Optimal Method for Identification of Cracks in Different Beams using Fuzzy with Elephant Based Neural Network

D. Pitchaiah, Putti Srinivasa Rao

Abstract: ***Failure of Structures i.e., beams can be avoided by identifying the damage in the structure at its beginning and proper retrofitting. Recently, the researchers created a structure to recognize crack damage using a cracked beam component model that originates from the fracture mechanics and local flexibility rules. The present work exhibits the analysis of cracked beam with a machine learning model to assess the stiffness of the structure. Here Fuzzy Optimal Neural Network (FONN) is considered, in addition, the stiffness reduction technique, especially concerning thick beams, is featured with a survey of other crack models. The extricated model data are utilized to conversely recognize the cracks with the cracked beam component model through a model updating technique. The optimal Neural Network based stiffness computation utilizes a global searching procedure using Adaptive Elephant Herding Optimization (AEHO) to identify the number of cracks in various beams. From the proposed model, the attained results are compared with the existing research work, and other optimization and machine learning models.***

Keywords: Cracked beam component model, Neural Network, Adaptive Elephant Herding Optimization, machine learning models.

I. INTRODUCTION

As an essential piece of structural health checking, damage identification incorporates four angles, specifically detecting the existence, the location, the seriousness of structural damage and the valuable existence of this structure. Because of the intricacy of the building structures, notwithstanding, the deliberate data and structural model of this technique have a solid vulnerability, frustrating the utilization of structural recognizable proof in structural health analysis [1]. Among the different, examined systems time-scale and time-frequency investigation strategies, especially the wavelet examination apparatus has been ended up being among the fruitful techniques for evaluation of structural wellbeing and damage location. Early investigations using wavelet examination were led to neighborhood damage recognition in machinery [2, 3].

Revised Manuscript Received on December 30, 2019.
***** Correspondence Author
Dasaripalli. Pitchaiah*, Research Scholar, Mechanical Engineering Department, Andhra University, Visakhapatnam, India.
Dr. Putti Srinivasa Rao, Professor of Mechanical Engineering, Andhra University College of Engineering, Andhra University, Visakhapatnam, India.

For damage identification, nonparametric worldwide damage identification techniques utilize measurable intends to dissect the vibration reaction of the structure [4]. For all of a sudden happened structural failure, there is an oscillatory process starting from damage happening and proceeding to the minute when the irregular displacement amplitude achieves steady state. This transient time relies upon structural damage scale and size of load [5]. Most vibration-based damage unmistakable evidence methodology can be considered as some sort of the case affirmation issue as they look for the isolation between no less than two signal classifications [6], e.g. beforehand, at that point, a structure is harmed, or complexities in the harm levels or ranges [7].The crack detection technique depends on the way that an enclosed crack in an empty area brings mutual vibration amongst bending and longitudinal vibrations [8], and in this way, an additional resonant peak appears in the FRF (frequency response function) of the beam with a crack. This strategy is able to detect the presence of cracks, however, it is hard to anticipate the location parameters and depth of the crack particularly while numerous cracks exist [9]. All together for identifying the parameters of the crack precisely through this methodology, initially a cracked-beam component is created for the cracked beams with express portrayals of the crack parameters, including the seriousness of the crack and its relative area inside a component [10,11].

The Artificial Neural Network (ANN) has been applied for identifying the pattern, analyzing the damage, programmed control and numerous different areas [12]. As indicated by the reaction of the structure in various stages, parameters responsible for structural damage are picked as the system input vector, structural damage stages are selected as output vector, and the preparation test set is set up through the feature extraction [13]. In a numerical reenactment study in which the genuine impact of the crack on the dynamic properties of the beam was reenacted by a precise solid finite component model permitting unequivocal portrayal of the cracks and after that contrasted with the forecasts utilizing the cracked beam component [14, 15]. Be that as it may, if different damage situations are seen from the distance along the beam, Artificial Neural Network will be utilized to additionally affirm the areas damaged and additionally to evaluate damage severities in all areas. ANN is to foresee the damaged location(s) and seriousness in the steel beam by using at various locations as the input layer of Artificial Neural Network [16].

The impacts of using standardized adaptability change vectors as the input layer for ANN yet simply comparative damage forces at both damage locations were explored for different damage situations [17].

II. LITERATURE REVIEW

In 2017 Shuai He and Ching-Tai Ng.[18] had proposed the Bayesian model class determination calculation was utilized to decide the number of cracks, and after that, the Bayesian factual system was utilized to recognize the parameters of the crack and the related vulnerabilities. To enhance the productivity and guarantee the reliability of the detection, the Transitional Markov Chain Monte Carlo (TMCMC) strategy was actualized in the Bayesian technique. The proposed technique was experimentally checked by utilizing guided wave data attained from laser Vibrometer. The outcomes demonstrated that the suggested technique can precisely recognize the crack size, location, number and furthermore evaluate the related vulnerabilities. Moreover, the proposed strategy was powerful under the measurement of noise and distinctive circumstances of the cracks.

A connection between the cracking load that makes a beam crack at the center of the shear length and the shear capacity of the beam was affirmed in view of the test consequences of 29 beams by Alamo and Hussein in 2017 [19]. All examples were strengthened the longitudinal way just and tried as basically upheld the conditions exposed to four-point bending. The solid compressive qualities, shear span to depth proportion, reinforcement ratio, and effective depth of the beams in the database was in the scope of 0.12– 2.63%, 24.1–88.3 MPa, 1.1– 6.45, and 141– 1111 mm, individually. The correlation established a solid connection among the shear capacity and the cracking load of the individuals.

The ordinary methods are rendered to a couple of restrictions because of the inconsistent scientific simulation utilized for the real situation by Deepak Agarwalla et al in 2016[20]. The Hybrid Artificial Intelligence (AI) was used as an effective, refined tool for damage detection in beam members. In the proposed work, a hybrid framework of Fuzzy Inference System (FIS) and Genetic algorithms (GAs) had been defined to detect damages in a steel cantilever beam subjected to common vibration. The outcomes attained from the suggested method have been in great concurrence with the exploratory outcomes.

Swapnil Dokhe and Shailesh Pimpale [21] identified that a crack in a structural part presents local flexibility that could diminish stiffness of the beam and causes an expansion in the damping of the member. A deviation in the mode shape and a diminishment in the regular frequencies are caused by the above progressions of the physical properties. It was proposed that the crack location and crack depth can be foreseen by reading the changes in the vibration parameters. In this process, the changes in characteristic frequencies were considered likely because of less influence of trial errors than the deviation of mode shapes. This feature was utilized to distinguish the presence of a crack along with its depth in the structural part and location.

Elephant Search Algorithm (ESA) [22], a novel bio-inspired optimization algorithm was proposed based on the movement of male and female elephants. It was observed that the ESA simulations outperform other standard optimization approaches in finding cracks in beams.

Liu Simeng et al. [23] have proposed the new creating, making mode-specific mischief discovery techniques with an endorsement of shaft members. Initially, the auxiliary conduct was examined from the point of view of stochastic qualities and the theory of structure design. It was induced such creating harm location strategies for probabilistically winning modes could enhance the sufficiency of the recognizing confirmation on a very basic level. Plus, the system was associated with simply maintain bars with the true objective of the check. Thirdly, explores Reinforced concrete (RC) columns were coordinated. The outcomes demonstrated that both the flexural mode and the typical for the changed avoidance blends was seen in all cases; that there was a strong connection between the harm seriousness document and the state of the disfigurements on the poles; that the territory records contrasting with hurt and set up sections shifted absolutely contrastingly in quality and amount.

Sandeep Das et al [24] investigated the effect of an open crack on the particular parameters of the cantilever beam subjected to free vibration. Adaptive Neuro-fuzzy Inference System (ANFIS) is a delicate processing method, appropriate for non-quick, boisterous and complicated issues like a shortcoming. For nonlinear limit estimation, the proposed structure joins the training capacities of neural networks with fuzzy derivation framework. It had been identified that the response of the single-output Sugeno-sort Fuzzy Inference System (FIS) utilizing network allocation is acceptably effective based on the results obtained from Finite Element Method (FEM) using ANSYS. Similar Analysis was done in [25].

Dasaripalle Pitchaiah and Putti Srinivasa Rao [26] investigated that the impact of a break on the vibration of a structure is a customary issue, and diverse models from the basic strength diminishment strategy in perspective of the additional flexibility in account of a split. Various experts have been concentrating the feasibility of using Neural Networks (NN) for split identification in the column. NNs are inspired by human neurons. NNs can pick up from cases and after that conform to changing conditions when satisfactory input/output data are available. This paper modeled the perfect NN can give the gauge of softened parameters up the column. Evaluate the parameters like length, young modulus et cetera. This perfect model uses Genetic-based particular optimizations; among these strategies, OGA is best for perfect NN structure. From the results viably predict the shift, MAC, and stiffness in the beam with minimum MSE.

III METHODOLOGY

Generally, vibrational signals affect the human body in different ways. The retort to a vibration exposure is mainly reliant on the frequency, amplitude, and interval of exposure to damage identification in construction structures. With the cracked beam component, both forward estimation and damage detection can be completed.

The primary favorable position of this model is that a realistic distribution of bending stiffness encompassing the crack is utilized and expressed with parameters of the crack in the model. Our New Research work considered the Free –free, simply supported and Cantilever beams with constraints. We will implement the Fuzzy logic process with Optimal Neural Network i.e., Fuzzy Optimal Neural Network (FONN). The fuzzy modeling approach requires less computational time and also it has excellent learning capabilities. The utilization of subtractive clustering technique is; which operates on raw numerical data. When the number of inputs in the fuzzy system increases, it affects the prediction system to a small extent. After developing the fuzzy model considered the NN with different Hidden Layer and Neurons (HLN) optimization process. For optimizing the HLN in NN used Swarm Intelligence approach that is Elephant Herding Optimization with Adaptive capacity, so this proposed optimization as Adaptive EHO (AEHO). This Algorithm was roused by herding behavior of elephants. As a result of the algorithm, various networks must be trained to locate the optimum network structure which takes a long time. In view of this technique, the boundary conditions at the crack location can be set up with the coherence of moment, shear force, displacement and a fall in the slope which can be figured with the rotational stiffness of the shaft.

A. Crack Beam Model

In the present work, a cracked beam element model is adopted with a formulation of element stiffness matrix which incorporates the effect of a crack. In this formulation, additional local flexibility is considered which is derived from principles of fracture mechanics. In this way the parameters defining the crack location and its depth are used in cracked stiffness matrix. This formulation also takes into account the coupling between the longitudinal and transverse deformation, and shear deformation. This crack element model is appeared in beneath Figure 1.

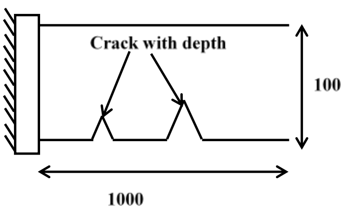


Fig 1: Crack Beam Specimen

In the present work, the cracked element stiffness matrix has been defined by considering the crack-induced additional flexibility based on Timoshenko beam element with the axial force effect. The performance of the cracked beam model is verified with results from a mathematical model with a refined finite element continuum model. A run of the mill correlation between the anticipated stiffness of the crack model is introduced.

B. Simulation analysis

Any In Crack beam identification model, proposed FONN model to evaluate stiffness, Shift, Modal Assurance Criterion (MAC) are evaluated, initially consider the fuzzy approach to generate membership and rules of particular beam constraints and utilized NN technique in the prediction process. Moreover better crack parameters of Cantilever beam, simply supported beam and Free –free beams swarm based inspired optimization model that is AEHO model. From this, the cracked beam element model was used for modelling the cracked portion of the beam while the intact beam element model was used for the remaining portion of the beam.

- **Fuzzy approach**

The objective type fuzzy demonstrating has incredible learning capacities and requires less computational exertion. A normal fuzzy model has fundamentally 4 stages: fuzzification with input constraints to the fuzzy territory, (ii) fuzzy rules generation help of membership function (iii) fuzzy inference system which processes fuzzy variable inputs to acquire fuzzy outputs, and (iv) defuzzification strategy to change over the fuzzy output back to the general input imperatives. In fuzzy rationale, estimations of various criteria are mapped into linguistic values that describe the level of fulfillment with the numerical estimation of the targets [28]. As indicated by three sorts of trust value: friend, acquaintance, and stranger, characterize three fuzzy sets: high, medium and low, individually.

Fuzzification

The numerical input data from the frequent evaluation are converted to fuzzy data. Fuzzifying is changing numerical input data, first normalizing from 0 to 1 and the normalized values are separated into different membership functions.

Membership and rule generation

A relationship task is talented by different shapes for the examination in the fuzzy reason the easiest alliance undertaking is made by utilizing straight lines. From between them, the simplest disparate relationship undertaking is utilized. The set of IF-THEN standards is built to acquire the desired behavior of the system on the premise of information of human experts. IF x is C THEN y is D, Where C and D are linguistic variables of the semantic factors x and y, individually. The level of fact of a fuzzy set A (exact factors, for example,high,medium, low and so forth.) is characterized by an estimation of Membership Function (MF), µA, in the interim [0, 1] and furthermore here Trapezoidal Membership Function (TRAPMF) used to dissect the crack beam element and it is shown in Figure 2.

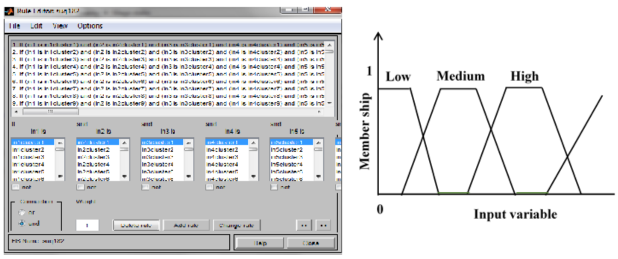


Fig 2: Membership and Rule generation

TRAPMF

A trapezoidal MF is specified by four parameters {l, m, n, and o}as follows:

$$TRAPMF(x:l,m,n,o)=\begin{cases} 0 & x<l \\ (x-a)/(b-a) & l\le x<m \\ 1 & m\le x<n \\ (d-x)/(d-c) & n\le x\le o \\ 0 & x\ge o \end{cases}$$

The limits {{l, m, n, o} (with l < m <= n < o) resolve the x coordinates of the four spot of the fundamental trapezoidal MF. Because of their easy prescription and computational effectiveness, trapezoidal MFs have been employed widely, especially in concurrent execution.

Defuzzification model

The output inferred by the base- rule can't be utilized specifically because it requires a numerical number, not a fuzzy number. The final stage is the defuzzification method that fuses distinctive fuzzy sets to give an individual crisp value in the deterministic space for the two outputs. Based on this step linguistic variables are converted to input values.

- **Neural Network (NN) Model**

Neural Network (NN) models the structure and the functional parts of organic neural networks numerically. There is an interconnected group of artificial neurons which forms the data utilizing a connectionist approach. The response of the each processing element depends upon its weighted sum of inputs. Artificial Neural Networks consists of three types of layers: input layer, output layer and hidden layers. The hidden layers are in between the input layer and output layer. The functionality of each element is similar to the neurons in the human brain. That is why the processing elements are also called as as cells, neuromines, or artificial neurons. This NN prediction approach mainly consists of Basics Function (BF) and Activation Function (AF). This procedure of NN prediction of crack beam model discussed in below section.

• Select input and output parameters of crack beam model.

• Normalized data with BF and AF of NN training process.

• Testing process fit of the model help of training data.

(i) **Input and output data in beam model**

To accurately identify the severity of beam and damage location, consider input constraints as length, height and depth of the element, Poisson's ratio,density, young's modulus and length of the cracked beam,. Then output parameters of the different beam as Shift, MAC and stiffness.

(ii) **Data Normalization process**

The input and the output data acquired must be standardized based on various units and generally, there won't be any connection between are the input and the output data.

Basic Function (BF): A significant non-zero response has been generated by the hidden layer only when the input is limited to a small localized region of the input-space. Our proposed work uses sigmoid function which is given below.

$$B_f = \sum_{j=1}^{N} P_i \times \beta_{ij}$$

Activation Function (AF): This function is similar to the physical process of firing of a neuron i.e., when inputs of a neuron combine in a particular way, it causes triggering of a nerve signal. It has to be chosen so as to cause reasonably proportionate outputs within a small range, for small changes of input. Sigmoid activation functions like the above ensure that the neuron can take real input and then produce an output in the interval (0, 1).

$$A_f = \sum_{j=1}^{h} \alpha_j * \left(\frac{1}{1+\exp(-\sum_{i=1}^{N} P_i \beta_{ij})} \right)$$

Above two equations (2) and (3) Different input parameters, Input and hidden layer weights and Number if data.

(iii) Training and Testing

Training process: This algorithm, in each iteration of data training, chooses the training set randomly but not a settled data set. This results different values of Mean Square Error (MSE), contingent on which 70 percent of the input data is used as the input to the training process, in each attempt of training the data.

Testing Process: When the error is below the tolerance levels and training of the data is complete testing can be followed. Based on training data the validation will be done, moreover, 30% of data considered for testing in the parameters of cracked beam.

C. OPTIMIZATION FOR NN

The Proposed optimization model would optimize hidden layer and Neuron (HLN) of NN structure for improving prediction accuracy and minimum MSE of the cracked beam model. Here we proposed an Adaptive Elephant Herding Optimization (AEHO) model, in which the elephant is treated as a social animal and the herd comprises of a few clans of female elephants and their calves. The movement of each clan is affected by a matriarch elephant. It's AEHO following some Assumptions it's shown in below.

• The whole populace of elephants is partitioned into clans and every clan contains a fixed number of elephants.

• A fixed number of ME quits their clan and live.

• Every clan moves under the initiative of a matriarch.

Steps Involved in ONN

Step 1: **Fitness Function**

The objective function of optimization model in NN process considers the number of hidden layer neurons with input constraints and the fitness as minimum Mean Square Error (MSE) as shown below.

$$F_i = Min(MSE_i)$$

$$MSE_i = \frac{1}{n} \sum_{i=1}^{n} (A_i - P_i)$$

Where $A_i \rightarrow$ Actual value and $P_i \rightarrow$ predicted output and n $\rightarrow$number of data

New HLN updating using AEHO

Step 2: Elephant position update

In this progression, the position of every elephant in different clans is updated except the male and matriarch elephant. It is assumed that the number of clans is elephants and each clan consists of elephants. The position of elephant and clan is represented by.

The present situation of elephant referenced as

$$N_{new,c_{i,j}} = N_{c\,i,j} + \alpha(N_{best,c\,i,j} - N_{ci,j}) \times r$$

Here $N_{new\,c\,i,j} \rightarrow$ updated position, $N_{c\,i,j} \rightarrow$ old position, $N_{best\,c\,i,j} \rightarrow$ Position of best in the clan and $r \in 0 to 1$. It is a kind of stochastic distribution that can significantly improve the diversity of the population in the later search phase. The best position which represents the matriarch cannot be updated by above steps.

Step 3: Movement update of fittest elephant of each clan

Elephants that move away from the clan are used to model exploration. The position update for best fit in the clan is given by

$$N_{new,ci,j} = \beta \times N_{center,c_j} \;\&\; L_{center,c_j} = \sum_{i=1}^{n} N_{ci,j} / n_l$$

Here $n_l \rightarrow$ total number of elephants in each clan and $\beta \in [0\,1]$

Step 4: Separating worst elephant's in clan

The convergence of the AEHO method is further improved by separating the individual worst elephants and male elephants from their family groups. The worst position updated as

$$N_{worst,ci,j} = N_{\min} + (N_{\max} - N_{\min} + 1) \times r$$

Where $L_{worst,ci,j} \rightarrow$ worst male elephants in clan and $L_{\max}$ *and* $L_{\min} \rightarrow$ maximum and minimum allowable boundary limits for the clan elephants.

Step 5: Adaptive Function

This process swarm algorithm velocity and position utilized. Until they reach an optimum position, the particles will move to different positions in each iteration. At every time , the velocity of the particle is revised using

$$N_i^{(t+1)} = w.N_i^{(t)} + h_1.r_1.(p^t{}_{Pbest} - p_i^t) + h_2.r_2.(p^t{}_{Gbest_k} - p_i^t)$$

$$p_i^{t+1} = p_i^t + p_i^{t+1}$$

Here $N^t \rightarrow$ particle velocity, $p^t \rightarrow$ current particle, h_1 *and* $h_2 \rightarrow$ learning factor, r_1 *and* $r_2 \rightarrow$ random value within the [0, 1]. In case of separating the velocity and location appraisal of the particles, the fitness value is again established for the newly evaluated velocity of the particles.

D. Our Proposed Fuzzy Optimal Neural Network (FONN)

A novel approach employed FONN structure for making optimal HLN in crack beam model prediction process shown in figure 3. The knowledge-based spectrum access based on three descriptors is found from groups of network expert. Initially the database into a fuzzy approach to defuzzification and defuzzification the data based on above mentioned procedures. Fuzzy rule-based system uses a collection of fuzzy conditional statements derived from a knowledge-based to approximate and construct the cracked beam. Moreover busing NN with HLN optimization model improves the performance of the system of the proposed approach. In the decision making operation output of fuzzy is applied to the multilayer perceptron.

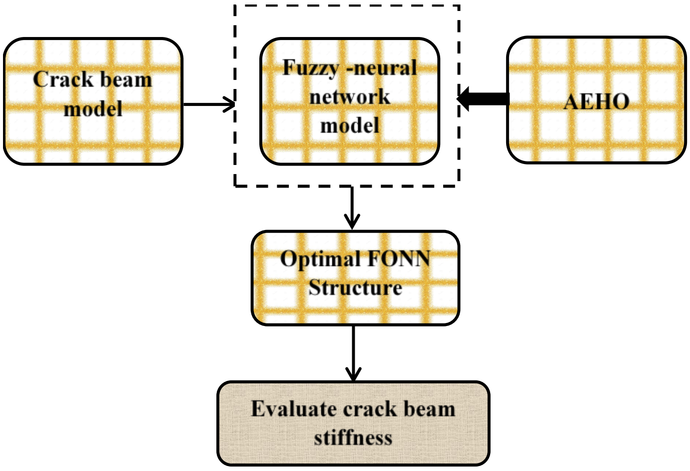


Fig 3: Block diagram for proposed Model

The optimal NN is fed forward neural network. It is composed of an interconnection of basic neuron processing units. From the proposed model, the results are stored in the workspace and a graph is plotted between the actual output and the predicted output so that a comparison can be made.

IV. SIMULATION RESULTS ANALYSIS

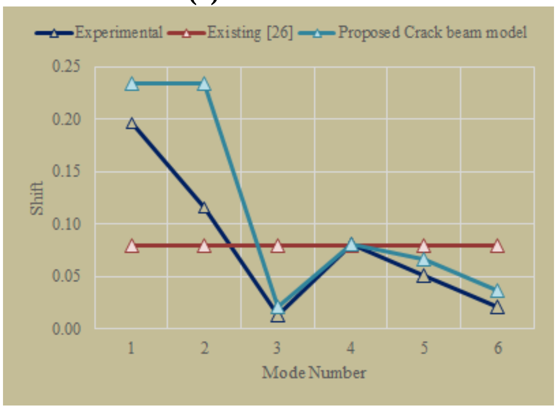
Crack beam model simulation analysis implemented in MATLAB 2015 as with i5 processors and 4GB RAM for our proposed model FONN. The proposed results are compared to existing techniques and existing literature.

Table 1: Shift (%) results for crack beam

Trial	FFB			SSB			CB		
	Exp.	Existing [25]	Proposed	Exp.	Existing [25]	Proposed	Exp.	Existing [25]	Proposed
1	0.04	0.05	0.01	0.03	0.04	0.02	0.04	0.06	0.05
2	0.05	0.05	0.03	0.02	0.08	0.04	0.02	0.06	0.04
3	0	0.05	0.01	0.20	0.08	0.23	0.15	0.06	0.03
4	0.20	0.05	0.12	0.12	0.08	0.23	0.10	0.06	0.07
5	0.12	0.05	0.09	0.01	0.08	0.02	0	0.06	0.01
6	0	0.05	0.09	0.08	0.08	0.08	0.05	0.06	0.06

Table 1 describes three different beam analysis, i.e. Free –Free Beams (FFB), Simply Supported Beam (SSB) and Cantilever Beams (CB). The cracked beam component model (cracked stiffness matrix) carries explicit parameters defining the location of the crack within the element as well as its severity (crack depth). The experimental, existing and the proposed crack beam is revealed in the table1.

(a) **Free- Free Beam**

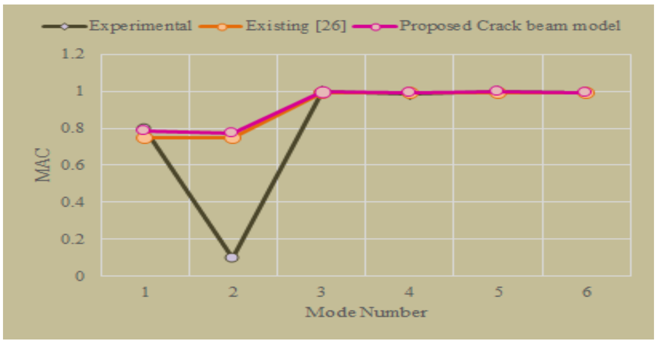


(b) **Simply Supported Beam**

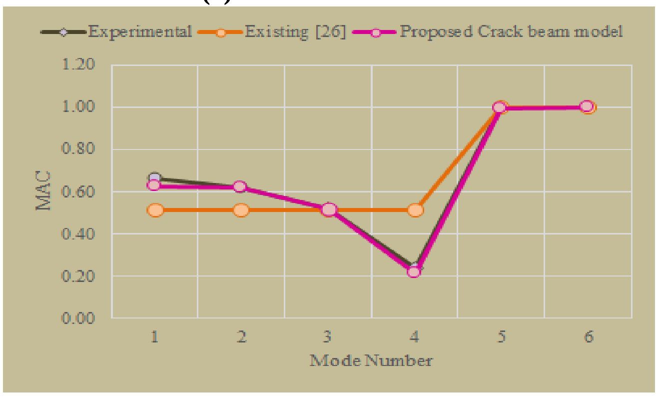
(c) **Cantilever Beam**

Fig 4: Comparison of Shift (%) results

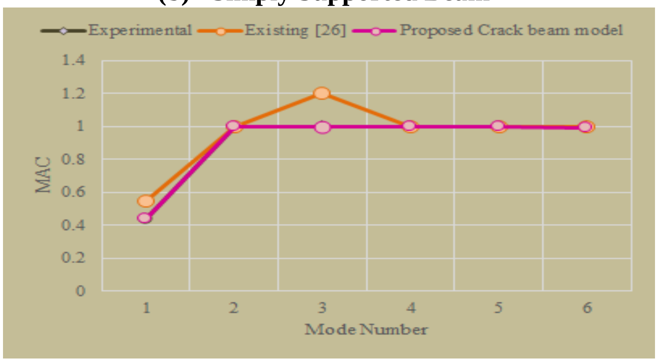
Figure 4 describes the shifting characteristics of the beam for different mode number. The graph clearly shows the comparative analysis of experimental, existing [26] and proposed crack beam model for three beams like FFB, SSB, and CB. Figure (a) explains the shifting characteristics of Free-Free Beam where the highest shift of 0.2% is attained in the experimental results. The proposed crack beam model attains 0.125% shift in mode1. Similarly, the shift is measured in the mode 2, 3, 4, 5 and 6 for the three beams. Figure (b) explains the shifting characteristics of SSB. For mode 3, the experimental analysis attains 0.025 %shift, existing [25] achieves 0.08%shift and the proposed model accomplishes 0.015% shift. For six different numbers of modes, the shifting characteristics of CB are analyzed in figure (c) and compare the values with the existing and proposed crack beam model. Table 2 illustrates the MAC results for crack beam and compared results with the existing, experimental and the proposed models. For the trial 6, the Modal Assurance Criterion (MAC) values are 0.72 for experimental, 0.75 for the existing [26] and 0.07 for the proposed crack beam in the free-free beam (FFB). Likewise, the MAC values are analyzed for the different number of trials.



(a) **Free- Free Beam**



(b) **Simply Supported Beam**



(c) **Cantilever Beam**

Fig 5: Comparison of MAC results

The MAC characteristics of the beam for different mode number are represented in figure 5. The graph clearly shows the comparative analysis of experimental, existing [26] and proposed crack beam model for three beams i.e. FFB, SSB and CB. Figure (a) describes the free-free beam with the three models. In specific, the proposed crack beam model attains 0.8 MAC in mode1.

Table 2: MAC results for crack beam

Trial	FFB			SSB			CB		
	Exp.	Existing [25]	Proposed	Exp.	Existing [25]	Proposed	Exp.	Existing [25]	Proposed
1	0.80	0.75	0.79	0.66	0.51	0.63	0.66	0.55	0.64
2	0.10	0.75	0.78	0.62	0.51	0.62	0.41	0.55	0.40
3	1	0.99	1	0.52	0.51	0.52	0.56	0.55	0.52
4	0.99	0.99	0.99	0.24	0.51	0.21	0.45	0.55	0.44
5	1	0.99	1	1	1	1	1	1	1
6	0.72	0.75	0.07	1	1	1	1	1	1

Similarly, the MAC is measured in the mode 2, 3, 4, 5 and 6 for the three beams. Figure (b) explains the MAC characteristics of SSB. For mode 3, the experimental analysis attains 0.50 existing [26] achieves 0.50 and the proposed model accomplishes 0.50. For six different numbers of modes, the MAC characteristics of CB are analyzed in figure (c) and compare the values with the existing and proposed crack beam model.

Table 3: Stiffness results for crack beam

Trial	Experimental	Existing [25]	Proposed
1	99.3	52.2	95.84
2	50.3	70.2	46.32
3	0	52.4	23.6
4	57.8	90	51.23
5	0	5.22	3.59
6	89.3	65.2	82.1

The stiffness of the proposed crack beam model is described in table 3 and compares the stiffness characteristics with the experimental, existing and the proposed method. Almost similar to the results which were obtained from beams made of normal concrete, in this case, that the increase in the diameter of the opening will lead to the reduction of stiffness in the beam. The highest stiffness is attained in the experimental analysis i.e. 99.3 and in case of the proposed method, 95.84 is obtained in the trial 1. Similarly, the stiffness characteristic is analyzed for other trial rounds 2, 3, 4, 5 and 6.

Fig 6: Comparison of stiffness results

The comparison analysis of stiffness characteristic of the crack beam is depicted in figure 6. For the mode number 1, experimental analysis and proposed crack beam obtain zero stiffness and the existing approach attains stiffness of about 50. Depend on the open crack models, most researchers assessed the presence of the crack by differing the modes, which was effective for identifying large cracks.

Table 4: MSE for proposed model

Testing data	Stiffness			Shift			MAC		
	Experimental	Predicted	MSE	Experimental	Predicted	MSE	Experimental	Predicted	MSE
1	0.78	0.63	0.15	1	1	0	0.20	0.12	0.08
2	0	0.02	0.02	0.99	0.99	0.01	0.12	0.09	0.03
3	0.41	0.36	0.05	1	1	0	0	0.09	0.09
4	1.00	1	0	1	0.99	0	0.01	0.02	0.01
5	0	0.02	0.02	0.24	0.21	0.03	0.08	0.08	0.00
6	1	0.97	0.04	1	1	0	0.05	0.06	0.02
7	0.30	0.35	0.05	1	1	0	0.04	0.05	0.00
8	0.99	0.96	0.03	0.975	0.97854	0	0.02	0.04	0.01
9	0.50	0.46	0.04	0.41	0.40	0.01	0.15	0.03	0.12
10	0	0.02	0.02	0.56	0.52	0.04	0.10	0.07	0.02

Table 4 demonstrates the Mean Square Error (MSE) for the parameters such as stiffness, shift, and MAC of the crack beam model. The analyzed parameters are compared with the experimental and predicted value. In case of the beam stiffness, the experimental value is 0.78, the predicted value is 0.63 and the MSE is 0.15 for the testing data 1. Likewise, the shifting characteristics of beam results are depicted in the above table. Also, the three parameters are analyzed and compared with the existing approaches and the analysis is carried out for ten different testing data.

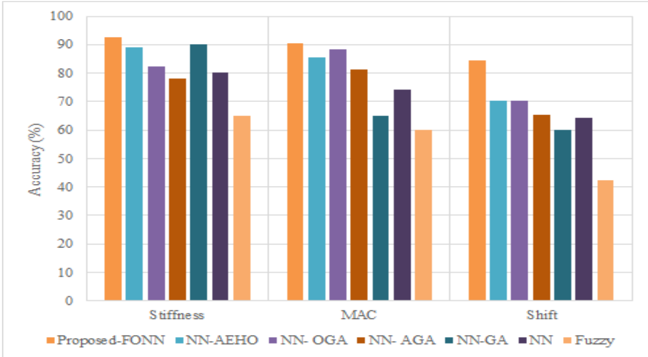


Fig 7: Crack Beam measures evaluation for different approaches

Figure 7 represents the accuracy analysis of Crack Beam measures Evaluation for different approaches such as proposed FONN, NN-AEHO, NN-OGA, NN-AGA, NN-GA, NN and Fuzzy. The graph clearly shows the efficiency of performance metrics like sensitivity, specificity and accuracy. The stiffness of proposed FONN is 92.86%, NN-AEHO is 89%, NN-OGA is 82.22%, NN-AGA is 78%, NN-GA is 90%, NN is 80% and Fuzzy is 65%. The MAC and shift characteristics of the proposed Crack Beam measures Evaluation accomplish 91.66% and the 85.22% respectively. On comparing all the evaluation performance, the proposed FONN attains a maximum accuracy of about 93%.

III. CONCLUSION

The present work investigated the simulation analysis of cracked beam with machine learning model to analyze the stiffness of the beam structure. Depending on the vibrational analysis of cracked beam structure, both forward calculation and damage detection are carried out. Distribution of bending stiffness enclosing the crack was analyzed and expressed with crack parameters for the three beams such as Free-Free, Simply Supported and Cantilever Beams. The extricated modal data were utilized to conversely recognize the cracks with the cracked beam element model through a model updating method. For the optimal NN based stiffness computation, Adaptive Elephant Herding Optimization (AEHO) was proposed to identify the number of cracks in various beams. The obtained results are compared with the existing research work. It is concluded that the proposed FONN attains a maximum accuracy of 92.86% when compared to other crack beam measure approaches.

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AUTHORS PROFILE

Dasaripalli Pitchaiah is a Research Scholar, Andhra University, Vishakhapatnam, India. He has 17 years of teaching and 4 years of research experience. He received B.Tech. degree in Mechanical Engineering from Nagarjuna University, India in 2000 and M.Tech. Degree in Machine Design from JNTUH Hyderabad in 2008.He has guided 5 M.Tech projects 15 B.Tech projects. He has published four research papers in International Journals. He has published two papers in International conferences. He attended 10 workshops / short-term courses. His areas of interest are Mechanical Vibrations

Dr. Putti Srinivasa Rao received B.E. from university of Bangalore in 1995, Bangalore, India, the M.Tech degree from the university JNTUH, Hyderabad, India, in 2000, and the PhD degree from Andhra University, Visakhapatnam, India, and in2012. He is currently a Professor in the Department of Mechanical Engineering at Andhra University, Visakhapatnam, A.P. India. His research interests are in vibrations, composite materials, health monitoring in welded structures, health monitoring mechanical structures. He wrote many books like Design of machine elements and instrumentation and control systems.