Vibration Based Damage Identification Method for Cantilever Beam Using Artificial Neural Network

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Abstract. This paper presents the use of Artificial Neural Networks (ANN) techniques to identify the damage in cantilever beams. We consider two cantilever beams of different materials i.e. aluminum and stainless steel. Different crack lengths are introduced on the beams from 0–10 mm with 2 mm interval. 0 mm, 2 mm, 4 mm, 6 mm, 8 mm and 10 mm cracks denotes damage level 0, 1, 2, 3, 4 and 5 respectively. The undamaged cantilever structure is treated as damage level 0. Experimental modal analysis is conducted for each case using impact hammer test. To validate the experimental values modal analysis is conducted in ANSYS software. From the modal analysis results it is observed that, for lower modes there is no change in frequencies but for higher modes the natural frequencies are decreasing with the increase in crack length. The FRFs obtained from experimental modal analysis are used as inputs to train the ANN. In the present paper, two types of networks are considered. One is Radial Basis Function (RBF) network and other is feed forward network. For each material total of 60 sets of data were collected. Part of the data is used to train the ANN and remaining data is used to test the trained ANN. From the results, the ANN is capable of identifying the damage and its severities.

Keywords: ANN · Vibration · Damage identification · Cantilever beam · ANSYS

1 Introduction

Mechanical components fail in many modes such as fatigue, creep, resonance structural defects may experience dynamic loads, prior to fail due to presence of cracks. Cracks in machine or any engineering systems may lead to catastrophic failure of the machine and must be detected early. For this reason, methods allowing early detection and localization of cracks have been the subject of intensive investigation. The cracks present in the system may be considered to develop the analytical model to study the effect of cracks on the modal response of the system. The damage [1] in the beam member introduces the stiffness, which can be used along with the prevailing boundary conditions to formulate the vibration characteristic equation to obtain the mode shape, natural frequency of vibration, crack parameters such as relative crack severities and relative crack positions. Utilization of the dynamic response of the member is one of

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the technique which has been widely accepted for crack diagnosis in different engineering systems. The structural health monitoring (SHM) [2] technique provides information on the life expectancy of structures simultaneously detects and locates structural damage. Vibration-based damage identification techniques are based on the principle that damage alters both the physical properties as well as its dynamic characteristics of the structure. Therefore, by analyzing a structure's dynamic properties from structural vibration, any damage, including its location and severity, can be identified. Among the Vibration-based damage identification methods, the ANNs as a very effective tool and have proven to be robust in the presence of noise. Many methods have been developed and studied to detect damage through the changes in the dynamic response of a structure. Due to its capability to recognize pattern and to correlate non-linear and non-unique problem, ANN have received increasing attention for use in detecting damage in structures based on vibration modal parameters.

Rytter [3] presented the four level classification of damage identification system. Cawley and Adams [4] have developed a technique based on experiment to estimate the location and depth of the crack from changes in the natural frequencies. Sahin and Shenoi [5] examined the effectiveness of using natural frequencies and mode shape curvatures as inputs for ANNs. Lee et al. [6] presented an ANN-based damage detection method using three different types of mode-shape-based parameters as inputs for the networks. Mayes and Davies [7] 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. Wu et al. [8] applied FRF data as an input to represent the undamaged and damaged condition of each member in a simulated three-storey building. Povich [9] verified the application of FRF as the input parameters to detect damage condition in a 20-bay planar truss composed of 60 structure. Ghate et al. [10] have proposed a multi-layer perceptron neural network based classifier for fault detection in induction motors which is inexpensive, reliable by employing more readily available information such as stator current. Liu et al. [11] use an autoregressive with exogenous inputs (ARX) model of a cantilever aluminum beam to extract vibration signatures, and employ multilayer, feed-forward neural networks (MFFNN) to locate damage and estimate its size. Narkis [12] developed a closed-form solution for the damage detection of a single crack in a simply supported beam by measuring the change in natural frequencies of the bending vibrating modes and the axial vibration modes. Masri et al. [13] carried out a study regarding the effect of different lengths of vibration signature to ANN performance.

The main aim of this paper is to develop ANN-based damage detection methods for severity estimation of cantilever beam by conducting laboratory investigations to validate experimentally and verify numerically with the finite element models.

2 Artificial Neural Network

The creation of neural networks was originally inspired by the human brain and the way it processes information. The human brain consists of about 10^{11} electrically active cells called neurons, which are heavily interconnected. The biological neural system provided the basis for a great deal of research into artificial neural network models.

This research was driven by the desire to build better pattern recognition and information processing systems. By definition, 'artificial neural systems, or neural networks, are physical cellular systems which can acquire, store, and utilize experiential knowledge'. To model such a system requires, first, a model of the network's basic building block, the single neuron.

ANN is composed of several processing elements, namely, neurons that are interconnected with each other. Figure 1 shows the model of an artificial neuron which consists of a neuron that receives weighted inputs (w) that are summed and passed through an activation function (f) to produce a single output.

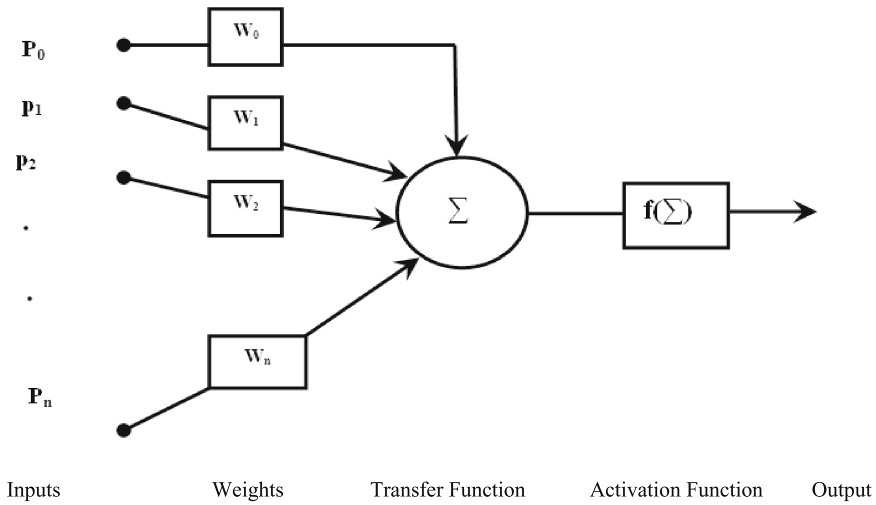

Fig. 1. Schematic structure of an artificial neuron.

A typical neural network has three layers, namely, the input layer, the hidden layer and the output layer. Signals are received at the input layer, pass through the hidden layer and reach the output layer. Each layer can have a different number of neurons and activation functions, such as sigmoid and linear functions. All neurons are interconnected to the neurons in the next layer through their weights.

3 Damage Identification Using ANN

The main use of the two vibration-based damage identification schemes for Artificial Neural Network (ANN) is pattern recognition and noise reduction. One scheme is a modal parameter method (based on the damage index (DI) method), and the other scheme is a frequency response function (FRF) method. To enhance damage signatures and to reduce the size of input data to neural networks, curve fitting techniques (CFT) are employed. Damage Identification Methods are:

Method 1: Damage identification method based on Damage Index (DI) method
Method 2: Damage identification method based on Frequency Response Functions (FRF)

In the present work, damage identification method based on FRF is used. FRF data are directly measured data and are one of the easiest to obtain in real-time as they require only a small no of sensors and very little human involvement. FRFs are normalized complex quantities that specify how vibration is transmitted as a function of frequency between points on the structure. Measured FRF data are usually the most compact form of data obtained from vibration tests of structures. As FRF data are sensitive to structural changes, they have been used as indicators in various forms to detect damage.

4 Modal Testing and Experimental Modal Analysis

Modal testing and experimental modal analysis [14] is the process of characterizing the dynamic properties of a test structure by exciting the structure artificially and identifying its modes of vibration. When a structure is damaged, e.g. its geometrical properties change, its boundary conditions modify or its material properties alter the dynamic characteristics of the structure change. These changes are the basis for the presented damage identification methods, and modal testing and experimental modal analysis serves as a means to extract the dynamic properties for the given structures. Modal analysis is used to determine the vibration characteristics such as natural frequencies and mode shapes of a structure or a machine component while it is being designed. It can also be a starting point for another more detailed analysis such as a transient dynamic analysis, a harmonic response analysis or a spectrum analysis. The natural frequency depends on specific stiffness and the length of particular components. Experimental modal analysis is based on the use of experimentally collected data from modal testing using transfer function method. This method involves the acquisition of point to point Frequency Response Functions (FRF's) at a set of points defined as dynamic model.

In the present work, two cantilever beams of aluminum and stainless steel are considered. The dimensions of the beams were 3 mm $\times$ 25.4 mm $\times$ 250 mm (ASTM standards). According to the manufacturer's specifications the modulus of elasticity of aluminum beam was 71 $\times$ 10^9 N/m^2, the Poisson's ratio was 0.33 and the density was 2770 kg/m^3 and for stainless steel beam young's modulus was 190 $\times$ 10^9 N/m^2, the Poisson's ratio was 0.305, and the density was 7861 kg/m^3. Using a C clamp, one end is fixed to a vice. To study damage scenarios of various intensities, a total of 5 single damage cases were investigated. These relate to damage at same location having five levels of severity. Damage was gradually inflicted by a saw cut from the 50 mm from free end of the beam. The five damage severities are 2, 4, 6, 8 and 10 mm depth with 1 mm width. Impact hammer test is performed to capture the FRF data. Total test setup is shown in Fig. 2.

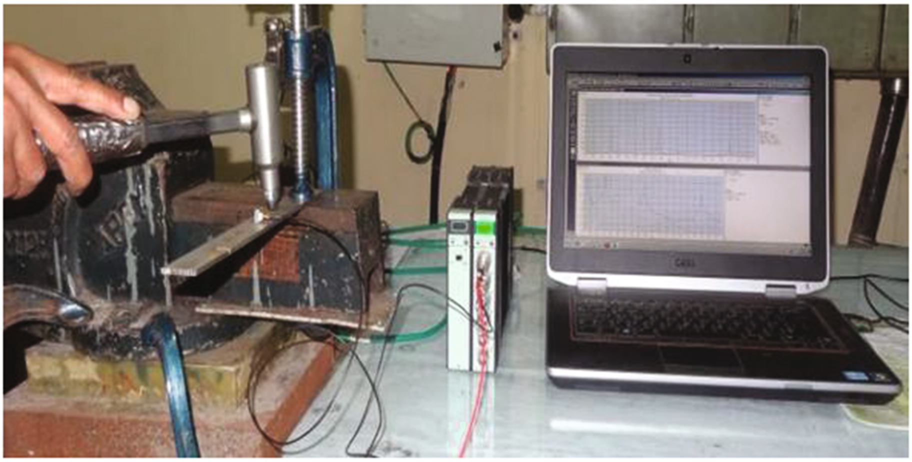

Fig. 2. Total test set up of modal testing and experimental modal analysis.

5 Finite Element Modelling

Finite Element Method (FEM) is a numerical method for solving a differential or integral equation. It has been applied to a number of physical problems, where the governing differential equations are available. The method essentially consists of assuming the piecewise continuous function for the solution and obtaining the parameters of the functions in a manner that reduces the error in the solution. It uses subdivision of a whole problem domain into simpler parts, called finite elements, and variation methods from the calculus of variations to solve the problem by minimizing an associated error function.

To perform finite element modeling for Cantilever beam with and without cracks for two different materials, ANSYS 15 is used. Modal Analysis was performed for same proposed models to validate experiment results. The geometric models for Modal Analysis were developed using CATIAV5R20 package. The modal parameters results were compared with the natural frequencies obtained from experimental modal analysis.

6 ANN Training and Testing

In the present work, ANN is trained by using Radial Basis Function Network method. The arrows in the Fig. 3 symbolize parameters in the network. The RBF network consists of one hidden layer of basis functions, or neurons. At the input of each neuron, the distance between the neuron center and the input vector is calculated. The output of the neuron is then formed by applying the basis function to this distance. The RBF network output is formed by a weighted sum of the neuron outputs and the unity bias.

There are total 6 cases (1 undamaged and 5 damaged cases). For damaged cases, width of the crack is 1 mm and depth of the crack is 2, 4, 6, 8 and 10 mm.

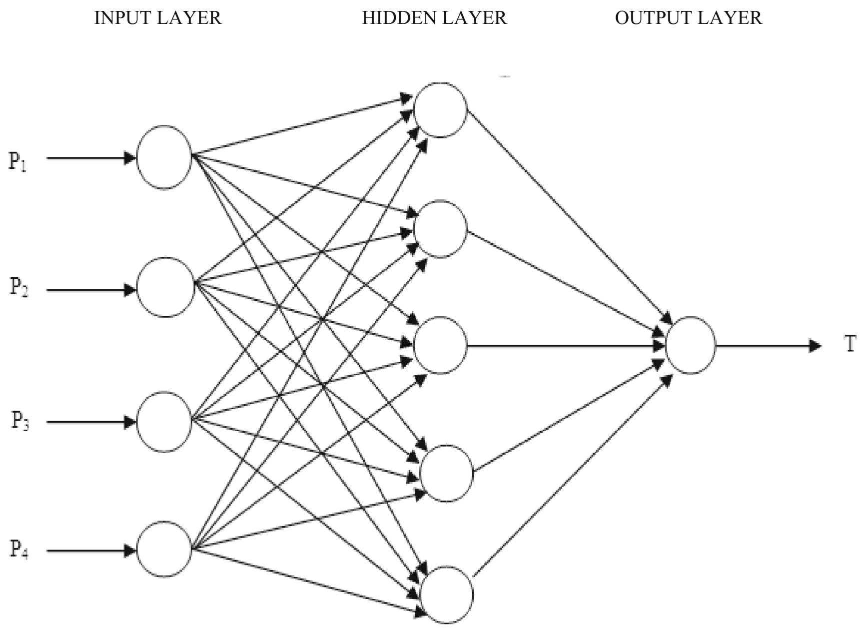

Fig. 3. RBF network with one output.

For each case 10 sets of data was collected. So 60 sets of data each for both aluminum beam and stainless steel beam. Total 120 sets of data was collected. Two separate neural networks are trained each for aluminum beam and stainless steel beam. 60 sets of data are used to train each neural network and 60 sets of noise polluted data are used for testing the trained neural network.

After assigning inputs and outputs to ANN the relations between input and output data was established by using Radial Basis Function Network, "newrbe" function. Testing the trained data using "sim" function and "reverse" function. Testing the trained data using "sim" function.

7 Results and Discussion

From modal analysis natural frequencies are obtained and compared theoretically, experimentally and ANSYS for undamaged case for both aluminum and stainless steel beams and the same is shown in Table 1. From the table we can observe that there is a change in natural frequency with change in crack size.

Similarly, natural frequencies are compared experimentally and ANSYS for all damaged cases, for both aluminum and stainless steel beams and the same is shown in Table 2. From the table we can observe that there is a change in natural frequency with change in crack size.

From the testing of the trained ANN results are obtained. FRF data of each set of a particular damage state is given as input and corresponding damage in mm is obtained

Table 1. Comparison of natural frequencies (Hz) for undamaged case from modal analysis.

Type of beam	Modal analysis	Aluminum beam			Stainless steel beam		
		Mode 1 (Hz)	Mode 2 (Hz)	Mode 3 (Hz)	Mode 1 (Hz)	Mode 2 (Hz)	Mode 3 (Hz)
Un-damaged (0 mm Crack)	Theory	53.05	332.79	931.91	51.56	323.16	904.94
	Experiment	52.5	323.75	927.5	51.25	317.5	906.25
	ANSYS	53.585	335.43	938.92	51.95	325.26	910.35

Table 2. Comparison of natural frequencies (Hz) of all damaged cases from modal analysis

Type of beam	Modal analysis	Aluminum beam			Stainless steel beam		
		Mode 1 (Hz)	Mode 2 (Hz)	Mode 3 (Hz)	Mode 1 (Hz)	Mode 2 (Hz)	Mode 3 (Hz)
Damaged beam 2 mm crack	Experiment	52.5	321.25	930	51.25	316.25	902.5
	ANSYS	53.64	335.76	940.08	52.01	325.53	911.3
Damaged beam 4 mm crack	Experiment	52.5	321.5	927.5	51.25	315	895
	ANSYS	53.66	335.39	936.95	52.02	325.17	908.28
Damaged beam 6 mm crack	Experiment	51.25	322.5	928.75	51.25	315	893.75
	ANSYS	53.67	334.85	932.26	52.03	324.6	903.55
Damaged beam 8 mm crack	Experiment	51.5	321.25	918.75	51.25	313.75	886.25
	ANSYS	53.69	334.02	925.12	52.05	323.86	896.92
Damaged beam 10 mm crack	Experiment	51.25	318.75	912.5	51.25	313.75	873.75
	ANSYS	53.69	333.07	917.41	52.06	322.97	889.32

Table 3. Results obtained from ANN training using RBF for aluminum beam.

Sl. no.	Crack length (mm)					
	0	2	4	6	8	10
1	0.0034	1.9966	3.9993	5.9994	7.9851	9.9991
2	0.0047	1.9940	4.0004	5.9999	7.9998	10.0003
3	0.0065	1.9977	4.0057	6.0007	8.0004	9.9993
4	0.0097	1.9982	3.9979	6.0109	8.0025	9.9995
5	0.0003	1.9967	3.9995	5.9994	8.0006	10.0014
6	0.0080	1.9998	3.9940	5.9998	7.9971	10.0020
7	0.0048	1.9986	3.9923	5.9908	7.9938	10.0008
8	0.0073	1.9990	3.9887	5.9977	7.9828	9.9998
9	0.0021	1.9943	3.0044	5.9997	7.9939	10.0013
10	0.0002	1.9990	3.9976	6.0114	7.9992	9.9988

Table 4. Results obtained from ANN training using RBF for stainless steel beam.

Sl. no.	Crack length (mm)					
	0	2	4	6	8	10
1	−0.0018	1.9967	4.0890	5.9637	7.9782	9.9547
2	−0.0083	1.9964	3.9734	5.9803	7.9488	9.9374
3	0.0000	1.9919	4.1906	5.9726	7.9716	10.0006
4	0.0000	1.9961	3.9902	5.9795	7.9557	9.9560
5	0.0000	1.9959	4.1789	5.9856	7.9859	9.9367
6	0.0000	1.9965	4.1959	5.9980	7.9809	9.9801
7	0.0000	1.9996	4.1716	5.9833	7.9964	9.9481
8	0.0000	1.9996	3.9689	5.9822	7.9899	9.9133
9	0.0000	1.9960	4.1818	6.0753	7.9585	9.9488
10	0.0000	1.9961	3.9657	5.9919	7.9852	9.9578

as output. For example, if FRF data of a damaged beam with 2 mm crack size is given as input for the trained ANN, then the output obtained is damage 2. Similarly, for damaged beams with 4, 6, 8 and 10 mm crack sizes the output obtained is damage 4, 6, 8 and 10 respectively for both aluminum and stainless steel beams. For all the sets of input corresponding outputs are shown in Tables 3 and 4 for aluminum and stainless steel beams.

8 Conclusions

1. The modal analysis for undamaged cantilever beam is conducted experimentally and it is validated with the theoretical values for both aluminum and stainless steel beams. The modal analysis is conducted for undamaged cantilever beam using ANSYS software for both aluminum and stainless steel. From this it is concluded that, for the first three modes the natural frequencies are coinciding and is shown in Table 1.
2. The modal analysis is also conducted for damaged cantilever beams experimentally and validated using ANSYS software for both aluminum and stainless steel. From this it is concluded that, for the first mode the natural frequencies are not varying much and for higher modes the natural frequencies are gradually decreasing with increase in crack length and is shown in Table 2.
3. Crack with larger crack depth imparts greater reductions in natural frequency than that of the smaller crack depth ratio. Hence, the accuracy of results improves as crack depth increases.
4. From the obtained experimental FRF data, the ANN is trained using RBF and feed forward networks. The trained network is tested and the results are tabulated in Tables 3 and 4 for aluminum beams and Tables 5 and 6 for stainless steel beams. From these results it is concluded that both RBF and feed forward networks are identifying the damage and its severity.

5. It is also concluded from the ANN results, the RBF network is giving more accurate results than feed forward network for the experimental data considered in this study. Hence RBF network is more suitable for this experimental data considered in this paper work.
6. From the above results, it is concluded that ANN is capable of identifying the damage and its severity for the cantilever beam considered in the experimental work based on the vibration FRF data.
7. The proposed approach has the ability to detect a crack in a cantilever beam using natural frequencies.

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