Diagnosis of steel plate damage using vibration signals

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Abstract: *In this paper the frame energy based statistical features extracted from the minimum and maximum values of the vibration signals are used for the detection of damages in steel plate. Two simple experimental prototypes are formulated to suspend the steel plate in fixed free and free-free conditions. Experimental modal analysis methods are considered and protocols are formed to capture vibration signals from the steel plate using accelerometers when subjected to external impulse. Algorithms are developed to compute the maximum and minimum values of the three accelerometers with respect to time index. From the derived maximum and minimum signals, frame energy based statistical features are extracted. A Feedforward Backpropagation Neural Network (BPNN) is developed to model and classify the condition of the steel plate. The results of the network model are validated.*

Keyword: *Experimental Modal Analysis, Frame energy, Statistical features, Feedforward Backpropagation Neural Network.*

I. INTRODUCTION

Damage can be defined as the changes introduced into a system that brings adverse effects in the present and future performance. Damage becomes expressive when it is compared between two different states of the system. Cracks are well-defined as any unintentional discontinuities in the shaft material. The occurrence of the faults or damages in the structures is quite unavoidable mainly due to environmental conditions, improper handling, poor maintenance and wear and tear. A detailed comprehensive survey on the nondestructive measuring techniques has been dealt by Brinksmeier [1]. Dimarogonas [2] presented a detailed review on nondestructive testing to detect and monitor cracks in beams, plates, rotors, and turbine plates. An extensive literature review of the state of art vibration analysis and damage detection has been published by S.W. Doebling [3]. A complete survey of the state of art in the damage detection field using modal analysis has been presented by Richardson [4]. A comprehensive review of the different vibration and acoustic methods such as the time and frequency domains, acoustic emission techniques are presented by Tandon and Nakra [5]. Using fracture mechanics method, Dimarogonas [2] and Anifactis [6] 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 [7]. The methodology of crack detection based on natural frequency changes has been closely studied by Shen and Pierre [8].

The nondestructive approach is engaged towards the identification of the damages in the steel plate. Non Destructive Testing (NDT) can be defined as the study of the impulse response of a system due to an external excitation that confronts the dynamic nature of the system under test. The vibration signal is recorded from the system when it is subjected to an external excitation. The presence of damage in the system is studied by closely studying the vibration pattern at an instance. The vibration pattern carries the dynamic characteristics of the system such as fundamental frequency, damping ratio and mode shape.

In this paper, the maximum value and the minimum value of the vibration signal obtained from the three accelerometers are used to study the existence of damages in the steel plate. The frame energy based statistical features from the vibration signals are extracted and a neural network classifier is modeled to classify the condition of the steel plate.

II. METHODOLOGY

Experimental Modal Analysis (EMA) is defined as a process of acquiring acceleration response data (excitation of the structure using external force and obtaining the response to the force) and identification of the modal parameters [9]. A cold rolled steel plate of size 60 cm width and 24 cm length and of thickness 2mm and mass 1.2 kg is considered for this study. To suspend the steel plate in a simply support boundary condition an aluminium framework is fabricated. The steel plate is suspended over the framework using two thin threads.

Using EMA, the vibration study can be performed in *x*, *y* and *z* planes Since the steel plate is an isotope, the characteristics of the vibration response in all three planes is similar, Hence the experimental design is developed to study the vibration response of the steel plate in *x-y* plane. There are two commonly used impact tests: Roving hammer and Roving accelerometer. In the roving hammer test the location of the impact hammer is changed during every test while the accelerometers are placed intact in the numbered locations. In the roving accelerometer test, the accelerometers are placed at even locations on the structure. The location of excitation is fixed at the same place throughout the test, while the accelerometer locations are changed during every trial of the test.

Materials and Protocol Design

The data collection protocol is the set of methods or rules framed to ensure the consistency of the measured vibration signals throughout the data collection process. The steel plate is divided into 6 rows and 15 columns. The area of the cell is 4 cm^2 and the cells are numbered sequentially from 1 to 36. An experimental protocol is designed based on both the roving hammer and roving accelerometer tests. The accelerometers are mounted over the corners of the cells based on the protocol design shown in Figure 1.

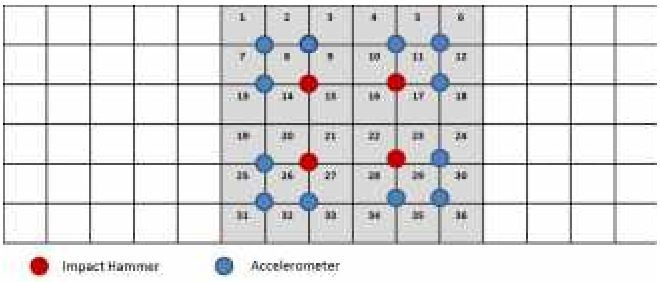

Figure 1: Experimental protocol design

An impulse is generated when the impact hammer strikes over the location on the steel plate. The accelerometers capture the vibration signal connected to the Data Acquisition System (DAQ). The experiment is carried out on all the 36 cells and 144 possible combinations of the 4 protocols by changing the positions of the accelerometers and the impact hammer. The recorded signals are sequentially numbered and saved. Small micro damages of size 531 μm to 1870 μm are created throughout the steel plate inside the 36 cells and the data collection is carried out for all the locations. The experimental data is collected at various locations of the steel plate under normal and fault conditions. The experiment is repeated and the vibration signal is obtained from 10 steel plates of similar dimensions. Thus 1440 samples are captured and recorded for normal conditions. Similarly 1440 samples for fault conditions are collected after drilling small holes on the steel plates. The data collected is stored in the native 'XLF' file format supported by the DAQ. The files are later converted into 'WAV' file format for further processing through MATLAB.

Maximum and Minimum Value Computation

The vibration signals are captured using an experimental protocol from the steel plate at a sampling rate of 4 kHz [10]. The vibration signal is recorded for 20 seconds during the impact test. Instead considering the three accelerometer responses, the maximum values of the three accelerometer responses are computed and the resulting signal is further investigated. Similarly, the minimum values of the vibration signal obtained from the three accelerometers are computed and the resulting signal is used for further analysis.

The computed maximum and minimum signals are trimmed for 15 seconds by identifying the first peak and considered 0.5 seconds before the peak and 14.5 seconds after the peak to maintain uniformity throughout the analysis. The trimmed signal is then segmented into definitive frames of size 1024. The representation of the blocked frames is shown in Figure 2.

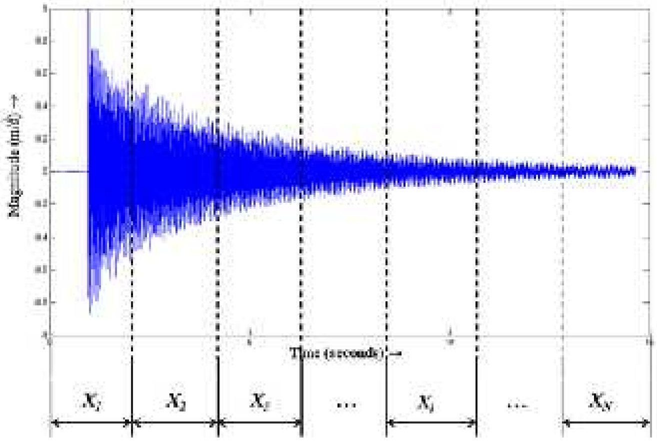

Figure 2: Vibration signal blocked into frames

Frame Energy

The total energy of a signal is defined as the sum of the squared magnitudes of the signal components. The law of conservation of energy states that, the energy can neither be created nor be destroyed, but can be transformed from one form to another. This law applies to this problem domain, where the energy in the form of mechanical force exerted by the impulse hammer is distributed all over the steel plate as vibration pattern. The energy in the form of vibration is affected by the damages present in the steel plate. The energy of the frame is calculated by computing the sum of the squared magnitudes of each frame. The Energy $\boldsymbol{E}$ of the signal is given in equation (1)

$$\boldsymbol{E} = [e_1, e_2, e_3, \ldots, e_i, \ldots, e_N] \qquad (1)$$

where e_i is the frame energy in the i^{th} frame and it is represented in equation (2).

$$e_i = \sum_{j=1}^{1024} x_{ij}^2 \qquad (2)$$

where x_{ij} is the j^{th} signal of the i^{th} frame. Typical frame energy of a normal and faulty signal is shown in Figure 3.

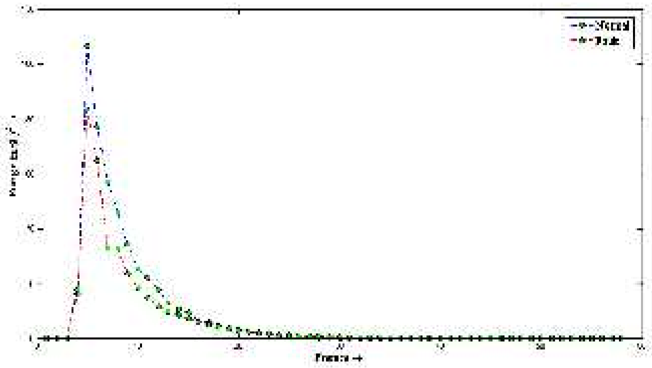

Figure 3: Typical Frame energy of normal and fault signals

Statistical Feature Extraction

Algorithms are developed to extract the fundamental statistical features for the frame energy computed from the vibration signal, namely:

1) Maximum (*Max*):

The maximum value of each frame of the vibration signal.

2) Skewness (*Skew*):

The Skewness value of each frame of the vibration signal.

3) Mean (*Mean*):

The mean value of each frame of the vibration signal.

4) Root Mean Square (*RMS*)

$$RMS = \sqrt{\frac{1}{N}\sum_{n=1}^{N} x_n^2} \qquad (1)$$

where N is the total number of frames in the signal and x_n^2 is the energy of each frame [11].

5) Variance (*Var*)

$$Var = \frac{\left(\sum_{n=1}^{N} x - \frac{x^2}{n}\right)^2}{n-1} \qquad (2)$$

where N is the number of frames.

6) Kurtosis (K)

$$K = \frac{\sum x_n^2 \left[y(n) - «\right]^2}{N\left(± ^2\right)^2} \tag{3}$$

where « is the mean of the signal and ± is the standard deviation of the signal.

7) Crest Factor (CF)

$$CF = \frac{Max}{\sqrt{Var}} \tag{4}$$

8) Delta energy (ΔE)

$$\Delta E = \sum_{k=1}^{n-1} \left(e_{k-1} - e_k\right) \tag{5}$$

where e_k is the kth frame energy,

9) Number of slope changes.

$$\Delta S = \sum_{i=1}^{N-2} f\left(\Delta e_{i+1} * \Delta e_i\right) \tag{6}$$

$$f\left(\Delta e_{i+1} * \Delta e_i\right) = \begin{cases} 1 & if\ \left(\Delta e_{i+1} * \Delta e_i\right) < 0 \\ 0 & if\ \left(\Delta e_{i+1} * \Delta e_i\right) \geq 0 \end{cases} \tag{7}$$

where Δe_i is the change in frame energy of the ith frame and $f\left(\Delta e_{i+1} * \Delta e_i\right)$ is the slope change

ANN Classification

Artificial Neural Networks are widely used for pattern classification. In this research work, a Feedforward Backpropagation Neural Network classifier is modeled to classify the condition of the steel plate. The features extracted from the vibration signal are provided as input and the condition of the steel plate as output to the neural network.

The nine statistical features extracted from the maximum signals are associated with the condition of the steel plate for the final feature matrix.

NN Training and Testing

The feature vectors contain the input - output association. The network model contains three layers namely input, hidden and output. The input layer is provided with the feature vectors which constitutes the input neurons to the network. The output layer is associated with the target vectors corresponding to the input vectors. The hidden neurons contribute towards the weighted connections of the neural network.

The nine statistical features extracted from the vibration signal are fed as input neurons. The condition of the steel plate: 0 in case of normal and 1 in case of fault is mapped as the output neuron. The hidden neurons in the hidden layer are allocated experimentally. The ‘trainlm’ function available in MATLAB neural network toolbox is used to model, train and simulate the neural network.

The training parameters such as hidden neurons, learning rate, hidden and output activation functions are experimentally set as 21, 0.01, *tansig* and *logsig* respectively. The training tolerance is set to 0.03.

Per each trial of training, the dataset is randomly divided into 60%, 70% and 80% samples and the remaining samples are used for testing. The trained network model is tested and validated against the remaining testing samples which include unseen inputs by the trained network. The trained network is tested and results are tabulated.

III. RESULTS AND DISCUSSION

The mean classification results of the BPNN trained networks using the maximum and minimum datasets of simply supported and fixed free experimental methods are tabulated in Tables 1 and 2.

Table 1: BPNN Training Results- Maximum Database

	60%	**70%**	**80%**
Simply supported	90.77	91.68	91.85
Fixed Free	91.24	91.97	92.79

Table 2: BPNN Training Results- Minimum Database

	60%	**70%**	**80%**
Simply supported	91.18	91.88	92.63
Fixed Free	91.26	92.11	92.84

The results show that 80 percent data samples of Fixed free minimum database samples produce better results compared to other models.

IV. CONCLUSION

In this work, two experimental frameworks were developed to suspend the steel plate. A simple protocol based on the roving hammer and roving accelerometer tests were designed to perform impact testing and capture the vibration signal from the steel structure. Unlike the previous works of the authors, the maximum values and the minimum values of the three accelerometers signals are computed instead of considering the three accelerometer signals and further frame energy based statistical features were extracted. Backpropagation Neural Network Classifier was modeled to classify the condition of the steel structure. The output of the network models show promising results with minimum number of signals considered for analysis. The authors will further investigate in the implementation of novel feature extraction methods.

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