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Efficient Method for Identification of Cracks in Beams Using Fuzzy With Neural Network

[1]D.Pitchaiah, [2]CH.Ramesh, [3]B.Suvarna Raju

[1] Assistant professor, [2]Assistant professor, [3]Assistant professor

[1,2&3] Department of Mechanical Engineering college , Rise Krishna sai prakasam Group of Institutions , NH-5, vallur , Ongole , prakasam Dist , Andhra Pradesh

Abstract

Structures like beams failure 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 in beams in view of a cracked beam component model, it originates from thefracture mechanicsand local flexibility rules. The present work exhibits the simulation analysis of cracked beam with 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 in addition with a survey of other crack models. The extricated modal data are utilized to conversely recognize the cracks with the cracked beam component model through a model updating technique. The optimal NN based stiffness computation utilizes a global searching procedure utilizing Adaptive Elephant Herding Optimization (AEHO) the number of cracks identified from various beams. From the proposed model, the attained results are compared with the current research paper and other optimization, machine learning models.

Keywords: Cracked beam, Damage Identification, Neural Network, optimization and stiffness.

1. 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 systemstime-scale andtime-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 for neighborhood damage recognition in machinery [2, 3]. 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 frequency growth starting from damage happening and proceeding to the minute when irregular displacement amplitude achieves substantial 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 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 to 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 component extraction [13]. In a numerical reenactment study in which the genuine impact of the fracture on the dynamic properties of the beam was reenacted by a precised solid finite component model permitting unequivocal portrayal of the cracks and afterward contrasted and the forecasts utilizing the cracked beam component [14, 15].

2. 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 Newark considered that is 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, displacementand a fall in the slope which can be figured with the rotational stiffness of the shaft.

2.1 Crack Beam Model

The cracked beam component model embraced in the current investigation for directly identifying the damage of the crack which consolidates the impact of a fracture into the stiffness matrix of the component. An extra regional flexibility, which is obtained from fracture mechanics gives the idea of detailing the fractured component stiffness matrix. Along these lines the cracked beam component conveys accurateparameters characterizing the location of the crack inside the component and additionally its seriousness (depth of the crack). The model additionally considers the couplingandshear twisting between the transverse andlongitudinaldistortions. This crack element model is appeared in beneath fig 1.

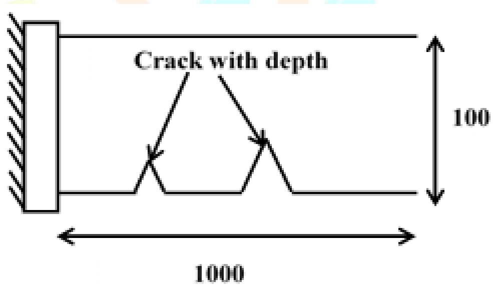


Fig 1: Crack Beam Specimen

In the current examination, the stiffness matrix of the cracked component considering the beforehand specified crack-actuated extra adaptability had it shaped on the premise of a Timoshenko beam component with the effect of axial force. The cracked beam component model indicates the impact of a fracture on the vibration properties of generally thick beams had it checked utilizing simulation modal data created from a numerical experiment with finite-element model. A run of the mill correlation between the anticipated stiffness of the crack model is introduced.

2.2 Simulation analysis

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 to the prediction process. Moreover better crack parameters ofCantilever beam, simply supported beam and Free –free beams swarm based inspired optimization model that is AEHO model. From this, thecracked beam element model was used for modelling the cracked portion of the beam while theintact beam element model was used for the remaining portion of the beam.

2.2.1 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.

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 of straight lines. From between them, the simplest disparate relationship undertaking is utilized. The Set of IF-THEN standards are built to acquire the desired behavior of the system on the premise of information of human expert. 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 dissected the crack beam element and it is shown in fig 2.

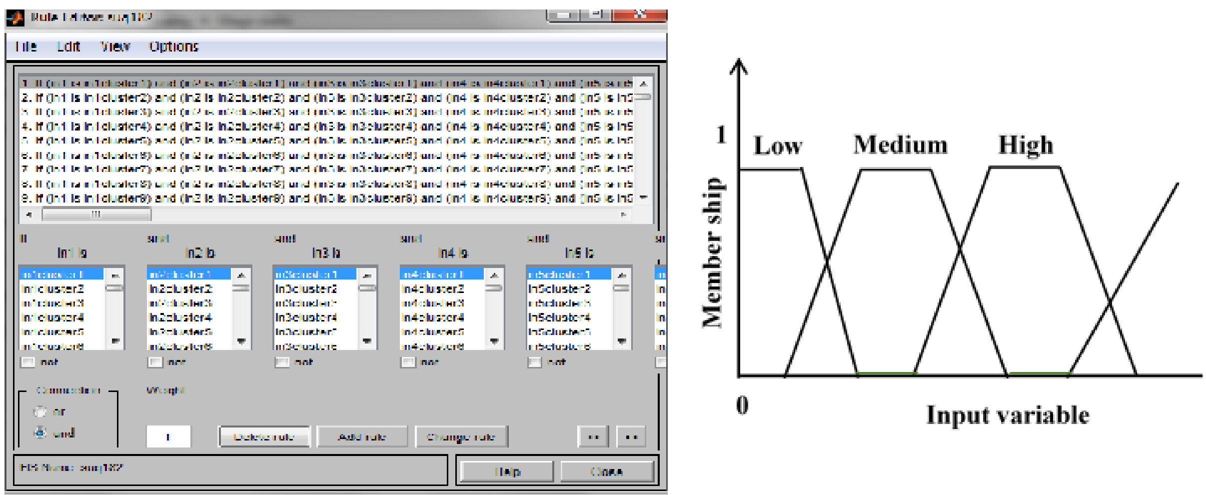


Fig 2: Membership and Rule generation

2.3 Optimization for NN

Inspired optimization model held to optimize hidden layer and Neuron (HLN) of NN structure for improving prediction accuracy and minimum MSE of crack beam model. Here we proposed adaptive function based Elephant herding Optimization (AEHO) model, in general, the elephant is likewise considered as a social creature and the crowd comprises of a few clans of female elephants and their calves. Every clan moves affected by an authority or a pioneer elephant.It's AEHO following some Assumptions it's shown in below.

- The wholepopulace 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.

<u>Steps Involved in ONN</u>

(a) Fitness Function

The objective function of optimization model in nn process consisder number of hidden alayer and neurons with input constraints and the fitness as minimum Mean Square Error (MSE), the equation 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

(b) Elephant position update

In this progression, the position of every elephant in various clans aside from the matriarch and male elephant that holds the best and worse solution in each clan C_i elephants and each clan have E elephants. The position of i^{th} elephant $i = 1,2,\ldots E$ and j^{th} clan $j = 1,2,\ldots C$ is represented by $N_{i,j}$. 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. α And $r \in 0\,to\,1$. It is a kind of stochastic distribution that can significantly improve the diversity of population in the later search phase. The best position which represents the matriarch cannot be updated by above steps.

(c) 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

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

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

(d) Separating worst elephant's in clan

This separating procedure can be modeled into separating operator when solving optimization problems. So as to additionally improve the search capacity of the EHO technique,let us assume that the elephant individuals with the worst elephant's individual or male elephants will be isolated 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.

(e) Adaptive Function

This process swarm algorithm velocity and position utilized. Until they reach an optimum position, the particles will moveto different positions in each iteration. At every time t, the velocity of the particle P 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* $r_2 \rightarrow$ $_a$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.

2.4 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 mention 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 proposed approach. In the decision making operation output of fuzzy is applied to the multilayer perceptron.

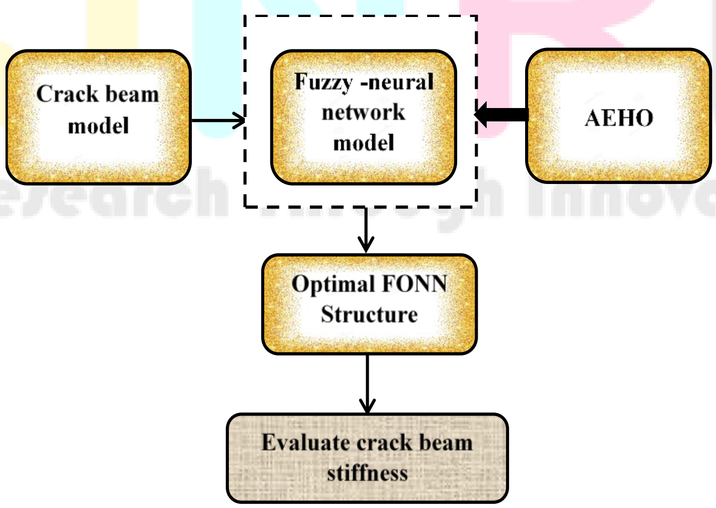


Fig 3: Block diagram for proposed Model

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.

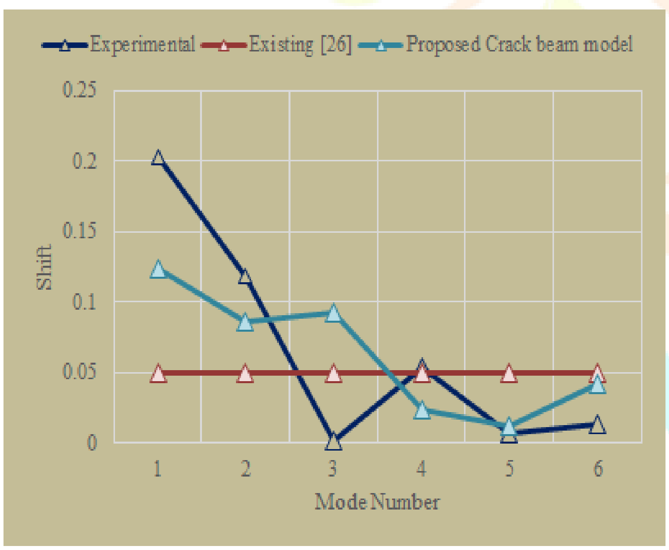
3. Simulation results analysis

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.

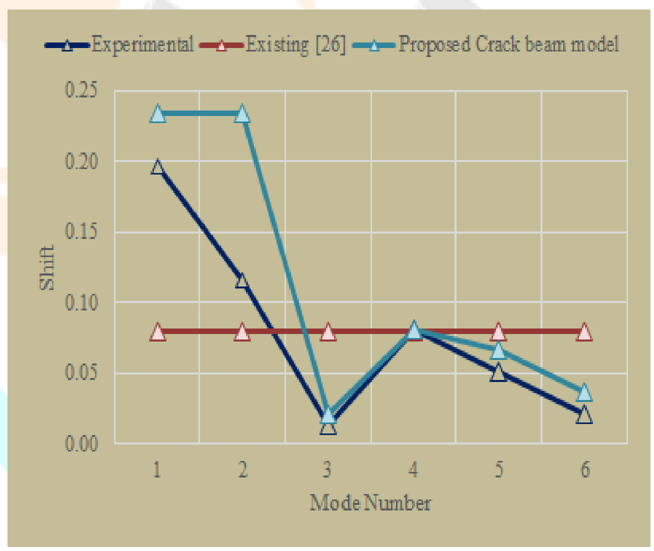
Table 1: Shift (%) results for crack beam

Trial	FFB			SSB			CB		
	Experi	Existing [26]	Proposed	Experi	Existing [26]	Proposed	Experi	Existing [26]	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

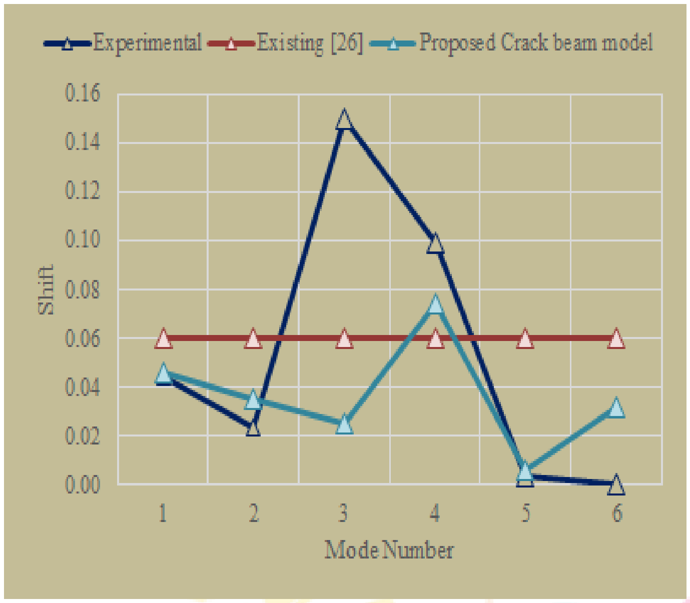
Table 1 describes three different beam analysis i.e. Free –Free Beams (FFB), Simply Supported Beam (SSB) and Cantilever Beams (CB). The cracked beam component model (cracked stiffness matrix) carries explicit parameters defining the location of the crack within the element as well as its severity (crack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



(a) Free- Free Beam



(b) Free- Free Beam



(c) Cantilever Beam

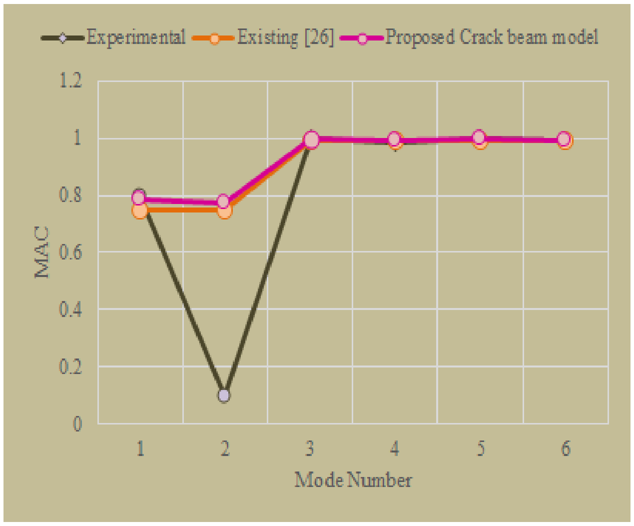
Fig 4: Comparison of Shift (%) results

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 [26] 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: MAC results for crack beam

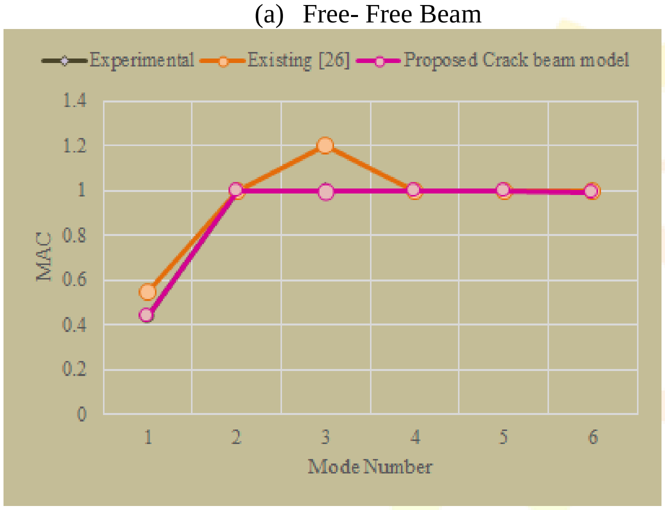
Trial	FFB			SSB			CB		
	Experi	Existing [26]	Proposed	Experi	Existing [26]	Proposed	Experi	Existing [26]	Proposed
1	0.80	0.75	0.79	0.66	0.51	0.63	0.66	0.55	0.64
2	0.10	0.75	0.78	0.62	0.51	0.62	0.41	0.55	0.40
3	1	0.99	1	0.52	0.51	0.52	0.56	0.55	0.52
4	0.99	0.99	0.99	0.24	0.51	0.21	0.45	0.55	0.44
5	1	0.99	1	1	1	1	1	1	1
6	0.72	0.75	0.07	1	1	1	1	1	1

Table 2 illustrates the MAC results for crack beam and compare the results with the existing, experimental and the proposed model. 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

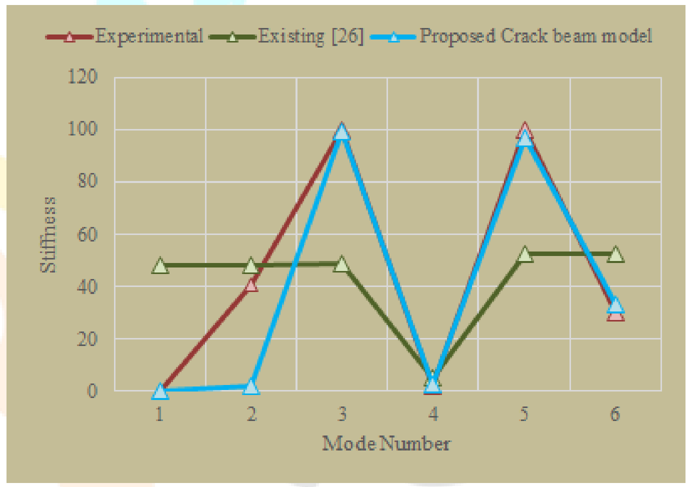


Fig 6: Comparison of stiffness results

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. 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 [26]	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

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

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. 4: MSE for proposed model

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.

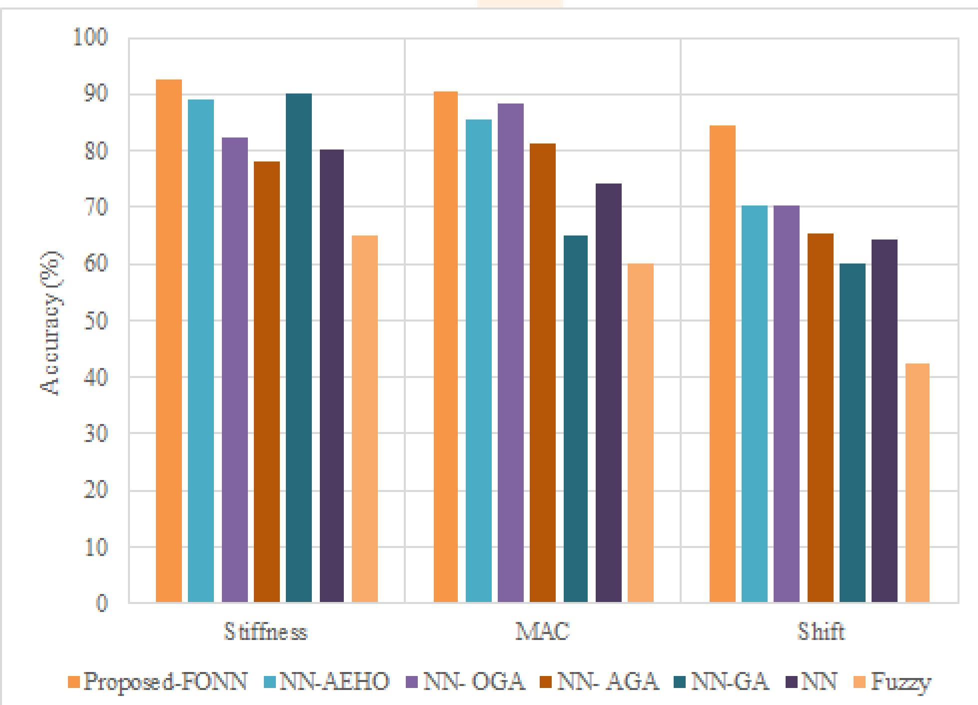


Fig 7: Crack Beam measures Evaluation for different approaches

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%.

4. Conclusion

The study investigated the simulation analysis of cracked beam with machine learning model to analyze the stiffness of the beam structure. Depend on the vibrational analysis of cracked beam structure, both forward calculation and damage detection can be carried out. Distribution of bending stiffness enclosing the crack was analyzed and expressed with crack parameters for the considered 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 from various beams. From the proposed model, the attained results are compared with the current research paper and other optimization, machine learning models. It concluded that the proposed FONN attains a maximum accuracy of 92.86% when compared to other crack beam measure approaches.

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