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Prediction of Cracks from Vibration Data Using Artificial Neural Network

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Abstract— **It is very important to monitor structures for the occurrence of cracks as such damages often leads to catastrophic failure. The detection of cracks using the vibration based techniques has been an area of intense research for the past few years and various approaches have been developed by researchers. When crack is present in a structure the consequence is a change in its modal parameters such as natural frequencies and mode shapes. In the present study, vibration analysis is carried out on a cantilever beam with two open transverse cracks, to study the response characteristics. The simulations have done with the help of ANSYS14.5 software. 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. Feed-forward multi-layer neural networks trained by back-propagation are used to learn the input (the location and depth of a crack)-output (the structural natural frequencies) relation of the structural system. By incorporating the training data, Artificial Neural Networks are capable of producing outputs in terms of crack severity using the first few natural frequencies.**

Index Terms—**modal analysis, Artificial Neural Network, crack parameters, natural frequencies**

I. Introduction

MANY engineering components used in the aeronautical, aerospace and naval construction industries are considered by designers as vibrating structures, operating under a large number of random cyclic stresses. Cracks found in structural elements like beams and columns have different causes. They may be fatigue cracks that take place under service conditions as a result of the limited fatigue strength. They may be also due to mechanical defects, as in the turbine blades of jet engines. In these engines the cracks are caused by sand and small stones sucked from the surface of runway. Another group involves cracks which are inside the material. They are created as a result of manufacturing processes. The presence of vibrations on structures and machine components leads to cyclic stresses resulting in material fatigue and failure.

Experimental based testing has been widely used as a means to analyse individual elements and the effects of beam strength under loading. While this is a method that produces real life response, it is extremely time consuming and the use of materials can be quite costly. The use of finite element analysis to study these components has also been used. In recent years, however, the use of finite element analysis has increased due to progressing knowledge and capabilities of computer software and hardware. It has now become the choice method to analyze such structural components.

A crack on a structural member introduces a local flexibility which is a function of the crack depth. Major characteristics of structures, which undergo change due to presence of crack, are (a) The natural frequency, (b) The amplitude response due to vibration and (c) Mode shape. Hence it is important to use natural frequency measurements to detect crack and its effects on the structure.

Damage in structures is defined as any reduction in structural stiffness and mass that negatively affects the functionality of the structures, also their serviceability and safety and finally may lead to failure. There are four levels of damage identification consisting of the determination of the presence of damage in the structure, the determination of damage location and the determination of the severity of damage. Thus, damage assessment is one of the most important factors in maintaining the integrity and safety of structures and has been seen to be very important in monitoring structures for existence, location and severity of damage.

It is very important to monitor the structural behavior, especially when damage is not observable. Some artificial intelligence approaches such as the Artificial Neural Networks (ANNs), Genetic Algorithm (GA) and fuzzy logic have been used extensively for damage assessment with varying degrees of success.

Among the damage identification methods, the ANNs as a very effective tool used in solving many real life problems and inspired by the human brain, have been applied dramatically to damage identification. ANNs are a very strong method especially when implemented in the field of the structural dynamics. Also, the ANNs under the topic of structural dynamic based-damage assessment can simulate complex relationships and have proven to be robust in the presence of

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noise. Some advantages of ANNs in damage identification as opposed to the traditional damage assessment approaches are as follows:

- Trained ANNs using given data, have the ability to identify damage reliably, even when trained with incomplete data.
- When ANNs are properly and completely trained, the speed of damage identification is relatively high and numerical simulations do not need to be constructed.
- ANNs are more robust over the noise and uncertainties.
- Any vibration parameters can be selected as inputs of ANNs without increasing the neural network training complexity.

In recent decades there has been an increasing interest in using ANNs to estimate and predict the damage in structures. Based on recent studies, different types of vibration signatures of the structure consisting of time domain data, frequency response functions as frequency domain data and modal parameters as inputs to ANNs have been applied.

A great deal of the preceding works has used modal parameters for damage identification. However, significant information such as natural frequencies, mode shapes and damping ratios may not be exactly expressed through the application of the modal parameters. This explains why the direct use of frequency domain data in terms of FRFs appears to be more useful. However, some researchers have directly applied FRFs measurements instead of modal parameter data to prevent loss of information. This review paper summarizes damage identification and structural health monitoring studies based on FRFs which have adopted the ANNs within the last three decades.

A. *Artificial Neural Networks*

General definition: The human brain consists of about cells called neurons that are interconnected and has the capability to perform certain computations many times faster than the most rapidly working computers. As depicted in Figure 1 a basic biological neuron is composed of a cell body, axons, dendrites and synapses. In terms of their functions, the dendrites carry signals as input information into the cell body, axons as outputs for carrying the electrical signals from the neuron to other neurons, whereas the synapse is the point contact between a dendrite of one cell and axon of another cell.

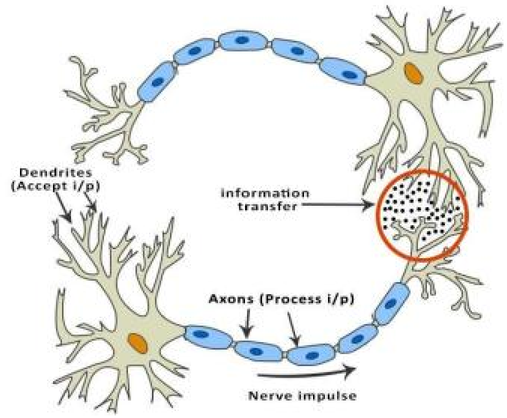

Figure 1 The basis biological neuron

In summary, a neuron receives signals from synapses either located at the cell body or its dendrite, determines its state and finally sends the output down to the axon. ANNs that are inspired by human biological neurons are computational models which consist of many simple processing elements (neurons) and are highly interconnected with each other. They function to process information and establish complex and non-linear relationships by using certain rules and large sets of data to achieve suitable results.

An ANN has the abstraction capabilities, self- adaptiveness and generalization. Therefore, it is very useful to accomplish information processing tasks and pattern recognition and classification. However, ANNs can discover about the relationships between inputs and outputs and generalize the problems even when there is not enough data or when input data contain errors.

As shown in Figure 2, the architecture of ANN consists of an input layer, an output layer and at least one hidden layer. The appropriate number of neurons in each layer depends on the type of problem that arises.

Each neuron in the input layer represents the value of one independent variable. The neurons in the hidden layer are only for computation purposes. Each of the output neurons computes one dependent variable. Signals are received at the input layer, before passing through the hidden layer and reaching the output layer. Each layer can have a different number of neurons. All neurons are interconnected to the neurons in the next layer through their weights.

samples require only an input vector. On the other hand, in supervised learning a network require correct response as output during training, but in unsupervised learning knowing the correct response as output is not necessary.

Among various neural networks, the Multi-Layer Perceptron (MLP) is most commonly used in structural identification problems. The reason is that MLP networks have been used successfully to address many different problems and can approximate any continuous multivariate function to any degree of accuracy. In MLP neurons in each

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layer, they are connected to all the neurons in both the previous and the subsequent layer. The outputs of the first layer are the inputs for the second layer; the outputs of the second layer are then again the inputs for the third layer and so on. As the information in a multi-layer perceptron network moves in forward from the input neurons, through the hidden neurons to the output neurons, the type of network is called a feed forward neural network.

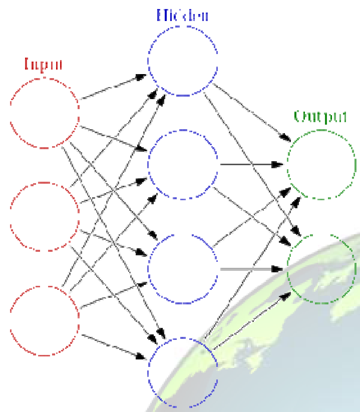

Figure 2 Architecture of ANN

The back propagation is one of the best algorithms, as it can train and update the synaptic weights of multilayer perceptron feed forward networks to perform function approximation, pattern association and pattern classification and is considered to be the most applicable due to the mathematical design of the training's complex non-linear relationships.

The back propagation algorithm has a performance index, which is the least Mean Square Error (MSE). In the MSE algorithm, the error is calculated as the difference between the target output and the network output.

Rest of the paper is organized as follows. Section 2 presents a detailed review of the literature work done earlier in the field of vibration analysis of beams. Section 3 presents the methodology followed. Section 4 presents the numerical work carried out in the ANSYS14.5 Workbench, modeling details of the beams and the experimental work carried out in this project work under various boundary conditions. Section 5 presents the Artificial Neural Network method used in this work to determine the crack size and location. Finally, conclusions and recommendations are presented in Section 6.

II. Literature Review

Kumar et al. (2016)[1] carried out vibration analysis on a cantilever beam with two open transverse cracks, to study the response characteristics Suitable boundary condition are used to find out natural frequency and mode shapes. The simulations have done with the help of ANSYS14.0 software. 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. Feed-forward multi-layer neural networks trained by back-propagation are used to learn the input (the location and depth of a crack)-output (the structural natural frequencies) relation of the structural system. With this trained neural network minimizing the difference from the measured frequencies and also carried out Multiple Regression Analysis to learn input-output relation in similar fashion. A comparative study is performed to check the crack depth and location effects on natural frequencies for beams of rectangular and I cross section. It is verified from the present analysis that the presence of crack decreases the natural frequency of vibration. The mode shapes also changes considerably due to the presence of crack. The frequency of the cracked cantilever beam decreases with increase in the crack depth for the all modes of vibrations.

Dynamic behavior of simply supported cracked beam subjected to loading condition is analyzed by Deokaret al. (2015) [2]. A systematic approach has been adopted in the investigation by FEA Software ANSYS 11 for evaluation of natural frequencies and mode shapes. A simple elastic simply supported beam with crack at the different locations and also having different crack depth is considered for the modal analysis. It is found that the frequency of beam when the crack is in the middle position is less than the frequency with crack near the end position and the natural frequency of beam decreasing with increasing of crack depth due to decreasing of beam stiffness at any location of crack in beam.

Kolheet al. (2015)[3] performed the modal analysis on cracked beams and a healthy beam, to calculate natural frequency. The first three natural frequencies were considered for vibration analysis of beams. The vibration analysis result to shows the plot the effect of the second crack on the natural frequency and mode frequency ratio in terms of crack depth for various crack positions of the cantilever bar.

A. *Overview of Neural Network Technique*

ANNs are computational parallel distributed information processing system. It is therefore effectively applied in many industrial applications such as fault diagnosis control & optimization, industrial process, and sale forecasting, etc. The ability to work under challenging environment and parallel computing ability make ANNs most efficient and robust to solve the problem easily unlike using analytical methods. An artificial neuron is acted like a device with many inputs and one output. The neuron is working on two modes of operation, one is training mode and another is using mode. The training mode of ANNs is more significant for potential and smooth results. In the training mode, neuron can be trained to fire (or not) for the specific input array. In the using mode, a learned input array is detected as the input, allied output becomes present output. If the input array does not belong in the learned input array list, the firing role is used to determine whether to fire or not.

The important characteristics of the neural network are

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depicted bellow.

(1) The input variables with synaptic weights are assigned to train neuron that turn upset the decision-making capacity of ANN.

(2) These weighted inputs are then summed together in summing point and if they exceed with pre-set threshold value, the neuron fires.

(3) For limiting the output of neuron, an activation function is provided. The most popular activation function is sigmoidal.

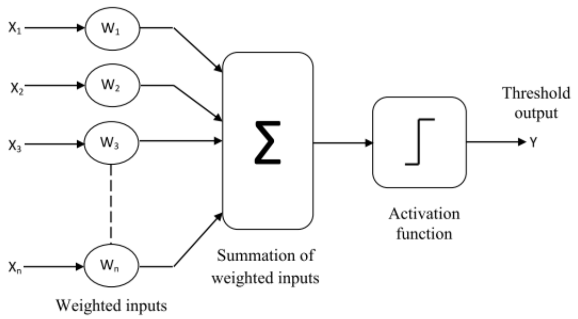

Figure 3 Simple model of an artificial neural network

The multilayers neural network has been trained using back propagation algorithm and performance of the network is based on sum square error also called as approximate steepest gradient algorithm. The weights should be adjusted in such a way that the error between the actual and desired outputs is minimum. This is the training process of neural network. The change in error has been calculated by managing the input weights.

III. Methodology

In the present work, vibration analysis is carried out on a simply supported beam with a two open transverse cracks. The work focuses on predicting the depth and location of cracks present in the simply supported beam. Free vibration analysis of crack free beam and cracked simply supported beams with varying sizes and locations of the two cracks are performed. The natural frequencies corresponding to different modes of vibrations are obtained through the free vibration analysis. The simulations have done with the help of ANSYS 14.5 software. The data obtained through the vibration analysis is then used for training the Artificial Neural Network.

Artificial Neural Network is trained for detection of different crack location and depth. The inputs are six variables, first three natural frequencies and first three natural mode shapes and output are depth and location. The MATLAB Neural Network Toolbox is used for this purpose. Once the training is complete simulation is performed to predict probable location of crack and its depth.

The simply supported beam with two cracks with various parameter settings are modeled in ANSYS. The modal analysis is done and first six modal frequencies are obtained. There were a total of 216 different combinations of crack parameters. Using the Neural Network toolbox in Matlab, ANN is modeled for the prediction of crack parameters from experimentally obtained modal frequencies. The ANN was trained using 216 sets of input data obtained from the experiments using model in ANSYS. The ANN thus trained is then used for predicting crack parameters from the modal frequencies.

IV. Computational Experiments and Results

A. *Finite Element Analysis*

The model used for prediction of crack parameters is given in Figure4.

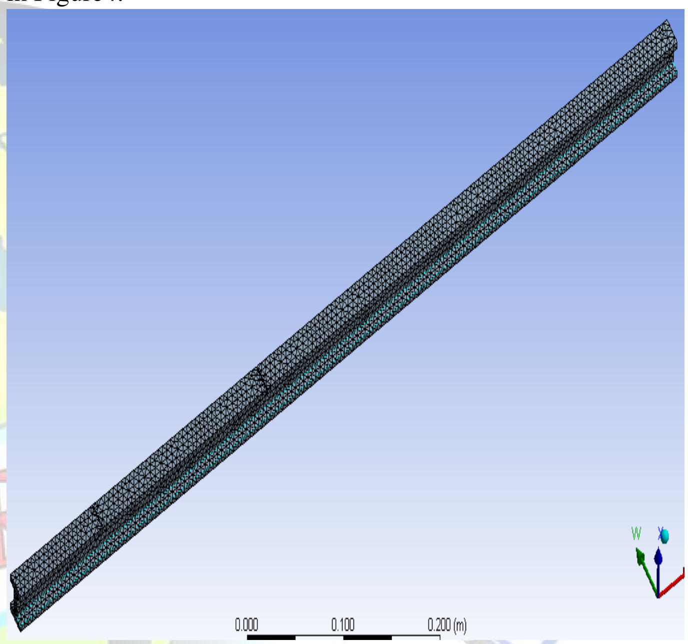

Figure4 Model in Ansys

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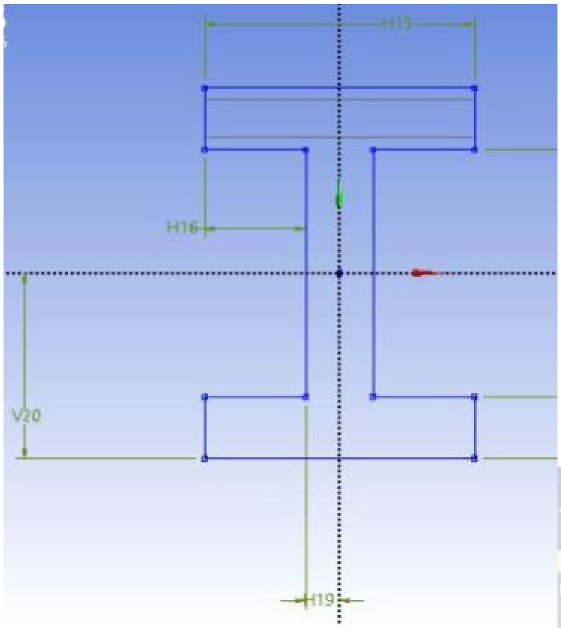

Figure5 Cross-section of Beam

The properties of the material used are given in Table 1.

Table1 Beam Characteristics

Property	Value
Density of Material (kg/m^3)	2770
Poissons Ratio	0.33
Modulus of Elasticity (GPa)	7.1E^{10}
H15 (mm)	20
H16 (mm)	7.5
H19 (mm)	2.5
V17 (mm)	20
V18 (mm)	5
V20 (mm)	15

Natural frequencies of first six modes of vibration for 216 different combinations of crack parameters are tabulated. The normalised frequencies for each combination of parameters are tabulated and following equation are

Normalised Frequency = (Modal Natural Frequency of the Beam with Crack)/(Modal Natural Frequency of the Beam without Crack)

B. *Artificial Neural Network*

The results obtained from the FEA are used as the training set for the ANN. The ANN model created consists of one input layer with six neurons, one hidden layer with 48 neurons and one output layer with six neurons. The parameters used for ANN are given in Table 2

Table 2 Parameters for ANN Model

Parameter	Value
Type:	Feed forward Back Propagation
No. of Layers:	3 (Input, Output and Hidden)
No. of neurons in hidden layer:	48
Training Function Used:	trainbr
Performance Function:	SSE
No. of Epochs:	25000
SSE Achieved:	82.0986

After training the ANN model using the 216 data created using FEA, a set of ten random frequency combinations are input to the ANN and the results are obtained. Table 3 gives the input data and the output obtained through the ANN is given in Table 4.

Table 3 Input data for ANN

Sl. No	Frequencies					
	1	2	3	4	5	6
1	80.96	131.64	261.74	446.15	498.64	546.97
2	81.53	131.00	269.86	446.50	495.50	560.26
3	81.23	126.06	258.51	444.04	469.03	544.76
4	77.47	123.69	266.39	452.56	494.25	563.85
5	82.22	132.18	270.61	452.86	509.48	573.32
6	80.62	130.56	261.17	446.71	497.22	544.80
7	80.82	132.34	271.43	446.61	507.07	575.24
8	82.08	127.14	259.09	449.43	479.66	552.71
9	81.20	117.15	249.07	426.94	440.19	521.41
10	74.73	106.17	257.95	451.91	463.75	548.68

Table 4 Output from ANN

Sl. No	Parameter Values					
	W1	D1	P1	W2	D2	P2
1	1.29	4.11	29.68	1.84	6.91	759.50
2	1.22	4.21	154.02	1.45	6.80	219.71
3	1.19	9.03	205.72	0.87	7.31	281.56
4	1.17	8.94	499.48	1.54	1.01	255.51
5	1.30	3.85	201.43	1.40	0.89	26.25
6	1.23	3.79	501.54	1.78	6.99	130.26
7	1.19	8.80	51.12	1.21	1.07	529.81
8	1.29	8.87	201.66	1.44	1.06	680.73
9	1.39	14.72	218.87	2.62	6.90	136.70
10	1.35	15.54	500.22	2.07	6.86	230.64

V. VERIFICATION OF THE RESULTS OBTAINED

Table 5 Modal Frequencies from Ansys for the Predicted Crack Parameters

Sl. No	Frequencies					
	1	2	3	4	5	6
1	81.81	132.58	269.64	448.30	510.86	567.03
2	82.01	128.05	258.47	450.88	487.80	558.26
3	80.56	121.20	250.42	449.13	470.50	552.03

4	77.41	123.73	266.25	453.05	494.53	563.55
5	82.34	132.18	271.02	453.24	510.02	574.21
6	81.60	129.90	268.07	448.03	491.57	552.17
7	80.89	132.29	271.71	446.75	506.89	575.75
8	82.04	127.04	258.83	449.09	479.73	553.11
9	81.40	115.43	253.92	435.29	443.60	539.54
10	76.59	106.38	250.62	443.00	450.33	548.38

Table6 Average Percentage Deviation of Modal Frequencies from Ansys for the Predicted Crack Parameters

Sl. No.	**APD (%)**						
	1	**2**	**3**	**4**	**5**	**6**	**Average**
1	1.04	0.71	2.93	0.48	2.39	3.54	**1.85**
2	0.58	2.30	4.41	0.97	1.58	0.36	**1.70**
3	0.83	4.01	3.23	1.13	0.31	1.32	**1.81**
4	0.07	0.03	0.05	0.11	0.06	0.05	**0.06**
5	0.15	0.00	0.15	0.08	0.11	0.15	**0.11**
6	1.20	0.51	2.57	0.29	1.15	1.33	**1.18**
7	0.09	0.04	0.10	0.03	0.04	0.09	**0.06**
8	0.05	0.08	0.10	0.08	0.01	0.07	**0.06**
9	0.25	1.49	1.91	1.92	0.77	3.36	**1.62**
10	2.42	0.20	2.92	2.01	2.98	0.05	**1.76**
						Average	**1.02**

To verify the predicted crack parameters, the cracks obtained from the ANN are modelled in Ansys and the corresponding modal frequencies are obtained as given in Table 5. The absolute percentage deviation of the obtained frequencies from the input frequencies are calculated using the equation

Absolute Percentage Deviation (APD) = (Obtained Frequency-Input Frequency)/(Input Frequency)×100%.

The APD values are given in Table 6. From the table it can be seen that most of the frequencies shows less than 1% deviation and the average deviation is small giving a value of 1%. From this we can conclude that the ANN model generated is efficient in finding out the location of the cracks in an I beam of given material and dimensions if the modal frequencies can be measured.

VI. CONCLUSION

Finding out cracks in structural elements well before the failure is important in a safety point of view. The modal frequencies of a structural element depend on the structural health of the element. Thus the modal frequencies can be used to predict the presence of cracks present in a structural member. In this work we propose an ANN for finding out the parameters of cracks present in an I-beam made of Aluminium alloy. We consider that there are two cracks present in the beam. Modal frequencies for a simply supported beam without crack and with two cracks at various positions have obtained. The ANN model is then created and it is trained using the data set containing 216 simulation data created using the FEA model. The input to the ANN is the normalized modal frequencies and the output is the parameters of the cracks. In order to verify the output of the ANN, ten combinations of modal frequencies are input into the ANN and the results are obtained. Verification of the results obtained from ANN is done by modeling the cracks in Ansys and the modal frequencies are obtained. The Average Percentage Deviation values are calculated and the values are very small giving an average value of 1%. Thus the efficiency of the proposed ANN is proved.

In this we considered I-beam of Aluminium alloy with two cracks presents. But in actual case the number of cracks cannot be determined before doing the inspection. Hence creating an ANN model to find out the number of cracks and there parameters is an improvement over this work.

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