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Statistical Time Energy Based Damage Detection in Steel Plates Using Artificial Neural Networks

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Abstract- **In this paper, a simple method for crack identification in steel plates based on statistical time energy is presented. A simple experimental procedure is also proposed to measure the vibration at different positions of a steel plate. The plate is excited by an impulse signal and made to vibrate; statistical features are then extracted from the vibration signals which are measured at different locations. These features are then used to develop a neural network model. A simple neural network model trained by back propagation algorithm is then developed based on the statistical time energy features to classify the damage location in a steel plate. The effectiveness of the system is validated through simulation.**

Keywords- Time domain, Damage Detection, Back Propagation neural network.

I. INTRODUCTION

Health monitoring of vibrating structure in machines is a important task in industries. Damages can put human safety at risk, cause long term machine downtimes, interruption in the production and subsequently increase the production cost. Early damage detection and possible location of the faults from the vibration measurements is one of the primary task of condition monitoring. Condition monitoring enables early detection of faults. In recent years there has been an increasing interest in the development of online condition monitoring systems due to the success in several applications.

A damage condition of a steel plate can be detected by the vibration signal propagating through it, when it is subjected to an impulse force. There are many technologies that have been developed to detect the faults in a gear box, bridge structures and bearings.

The existence of a crack in a steel plate reduces the stiffness of the plate and this reduction in stiffness ultimately reduces the natural frequencies. Further, this also changes the mode shape of vibration. An analysis of the propagation of the vibration signal makes it possible to detect the fault.

An extensive literature review of the state of art of vibration analysis and damage detection has been recently published by S.W. Doebling [1]. A detailed survey of the state of art in the damage detection field using modal analysis has been presented by Richardson[2[. A detailed review of the different vibration and acoustic methods such as the time and frequency domains, acoustic emission technique are presented by Tandon and Nakra [3]. Using fracture mechanics method, Dimarogonas [4] and Anifactis [4] computed the equivalent stiffness and developed a model for crack detection in beams. An experimental technique to estimate the location and depth of a crack in a beam has been developed by Adams and Cawley [6]. The methodology of crack detection based on natural frequency changes has been closely studied by Shen and Pierre [7]. In this paper, it is proposed to detect a faulty location based on the statistical time energy based features extracted from the vibration signal.

II. EXPERIMENTAL DESIGN AND DATA AQUISITION

A. Data Acquisition System (DAQ)

Measurements of the vibration signals are acquired using a LMS SCADAS Mobile SCM01 Data Acquisition System. This system has 4 input channels and Ethernet connectivity to the LMS Test Lab 8A software. The features supported by the LMS SCADAS are: a maximum sampling frequency range of up to 102.4 kHz per channel, 105 dB signal to noise ratio and a high speed Ethernet connection. The DAQ system is monitored through the LMS Test Lab software which supports a wide range of applications.

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B. Vibration and Pressure Transducers

Accelerometers are Vibration transducers which possess high natural frequencies compared to the vibration to be measured and indicate acceleration [8]. The piezoelectric accelerometers are widely preferred over the digital accelerometers in many applications due to its high accuracy and sensitivity. The general purpose Piezoelectric accelerometer with an input sensitivity of 10 / 31.6 / 100mV/g ($g = 9.82\ m/s^2$) and a resonant frequency of 28 kHz is used in this experimental work.

Force transducers are used to produce impulse forces and commonly used for impact tests. The general purpose force transducers or so called impact hammer (Dytran 5800B2 - 50LbF range, 100 mV/LbF) is used in this research work.

C. Experimental Setup

A simple experimental design to test the structure in a simply supported condition is proposed in this paper. An aluminum test rig of dimensions (90x60x3) cm is fabricated and used as a test bed. Two thin threads are tied across the test bench to hold the steel plate in a simply supported manner. The distance between the two threads is 40 cm. A fresh stainless steel plate of dimensions (60x24x1) cm without any crack is considered for the experiment. The Steel plate is then mounted on the test rig as shown in the figure 1.

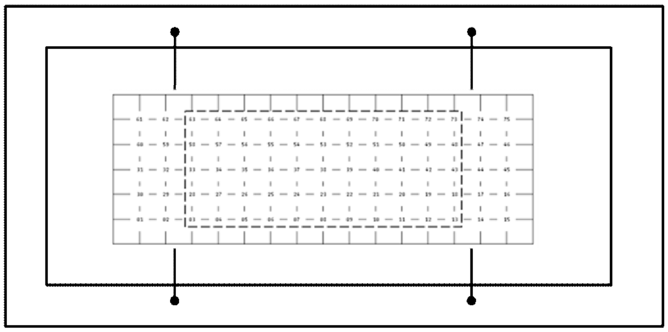

Fig. 1. Experimental Setup to simply support the steel plate

C. Estimation of Natural Frequency of Steel plate

The natural frequency or eigen frequency of a system is the frequency at which the system oscillates. Any material possesses its own natural frequency. The natural frequency is a physical property which subsequently gets affected when there is a damage caused to the system. The sample steel plate has the following values: Poisson ratio(μ) = 0.3, Young's modulus(E)=210N/mm^2, Length(l)=60x 10^{-1}m and Thickness(h)=1x10^{-2}m,. The calculation for the natural frequency of the steel plate structure is computed [9] using the equation (1)

$$D = \frac{Eh^2}{12(1-\mu^2)} \text{Nm} \tag{1}$$

$$f_n = \frac{1}{a^2}\sqrt{\frac{D}{\rho h}} \text{ Hz} \tag{2}$$

where D is the stiffness of the plate, *(D)*=1750Nm and f_n is the calculated natural frequency of the plate, *(f_n)*=41.316 Hz.

D. Data Capturing Procedure

The steel plate is divided equally into 16 columns and 5 rows thus forming cells of size (4x4) cm^2. The cell contact points(nodes) are numbered continuously. Based on the physical properties of the steel plate such as natural frequency (f_n) and mode shape, the sampling frequency *(f_s)* is set to 2048 Hz. The impact test is limited to 16 cells and 9 impact nodal points as depicted in the fig 2. The impact hammer is connected to the first ICP channel of the DAQ system. Three accelerometers are connected to the second, third and fourth ICP channels respectively. An impulsive force is generated by hitting the impact hammer on a nodal point on the steel plate. The force of impact hammer hit is measured and recorded. The vibration propagated is measured at the nearest three node points using the accelerometers. The above experiment is repeated for a minimum of 5 times and for 15 seconds and is recorded. Similarly this procedure is repeated for all the nodal points considered in the experiment. The above measurements are done in the undamaged situation of the steel plate. Damages of micro cracks are made externally through sharp nails inside the cells and the above experiment is repeated for the damaged situation. The signals captured are in the '.xdf' format, which are then exported to '.wav' format using the LMS Text Lab software for analysis.

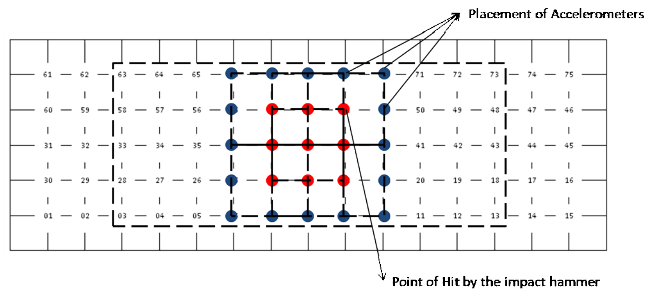

Fig. 2. Placement of Accelerometers and the point of hit

III. FEATURE EXTRACTION

A. Signal conditioning

The time domain representation of the vibration signal is written as.

$$A = \{x_1, x_2, x_i \ldots x_n\} \tag{3}$$

where i = 1,2,3,…N and $x_1, x_2, \ldots x_n$ are the window frames each having 256 samples. The vibration signal which is sampled at 2048 Hz and segmented in windows of 0.125s. For each Hamming window function as described below is applied to each window frame.

$$w(n) = \alpha - (1-\alpha)\cos\left(\frac{2\pi N}{N-1}\right) \tag{4}$$

where $\alpha = 0.54$

B. Statistical Time Energy Feature Extraction

The following statistical time energy features are extracted using a simple matlab program for the processed signal.

Root Mean Square (RMS): The root mean square value of a vibration signal is a time analysis feature that is the measure of the power content in the vibration signature. [10] The equation used to calculate the root mean square value of a data series; x_n over length N,

$$RMS = \sqrt{\frac{1}{N} * \sum_{n=1}^{N} x_n^2} \tag{5}$$

Kurtosis (K): Kurtosis is defined as the fourth moment of the distribution and measure of the size of the tails of distribution and is used as an indicator of the major peaks in a set of data [10] The equation for kurtosis is given by

$$K = \frac{\sum x_n^2 \left[y(n) - \mu\right]^4}{N * \left(\sigma^2\right)^2} \tag{6}$$

Delta Energy (ΔE)*:* The sum of change in energy of successive frames is referred to as Delta Energy and it is calculated using the following equation.

$$\Delta E = \sum_{k=1}^{n-1} \left(e_{k-1} - e_k\right) \tag{7}$$

Number of Slope Changes (SC): A change in slope is considered when there is a change between two successive frame energies.

IV. Classification Using Artifical Neural Networks

A. Artificial Neural Networks

An artificial neural network is an information processing system that has been developed as a generalization of the mathematical model for human cognition. [11]

Artificial Neural Networks (ANN) provides alternative form of computing that attempts to mimic the functionality of the brain. One of the most used learning methods in ANN is back propagation. The back propagation method (BP) is a learning procedure for multilayered feed forward neural networks.

BP is being used in a wide variety of application such as information processing, pattern recognition etc., BP procedure can be considered as a non linear regression technique which trains a neural network to acquire an input output association using limited number of samples chosen for a population of input output pattern. BP is most widely used learning algorithm since it is very simple to implement.

B. Neural Network Architecture

The neural network architecture consists of 4 layers, the first layer is for the input neurons, the second and third layers are for the hidden layers 1 and 2 respectively. The last layer are for the output neuron.

For training the neural network, 13 input neurons are used, 1 input neuron to indicate the magnitude of the impulse signal, 1 input neuron for the number of slope changes, 3 input neurons for the root mean square, kurtosis and delta energy for the computed frame energies for the captured accelerometer signals. The output neuron is used to classify whether there is a fault present in the cell or not. Among the recorded 406 samples, 60 percent (243), 65 percent (263) and 70 percent (284) data samples are used for training and all the 406 data samples are used for testing the network model.

C. Neural Network Training and Results

A 4 layer neural network with 13 input neurons, 25-25 hidden neurons and 1 output neuron is considered. Each trial consists of 2000 sets of randomized weight samples. The sum squared tolerance is fixed as 0.01. The input and hidden neurons are activated by the sigmoidal activation function. The network is trained by Levenberg Marquardt back propagation procedure. The results for training the network is tabulated in Table 1 which shows the mean epoch and the mean classification rate.

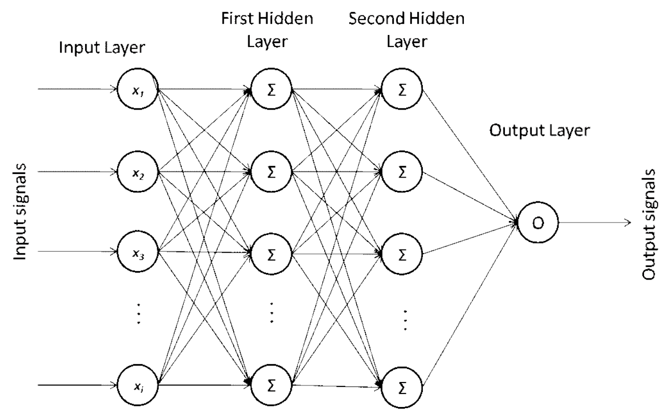

Fig. 3. Architecture of a multi layer perceptron with two hidden layers.

TABLE I
RESULTS OF THE NEURAL NETWORK TRAINING

Input neurons		13		Training Tolerance	0.01	
Output neurons		1		Testing Tolerance	0.2	
Hidden neurons		25, 25		Testing Samples	406	
Activation function		sigmoidal		Maximum Epochs	2000	
	60 % = 243 samples		65 % = 263 samples		70 % = 284 samples	
No	**Epochs**	**CR (%)**	**Epochs**	**CR (%)**	**Epochs**	**CR (%)**
1	1192	86.1083	1564	83.0049	1421	90.886
2	1070	79.6453	2000	79.3103	1192	84.7290
3	1594	84.6305	1070	89.4088	1176	84.4827
4	2000	80.3103	1594	80.0492	1594	83.7438
5	1230	83.7438	2000	82.7586	736	86.4532
Mean	**1417.2**	**82.88**	**1645.6**	**82.90**	**1223.8**	**86.05**

V. Conclusion and Future work

This paper presented a simple testing method for the vibration based damage detection. A simple neural network is modeled and the faults are identified based on the statistical time energy features extracted from the captured vibration signal. By this we conclude that the presented method provides a foundation for using time domain features for the detection of defects in the steel plate structure.

Further work is needed, by using frequency and time frequency methods for better feature extraction. Furthermore development of an improvised neural network to be investigated for better accuracy and less computation complexity.

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