Structural Steel Plate Damage Detection using Artificial Neural Network

Paulraj M P[1] Mohd Shukry A M[1] Sazali Yaacob[1] Abdul Hamid Adom[1]
Manigandan T[2] R Pranesh Krishnan[1]
[1]School of Mechatronics Engineering, Universiti Malaysia Perlis,
Ulu Pauh Campus, Arau, 02600, Perlis, Malaysia.
[2]Kongu Engineering College, Perundurai, Erode, 638052, Tamilnadu, India.
paul@unimap.edu.my, praneshkrishnan@gmail.com

Abstract- In this paper, simple methods for crack identification in steel plates and their classification based on the frame energy based discrete cosine transform moment features is presented. Based upon the boundary conditions and experimental modal analysis, two simple experimental methodsare designed and used to measure the vibration at different positions of a steel plate. The plate is excited by an impulse signal and made to vibrate. The signal is then blocked into frames and the absolute discrete cosine transformation coefficients are computed. The moments from the absolute DCT Coefficients are extracted as features. The condition of the steel plate is associated with the extracted features to form a final feature vector. A simple neural network model is developed, trained by Back Propagation algorithm. The effectiveness of the system is validated through simulation.

Keywords-Vibration Signal, Experimental Modal Analysis, Statistical features, Discrete Cosine Transformation, 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. Structural Health Monitoring (SHM) is a inverse problem which mainly concentrates on damage existence, damage localization and damage extent measurement. The purpose of SHM is to ensure high reliability and less maintenance cost throughout the lifetime of the structure.

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, aircraft 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 non-destructively.

An extensive literature review of the state of art vibration analysis and damage detection has been 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 techniques are presented by Tandon and Nakra [3]. Using fracture mechanics method, Dimarogonas [4] and Anifactis [5] 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 setup two experimental arrangements to capture the vibration signals from a stainless steel plate in pre and post damage conditions. The frame energy based discrete cosine transformation moment features are extracted from the vibration signal. The features are associated with the condition of the steel plate. A Feed Forward Back Propagation network model is developed, and the features are trained using Levenberg-Marquardt method and tested. The results obtained are tabulated.

II. EXPERIMENTAL DESIGN AND DATA ACQUSITION

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. The features supported 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.

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/s2) 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.

Experimental Setup

A clean 2B Stainless steel plate of length 60 cms, breadth 24 cms and thickness 1.2 mm are subjected for this testing. The steel plate is divided into 6 rows and 15 columns forming a grid structure of cell size 4x4 cm^2 as shown in the figure 1 and figure 2. The cells of 6 rows and 6 columns are numbered sequentially as represented in figure 2. Two simple experimental test setups are fabricated to test and evaluate the condition of the steel structure using non-destructive experimental modal analysis (NDEMA).

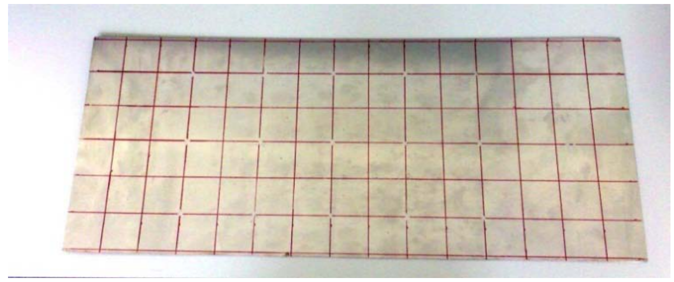

Fig.1. 2B Stainless Steel Plate divided into cells

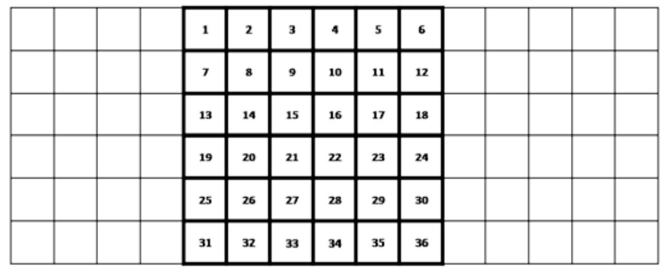

Fig.2. Grid formation of the steel structure

Test Setup 1. Case A

An aluminum test rig of length 90 cms, breadth 60 cms and height 3 cms is fabricated. The rectangular stainless steel plate of mass 1.2 kilogram is freely placed over the test setup. The plate is simply supported by two thin threads tied across the test bench 30 cms apart from each other as shown in figure 3a. The test setup is placed on a rubber mattress to avoid external vibrations.

Test Setup 2. Case B

An Iron swing frame setup of height 5 feet and width 3 feet is constructed. The Stainless Steel plate is clamped and hinged between the two holders while the other end of the steel plate is set free as shown in the figure 3b. The distance between the two holders is 40 cms.

Natural Frequency estimation of Steel Plates

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 fundamental frequency estimation becomes important since the test object is subjected to non destructive experimental modal testing. The sample stainless steel plate has the following values: Poisson ratio (μ) = 0.3, Young's modulus (E) = 210 N/mm^2, Length (l) = 60x$10^{-1}$$m$ and Thickness (h) =

$1.2\text{x}10^{-2}$ m. The natural frequency can be computed [9] using the equation (2)

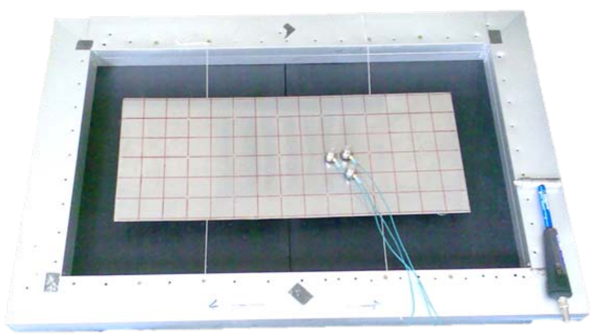

Fig.3a. Experimental Test Setup of Steel Plate Simply Supported

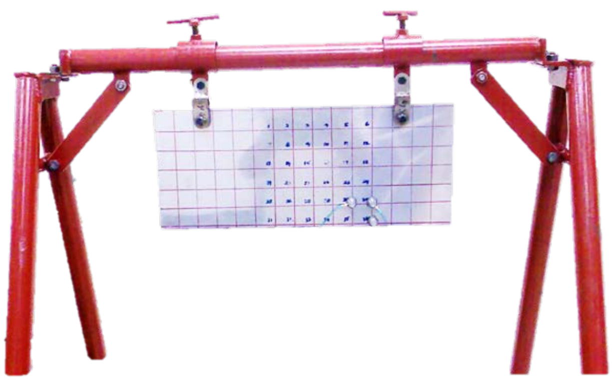

Fig.3b. Experimental Test Setup of Steel Plate Hinged one side

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

$$f_n = \frac{\frac{1}{a^2}}{\sqrt{\frac{D}{\rho h}}} Hz \qquad (2)$$

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

Data Capturing Protocol and Procedure

Based on the physical properties of the steel plate such as natural frequency, mode shape, the sampling frequency is set to 4 kHz [16]. The impact hammer is connected to the first ICP channel of the Data Acquisition System. Three general purpose mono axis accelerometers are connected to the second, third and fourth ICP channels respectively. An impulse force is generated by striking the impact hammer on a nodal point on the steel plate. The vibration generated due to the external impulse force is propagated throughout the plate.

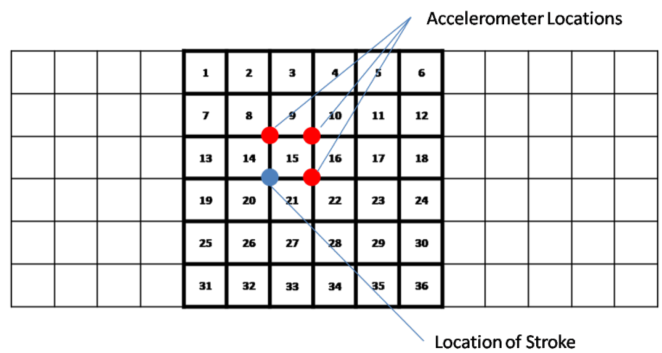

Fig.4.Location of Strike – Protocol 1

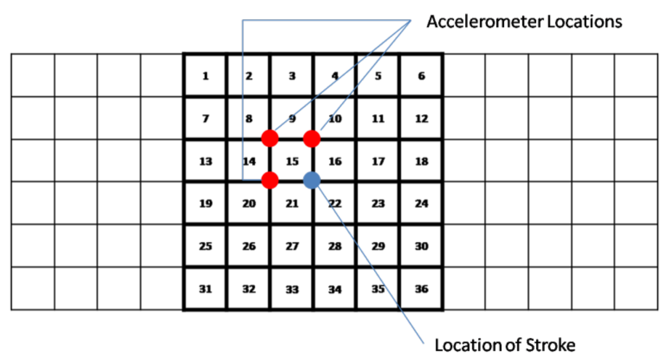

Fig.5.Location of Strike – Protocol 2

The level of vibration at the nearest three nodal points is measured using the accelerometers. The placement of the accelerometers and the location of strike are now changed at the same cell as represent are depicted in the figures 5, 6, 7 and 8. The impulse force and the level of vibration at the nearest locations are recorded for 20 seconds at a sampling rate of 51.2 kHz. This procedure is executed in all the 36 cells and the vibration signal is recorded in all the 144 nodal locations during the healthy condition of the stainless steel plate. A total of 1440 signals are recorded for the healthy condition by executing 10 similar trials. The signals recorded using the two experimental setups and the data is considered as Case A: Simply supported and Case B: Hinged Free.

Damages in the form of micro holes of dimensions 0.1 – 0.5 microns are created randomly on the surface of the stainless steel plate using drill heads within the cells. The damages are made in all the 36 cells. The vibration signal is recorded in all the 144 nodal locations during the faulty condition using the same procedure described above. A total of 1440 signals are recorded for the faulty by executing 10 similar trials. These captured signals are in default file format '.xdf' of the Data Acquisition System, which are then exported as Microsoft '.wav' file format for further analysis through MATLAB.

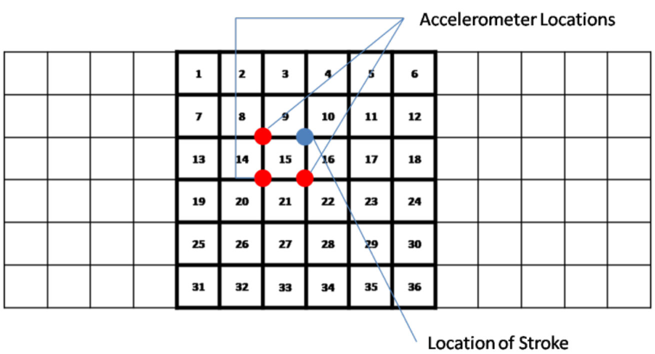

Fig.6.Location of Strike – Protocol 3

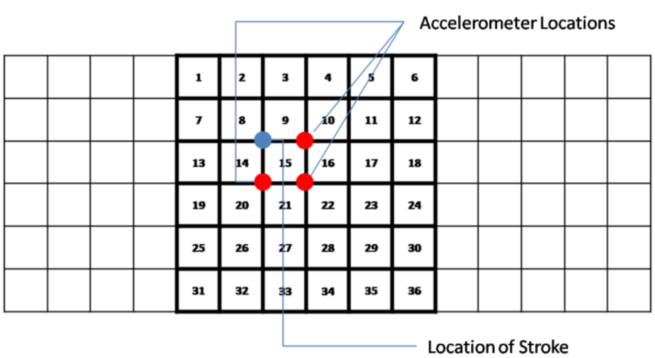

Fig.7.Location of Strike – Protocol 4

III. DATA PRE PROCESSING

Signal Downsampling

The vibration signals at various locations are recorded at a sampling frequency of 51.2 kHz. The vibration signal is then down sampled using a FIR Decimator to a sampling frequency of 4 kHz (4000 samples per second).

Signal Clipping

In the time domain signal recorded during the data acquisition process, the time of the strike of the impact hammer is a variable factor. The signal is recorded for 20 seconds, whereas the location of the occurrence of the peak falls anywhere before the first 5 seconds. In order to provide consistency throughout the data analysis, the vibration signal recorded is clipped to 15 seconds leaving 0.5 seconds before the occurrence of the peak and 14.5 seconds after the peak. The final length of clipped signal is 60000 samples at a sampling frequency of 4000 samples per second.The figure 8 shows a typical clipped signal.

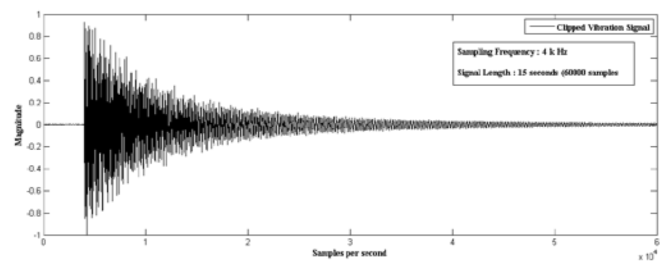

Fig.8.Clipped Vibration Signal

IV. FEATURE EXTRACTION

Signal Framing

The transient vibration signal is divided into 117 frames such that each frame has 512 samples.

$$X = \{x_1, x_2, x_3, \dots, x_{117}\} \quad (3)$$

Frame Energy Computation

For each frame the total energy is computed using the equation (4).

$$e_i = \sum_{j=1}^{512} x^2_{(i-1)w+j} \quad (4)$$

where

$$x_i = \{x_{(i-1)w+1}, x_{(i-1)w+2}, x_{(i-1)w+3}, \dots, x_{(i-1)w+w}\}$$

and w = frame width.

Discrete Cosine Transformation Coefficients

The Discrete Cosine Transformation (DCT) represents the signal as a sum of sinusoids of varying magnitudes and frequencies.

$$y(k) = w(k) \sum_{n=1}^{N} x(n) \cos\left(\frac{\pi(2n-1)(k-1)}{2N}\right) \quad (5)$$

where $k = 1,2,3, \dots, N$

$$w(k) = \begin{cases} \frac{1}{\sqrt{N}} \\ \sqrt{\frac{2}{n}} \end{cases} \quad (6)$$

where $2 \leq k \leq N$ and $k = 1$

Using equation (5) and (6) the DCT is applied to the discrete frame energies. The absolute values of the DCT coefficients are considered for further analysis.

Moments of DCT Coefficients

The maximum amplitude (moments) values and their corresponding index values are calculated from the DCT Coefficients. The first 4 DCT Coefficients moments is extracted from each signal. The DCT moment features from the three accelerometers form the feature matrix of 12 features per each sample.

V. DATA POST PROCESSING

Feature Selection and Reduction

The features that contribute towards the better classification need to be identified. The important features are identified using feature selection methods or feature reduction methods based on the problem domain. In this work the principal components which contribute towards the better classification are calculated using Principal Component Analysis (PCA). The reduced set of features corresponding to better classification forms the final feature vector. On applying the PCA the principal components are identified to be 8input vectors in Case A and 7 input vectors in Case B.

Data Normalization

Data Normalization is the process of rescaling of the data into a definite boundary. Normalization of data improves speed and reduces complexity during classification. Each feature in the final feature vector is normalized using a normalization criterion. In this work a binary normalization algorithm is applied to normalize the input data to a definite range between 0 and 1, the associated target vector remains 0 for healthy and 1 for faulty.

The final feature vectors formed using the DCT moments are associated with the condition of the steel plate.The database consists of a total of 2880 samples in which 1440 are healthy samples and 1440 are faulty samples. These datasets are randomized and fed as input for the Classifier.

VI. CLASSIFICATION USING ARTIFICIAL NEURAL NETWORK

Artificial Neural Network

An artificial neural network is an information processing system that has been developed as a generalization of the mathematical model for human cognition. [8]

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.

Neural Network Architecture

The neural network architecture consists of 3 layers, the first layer is the input layer, the second layer is the hidden layer and the third layer is the output layer.
For Case A, to trainthe neural network, 8 input neurons are used. The hidden layer has 15 neurons and the output layer has only one neuron. The output neuron is used to classify whether there is a fault present in the cell or not.
For Case B to train the neural network, 7 input neurons are used. The hidden layer has 15 neurons and the output layer has only one neuron. Among the recorded 2880 samples, 60 percent (1728), 70 percent (2015) and 80 percent (2304) data samples are used for training and all the 2880 data samples are used for testing the network model.

Neural Network Training and Results

A 3 layer neural network with 8 input neurons, 15 hidden neurons and 1 output neuron is considered. Each trial consists of 1000 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 trained neural network is tested with the test data containing 2880 samples with a testing tolerance of 0.1. The results for training the network is tabulated in Table 1 and Table 2 which shows the mean epoch and the mean classification rate.The network is trained using 60, 70 and 80 percent of samples and tested using 100 percent samples by simulation.

TABLE 1
NEURAL NETWORK TRAINING RESULTS -SIMPLY SUPPORTED

Input Neurons : 8 Output Neurons : 1 Hidden Neurons : 20 Maximum Epoch : 1000			Training Tolerance : 0.01 Testing Tolerance : 0.1 Testing Samples : 2880 Activation Function : Sigmoidal			
	Training Samples					
	60 % = 1728		70 % = 2015		80 % = 2304	
No	Epochs	CR (%)	Epochs	CR (%)	Epochs	CR (%)
1	809	79.93	875	85.2	374	87.17
2	699	79.89	407	84.87	501	85.52
3	1000	80.04	676	83.79	1000	86.76
4	1000	78.42	1000	85.45	1000	88.67
5	712	82.67	1000	84.78	1000	88.34
Mean		**80.19**		**84.81**		**87.29**

TABLE 2
NEURAL NETWORK TRAINING RESULTS–CASE B.HINGED FREE

Input Neurons : 7 Output Neurons : 1 Hidden Neurons : 20 Maximum Epoch : 1000			Training Tolerance : 0.01 Testing Tolerance : 0.1 Testing Samples : 2880 Activation Function : Sigmoidal			
	Training Samples					
	60 % = 1728		70 % = 2015		80 % = 2304	
No	Epochs	CR (%)	Epochs	CR (%)	Epochs	CR (%)
1	870	82.22	789	87.57	1000	88.19
2	1000	79.16	1000	83.59	1000	86.32
3	672	81.59	1000	85.87	800	90.72
4	508	80.17	1000	86.28	561	89.34
5	1000	82.56	459	87.59	897	88.77
Mean		**81.14**		**86.18**		**88.66**

V. CONCLUSION AND FUTURE WORK

This paper presented two simple experimental methods for the non-destructive vibration based damage detection. DCT moments features extracted from the frame energy are used in analyzing the vibration signals. The features are associated with the condition of the steel plate to form the final feature matrix. A simple neural network is modeled and trained using Back Propagation algorithm. The mean classification accuracy in Case A and Case B is tabulated.

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