 7. NDM values were obtained as unity at the exact locations of damage itself, post training and testing.

The FRF-based ANN model was able to predict a damage of severity as low as 5% with an error of 1.9% (Fig. 15). The least damage considered in this study for simulating damage in the FE model was 5% and the FRF-based ANN model succeeded in predicting the damage with minimum error. NDM value peaked at the exact location of damage alone as well without any false alarm.

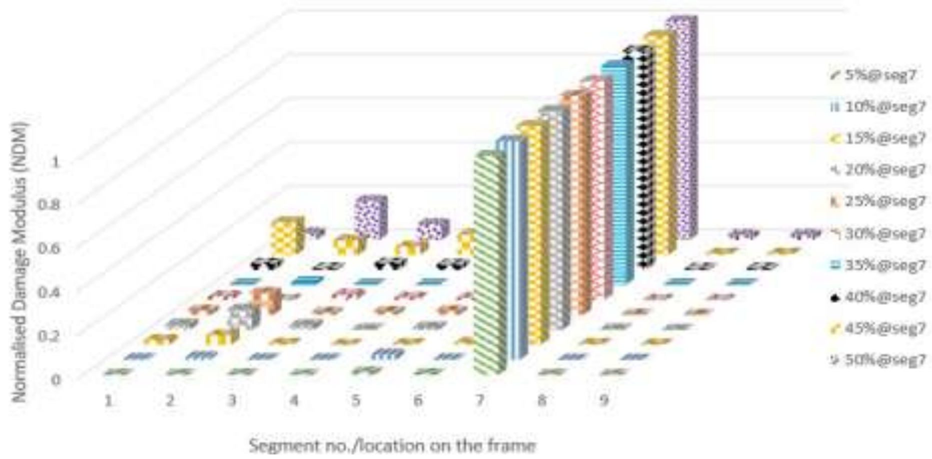


Fig. 15 Prediction of damage location using ANN model based on resampled FRFs (actual damage at segment 7.)

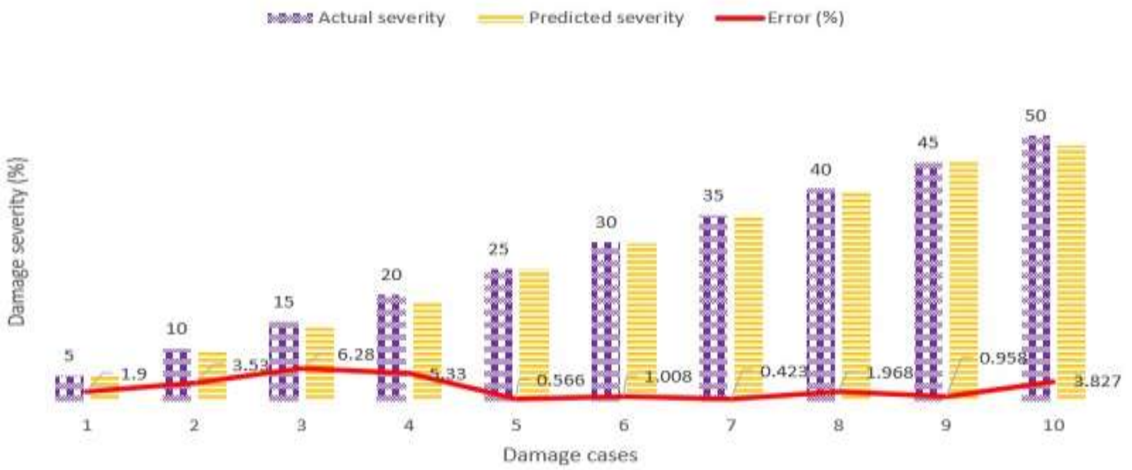


Fig. 16Test for sensitivity: error in damage severity prediction by ANN model using resampled FRF peaks.

Damage sensitivity of mode shape curvature-based ANN model

ANN model damage prediction using resampled mode shape curvatures as damage indicators, for 9 damage instances, with actual damage location being segment 2, is shown in Fig. 17. Though false peaks were found in the plot obtained for mode shape-based ANN in Fig. 13, they are negligible in magnitude for mode shape curvature-based ANN in Fig. 17. It is interesting to note that resampling combined with pre-processing of mode shapes (to obtain its curvatures) could transform less damage-sensitive modal data into a structured and sensitive one. The role of curve fitting techniques in enhancing their damage predictability is also undeniable.

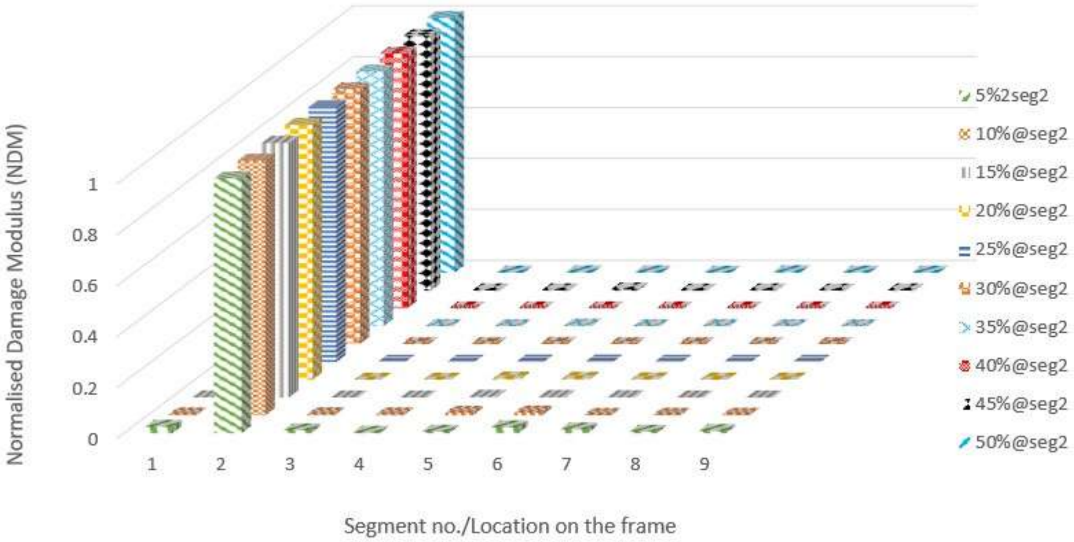


Fig. 17Prediction of damage location using ANN model based on resampled absolute mode shape curvatures with actual damage location being segment 2

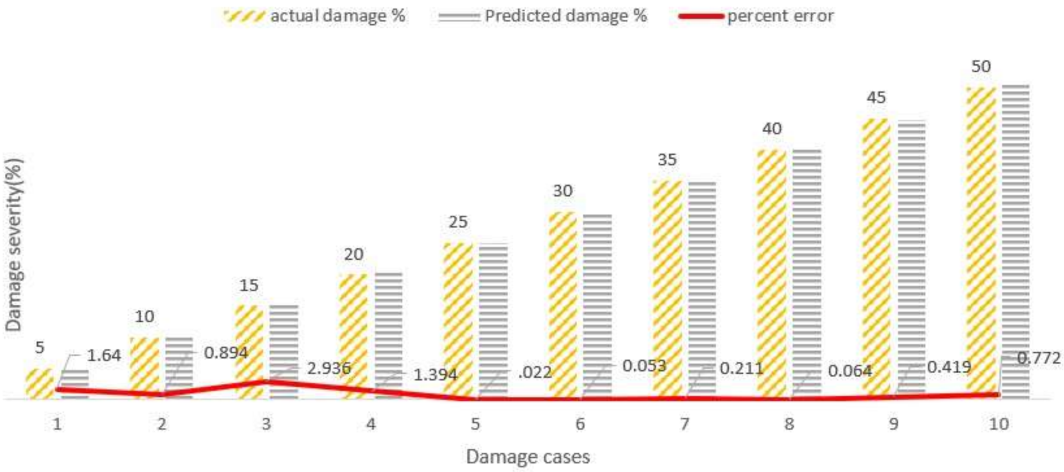


Fig. 18Test for sensitivity: error in damage severity prediction by ANN model based on resampled mode shape curvatures, each damage case representing a damage extent in segment 2

The ANN model based on mode shape curvatures performed better than FRF-based ANN in terms of damage extent prediction as well. The model was able to predict a damage of severity as low as 5% with an error of 1.64% (Fig. 18). This improvement in the predictability of mode shape curvatures was achieved using a limited number of training samples and a minimum number of sensors i.e., mode shape data sampling locations. The damage detection model devised in this paper proved to be efficient in locating and predicting even minor damages in the structure.

Effect of measurement noise

The low-test accuracy of 0.6643 in the regression plots (Fig. 19) obtained from ANN model using noise-contaminated FRFs for training, clearly signifies its contamination. With the implementation of *k*-fold CV, the overall accuracy of ANN model based on FRFs with noise, improved to 0.97, with a standard deviation as low as 0.007. Damage sensitivity of resampled noise-contaminated FRFs-based ANN model in terms of damage localization and quantification is presented in Fig. 20 and Fig.21.

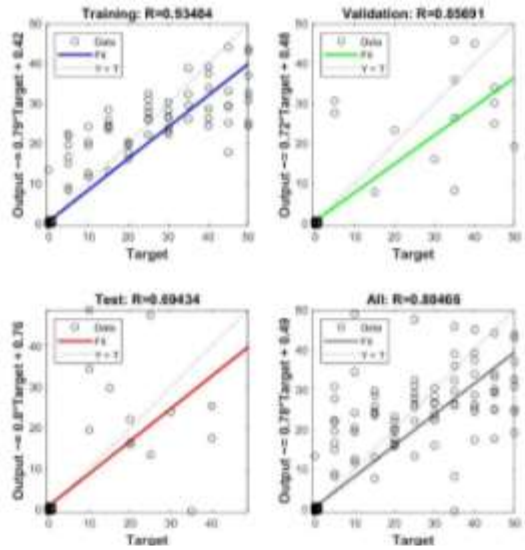


Fig. 19 Regression plots obtained in training and testing ANN model based on noise-contaminated FRF

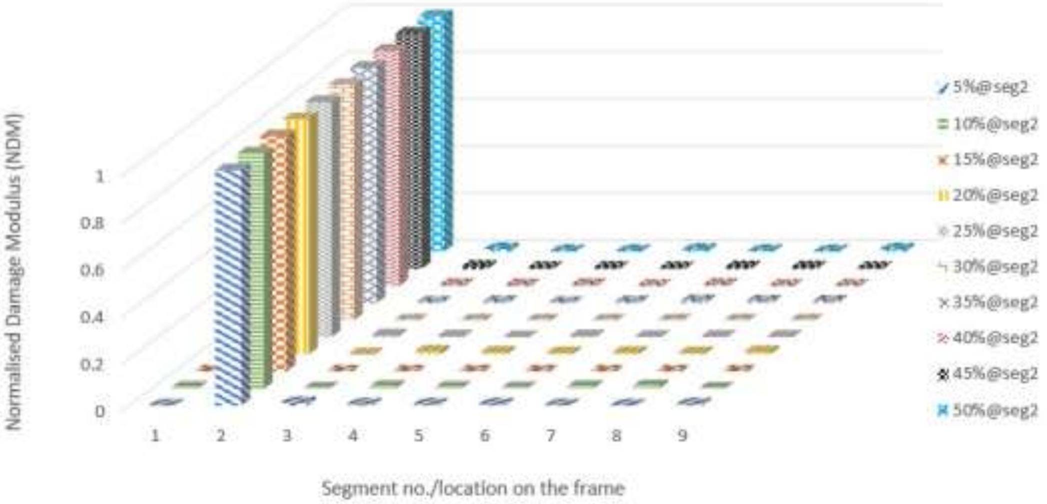


Fig. 20Prediction of damage location using ANN model based on resampled FRFs with SNR 10 dB with actual damage simulated at segment 2

Damage originally simulated at segment-2 of the structure model and varied in severity from 5 to 50% was accurately located by the ANN model using FRFs with noise (Fig. 20). Absolute peaks in all the rows are predominant, and the magnitude of NDM at all other segment locations is negligible. For the same damage instances, the percentage error in predicting the damage severity is presented in Fig. 21. With the minimum damage simulated in this context being 5%, and the percentage error recorded in predicting this damage being 2.414%, it is evident that the ANN model based on noise-contaminated FRFs achieved a damage sensitivity comparable with noise-free damage indicators discussed in this paper.

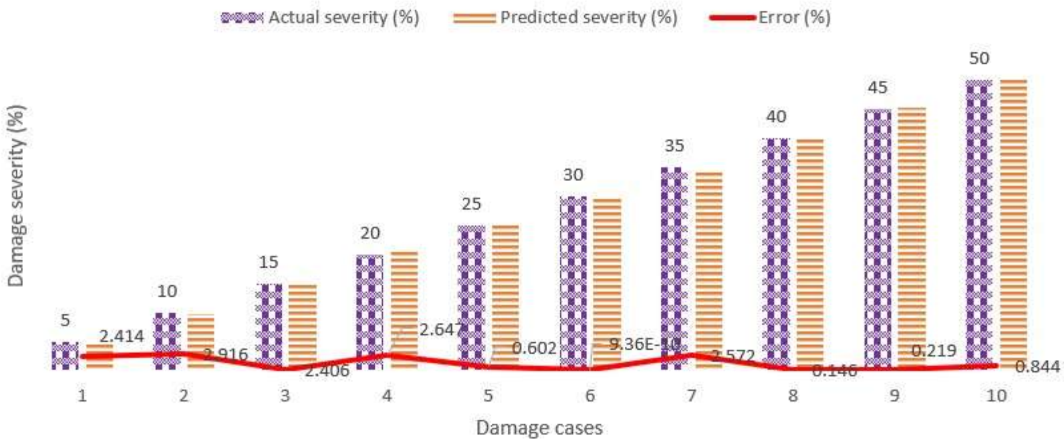


Fig. 21 Error in prediction of damage severity using ANN model based on resampled FRFs with SNR 10 dB with actual damage simulated at segment 2.

IV. Conclusions

A unique single-stage ANN model which utilizes various modal test data, for the simultaneous identification of damage location and severity in structures is proposed. The proposed ANN model comprises of a hidden layer with ten neurons, and the output layer consists of (n+1) neurons, with n representing the number of segments the structure is divided for the sake of damage localization. One output neuron is assigned per segment for locating damage in each of the segments in the structure model. One additional neuron is assigned for severity estimation, which gives the percentage error in predicting the damage severity in each scenario. This facilitated simultaneous localization and quantification of damage in the entire structure model. Though being widely used, the model R-value was observed to be insufficient as a marker of model performance. Consequently, two additional performance indices were introduced in the paper viz. the NDM and the percentage error to quantify the damage sensitivity of ANN models. Modal data for training and testing of ANN was simulated using 3D finite element models with damage simulated as discrete cracks. A special meshing strategy was followed to ensure mesh-independent modal parameters. Alternatively, realistic modal data from field observations can also be used to train the proposed model.

The low sensitivity of frequencies and mode shapes to structural damage has been widely reported in the early literature on vibration-based damage detection. But recent ANN-based studies on damage detection accepting frequencies and mode shapes as training data recommendthe use of these data. Such observations, in fact, were based on modal data generated using discrete spring-mass idealization of structures, with damage simulated as a uniform reduction of entire storey stiffness.

This paper initially revisited the suitability of using raw frequencies and mode shapes as vibration signatures for training ANN-based models for damage localization and quantification. Despite the high value of training accuracies, the performance of ANN models based on frequencies and mode shapes was observed to be low in damage prediction. False predictions were noticed in most of the damage scenarios. This observation from the present study based on refined damage models contradicts the observations in recent studies on machine learning-based damage detection which reports frequencies and mode shapes as good indicators. It is worth noting that shear frame building models combined with discrete spring-mass idealizations for the same and spring stiffness reduction-based damage models could have contributed to arriving at such conclusions.

The paper subsequently considered FRFs and mode shape curvatures derived from thedeveloped FE structure models as damage indicators. Peak-picking was used as an alternative to the PCA-based dimensionality reduction of FRFs. To address the accuracy issues related to limited modal ordinates resulting from minimum sensor deployment and numerical differentiation for estimation of mode-shape curvatures, a Lagrangian polynomial fit was made over the sampled modal ordinate data and symbolic differentiation was performed using MATLAB to obtain mode shape curvatures. Instead of symbolic differentiation, numerical differentiation can also be performed using additional modal data generated from Lagrangian polynomial fits to reduce numerical errors associated with differentiation on limited data.

The scarcity of structural response data resulting from the limited deployment of sensors is a major issue associated with monitoring of civil engineering structures. To simulate such an experimental scenario in the current numerical investigation, modal response data from a single location from each segment of the structural element (representative of the sensor location in field investigation) alone was utilized as input data for network training. This data scarcity affected the model performance in the form of an overfitting tendency. This was reflected as a higher testing accuracy relative to training accuracy as the training was repeated using randomly selected test sets from the same dataset. In all, the Coefficient of Variation associated with testing accuracies was as high as 9.24% and 7.604% respectively for ANN models based on FRFs and mode shape curvatures.

To circumvent the adverse effects of data scarcity, this paper proposes the use of *k*-fold cross-validation to resample the vibration signatures for ANN training. Notably, there is a drastic improvement in the overall accuracies (R values) of ANN models based on FRFs and mode shape curvatures from 0.8092 and 0.8690 to 0.92 and 0.98 respectively. This revised strategy could eliminate false damage predictions by the above models. For all damage scenarios, the Normalised Damage Modulus (NDM) peaked at the exact location of the damage alone. The proposed ANN models could even quantify a crack of order as low as 5%, with errors as low as 1.9% and 1.64% respectively using FRFs and mode shape curvatures as input. This improvement in damage predictability of FRFs and mode shape curvatures achieved using a dataset of limited population is a major highlight of this paper.

It is worth noting at this juncture that, even after the implementation of k-fold cross-validation, the performance of ANN models based on frequencies and mode shapes was very low, the error in prediction being of the order of 63%. False predictions of damage locations were also observed using the models.

The paper also investigated the sensitivity of the proposed models in the prediction of damage location and severity in a noisy environment. FRF data was artificially contaminated with Gaussian random noise having SNR 10. The proposed ANN model based on FRF was able to exactly predict the damage location and very low extent of damage, of the order of 5%, representative of early-stage damages, with error less than 2.5%.

The present study utilized simulated vibration data for demonstrating the efficacy of the developed model. Alternatively, measured data from field investigations can be employed for training the proposed model. The focus of this study was to make data more efficient and systematic to address its scarcity, rather than concentrating on the model architecture.

The novelty of the paper lies in the following aspects.

(1) Damage simulation: traditional approach of damage simulation involves stiffness reduction for an appreciable length of the structural member. The present study uses a 3D finite element model for the structure, damages modelled as discontinuity of definite dimension depending on the extent of damage to simulate damages in the form of structural cracks. A special meshing strategy is used to ensure mesh independence of modal properties of the structure.
(2) Use of FRF local peaks alone for network training to address the issue of ANN training arising from the huge dimensionality of the FRF matrix.
(3) Use of curve fitting technique over mode shape information from limited locations to reduce the error associated with numerical differentiation for estimation of modal curvatures.
(4) Use of a unique single-stage ANN model for simultaneous localization and quantification of damage for the entire structure.

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