

Experimental Validation of a Fuzzy Model for Damage Prediction of Composite Beam Structure

Deepak K. Agarwalla, Amiya K. Dash and Biswadeep Tripathy

Abstract Damage detection of beam structures have been in practice for last few decades. The methodologies adopted have been upgraded over the time depending upon the complexities of the damage or crack and the desired accuracy. The utilization of artificial intelligence (AI) techniques have also been considered by many researchers. In the current research, damage detection of a glass fiber reinforced cantilever beam has been done. A fuzzy based model using trapezoidal membership function has been developed to predict the damage characteristics i.e. damage position and damage severity. The inputs required for the fuzzy based model such as first three relative natural frequencies and first three mode shape differences have been determined by finite element analysis of the damaged cantilever beam subjected to the natural vibration. The results obtained from the proposed analysis have been experimentally validated.

Keywords Damage · Cantilever · Fuzzy · Finite element analysis · Trapezoidal membership function

1 Introduction

Damage detection of beam elements attracts various researchers in the past to carry out their research in the development of damage diagnostic techniques. A large number of damage detection tools are available for the beam members made of isotropic material. The AI techniques have also been used to diagnose the damage

D.K. Agarwalla (✉) · A.K. Dash · B. Tripathy
Department of Mechanical Engineering, Institute of Technical Education
and Research, Siksha 'O' Anusandhan University, Bhubaneswar, India
e-mail: deepak.cet08@gmail.com

A.K. Dash
e-mail: dash.amiya@gmail.com

B. Tripathy
e-mail: biswadeep143@gmail.com

effectively. Recently the composite materials are found to be engaged widely in various engineering applications. Therefore it is evident in the present scenario that a diagnostic tool for the damage diagnosis of composite beam members is highly required. The fuzzy system for damage diagnosis has been designed with six inputs (first three relative natural frequencies and first three relative mode shape differences) and two outputs (relative damage position, relative damage severity). A number of fuzzy linguistic terms and fuzzy membership functions (trapezoidal) have been used to develop the proposed damage identification technique. Chandrashekhar and Ganguli [1] have developed a fuzzy logic system (FLS) for damage detection. The probabilistic analysis has been performed using Monte Carlo simulation on a beam finite element (FE) model to calculate statistical properties. The frequencies were varied and the damage detection in the steel beam has been identified with 94 % accuracy. Moreover the FLS accurately classifies the undamaged condition reducing the possibilities of false alarms. Chandrashekhar and Ganguli [2] have come up with an idea that geometric and measurement uncertainty cause considerable problem in damage assessment which can be alleviated by using a fuzzy logic based approach for damage detection. Curvature damage factors (CDF) has been used as damage indicators and Monte Carlo simulation (MCS) has been used to study the changes in the damage indicator of a tapered cantilever beam. They have found that the method identifies both single and multiple damages in the structure. Silva et al. [3] have proposed an idea for structural health monitoring (SHM) using vibration data. The approach has been applied to data to a benchmark structure from LOS almost national Lab, USA. The two fuzzy clustering algorithms are compared and it shows that the Gustafson-Kessel algorithm marginally outperforms the fuzzy c-means but both are effective. Beena and Ganguli [4] have developed a new algorithmic approach for structural damage detection based on fuzzy cognitive map (FCM). A finite element model of a cantilever beam has been use to calculate the change in frequencies. The FCM works well for damage detection for ideal and noisy data and for further improvement in performance the hebbian learning have been used both FCM and hebbian learning give accurate results and represents a powerful tool for structural health monitoring. Radzienski et al. [5] have introduced a new method for structural damage detection. They have used damage indicators based on measured modal parameters in an aluminum cantilever beam. The special signal processing technique has been proposed to improve the effectiveness; however it has not been satisfactory. Hence new techniques have been proposed and were suitable for damage localization in beam like structure. Yan et al. [6] have reviewed about the development of vibration based on structural damage detection. The evaluation of the structural damage detection has been done and its diagnosis, application and development in the recent trends have been put forward. Reda Taha and Lucero [7] have come up with an idea of intelligent structural health monitoring with fuzzy sets to improve pattern recognition and damage detection. They have examined a pre stressed concrete bridge using data simulated from finite element analysis with new techniques. KO and NI [8] have investigated on recent technology development in the field of structural health monitoring. The aim was to evaluate structural health of the bridge which has been helpful for rehabilitation, maintenance and emergency

repair. Erdogan and Bakir [9] have presented a fuzzy finite element model updating (FFEMU) method for damage detection problem. They have performed a probabilistic analysis using Monte Carlo simulation (MCS) and results are compared with the present method. Both the methods are accurate but the present method is not as computational expensive than MCS method. Radriguez and Arkkio [10] have come up with an idea for the detection of stator winding faults. They have used fuzzy logic to determine the stator motor condition. The finite element method (FEM) has been used and implemented in MATLAB. The proposed method has the ability to work with high accuracy which identifies the condition of motor. Kemru [11] have proposed a fuzzy logic method so as to improve the visual inspection and assessment of visual quality of industrial products. It is a unique application of vitreous china ceramic sanitary wares. Asnaashari and sinha [12] have proposed a probability distribution function which performs all the data processing in time domain for crack detection in beam. They have illustrated the numerical and experimental examples and their results are presented. Hasanzadeh et al. [13] have proposed an aligning method by a fuzzy recursive least square algorithm. The method of the adaptation for different crack shapes provides sufficient information for the training system which reduces the need for a large crack databases. Reza et al. [14] have proposed the fuzzy clustering method and logic rules which classified the defects. The detection and error has been compared with the bayes classifier. They have investigated the experimental images from eddy current, ultrasonic and radiography techniques which reduces the noise and drift leading to a better detection of defects. Saravanan et al. [15] have presented the use of decision tree that discriminates the fault conditions of the gear box from the vibration signals extracted. The vibration signal from a piezo-electric transducer captures different conditions for various loading and lubricating conditions. The statistical features have been extracted using decision tree which discriminate the fault conditions of the gear box.

From the literatures cited above, it has been observed that damage detection of different beam structures of various isotropic materials have been done in the past by various researchers. Various AI techniques have also been used by researchers to identify the damage position and damage severity for isotropic materials such as aluminum, steel etc. Damage identification of composite beam using AI techniques is still a potential area of research.

2 Finite Element Analyses

Finite element analysis (FEA) is a numerical method for solving a differential or integral equation. FEA is realized, first by dividing the structure into a number of small parts which are known as finite elements and the procedure adopted to attain these small elements is known as discretization. The solution for each finite element brought together to attain the global mass and stiffness matrix describing the dynamic response of the whole structure.

In the present research for damage identification in structural beam members, finite element based model is adopted to characterize the damage with respect to its severity and position. The dynamic behavior of the structure is altered with the presence of damage. The results obtained from finite element analysis of the damaged and undamaged structural beam members of Glass fiber reinforced composite is used as the inputs for the development of the fuzzy based model for damage diagnosis.

2.1 Finite Element Analysis of Damaged Cantilever Beam

In the current section, FEA is used for vibration analysis of a composite cantilever damaged beam (Fig. 1). The relationship between the displacement and the forces can be expressed as;

$$\begin{Bmatrix} u_j - u_i \\ \theta_j - \theta_i \end{Bmatrix} = C_{ovl} \begin{Bmatrix} U_j \\ \phi_j \end{Bmatrix} \tag{1}$$

where overall flexibility matrix C_{ovl} can be expressed as;

$$C_{ovl} = \begin{pmatrix} R_{11} & -R_{12} \\ -R_{21} & R_{22} \end{pmatrix}$$

The displacement vector in Eq. (1) is due to the damage.

The forces acting on the beam element for finite element analysis are shown in Fig. 1.

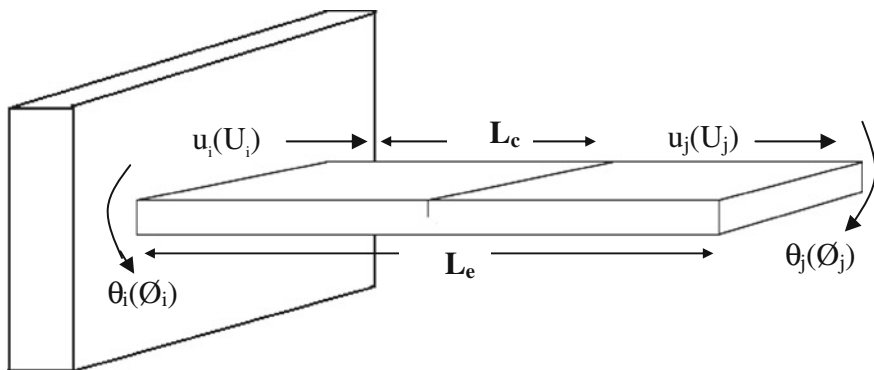


Fig. 1 Damaged beam element subjected to axial and bending forces

Where,

R_{11} : Deflection in direction 1 due to load in direction 1

$R_{12} = R_{21}$: Deflection in direction 1 due to load in direction 2

R_{22} : Deflection in direction 2 due to load in direction 2.

Under this system, the flexibility matrix C_{intact} of the intact beam element can be expressed as;

$$\begin{Bmatrix} u_j - u_i \\ \theta_j - \theta_i \end{Bmatrix} = C_{\text{intact}} \begin{Bmatrix} U_j \\ \phi_j \end{Bmatrix} \tag{2}$$

where,

$$C_{\text{intact}} = \begin{pmatrix} Le/EA & 0 \\ 0 & Le/EI \end{pmatrix}$$

The displacement vector in Eq. (2) is for the intact beam.

The total flexibility matrix C_{tot} of the damaged beam element can now be obtained by

$$C_{\text{tot}} = C_{\text{intact}} + C_{\text{ovl}} = \begin{bmatrix} Le/EA + R_{11} & -R_{12} \\ -R_{21} & Le/EI + R_{22} \end{bmatrix} \tag{3}$$

Through the equilibrium conditions, the stiffness matrix K_c of a damaged beam element can be obtained as

$$K_c = DC_{\text{tot}}^{-1}D^T \tag{4}$$

where D is the transformation matrix and expressed as;

$$D = \begin{pmatrix} -1 & 0 \\ 0 & -1 \\ 1 & 0 \\ 0 & 1 \end{pmatrix}$$

By solving the stiffness matrix K_c , the natural frequencies and mode shapes of the damaged cantilever beam can be obtained. This mathematical approach has been conceived by Computerized Analysis Software to estimate the natural frequencies and mode shapes of beam structures. In the current analysis, Computerized Analysis Software has been used to determine the vibration responses of damaged and undamaged cantilever of Glass fiber reinforced composite. The results of the finite element analysis for the first three modes of the damaged beam are used for the development of fuzzy model.

3 Fuzzy Based Model for Damage Diagnosis

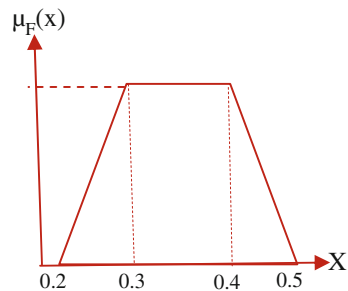
The fuzzy system for damage diagnosis has been designed with six inputs (first three relative natural frequencies and first three relative mode shape differences) and two outputs (relative damage position, relative damage severity). A number of fuzzy linguistic terms and fuzzy membership functions (trapezoidal) have been used to develop the proposed damage identification technique. The trapezoidal membership function as shown in Fig. 2 has two base points (0.2, 0.5) and two shoulder points (0.3, 0.4). A mathematical expression for the trapezoidal membership function is presented below. The modal parameters obtained from the finite element analyses have been used to establish the rule base for designing of the fuzzy system. The performance of the proposed fuzzy based system for damage diagnosis has been compared with the results obtained from experimental analysis and presented in Table 3. A fuzzy logic system (FLS) essentially takes a decision by nonlinear mapping of the input data into a scalar output, using fuzzy rules. The FLS maps crisp inputs into crisp outputs. It can be seen from the figure that the FIS contains four components: the fuzzifier, inference engine, rule base, and defuzzifier.

3.1 Fuzzy Based Model Using Fuzzy Rule

$$\mu_F(X, 0.2, 0.3, 0.4, 0.5) = \begin{cases} 0 & \text{when } x \leq 0.2 \\ (x - 0.2)/(0.3 - 0.2) & \text{When } 0.2 \leq x \leq 0.3 \\ 1 & \text{when } 0.3 \leq x \leq 0.4 \\ (0.5 - x)/(0.5 - 0.4) & \text{When } 0.4 \leq x \leq 0.5 \end{cases}$$

Fuzzy inference system posses the approximation features by the help of fuzzy membership functions and fuzzy IF-THEN rules. This membership functions are designed by using the suitable fuzzy linguistic terms and fuzzy rule base. The fuzzy

Fig. 2 Trapezoidal membership function



rule base or the conditional statements are used for fuzzification of the input parameters and defuzzification of the output parameters. Hence, the fuzzy model takes the input parameters from the application at a certain state of condition and using the rules it will provide a controlled action as desired by the system. A general model of a fuzzy inference system (FIS) is shown in Fig. 3.

The inputs to the fuzzy model for damage identification in the current analysis comprises,

- Relative first natural frequency = FNF;
 - Relative second natural frequency = SNF;
 - Relative third natural frequency = TNF;
 - Relative first mode shape difference = FMD;
 - Relative second mode shape difference = SMD;
 - Relative third mode shape difference = TMD.
- The linguistic term used for the outputs are as follows;
- Relative damage position = RDP;
 - Relative damage severity = RDS.

The relationship between the fuzzy output set (F), defuzzifier and crisp output (K_0) can be established in the following equation;

$$K_0 = \text{defuzzifier (F)};$$

There are several defuzzification methods used for development of fuzzy system. Some of them are listed below;

- Centroid of the area
- Mean of maximum
- Weighted average method

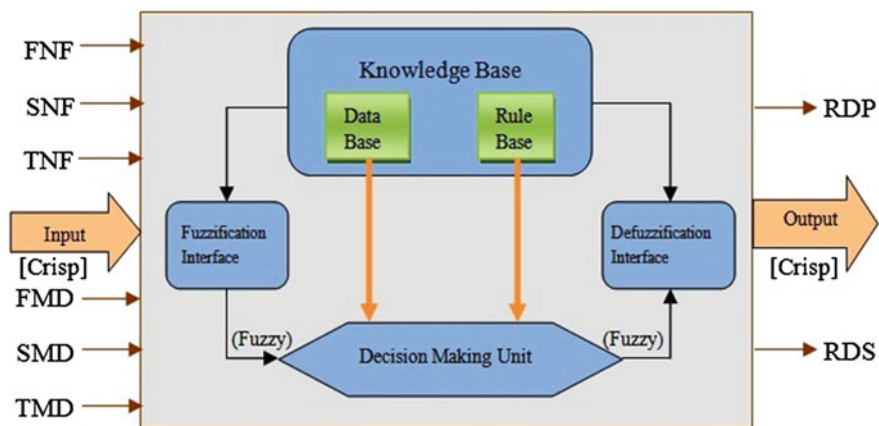


Fig. 3 Fuzzy controller for current analysis

3.2 Fuzzy Model Analysis

The pictorial view of the trapezoidal membership fuzzy models is shown in Fig. 4. Nine membership functions have been used for each input parameters to the fuzzy model. In designing the output membership functions for the output parameters such as relative damage position (RDP) and relative damage severity (RDS), twelve membership functions are considered. The fuzzy linguistic terms have been described in Table 1.

Based on the above fuzzy subsets, the fuzzy control rules are defined in a general form as follows:

If (FNF is FNF_i and SNF is SNF_j and TNF is TNF_k and FMD is FMD_l and SMD is SMD_m and TMD is TMD_n) then RDP is RDP_{ijklmn} and RDS is RDS_{ijklmn}

Where i = 1 to 9, j = 1 to 9, k = 1 to 9, l = 1 to 9, m = 1 to 9, n = 1 to 9

As “FNF”, “SNF”, “TNF”, “FMD”, “SMD”, “TMD” have ten membership functions each. From Eq. (4) , two set of rules can be written as,

If (FNF is FNF_i and SNF is SNF_j and TNF is TNF_k and FMD is FMD_l and SMD is SMD_m and TMD is TMD_n) then RDS is RDS_{ijklmn}

If (FNF is FNF_i and SNF is SNF_j and TNF is TNF_k and FMD is FMD_l and SMD is SMD_m and TMD is TMD_n) then RDP is RDP_{ijklmn}

According to the usual fuzzy logic control method [16, 17], a factor W_{ijklmn} is defined for the rules as follows:

$$W_{ijklmn} = \mu_{fnf_i}(freq_i) \wedge \mu_{snf_j}(freq_j) \wedge \mu_{tnf_k}(freq_k) \wedge \mu_{fmd_l}(moddif_l) \wedge \mu_{smd_m}(moddif_m) \wedge \mu_{tmd_n}(moddif_n)$$

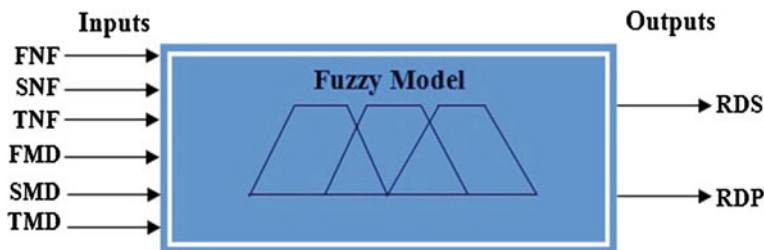


Fig. 4 Trapezoidal fuzzy model

Table 1 Description of fuzzy linguistic terms

Membership Functions Name	Linguistic Terms	Definition of the Linguistic terms
L1F1,L1F2,L1F3	FNF _{1 n 3}	Low ranges of relative natural frequency for first mode of vibration
M1F1,M1F2,M1F3	FNF _{4 n 6}	Medium ranges of relative natural frequency for first mode of vibration
H1F1,H1F2,H1F3	FNF _{7 n 9}	Higher ranges of relative natural frequency for first mode of vibration
L2F1,L2F2,L2F3	SNF _{1 n 3}	Low ranges of relative natural frequency for second mode of vibration
M2F1,M2F2,M2F3	SNF _{4 n 6}	Medium ranges of relative natural frequency for second mode of vibration
H2F1,H2F2,H2F3	SNF _{7 n 9}	Higher ranges of relative natural frequencies for second mode of vibration
L3F1,L3F2,L3F3	TNF _{1 n 3}	Low ranges of relative natural frequencies for third mode of vibration
M3F1,M3F2,M3F3	TNF _{4 n 6}	Medium ranges of relative natural frequencies for third mode of vibration
H3F1,H3F2,H3F3	TNF _{7 n 9}	Higher ranges of relative natural frequencies for third mode of vibration
S1M1,S1M2,S1M3	FMD _{1 n 3}	Small ranges of first relative mode shape difference
M1M1,M1M2,M1M3	FMD _{4 n 6}	medium ranges of first relative mode shape difference
H1M1,H1M2,H1M3	FMD _{7 n 10}	Higher ranges of first relative mode shape difference
S2M1,S2M2,S2M3	SMD _{1 n 3}	Small ranges of second relative mode shape difference
M2M1,M2M2,M2M3	SMD _{4 n 6}	medium ranges of second relative mode shape difference
H2M1,H2M2,H2M3	SMD _{7 n 10}	Higher ranges of second relative mode shape difference
S3M1,S3M2,S3M3	TMD _{1 n 3}	Small ranges of third relative mode shape difference
M3M1,M3M2,M3M3	TMD _{4 n 6}	medium ranges of third relative mode shape difference
H3M1,H3M2,H3M3	TMD _{7 n 10}	Higher ranges of third relative mode shape difference
SP1,SP2,SP3,SP4	RDP _{1 n 4}	Small ranges of relative damage position
MP1,MP2,MP3,MP4	RDP _{5 n 8}	Medium ranges of relative damage position
HP1,HP2,HP3,HP4	RDP _{9 n 12}	Higher ranges of relative damage position
LS1,LS2,LS3,LS4	RDS _{1 n 4}	Lower ranges of relative damage severity
MS1,MS2,MS3,MS4	RDS _{5 n 8}	Medium ranges of relative damage severity
US1,US2,US3,US4	RDS _{9 n 12}	Upper ranges of relative damage severity

Where $freq_i$, $freq_j$ and $freq_k$ are the first, second and third relative natural frequencies of the cantilever beam with damage respectively; $moddif_i$, $moddif_m$ and $moddif_n$ are the average first, second and third relative mode shape differences of the cantilever beam with damage respectively. By applying the composition rule of inference [16, 17], the membership values of the relative damage position and relative damage severity, $(position)_{RDP}$ and $(severity)_{RDS}$ can be computed as;

Table 2 Examples of twenty fuzzy rules to be implemented in fuzzy model

Sl. No.	Examples of some rules used in the fuzzy model
1	If FNF is H1F1, SNF is M2F2, TNF is M3F1, FMD is H1M2, SMD is H2M4, TMD is H3M3, then RDS is LS4 and RDP is SP3.
2	If FNF is L1F4, SNF is L2F4, TNF is L3F4, FMD is H1M1, SMD is H2M1, TMD is H3M2, then RDS is LS2 and RDP is SP4.
3	If FNF is L1F3, SNF is L2F4, TNF is L3F4, FMD is M1M2, SMD is H2M2, TMD is H3M3, then RDS is LS3 and RDP is SP2.
4	If FNF is H1F2, SNF is H2F1, TNF is H3F1, FMD is H1M3, SMD is H2M4, TMD is H3M4, then RDS is MS2 and RDP is SP3.
5	If FNF is M1F1, SNF is L2F2, TNF is L3F3, FMD is H1M1, SMD is H2M1, TMD is H3M2, then RDS is MS1 and RDP is SP2.
6	If FNF is L1F1, SNF is L2F2, TNF is L3F3, FMD is H1M3, SMD is M2M1, TMD is H3M4, then RDS is MS2 and RDP is MP1.
7	If FNF is L1F4, SNF is L2F4, TNF is L3F4, FMD is M1M2, SMD is H2M1, TMD is H3M1, then RDS is MS1 and RDP is SP1.
8	If FNF is H1F1, SNF is M2F2, TNF is M3F1, FMD is H1M2, SMD is H2M2, TMD is H3M2, then RDS is MS2 and RDP is SP2.
9	If FNF is L1F1, SNF is L2F4, TNF is L3F4, FMD is M1M1, SMD is M2M1, TMD is H3M2, then RDS is LS1 and RDP is MP2.
10	If FNF is M1F1, SNF is L2F2, TNF is L3F1, FMD is M1M2, SMD is M2M2, TMD is H3M1, then RDS is LS1 and RDP is SP2.
11	If FNF is M1F1, SNF is M2F1, TNF is M3F1, FMD is H1M3, SMD is H2M3, TMD is H3M4, then RDS is MS1 and RDP is SP4.
12	If FNF is M1F1, SNF is L2F1, TNF is L3F1, FMD is H1M3, SMD is H2M2, TMD is H3M3, then RDS is LS2 and RDP is MP1.
13	If FNF is M1F2, SNF is M2F1, TNF is M3F1, FMD is M1M1, SMD is H2M1, TMD is H3M2, then RDS is MS2 and RDP is MP2.
14	If FNF is H1F2, SNF is H2F1, TNF is H3F1, FMD is H1M4, SMD is H2M1, TMD is H3M1, then RDS is MS1 and RDP is SP4.
15	If FNF is M1F1, SNF is L2F1, TNF is L3F2, FMD is S1M1, SMD is S2M2, TMD is H3M1, then RDS is LS2 and RDP is MP1.
16	If FNF is L1F4, SNF is L2F4, TNF is L3F4, FMD is H1M2, SMD is S2M1, TMD is H3M2, then RDS is LS1 and RDP is MP3.
17	If FNF is M1F1, SNF is L2F3, TNF is L3F1, FMD is S1M2, SMD is M2M1, TMD is S3M1, then RDS is LS2 and RDP is MP3.
18	If FNF is L1F1, SNF is L2F1, TNF is L3F1, FMD is H1M2, SMD is H2M2, TMD is H3M2, then RDS is LS3 and RDP is MP2.
19	If FNF is H1F2, SNF is H2F1, TNF is H3F1, FMD is S1M2, SMD is H2M3, TMD is H3M1, then RDS is LS4 and RDP is MP1.
20	If FNF is L1F3, SNF is L2F4, TNF is L3F4, FMD is S1M3, SMD is S2M2, TMD is S3M3, then RDS is LS3 and RDP is SP3.

$$\mu_{RDP_{ijklmn}}(\text{position}) = W_{ijklmn} \wedge \mu_{RDP_{ijklmn}}(\text{position})$$

$$\mu_{RDS_{ijklmn}}(\text{severity}) = W_{ijklmn} \wedge \mu_{RDS_{ijklmn}}(\text{severity})$$

The overall conclusion by combining the outputs of all the fuzzy rules can be written as follows:

$$\mu_{RDP}(\text{position}) = \mu_{RDP_{111111}}(\text{position}) \vee \dots \vee \mu_{RDP_{ijklmn}}(\text{position}) \vee \dots \vee \mu_{RDP_{1010101010}}(\text{position})$$

$$\mu_{RDS}(\text{severity}) = \mu_{RDS_{111111}}(\text{severity}) \vee \dots \vee \mu_{RDS_{ijklmn}}(\text{severity}) \vee \dots \vee \mu_{RDS_{1010101010}}(\text{severity})$$

The crisp values of relative damage position and relative damage severity are evaluated using the Centre of gravity method as:

$$\text{Relative damage position} = RDP = \frac{\int (\text{position}) \cdot \mu_{RDP}(\text{position}) \cdot d(\text{position})}{\int \mu_{RDP}(\text{position}) \cdot d(\text{position})}$$

$$\text{Relative damage severity} = RDS = \frac{\int (\text{severity}) \cdot \mu_{RDS}(\text{severity}) \cdot d(\text{severity})}{\int \mu_{RDS}(\text{severity}) \cdot d(\text{severity})}$$

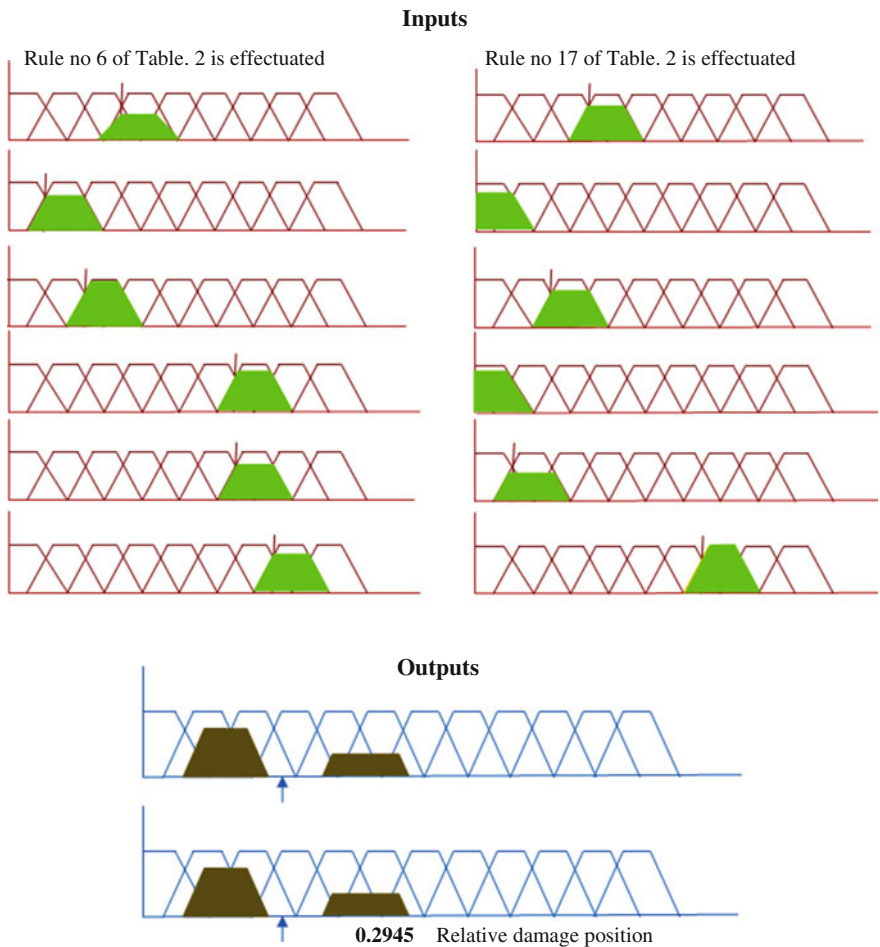


Fig. 5 Resultant values of relative damage severity and relative damage position from trapezoidal fuzzy model when Rules 6 and 17 of Table 2 are effectuated

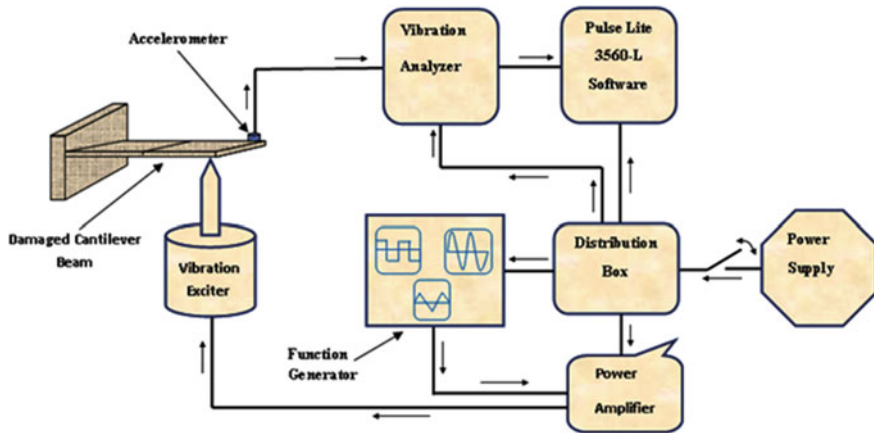


Fig. 6 Schematic diagram of experimental set up with cantilever beam

4 Experimental Validation

Experiments have been performed using the developed experimental set up (Fig. 6) for measuring the vibration responses (natural frequencies and amplitude of vibration) of the cantilever beams composite with dimension $1000 \text{ mm} \times 50 \text{ mm} \times 8 \text{ mm}$. During the experiment, the damaged and undamaged beams have been subjected to vibration at their 1st, 2nd and 3rd mode of vibration by using an exciter and a function generator. The vibrations characteristics of the beams correspond to 1st, 2nd and 3rd mode of vibration have been recorded by placing the accelerometer along the length of the beams. The signals from the accelerometer which contains the vibration parameters such as natural frequencies and mode shapes are analyzed and shown on the vibration indicator.

5 Results and Discussion

The results obtained from the fuzzy based model and experimental analyses have been presented in Table 3. The first three columns of Table 3 represent the first three relative natural frequencies and the next three columns represent the first three mode shape differences of the composite cantilever beam. Figure 5 depicts the relative damage severity and relative damage position of the beam member using the fuzzy based model with the trapezoidal membership function. The results obtained from the fuzzy based model are found to be in very good agreement with the experimental results for damage detection. The percentages of error for relative damage severity and relative damage position are found to be 2.85 and 3.1 % respectively.

Table 3 Comparison of modal parameters and damage characteristics of composite cantilever beam obtained from Fuzzy logic (Trapezoidal) based model and experimental analysis

FNF	SNF	TXF	FMD	SXD	TXD	Fuzzy trapezoidal		Experimental	
						RDS	RDP	RDS	RDP
0.9940	0.9999	0.9918	0.0043	0.0091	0.0066	0.3731	0.481	0.374	0.501
0.9872	0.9998	0.9828	0.0080	0.0123	0.0237	0.4982	0.490	0.500	0.501
0.9755	0.9997	0.9676	0.0119	0.0087	0.0411	0.6232	0.490	0.624	0.503
0.9999	0.9944	0.9937	0.1237	0.0265	0.0761	0.3733	0.273	0.376	0.255
0.9998	0.9883	0.9870	0.3741	0.0465	0.0380	0.5028	0.243	0.501	0.254
0.9995	0.9768	0.9751	0.3699	0.0531	0.0534	0.6221	0.261	0.624	0.253

6 Conclusions

The fuzzy modeling implemented in the current section has been analyzed to get the following conclusions. The presence of damage in composite structural member has remarkable impact on the modal parameters of the dynamic structure. The first three relative natural frequencies and first three relative mode shape differences are engaged as inputs to the fuzzy model and relative damage positions and relative damage severity are the output parameters. The reliability of the proposed model has been established by comparing the results from the fuzzy models (trapezoidal) with that of the experimental analysis. The results are found to be well in agreement. Hence, the proposed trapezoidal fuzzy model can be effectively used as damage identification tools in vibrating composite structures.

References

1. Chandrashekar, M., Ganguli, R.: Uncertainty handling in structural damage detection using fuzzy logic and probabilistic simulation. *Mech. Syst. Signal Process.* **23**, 384–404 (2009)
2. Chandrashekar, M., Ganguli, R.: Damage assessment of structures with uncertainty by using mode-shape curvatures and fuzzy logic. *J. Sound Vib.* **326**, 939–957 (2009)
3. Silva, S.D., Junior, M.D., Junior, V.L., Brennan, M.J.: Structural damage detection by fuzzy clustering. *Mech. Syst. Signal Process.* **22**, 1636–1649 (2008)
4. Beena, P., Ganguli, R.: Structural damage detection using fuzzy cognitive maps and Hebbian learning. *Appl. Soft Comput.* **11**, 1014–1020 (2011)
5. Radzienski, M., Krawczuk, M., Palacz, M.: Improvement of damage detection methods based on experimental modal parameters. *Mech. Syst. Signal Process.* **25**, 2169–2190 (2011)
6. Yan, Y.J., Cheng, L., Wu, Z.Y., Yam, L.H.: Development in vibration-based structural damage detection technique. *Mech. Syst. Signal Process.* **21**, 2198–2211 (2007)
7. Reda Taha, M.M., Lucero, J.: Damage identification for structural health monitoring using fuzzy pattern recognition. *Eng. Struct.* **27**, 1774–1783 (2005)
8. Ko, J.M., Ni, Y.Q.: Technology developments in structural health monitoring of large-scale bridges. *Eng. Struct.* **27**, 1715–1725 (2005)
9. Erdogan, Y.S., Bakir, P.G.: Inverse propagation of uncertainties in finite element model updating through use of fuzzy arithmetic. *Eng. Appl. Artif. Intell.* **26**, 357–367 (2013)

10. Rodriguez, P.V.J., Arkkio, A.: Detection of stator winding fault in induction motor using fuzzy logic. *Appl. Soft Comput.* **8**, 1112–1120 (2008)
11. Kemru, M.: Assessing the visual quality of sanitary ware by fuzzy logic. *Appl Soft Comput.* **13**, 3646–3656 (2013)
12. Asnaashari, E., Sinha, J.K.: Crack detection in structures using deviation from normal distribution of measured vibration responses. *J. Sound Vib.* **333**, 4139–4151 (2014)
13. Hasanzadeh, R.P.R., Sadeghi, S.H.H., Ravan, M., Moghaddamjoo, A.R., Moini, R.: A fuzzy alignment approach to sizing surface cracks by the AC field measurement technique. *NDT & E Int.* **44**, 75–83 (2011)
14. Reza, H.P.R., Rezaie, A.H., Sadeghi, S.H.H., Moradi, M.H., Ahmadi, M.: A density-based fuzzy clustering technique for non-destructive detection of defects in materials. *NDT & E Int.* **40**, 337–346 (2007)
15. Saravanan, N., Cholairajan, S., Ramachandran, K.I.: Vibration-based fault diagnosis of spur bevel gear box using fuzzy technique. *Expert Syst. Appl.* **36**, 3119–3135 (2009)
16. Dash, A.K., Parhi, D.R.K.: Development of an inverse methodology for crack diagnosis using AI technique. *Int. J. Comput. Mater. Sci. Surf. Eng.* **4**, 143–167 (2011)
17. Parhi, D.R.: Navigation of mobile robots using a fuzzy logic controller. *J. Intell. Robot. Syst. Theory Appl.* **42**, 253–273 (2005)