"VIBRATION ANALYSIS OF A BEAM USING NEURAL NETWORK TECHNIQUE"

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BACHELOR OF TECHNOLOGY

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MECHANICAL ENGINEERING

By

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CERTIFICATE

This is to certify that the project entitled," **VIBRATION ANALYSIS OF A BEAM USING NEURAL NETWORK"** submitted by **'Mr. Parthasarathi Behera'** in partial fulfillments for the award of Bachelor of Technology Degree in Mechanical Engineering at National Institute of Technology, Rourkela(Deemed University) is an authentic work carried out by him under my supervision and guidance.

To the best of my knowledge, the matter embodied in the report has not been submitted to any other University/Institute for the award of any Degree or diploma.

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(PARTHASARATHI BEHERA)

ABSTRACT

Using changes in global dynamic characteristics for detection of cracks has been a hot research topic now a days and is a source of attraction for civil, aerospace, and mechanical engineering communities in recent years. Crack in vibrating components causes a change in physical properties of a structure which in turn affects dynamic response characteristics. Therefore we have to study the dynamic response characteristics in order to avoid any catastrophic failures and to follow structural integrity and performance for which the parameters considered are crack depth and its location.

In the present study, vibration analysis is carried out on a cantilever beam with two open transverse cracks, to study the response characteristics. Its natural frequency and mode shapes are determined by applying suitable boundary conditions. The results obtained numerically are compared with the results obtained from the simulation. The simulations have done with the help of ALGOR software.

Then by using Feed-forward, back propagation neural network the relationship between the location and the depth of the crack as input and the structural eigenfrequencies as output are studied.

At the end by performing both the simulation and computational analysis it is proved that the presence of cracks affects the natural frequency and the mode shapes of the structure. The results indicate that the current approach can identify both the location and the extent of damages in the beam.

CHAPTER 1

INTRODUCTION

1. INTRODUCTION

Damage detection and location, and condition assessment of structures have always been important subjects. Damage in a structure generally causes a local increase in flexibility, which depends on the extent of the damage. This reduces the natural frequencies of vibration and affects the natural mode shapes -effects which have been used, with somewhat mixed success, to evaluate the deterioration [1].

Cracks present a serious threat to the performance of structures since most of the structural failures are due to material fatigue. For this reason, methods allowing early detection and localization of cracks have been the subject of intensive investigation the last two decades. As a result, a variety of analytical, numerical and experimental investigations now exist. A review of the state of the art of vibration based methods for testing cracked structures has been published by Dimarogonas (1996).

The most important aspects of structural health monitoring is that the technique provides information on the life expectancy of structures, simultaneously detects and locates structural damage. This needs idea of the model of structures in great detail, which is always not possible. In addition to it, dynamic systems usually posses non-linear characteristics, which causes practical difficulties on the model-based damage detection techniques.

In the present survey a number of papers published so far have been surveyed, reviewed and analyzed. Most of researchers studied the effect of single crack on the dynamics of structures. However in actual practice structural members are highly susceptible to transverse cross-sectional cracks due to fatigue. Therefore attempt has been made to monitor the dynamic behavior of basic structures with crack systematically. Here vibration analysis on a cantilever beam with and without crack is carried out. First the results are obtained analytically and then they are compared with simulation results. In first phase two transverse surface cracks are considered in developing the analytical expressions in dynamic characteristics of structures. These cracks introduce new boundary conditions for the structures at the location of the cracks. These boundary conditions are derived from strain energy equation using castiligiano's theorem. Presence of crack also causes reduction of stiffness of the structures which has been derived from stiffness matrix. The detailed analyses of crack modeling and stiffness matrices are presented in subsequent sections. Euler-Bernoulli beam theory is used for dynamic characteristics of beams with transverse cracks. Modified boundary conditions due to presence of crack have been used to find out the theoretical expressions for natural frequencies and mode shape for the beams.

Artificial Neural Networks (ANN) has emerged as a promising tool for monitoring and classification of fault in machine and equipment. This technique is well prepared for solving inverse variational problems in the context of monitoring and fault detection because of their pattern recognition and interpolation capabilities (Lopes, Jr. et al., 1997). ANN also successfully approach and classify the problems associated with non-linearities, provided they are well represented by input patterns, and also can avoid the complexity introduced by conventional computational methods. Furthermore, the learning capabilities of neural networks are well suited to process a large number of distributed sensors, which is ideal for smart structures.

In this study a feed-forward back-propagation neural network is used to learn the input (the location and depth of a crack)-output (the structural eigen frequencies) relation of the structural system. A neural network for the cracked structure is trained to approximate the response of the structure by the data set prepared for various crack sizes and locations.

CHAPTER 2

LITERATURE REVIEW

2. LITERATURE REVIEW

Local flexibility are induced due to the presence of cracks in the structure which affects the dynamic behavior of the whole structure to a considerable degree. It causes reduction in natural frequencies and changes in mode shapes of vibrations. Any analysis of these changes makes it possible to identify cracks.

The effect of cracks upon the dynamic behaviour of cracked beams has been studied by many authors. Dimarogonas [11, Chondros [2] and Chondros and Dimarogonas [3,4] modeled the crack as a local flexibility computed with fracture mechanics methods and measured experimentally, and they developed a spectral method to identify cracks in various structures relating the crack depth to the change in natural frequencies of the first three harmonics of the structure for known crack position.

Cawley and Adams [5] have developed a technique based on experiment to estimate the location and depth of the crack from changes in the natural frequencies. Anifantis et al. [6] developed the spectral method for identification of earthquake-induced defects in reinforced concrete frames by analyzing the changes in the vibration frequency spectrum. They also showed that any localized damage, such as a crack, would affect each vibration mode differently, for different structures, depending on the particular location, orientation and magnitude of the crack.

Kirshmer [7], Thomson [8] and Petroski [9, lo] explained the effects of cracks on structural response through simple reduced section models of cracked beams using energy methods, and elaborated the effect of the size and location of the crack to the natural frequency and vibration mode of the damaged beam.

Inagaki ef al. [11], in the case of transverse vibrations of cracked rotors, estimated the crack size and position by natural vibration analysis and by static deflection analysis. Grabowski [12] came to the conclusion that there is a strong dependence of vibrational behavior of cracked rotors on the crack position and magnitude using modal analysis. Mayes and Davies [13] proposed a method for the prediction of the magnitude of a rotating cracked and rotor crack location, from analytically obtained mode shapes and frequency measurements.

Christides and Barr [141 assumed an exponential stress distribution in the vicinity of the crack and applied a variational principle to study the dynamic behavior of the system. If the stress distribution be known, it would have made this method very rational. The exponential approximation is valid only for notches and the exponent is estimated experimentally. In fact, it was pointed out by Warburton [151that, for example, for torsional vibration of rods, the local flexibility approach could be used for the estimation of the Christides and Barr exponent. Yuen [16] presented a systematic study of the relationship between size and damage location and the changes in the eigenvectors and eigenvalues of a cantilever beam.

Stubbs and Kim,1996[17] proposed that to detect damage using modal based methods, the vibration response of a structure before and after damage occurs is usually desired although a baseline is not always required. If damage location is known in advance, such as at critical bolt joints, an electro-mechanical impedance method advanced by Rogers et al. (e.g. Liang, Sun and Rogers, 1996; Rogers and Giurgiatiu , 1997) has been shown to be very effective.

Wu, Ghaboussi and Garrett(1992)[18] adopted an NN model to portray the structural behavior before and after damage in terms of the frequency response function , and then used this trained model to detect location and extent of damages by feeding in measured dynamic response.

Masri , Ghassiakos and Caughey (1996)[19] used a multilayer perceptron NN model to monitor the change in the dynamic characteristics of a structure - unknown system. Zhao , Ivan and DeWolf (1998)[19] used a counter-propagation NN model to identify the damages in beams and frames.

Klenke and Paez (1994)[20] used two probabilistic techniques , one of which involved a probabilistic neural network model ,to detect the damages in the aerospace housing components.

The application of neural networks in the area of damage detection has also been studied by numerous researchers (Elkordy, ChangandLee, 1993; Leathand Zimmerman ,1993; Kirkegaard and Rytter,1994;Manning, 1994;Stephens and VanLuchene,1994; Chaudhry and Ganino, 1994; Pandey and Barai,1995). Comprehensive reviews on the damage detection using NN models have been documented by Bishop (1994) and Doebling et al. (1996).

Adams et al.[21] used the decrease in natural frequencies and increase in damping to detect cracks in fiber-reinforced plastics. Loland et al. [22] and Vandiver [23] used the same principle to detect damage in offshore structures. From relative changes in the natural frequencies of different modes, Loland et al. could predict the location of the damage. They demonstrated the use of their technique on some platforms in the North Sea. The essence of the methods developed by the other researchers is similar, but different methods of data analysis were used.

Dharmaraju et al.[24] considered Euler-Bernoulli beam element in the finite element analysis. In this the transverse surface crack is considered to remain open. A local compliance matrix of four degrees of freedom is considered for the modeling of a crack. This compliance matrix contains diagonal and off-diagonal terms. A harmonic force of given amplitude and frequency is used to excite dynamically the beam. The present identification algorithms have been illustrated through numerical examples.

Patil and Maiti [25,26] used a method for prediction of location and size of multiple cracks based on measurement of natural frequencies which has been verified experimentally for slender cantilever beams with two and three normal edge cracks. In this the crack is represented by a rotational spring and the analysis is based on energy method. In this the beam is divided into a number of segments and each segment is considered to be associated with a damage index. The damage index indicates the extent of strain energy stored in the rotational spring. The crack size is computed by the help of a standard relation between stiffness and crack size. Number of measured frequencies is equal to twice the number of cracks is used for the prediction of size and location of all the cracks.

Loutridis et al. [27] present a new method which is based on empirical mode decomposition and instantaneous frequency. A cantilever beam with a breathing crack is observed under harmonic excitation by both theoretically and experimentally to observe its dynamic behavior.

Suh et al. [28] has proved that a crack has a significant effect on the dynamic behavior of a structure. The location and depth of the crack plays an important role. To find out the location and depth of a crack on a structure, a method is cited in this paper which uses hybrid neuro-genetic technique. Feed-forward back propagation neural networks are used to learn the input and output relation of the structural system. With this trained neural network, genetic algorithm is used to find out the crack location and depth thus minimizing the difference from the measured frequencies.

Yoona Han-Ik et al.[29] examined the effect of two open cracks on the dynamic behavior of a double cracked simply supported beam both experimentally and analytically.By using Hamilton's principle the equation of motion is derived and then it is analyzed by numerical method.

Behera [30] in his research work has developed the theoretical expressions to find out the natural frequencies and mode shapes for the cantilever beam with two transverse cracks. Experiments have been conducted to prove the authenticity of the theory developed

CHAPTER 3

CRACK THEORY

3 .CRACK THEORY

3.1 Physical parameters affecting Dynamic characteristics of cracked structures:

The dynamic response of a structure is normally determined by the physical properties, boundary conditions and the material properties. The changes in dynamic characteristics of structures are caused by their variations. The presence of a crack in structures also modifies its dynamic behavior. The following properties of the crack influence the dynamic response of the structure.

- The depth of crack
- The location of crack
- The orientation of crack
- The number of cracks

3.2 Classification of cracks

On the basis of geometry, cracks can be broadly classified into:

- **Transverse cracks-** These cracks are perpendicular to the beam axis. Due to transverse cracks the cross-section of the structure got reduced and thus weaken the beam. Due to the reduction in the cross-section it introduces a local flexibility in the stiffness of the beam due to strain energy concentration in the vicinity of the crack tip.
- **Longitudinal cracks-** These cracks are parallel to the beam axis. It is dangerous when tensile load is applied at right angles to the crack direction i.e. perpendicular to beam axis or perpendicular to crack.

- **Slant cracks-** These cracks are at an angle to the beam axis. It influences the torsional behavior of the beam. Their effect on lateral vibrations is less than that of transverse cracks of comparable severity.
- **Breathing cracks-**These are the cracks that open when the affected part of the material is subjected to tensile stresses and close when the stress is reversed. When under tension the stiffness of the component is most influenced. A crack breathes when crack sizes are small, running speeds are low and radial forces are large.
- **Gaping cracks-** These cracks always remain open. They are more accurately known as **notches**.
- **Surface cracks-** These are the cracks that open on the surface. These can be easily detected by dye-penetrations or visual inspection. Surface cracks have a greater effect than subsurface cracks on the vibration behavior of shafts.
- **Subsurface cracks-** These are the cracks that are not on the surface. Special techniques such as ultrasonic, magnetic particle, radiography or shaft voltage drop are needed to detect them.

3.3 Modes of Fracture:-The crack experiences three specific types of loading which are-

- **Mode 1:-**Represents the opening mode. In this opening mode the crack faces separates in a direction perpendicular to the plane of the crack and the respective displacements of crack walls are symmetric with respect to the crack front. Loading is perpendicular to the crack plane, and I has the tendency to open the crack. Generally Mode I is considered the most dangerous loading condition.

- **Mode 2:-** Represents the in-plane shear loading. In this one crack face tends to slide with respect to another (shearing mode). Here the stress is parallel to the crack growth direction.
- **Mode 3:-**Represents the out-of-plane shear loading. Here the crack faces are sheared parallel to the crack front.

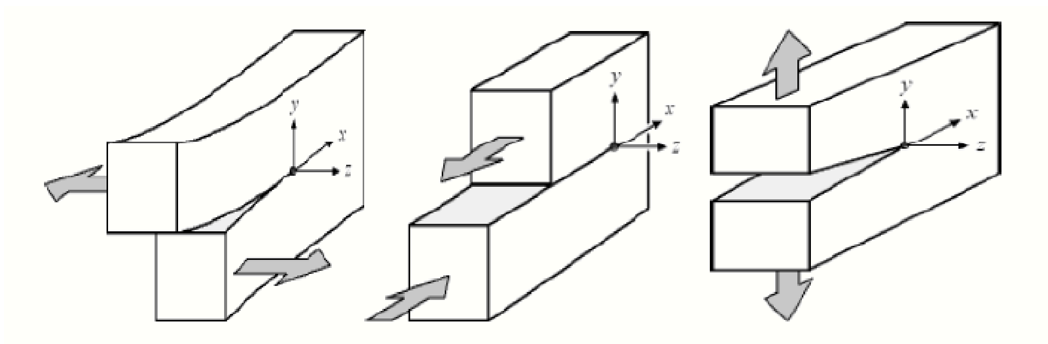


Fig.3.1. Three basic mode of fracture.

CHAPTER 4

FINITE ELEMENT ANALYSIS

4. Finite Element Analysis:

R. Courant[1] in 1943 was the first person who developed finite element analysis. In 1956 M. J. Turner et.al.[2] published a paper on the "stiffness and deflection of complex structures". FEA helps us to obtain new designs to meet the changing conditions inorder to avoid material failure. FEA uses a lot of algorithms for its functioning. 2-D and 3-D model analysis are done by FEA in industry.

4.1 Types of analysis done by FEA:

Structural Analysis:

Both linear and non-linear model comes under it. In case of linear models simple parameters are used and it is assumed that the material cannot plastically deformed. In case of non-linear models the material is stressed beyond its elastic properties for which the stress in the material vary with the amount of deformation.

Vibrational Analysis:

In this the material is tested for shock, impact and continuous and sudden vibrations. These situations affects the natural frequency of the structures and which may cause resonance and subsequent failure.

Fatigue Analysis:

It helps to predict the life cycle of a material by having cyclic loading on the material. It helps to know the areas more prone to propagation of cracks.

Heat Transfer Analysis:

It helps to predict the thermal conductivity or fluid dynamics of the material.

4.2 Role of FEA:

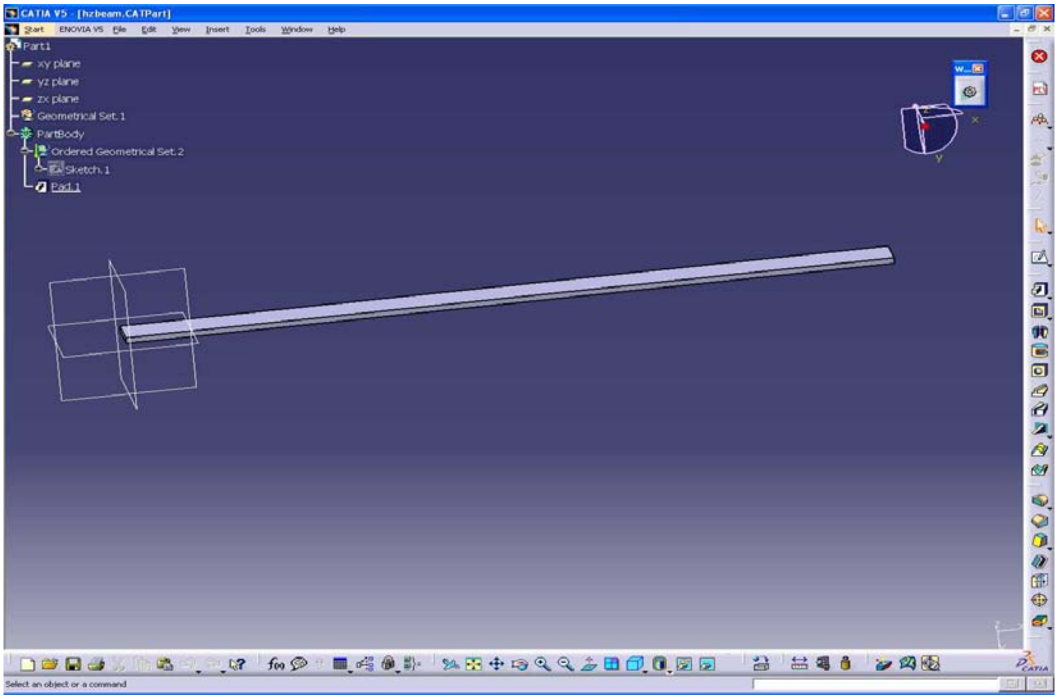
FEA helps the designer know all the theoretical stresses within the structure by showing all the problem areas in detail and thus helping the designer to predict the failure of the structure. It is an economic method of determining the causes of failure and the way the failures can be avoided.

In our study we are analyzing the cracked beam in the FEA method by using a software known as **ALGOR**. It has several application in mechanical event simulation and computational fluid dynamics.Here the model is first designed in **CATIA** and then imported to the ALGOR software where after giving proper boundary conditions gives output in three modes of natural frequencies.

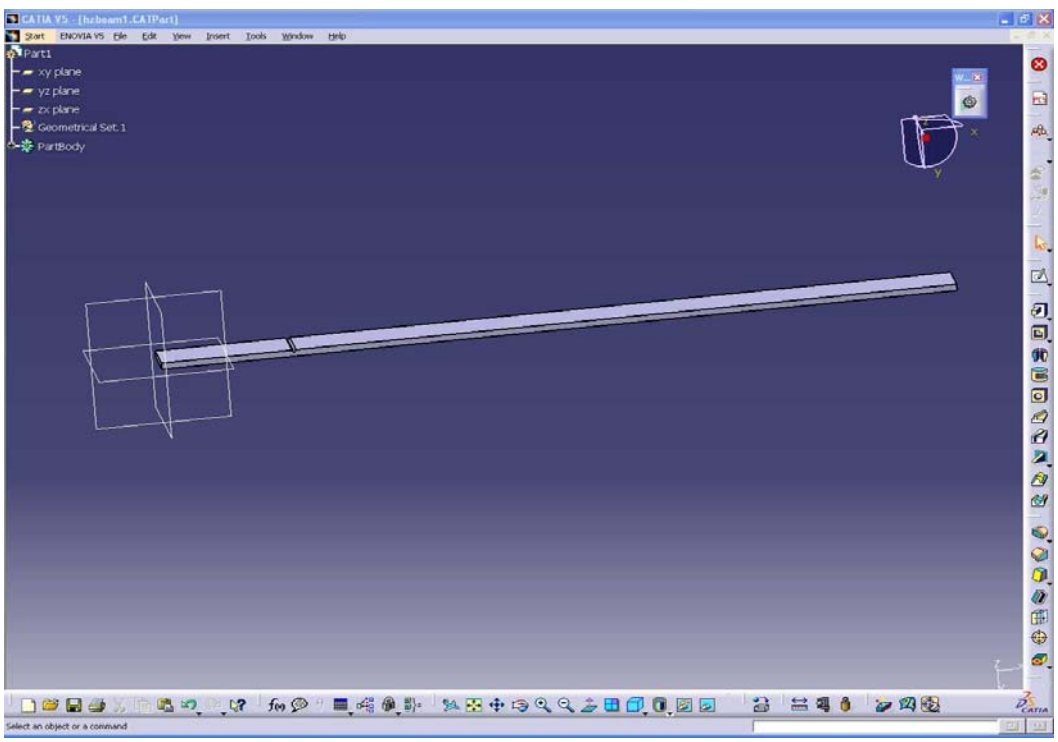
4.3 STEPS for FINITE ELEMENT ANALYSIS of cracked beam model using ALGOR:

1. Generating the model in designing software:

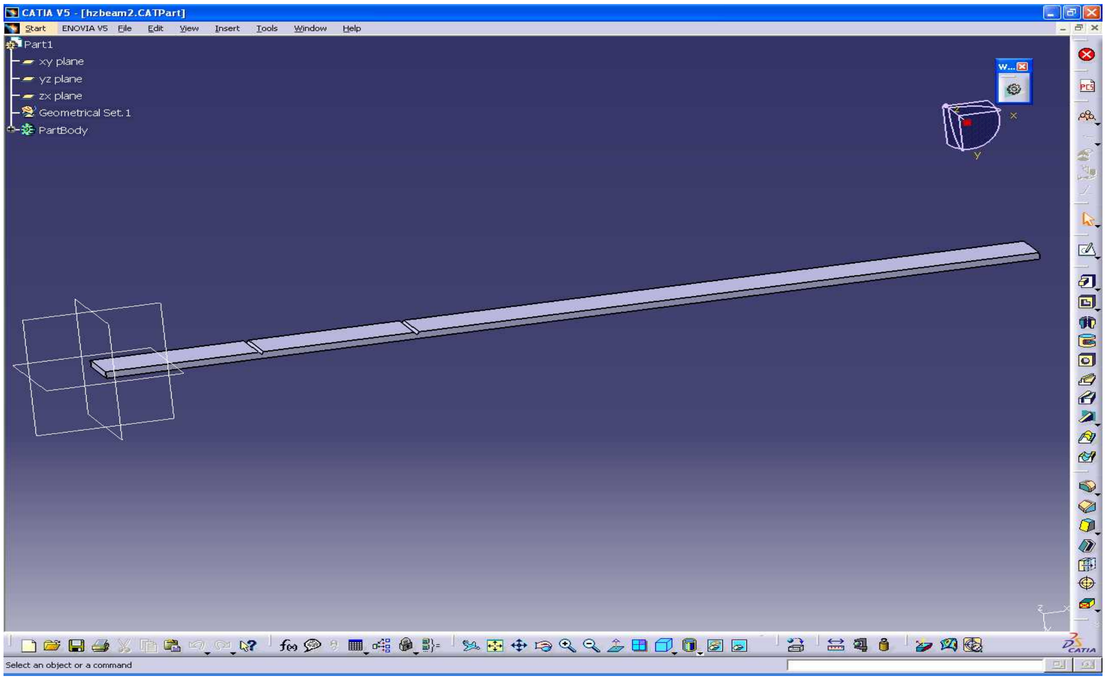
The designing software used here is **CATIA**. The model of the beam having crack is generated in CAD software i.e. CATIA with different crack location and crack depth. The figures given below are the example of how models are generated in CATIA.



4.1 Model having no crack in CATIA



4.2 Model having single crack in CATIA

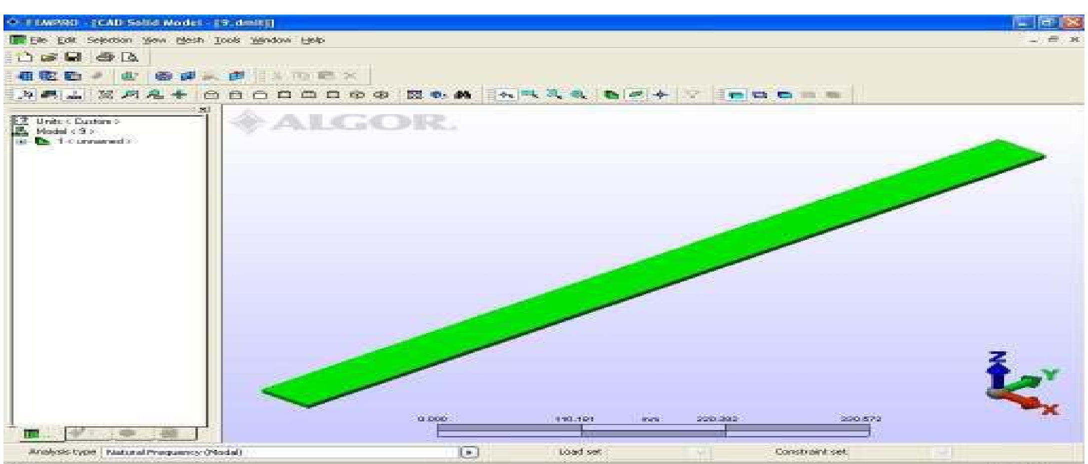


4.3 Model having double crack in CATIA

2: The obtained file is saved in .stp format and is given as input file for ALGOR software.

3: The file is opened in FEMPRO which is part of ALGOR for finite element analysis.

4: For design purpose natural frequency modal is selected and mesh settings are shown in the given figure,



5: Now mesh is obtained .

6: After meshing is over FEA editor is selected.

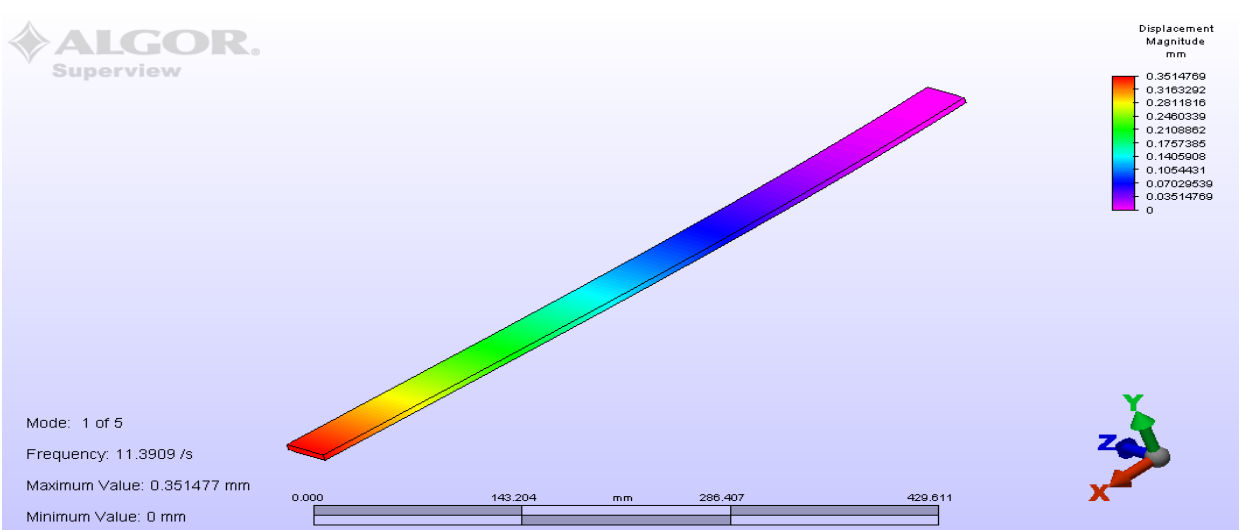
7: Element type is selected as brick type.

8: Material is chosen as per requirement. Here Aluminium 1050-H14 is taken,

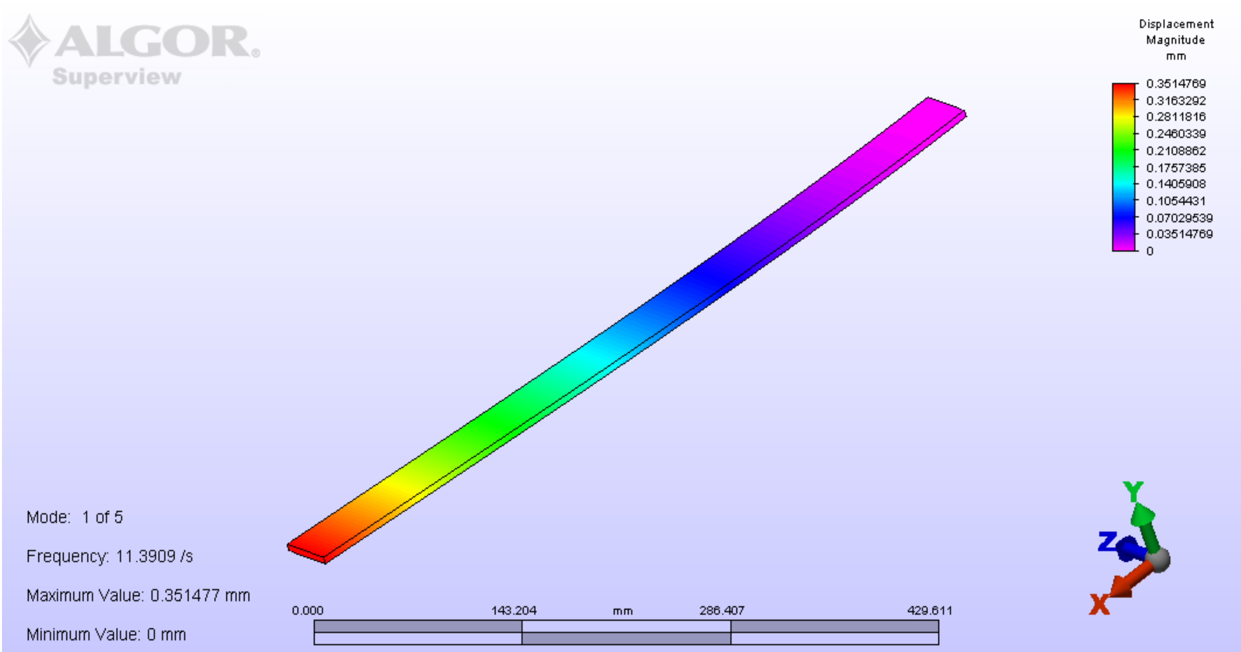
9: Then units are defined in SI.

10: In this required surface of modal is selected and required boundary conditions are given:

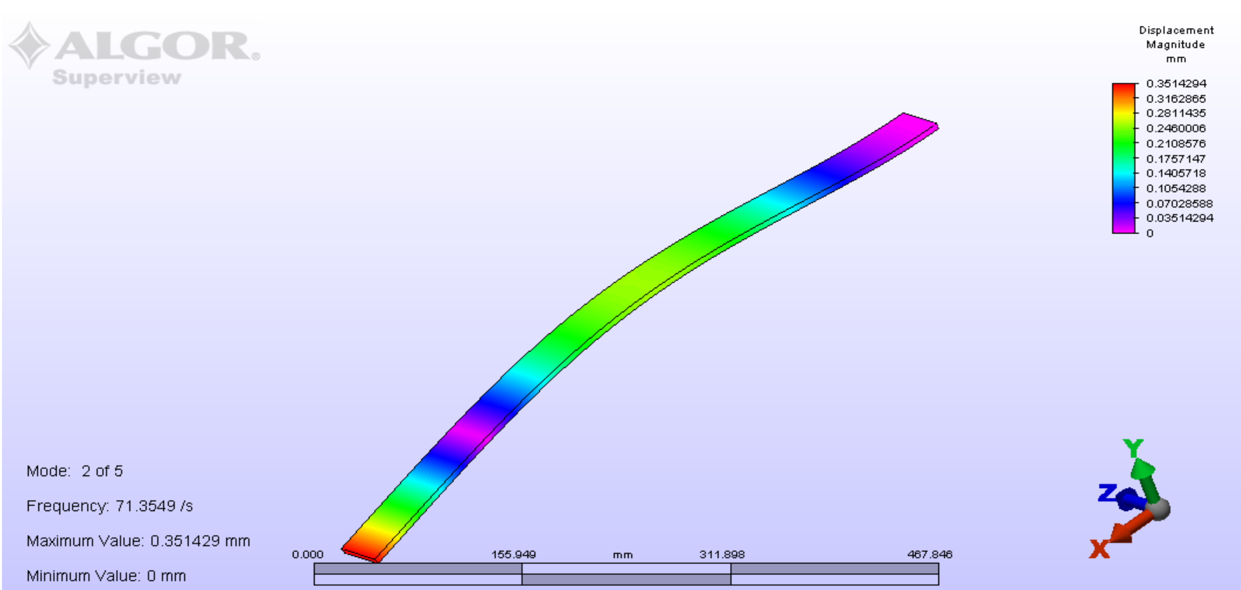
The modal would become like:



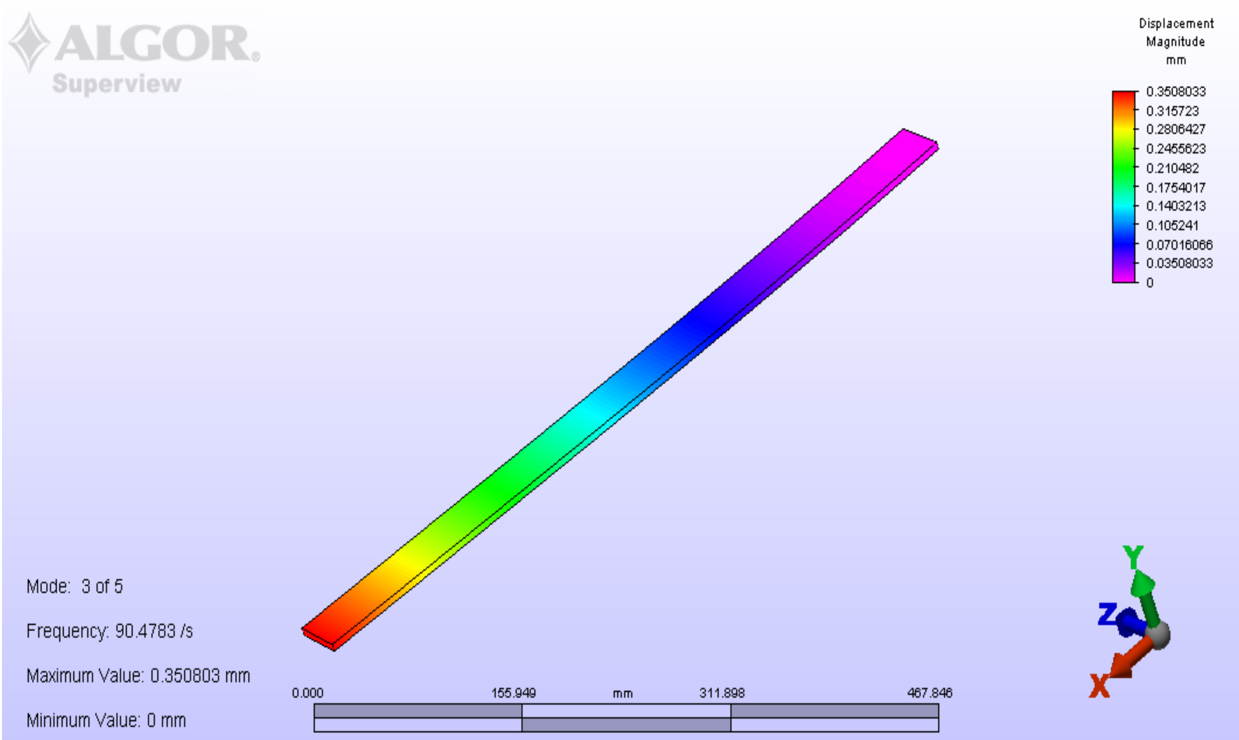
Step 10: Now we'll click perform analysis button in the toolbar and the three modes would be shown as below: First mode of vibration in cantilever beam.



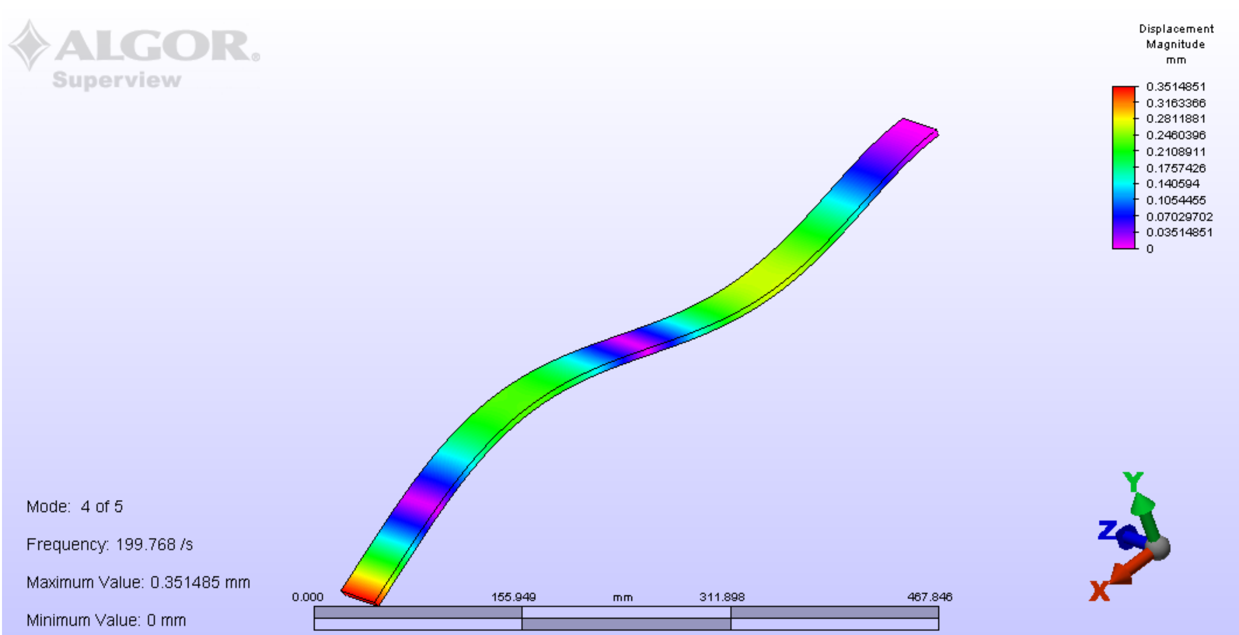
<u>4.4 First mode of vibration in the cantilever beam.</u>



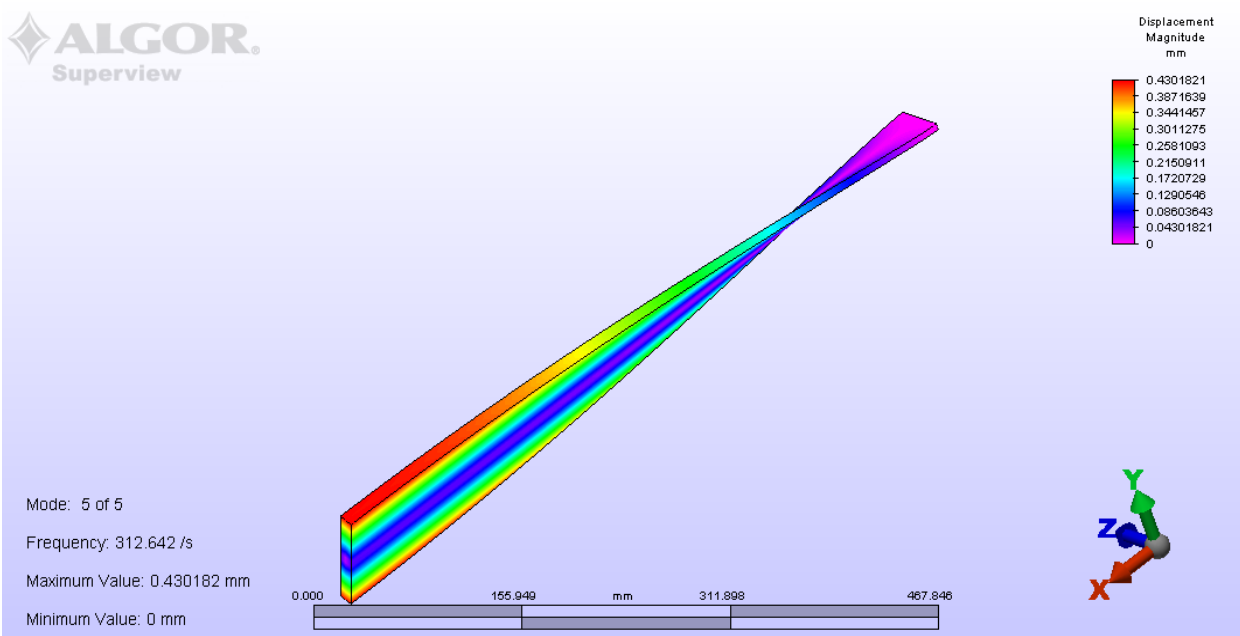
<u>4.5 Second mode of vibration in the cantilever beam.</u>



4.6 Third mode of vibration in the cantilever beam



4.7 Fourth mode of vibration in the cantilever beam



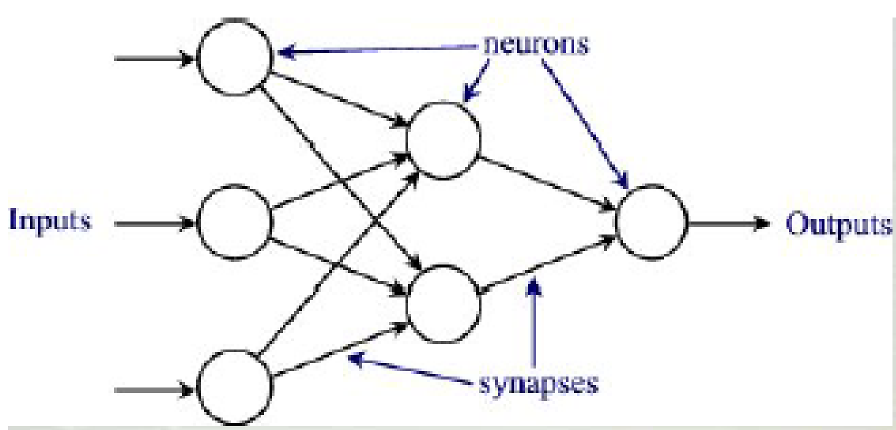
4.8 Fifth mode of vibration in the cantilever beam

CHAPTER 5

NEURAL NETWORK

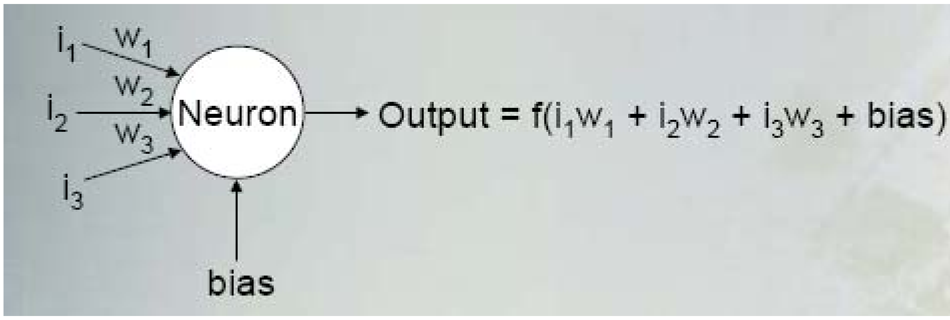
5. NEURAL NETWORK

Artificial Neural Networks (ANN) has emerged as a promising tool for monitoring and classification of fault in machine and equipment. This technique is well prepared for solving inverse variational problems in the context of monitoring and fault detection because of their pattern recognition and interpolation capabilities (Lopes, Jr. et al., 1997). ANN also successfully approach and classify the problems associated with non-linearities, provided they are well represented by input patterns, and also can avoid the complexity introduced by conventional computational methods. It consists of a given set of inputs for which desired outputs are determined by establishing proper and desired relationship between the inputs and there outputs. The mapping between the input and the output is not given but has to be learned and once the mapping is learned or trained the desired outputs can be obtained. It helps to increase the efficiency of design process.



5.1 Figure of a simple neural network

5.1 WORKING OF NEURAL NETWORK:



5.2. Figure showing working of a neural network

Actually the function of the entire neural network is simply the calculation of the outputs of all the neurons considered. The output of a neuron is considered as a function of the weighted sum of the inputs plus a bias. In the given figure only one neuron is considered

The output of a large number of neurons may be represented as,

$$y(n) = f\left[\sum_{j=1}^{N} w_j(n)x_j(n) + b(n)\right] \qquad (6.1)$$

where,

$b(n)$ = threshold to the neuron is called as bias,

$w_j(n)$ = weight associated with the j^{th} input, and

N = no. of inputs to the neuron.

5.2 ACTIVATION FUNCTIONS:

These are applied to the weighted sum of the inputs of a neuron to produce the output. The activation function is given by: $F(x) = 1 / (1 + e^{-k \Sigma (wixi)})$. In this by using a nonlinear function which approximates a linear threshold allows a network to approximate nonlinear functions. An extra variable was given by the bias and the networks having bias are more powerful than those of having no bias. The neuron having no bias always gives a net input of zero to the activation function when the network inputs are taken as zero. This may not be acceptable and can be avoided by the use of a bias.

Different Types Of Activation Functions:

NAME	MATHEMATICAL REPRESENTATION
Linear	$f(x) = kx$
Step	$f(x) = \begin{cases} \alpha, & if\ x \geq k \\ \beta, & if\ x < k \end{cases}$
Sigmoid	$f(x) = \frac{1}{1 + e^{-\alpha x}}, \alpha > 0$
Hyperbolic Tangent	$f(x) = \frac{1 - e^{-\gamma x}}{1 + e^{-\gamma x}}, \gamma > 0$
Gaussian	$f(x) = \frac{1}{\sqrt{2\pi\sigma^2}} e^{\left[-\frac{(x-\mu)^2}{2\sigma^2}\right]}$

5.3 Learning Method:

- Unsupervised
- Reinforcement learning
- Back propagation

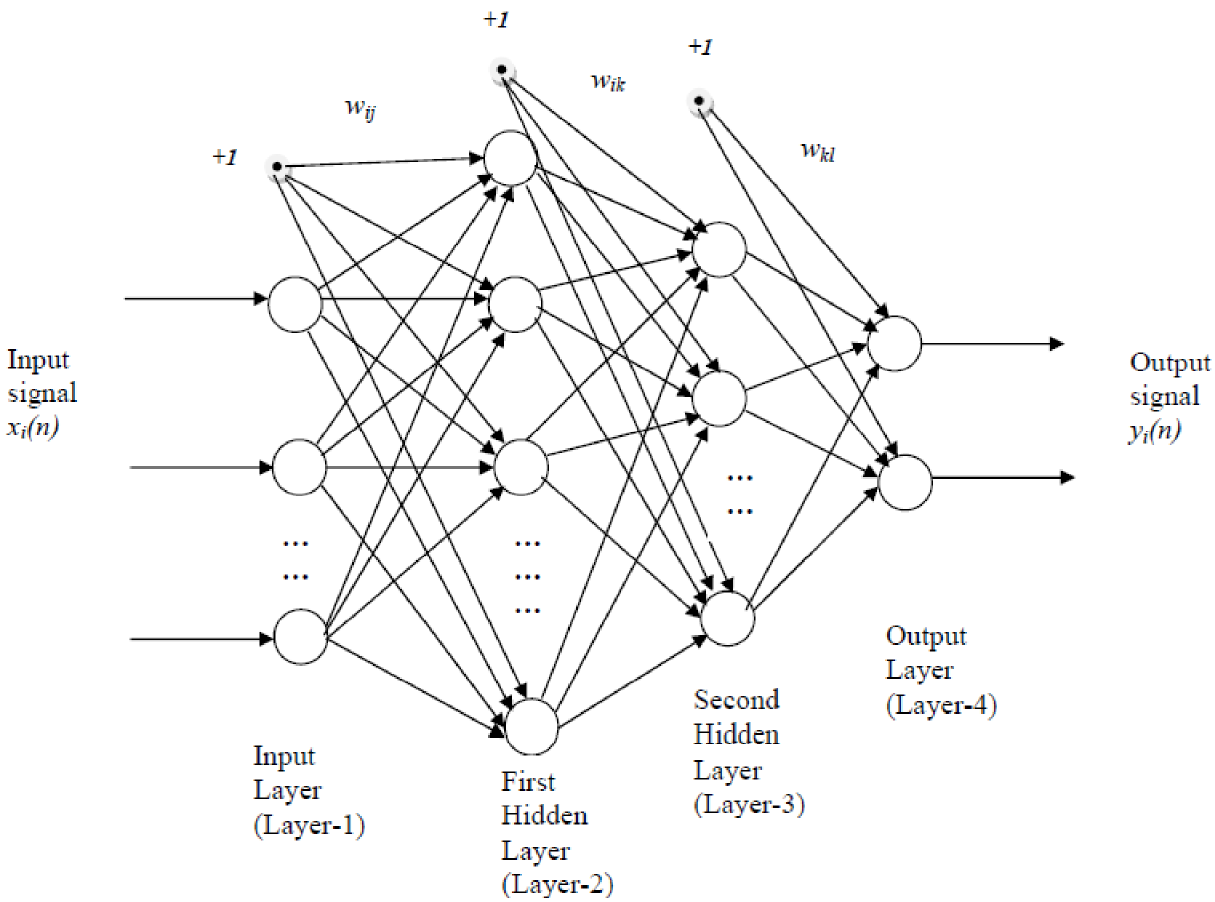
Unsupervised Learning: It takes no help from the outside. It has no training data, no information available on the desired output. It always learns by doing and facing different problems. It is used to pick out structure in the input i.e. clustering and reduction of dimensionality → compression. *Kohonen's Learning Law* is one of its example.

Reinforced Learning: In this the teacher scores the performance of the training example. Then by using performance score to weights are shuffled randomly. It is relatively a slow learning process due to 'randomness'.

Back Propagation Learning: In this we are able to get desired output of the training examples. Here the difference between actual & desired output gives the error. According to error size it changes the weight. Propagate back to previous layer after calculating output layer error. It improves the performance.

5.4 MULTILAYER PERCEPTRON

In multilayer perceptron (MLP), the input signal on a layer-by-layer basis propagates in a forward direction through the network. The network is trained in supervised learning method with error back propagation algorithm [33] to solve various types of problems .In the given scheme of multilayer perceptron using four layers, $x_i(n)$ shows the input, f_j and f_k shows the output of the two hidden layers and $y_i(n)$ shows the output of the final layer of the neural network.



5. 3 Structure of Multilayer Perceptron

Let in the first hidden layer, the number of neurons be P_1. So for the first hidden layer each element of the output vector can be obtained as,

$$f_j = \varphi_j\left[\sum_{i=1}^{N} w_{ij} x_i(n) + b_j\right], i = 1,2,\ldots N, j = 1,2,\ldots P_1 \quad (6.2)$$

b_j= threshold to the neurons of the first hidden layer,

N = the no. of inputs

φ= the nonlinear activation function in the first hidden layer chosen

Let in the second hidden layer the number of neurons be P_2.

$$f_k = \varphi_k \left[\sum_{j=1}^{P_1} w_{jk} f_j + b_k \right], \text{k= 1,2,…… } P_2 \tag{6.3}$$

Where,

b_k = threshold to the second hidden layer.

The output of the final output layer can be obtained by

$$y_l(n) = \varphi_l\left[\sum_{k=1}^{P_2} w_{kl} f_k + b_l\right], l = 1,2, \dots P_3 \tag{6.4}$$

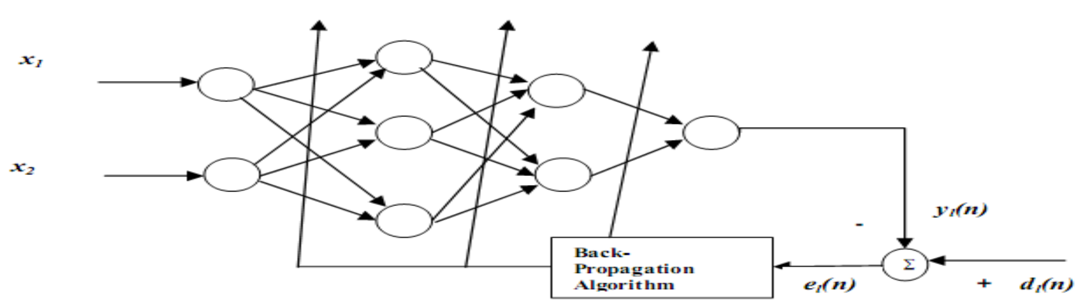
b_l = threshold to the final hidden layer

P_3 = Number of neurons in the output layer.

So the final expression for the output of MLP =

$$y_l(n) = \varphi_l\left[\sum_{k=1}^{P_2} w_{kl}\left(\varphi_k\left[\sum_{j=1}^{P_1} w_{jk}\left(\varphi_j\left[\sum_{i=1}^{N} w_{ij} x_i(n) + b_j\right]\right) + b_k\right]\right) + b_l\right] \tag{6.5}$$

5.5. Algorithm of Back Propagation:



5.4. Neural Network having Back Propagation Algorithm

An MLP network having 2-3-2-1 neurons i.e. 2 number of neurons in the input layer, 3 number of neurons in the first hidden layer, 2 number of neurons in the second hidden layer and 1 number of neurons in the output layer. Initially the weights and the thresholds are taken as small random values. The intermediate and the final outputs of the MLP are calculated by using (6.2), (6.3), and (6.4) respectively.

The final output $y_l(n)$ at the output of neuron l, is compared with the desired output $d(n)$ and the resulting error signal $e(n)$ is obtained as

$$e_l(n) = d(n) - y_l(n) \tag{6.6}$$

The instantaneous value of the total error energy is calculated by,

$$\xi(n) = \frac{1}{2} \sum_{l=1}^{P_3} e_l^2(n) \tag{6.7}$$

Inorder to update the weights and thresholds of the hidden layers and the output layers the error signal are used. The thresholds are updated in a similar way as that of the connecting weights. Unless the error signal become minimum, the weights and the thresholds are updated in an iterative method

For calculating the weights the following formulas are used,

$$w_{kl}(n+1) = w_{kl}(n) + \Delta w_{kl}(n) \tag{6.8}$$

$$w_{jk}(n+1) = w_{jk}(n) + \Delta w_{jk}(n) \tag{6.9}$$

$$w_{ij}(n+1) = w_{ij}(n) + \Delta w_{ij}(n) \tag{6.10}$$

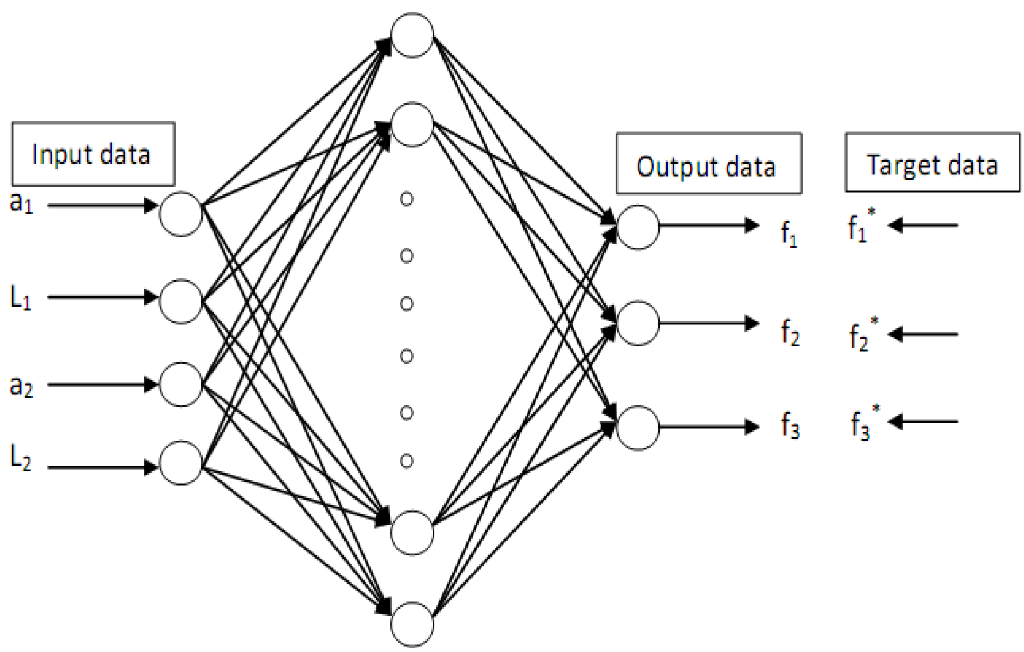
$$\Delta w_{kl}(n) = -2\mu \frac{\partial \xi(n)}{\partial w_{kl}(n)} = \mu e(n) \frac{dy_l(n)}{dw_{kl}(n)}$$

$$= \mu e(n)\varphi_l^{'}\left[\sum_{k=1}^{P_2} w_{kl} f_k + b_l\right] f_k \qquad (6.11)$$

μ= convergence factor (0< μ<1)

Similarly Δw_{jk}(n) and Δw_{ij}(n) can be obtained.

Here we are using the back-propagation network, which is a multi-layer feed-forward neural network topology with one hidden-layer. The feed forward back propagation network consists of three layers i.e. the input layer, the hidden layer and the output layer. In this computations are passed forward from the input to output layer, following which calculated errors are propagated back in the other direction to change the weights to get better performance.



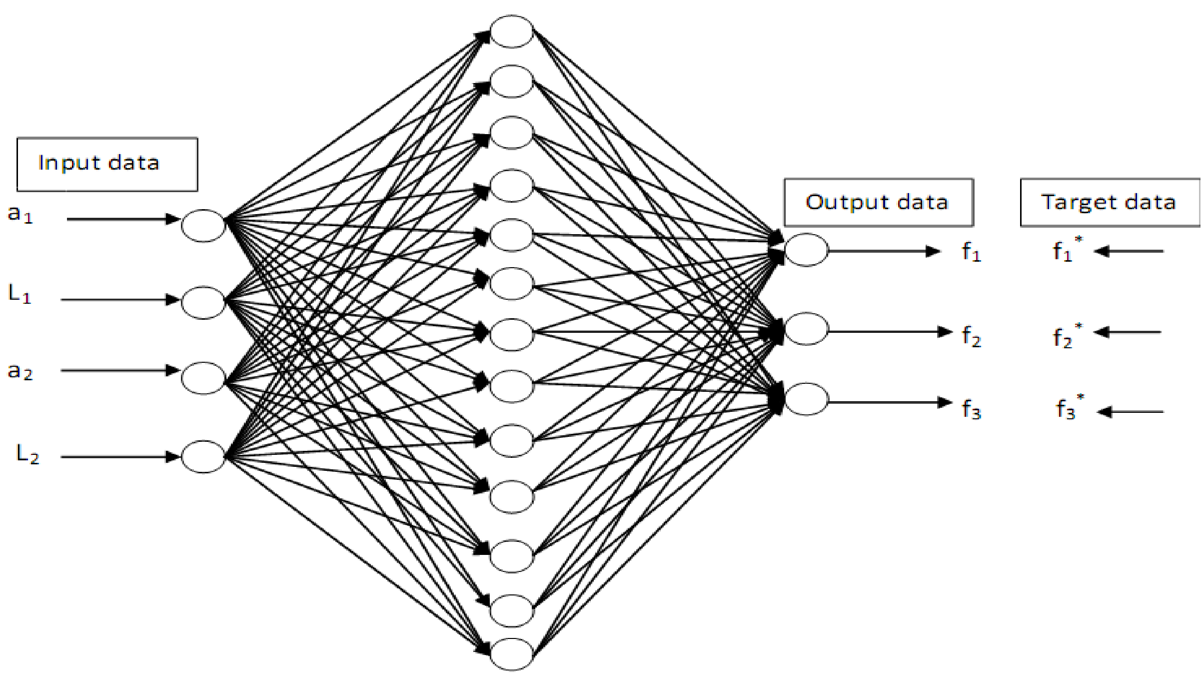
5.5.Three-layer neural network utilized in this study

5.6 TRAINING OF NEURAL NETWORK:

Because of the nature of the sigmoid activation function, i.e., saturation function, the output variables should be scaled by the user, to be within the most active range of the sigmoid function. Scaling rule that minimum and maximum values are set to 0.1 and 0.9 is usually suggested. Through some trials, a network with neuron arrangement (input-hidden-output) of 4-13-3 trained with 8 iteration for the 170 patterns are concluded to be the best for our application. Mean-square error (MSE) is employed as a measurement of modelling performance. The mathematical expression can be described as follows:

$$MSE = \frac{\sum_{i=1}^{N}(e_i)^2}{N}$$

Where e_i denotes an error at pattern i and N is the total number of patterns.



5. 6. Three-layer neural network with neuron arrangement of 4-13-3.

TABLE 5.1

Depth(D) in m	l_1 in m	l_2 in m	ω_1 in rad/s	ω_2 in rad/s	ω_3 in rad/sec
0.002	0.1	0.2	11.4224	71.239	89.85
	0.15	0.25	11.4234	71.025	89.87
	0.2	0.3	11.4241	71.256	89.87
	0.25	0.35	11.4240	71.255	89.86
	0.3	0.4	11.4239	71.236	89.84
	0.35	0.45	11.4254	71.256	89.82
	0.4	0.5	11.4246	71.237	89.84
	0.45	0.55	11.4257	71.248	89.83

TABLE 5.2

Depth(D) in m	l_1 in m	l_2 in m	ω_1 in rad/s	ω_2 in rad/s	ω_3 in rad/sec
0.0021	0.1	0.2	11.4167	71.177	89.72
	0.15	0.25	11.4177	71.192	89.74
	0.2	0.3	11.4182	71.196	89.74
	0.25	0.35	11.4181	71.195	89.73
	0.3	0.4	11.4170	71.180	89.70
	0.35	0.45	11.4193	71.196	89.73
	0.4	0.5	11.4185	71.181	89.71
	0.45	0.55	11.4196	71.190	89.74

TABLE5.3

Depth(D) in m	l_1 in m	l_2 in m	ω_1 in rad/s	ω_2 in rad/s	ω_3 in rad/sec
.0022	0.1	0.2	11.3117	71.1649	89.6657
	0.15	0.25	11.3127	71.173	89.68
	0.2	0.3	11.3132	71.177	89.68
	0.25	0.35	11.3131	71.176	89.67
	0.3	0.4	11.3120	71.167	89.64
	0.35	0.45	11.3143	71.177	89.67
	0.4	0.5	11.3131	71.168	89.65
	0.45	0.55	11.3142	71.171	89.68

TABLE 5.4

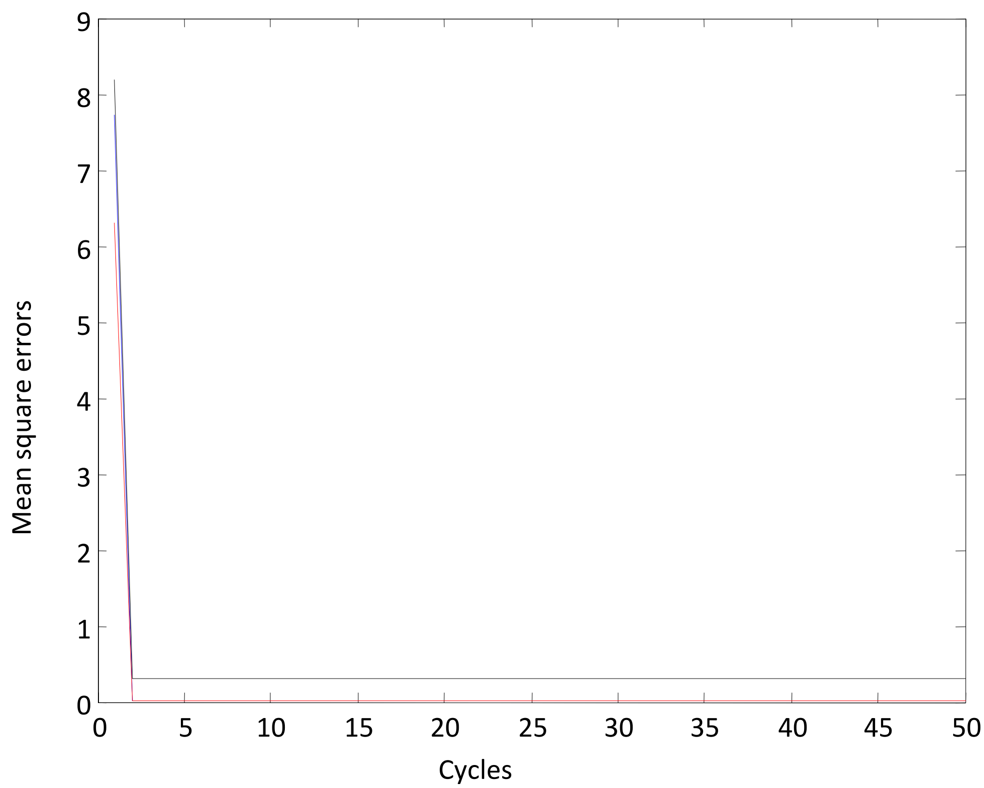
Depth(D) in m	l_1 in m	l_2 in m	ω_1 in rad/s	ω_2 in rad/s	ω_3 in rad/sec
0.0023	0.1	0.2	11.2537	71.058	89.404
	0.15	0.25	11.2547	71.072	89.42
	0.2	0.3	11.255	71.076	89.42
	0.25	0.35	11.2551	71.075	89.41
	0.3	0.4	11.2540	71.066	89.38
	0.35	0.45	11.2563	71.076	89.41
	0.4	0.5	11.2555	71.077	89.37
	0.45	0.55	11.2566	71.070	89.42

TABLE 5.5

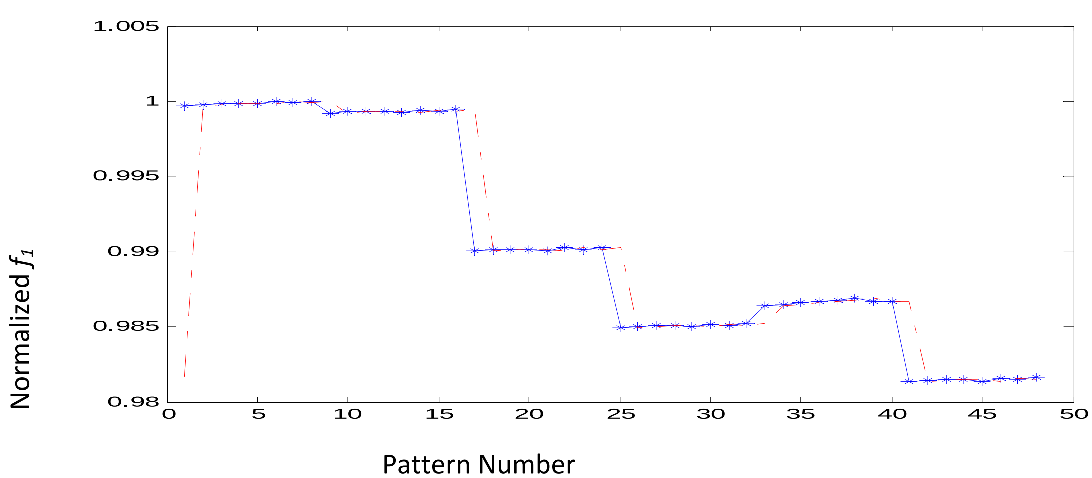
Depth(D) in m	l_1 in m	l_2 in m	ω_1 in rad/s	ω_2 in rad/s	ω_3 in rad/sec
.0024	0.1	0.2	11.2701	71.055	89.3756
	0.15	0.25	11.2713	71.065	89.382
	0.2	0.3	11.2728	71.072	89.393
	0.25	0.35	11.2736	71.076	89.408
	0.3	0.4	11.2744	71.079	89.417
	0.35	0.45	11.2759	71.080	89.423
	0.4	0.5	11.2738	71.065	89.407
	0.45	0.55	11.2740	71.070	89.415

TABLE 5.6

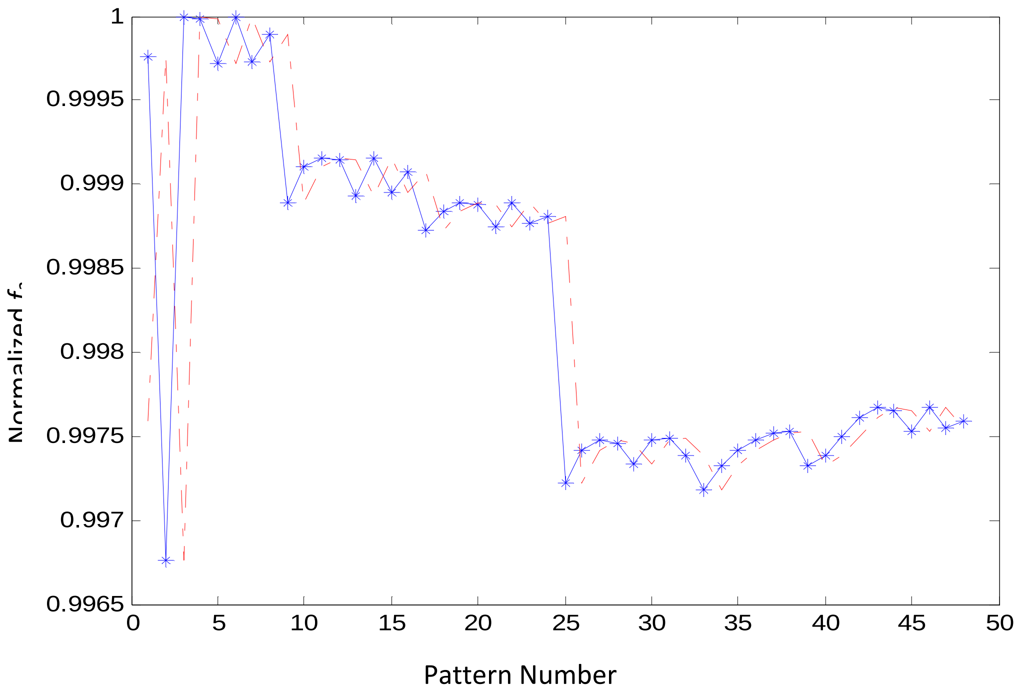
Depth(D) in m	l_1 in m	l_2 in m	ω_1 in rad/s	ω_2 in rad/s	ω_3 in rad/sec
0.0025	0.1	0.2	11.2127	71.0774	89.25
	0.15	0.25	11.2137	71.086	89.27
	0.2	0.3	11.2142	71.090	89.27
	0.25	0.35	11.2141	71.089	89.26
	0.3	0.4	11.2130	71.080	89.23
	0.35	0.45	11.2153	71.090	89.26
	0.4	0.5	11.2145	71.081	89.24
	0.45	0.55	11.2156	71.084	89.27



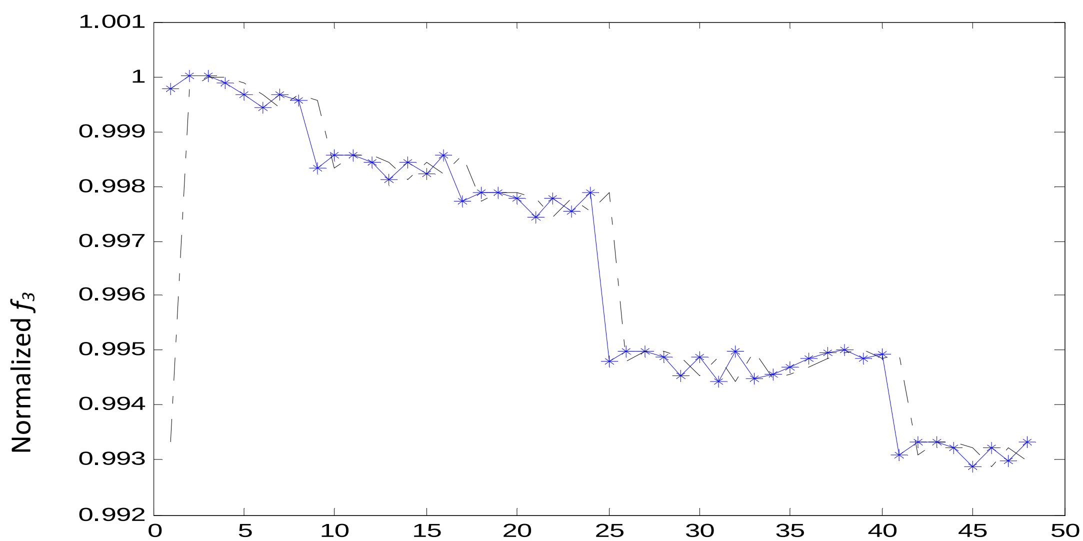
5.7 Neural network output.



5.8 Comparison of the First estimated eigenfrequencies from the neural network to target values:



5.9 Comparison of the Second estimated eigenfrequencies from the neural network to target values:



5.10 Comparison of the third estimated eigenfrequencies from the neural network to target values:

Pattern Number

DISCUSSION:

At first a cantilever beams having two cracks of different crack depths, starting from .002 to .0025m, and having different crack location, starting from .1 and .2m to .45 and .55m, are designed in CATIA software and exported to an analysis software ALGOR where FEA analysis are done. However remarkable changes are observed in transverse mode shapes at the crack positions. The transverse mode shapes for two cracks as shown in fig 4.4-4.8. In the FEA analysis using ALGOR software we get different frequencies for different crack depth and crack location.

The three-layer neural network having an input layer (I) with four input nodes, a hidden layer (H) with thirteen neurons and an output layer (O) with four output node employed for this work is shown in fig 5.6. Then by taking the different frequencies as input in the neural network we are able to get the same crack depth and crack location that we have considered during the FEM and the results are shown in the tables 5.1 to 5.6.

Mean-square error (MSE) is employed as a measurement of modeling performance which is shown in fig 5.7. In Fig.5.8 shows the first eigenfrequency f_1 is monotonously decreasing as the crack location moves from the clamped end to the free end when the crack depth $a_1=a_2$ is kept constant, where as, the second and the third eigenfrequencies oscillate under the same situation as shown in Fig.5.9and 5.10

CHAPTER 6

CONCLUSION AND SCOPE FOR FUTURE USE

6. CONCLUSION AND SCOPE FOR FUTURE USE

The presence of crack affects the natural frequency of the structure distinctly. The changes in the natural frequency is directly influenced by the crack depth and crack location. The presence and position of the crack can be detected from the comparison of the fundamental modes between the cracked and uncracked beam. The frequency of the cracked cantilever beam decreases with increase in the crack depth for the all modes of vibration.

In the Feed forward back propagation neural network, crack depth and crack location are taken as the input and the structural eigen frequencies are taken as output. From the neural network training, it is observed that the first eigen frequency f_1 is monotonously decreasing as the crack location moves from the clamped end to the free end when the crack depth a_1=a_2 is kept constant. Whereas, the second and the third eigen frequencies oscillate under the same situation.

A neural network for the cracked structure is trained to approximate the response of the structure by the data set prepared for various crack sizes and locations. Training data to train the neural network are properly prepared.

FUTURE USE:

- This process can be easily used for periodic inspection for an automated inspection of systems of remote structures, or for ones operating in a hostile environment.
- It can be used to monitor the growth of crack, taking initially undamaged structure as the baseline for future measurements.

CHAPTER 7

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7. REFERENCES

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