Malaysian Technical Universities Conference on Engineering and Technology (MUCET) 2012
Part 1- Electronic and Electrical Engineering [137-144]

Structural Steel Plate Damage Detection using Non Destructive Testing, Frame Energy based Statistical Features and Artificial Neural Networks

Paulraj M P, Sazali Yaacob, M S Abdul Majid, Mohd Nor Fakhzan Mohd Kazim, Pranesh Krishnan
School of Mechatronic Engineering,
Universiti Malaysia Perlis,
Perlis, Malaysia.

***Abstract* — This paper discusses about the detection of damages present in the steel plates using nondestructive vibration testing. A simple experimental model has been developed to hold the steel plate complying with the simply supported boundary condition. Vibration patterns from the steel structure are captured based on the impact testing using a simple protocol. The vibration signals in normal condition of the steel plate are recorded. The damages of size 512 μm to 1852 μm are simulated manually on the steel plate using drill bits. The vibration signals in the fault condition of the steel plate are collected. The captured vibration signals are preprocessed and time domain based feature extraction algorithms are developed to extract features from the vibration signals. The conditions of the steel plate namely healthy and faulty are associated with the extracted features to establish input output mapping. A feed-forward neural network is modeled to classify the condition. The neural network parameters are adjusted to train the network. The performance of the network is calculated using Falhman criterion.**

Keywords - non destructive testing, vibration signals, frame energy based statistical features, feed-forward neural network.

I. INTRODUCTION

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 tasks 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 is often used methodology in evaluating the health of a structure by studying the level of deterioration and the life of the structures [1]. This approach is widely applied to investigate bridges and buildings. The study on the structural health helps to improve the safety measures and life of the structure. 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. Non Destructive Testing (NDT) methods attain more importance in the damage detection and are extensively researched. The nondestructive approach is engaged towards the identification of the damages in the steel plate. 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 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 [2]. A detailed survey of the state of art in the damage detection field using modal analysis has been presented by Richardson [3]. 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 [4]. Using fracture mechanics method, Dimarogonas [5] 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].

In this work, a simply supported boundary condition based experimental arrangement to capture the vibration signal from a stainless steel plate in normal and fault conditions is developed. The vibration signal is recorded from the system using a data capturing protocol by subjecting the steel plate 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 at a certain location carries the dynamic characteristics of the system such as fundamental frequency, damping ratio and mode shape. 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 simple feed-forward neural network is modeled. The neural network parameters are adjusted to train the network. The performance of the network is calculated using Falhman criterion.

II. EXPERIMENTAL DESIGN AND DATA COLLECTION

A. *Experimental Modal Analysis (EMA)*

Non Destructive Testing / Evaluation (NDT/E) can be applied to any new structures. The objective of the test is to inspect and assess the quality and integrity of the structure under study. 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] The origin of EMA dates back in the late 1970's where the impact testing was widely used methodology in the vibration research. EMA for damage detection involves data acquisition, modal parameter estimation and observation of damage by further analysis. An optimal selection of excitation methods, transducers and measurement parameters is the fundamental part of the experimental modal analysis. EMA in their early stages was used to measure the modal parameters of any system such as natural frequency and mode shape.

B. *Experimental Setup*

The best possible selection of the parameters concerning the modal analysis measurement involves proper choice of the suspension type to hold the test subject, structural excitation and response point selection, transducers used for measurement, method of excitation and data acquisition.

A 2B type stainless steel plate of the dimensions 60 cm long and 24 cm wide and 1.2 mm thickness weighing a mass of 1.2 kg is used in the experiment. The test structure is cleaned to remove stains before the experiment. Fig. 1 shows a typical undamaged stainless steel plate.

The steel plate is marked with cell formation by dividing its area into equal cells of size 4 cm by 4 cm by forming grids of 6 rows and 15 columns. The steel plate with grid formation is shown in Fig. 2. The size of the cell was chosen based on the distance between the accelerometers placed adjacently.

Fig. 3 shows the 36 labeled excitation locations on the steel plate. Since resonance occurs at the locations where there is close contact of the threads, the excitation locations for the experiment are chosen at the middle of the cell structure with a 6 by 6 matrix formation. The cells are numbered sequentially. Ten similar steel plates are used in the experimental study. Similar pattern of labeling has been made in all the 10 steel plates.

1) Suspension methods: Modal analysis is made on a structure that is suspended under free-free conditions, or a structure suspended in operating conditions. The experimental test structures are fabricated into Simply supported boundary condition (free-free)

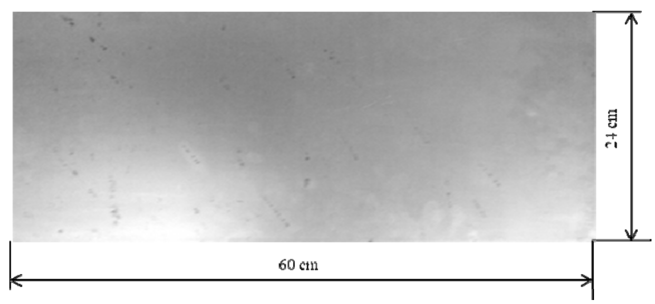

Figure 1. 2B Stainless steel plate

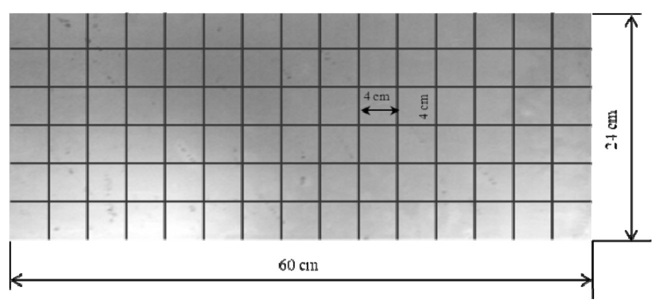

Figure 2. Steel plate with cell grids

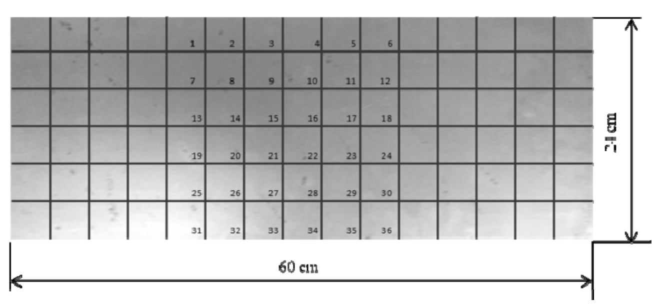

Figure 3. Steel plate with labeled excitation locations

2) Simply supported steel plate: A simple experimental setup framework is designed to hold the steel plate in a free-free condition. Hollow aluminium frames are used to fabricate the test bed structure with outer dimensions measuring 90 cm x 60 cm and inner dimensions measuring 75 cm x 45 cm. To provide suspension and to avoid external interference due to environment, the aluminium frame is placed over a rubber mattress. Two thin threads are tied across the frame at a distance of 30 cm apart from each other to freely suspend the steel plate. The thin threads are wounded so as to balance the steel plate evenly at both the ends and to avoid plate deflection and bounce. The steel plate weighing 1.2 kg is freely suspended over the threads with 7.5 cm away from its shorter sides and 10 cm away from its longer sides. The impact hammer is stroked on the excitation locations and the steel plate is made to vibrate several times to ensure no overloading problem during the experiment. The simply supported framework is depicted in Fig. 4.

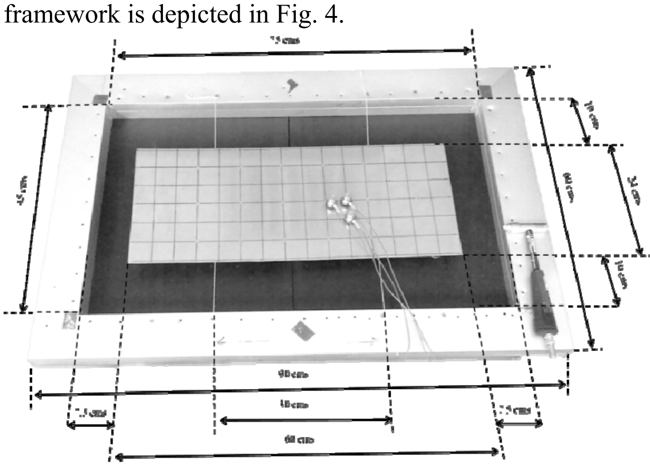

Figure 4. Simply supported steel plate

3) Force and vibration transducers: In this experiment, a general purpose impulse hammer (Model 5800B2) is used. The impulse hammer has a range of 50 lbf with a sensitivity of 100 mV/lbf. The head weight of the impulse hammer is 100 grams. This impulse hammer is compatible with Integrated Circuit Piezoelectric (ICP) and a Bayonet Neill Concelman (BNC) connection is established between the hammer and the Data Acquisition (DAQ) system. A general purpose Piezo-tronic voltage source accelerometer of Model A/120/V from DJB instruments is used in this experiment. The accelerometer has a resonant frequency of 28 kHz and is base tapped (10/32 UNF 4 mm deep). The accelerometer possesses a sensitivity of 31.6 mV/g ±5% @ 20°C using a two wire Charge / Voltage converter (QVC). The accelerometer is ICP compatible and is connected to the data acquisition System with a BNC Connection.

4) Data acquisition system(DAQ): The DAQ Model LMS SCADAS Mobile SCM01 is used in this experiment for data capturing. The DAQ contains 4 input channels and an Ethernet connectivity for interfacing with the Personal Computer. The DAQ supports a maximum sampling frequency of 102.4 kHz. The impulse hammer and three accelerometers are connected to the DAQ using a BNC connector cable. The DAQ contains an internal battery which lasts for a couple of hours depending on the usage. The DAQ is connected to the laptop computer running the LMS Test Lab software through a high speed Ethernet connection.

5) Roving hammer test: During this testing procedure, the structure under test is mounted on the experimental setup. The accelerometers locations are evenly distributed over the structure. An impulse signal is generated on the structure by striking the impact hammer at different locations and observing the vibration acceleration pattern at different locations. The location of strike of the impact hammer is randomly selected.

6) Roving accelerometer test: In this test the structure under test is mounted on the experimental setup and the location of strike of the impact hammer is fixed. 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. In this work, the data collection protocol is designed using both the roving hammer test and roving accelerometer test.

C. Data capture and data collection procedure

The database of vibration signals are collected from the steel plate in both healthy and damaged conditions which is explained in the forthcoming sections. The sampling frequency chosen in this experiment to be 4 kHz throughout the data collection process

1) Simulated damages: This experimental study is carried out to identify the damages in the steel plate. The vibration signatures from the steel plate under normal and healthy conditions are used as the reference signal. Simple damages are made on the steel plate by drilling small holes on the steel plate. Small drilled holes of diameter between 512 μm to 1852 μm and depth of 100 μm are manually made using drill bits on the surface of the steel plate. A maximum of 3 damages were made in each cell. Damages were made in all the 36 cells which constitute 144 possible excitation locations.

D. Data collection procedure and protocol design for data collection

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. The accelerometers are mounted over the corners of the cells.

The data collection protocol for the experimental modal analysis is designed by incorporating both the roving impact hammer and roving accelerometer test. The steel plate is suspended either in a free-free or fixed-free boundary condition. The three accelerometers are mounted at the 3 corners of a cell. Precautions were taken to avoid any external disturbances on the mounted accelerometers. The steel plate is then excited with an impact hammer at the impact point (at the 4th corner of the cell) and made to vibrate. The vibration pattern is observed using the three accelerometers which are placed at the three corners of the cell.

The impact point and the response points are interchanged among the 4 corners of the cell. The procedure is repeated for all the 36 locations marked on steel plate. The protocol design for the accelerometer placement and the impact point position are depicted in Fig. 5 to Fig. 8.

E. Vibration signal database

Using the data collection procedure 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 including minimum, medium and maximum damages are collected after drilling small holes on the steel plates. The experimental data collected using simply supported method comprises of 2880 samples. 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.

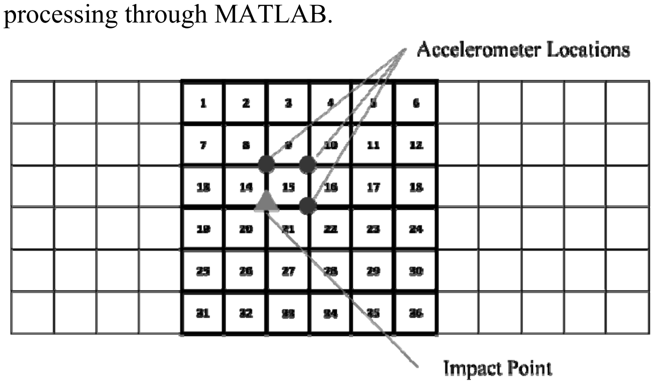

Figure 5. Accelerometer placement and impact point (Protocol 1)

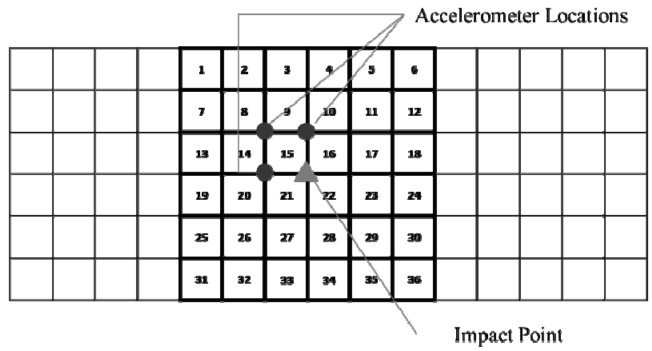

Figure 6. Accelerometer placement and impact point (Protocol 2)

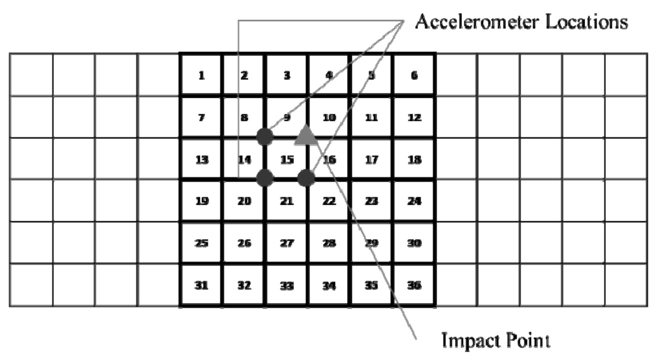

Figure 7. Accelerometer placement and impact point (Protocol 3)

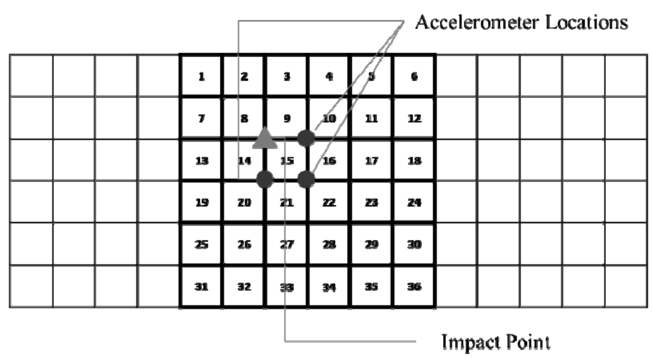

Figure 8. Accelerometer placement and impact point (Protocol 4)

III. FEATURE EXTRACTION AND DATA PROCESSING

The vibration response signal recorded from the accelerometers contains the time verses amplitude information for a time stamp of 20 seconds. The recorded signals are the response to an impulse signal. In this work, the features from the vibration signals are extracted using time domain based statistical features based on the frame energy. Feature Extraction Algorithms are developed to extract the statistical features namely Kurtosis, Root Mean Square, Total Delta Energy and Number of slope changes.

A. Frame energy

To effectively study the features, the vibration signal is decomposed into frames of definite size.

1) Frame blocking: To maintain simplicity, the signal is segment into frames of size 1024. A typical representation of the vibration signal clipped for 15 seconds is shown in Fig. 8. While performing the impact test on the steel plates, the recording time was set to 20 seconds. The time of strike of the impact hammer on the steel plate is not consistent. Hence to incorporate uniformity of the signal length, the signal corresponding to 15 seconds is extracted using the following signal trimming procedure.

2) Signal Clipping: The transient vibration signal is recorded for 20 seconds during the impact testing process. The time 't_p' corresponding to the first peak magnitude 'v_p' is identified. The vibration signal recorded from (t_p – 0.5) seconds to (t_p + 14.5) seconds are extracted. The period of the resulting extracted signal is 15 seconds and is used for further analysis.

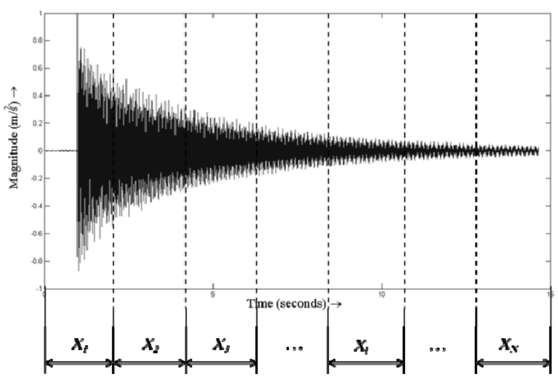

Figure 8. A typical vibration signal blocked into frames

3) Energy: The total energy of a signal is defined as the sum of the squared magnitudes of the signal components. 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. By studying the change in the energy decay in a frame by frame analysis provides an insight on the frame level energy decomposition.

4) Calculation of frame energy based features: The variation of frame energy of a normal and fault condition at the same location have been depicted in Fig. 9. From the Figure, it is observed that the frame energy decays exponentially with respect to time. The level of the exponential decay is analyzed in terms of the following statistical time domain features namely: Kurtosis, Root mean square, Total delta energy and number of slope changes are extracted. Simple MATLAB scripts are developed to extract these frame energy based statistical time domain features.

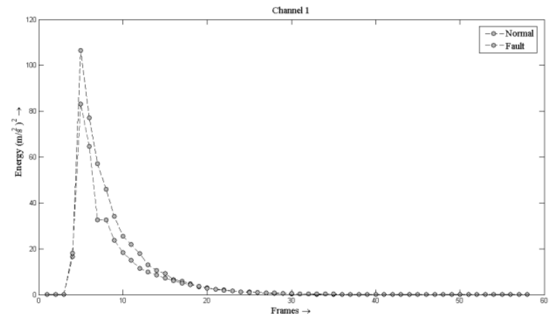

Figure 9. A typical representation of frame energy of a normal and fault signal captured from the same location.

5) Kurtosis (K)*:* The Kurtosis K 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 to the major peaks in a set of data. The kurtosis for the frame energy is computed using (1).

$$K = \frac{1}{N}\sum_{i=1}^{N}\left(\frac{e_i - e_\mu}{e_\sigma}\right)^4 \tag{1}$$

where $e_i = i^{th}$ frame energy,

e_μ = overall mean frame energy,

e_σ = standard deviation of frame energy and

N = total number of frames.

6) Root mean square (E_{rms})*:* The Root Mean Square is the time domain analysis feature which is a measure of the power content in the vibration signature [10]. The Root Mean Square (E_{rms}) is calculated using (2).

$$E_{rms} = \sqrt{\frac{1}{N}\sum_{i=1}^{N} e_i} \tag{2}$$

where $e_i = i^{th}$ frame energy and

N = total number of frames.

7) Total delta energy (ΔE)*:* The vibration response is a function of energy decay with respect to time. The sum of the change in energy between two successive frames in the signal is referred to as the total delta energy (ΔE) and is computed using (3).

$$\Delta E = \sum_{i=2}^{N-1}\left(e_{i-1} - e_i\right) \tag{3}$$

where $e_i = i^{th}$ frame energy,

i = frame number and
N = total number of frames.

8) Number of slope changes (ΔS)*:* The vibration response of the frames decays exponentially with respect to time. The slope of the energy decay depends on the plate condition and hence the frame energy values between two successive frames are compared and the changes in slope values are computed. If the product of two consecutive frame energies is less than zero then it is considered as a slope change. The total number of slope changes computed from the frame energy values constitutes a feature. The number of slope changes is computed using (4) and (5).

$$\Delta S = \sum_{i=1}^{N-2} f\left(\Delta e_{i+1} * \Delta e_i\right) \tag{4}$$

$$f\left(\Delta e_{i+1} * \Delta e_i\right) = \begin{cases} 1 & if\ \left(\Delta e_{i+1} * \Delta e_i\right) < 0 \\ 0 & if\ \left(\Delta e_{i+1} * \Delta e_i\right) \geq 0 \end{cases} \tag{5}$$

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

The extracted features: Kurtosis K, Root Mean Square (E_{rms}), Total delta energy (ΔE) and number of slope changes (ΔS) derived from the frame energy for all the three vibration channels are combined to form a feature sample. The feature extraction procedure is repeated for all the 1440 normal vibration signals and 1440 fault vibration signals to form the final feature matrix of size 2880 x 12. Each row of the feature matrix is a feature sample with 12 features. The feature vector is then associated with the condition (normal or fault) of the steel plate.

B. Data Preprocessing

Data preprocessing is referred to the set of procedures used to process the raw data for further processing such as classification or clustering. The data preprocessing involves labeling of inputs and outputs, identification and removal of outliers, feature selection, data dimensionality reduction and data normalization. The redundancy in data may cause misleading classification results. Hence the data preprocessing analyzes used to process and remove redundancy from the raw data. An '*m* x *n*' dataset comprises of '*m'* number of samples and '*n'* number of features. The input data samples are associated with their corresponding output vector and fed to the classifier model for classification. Identification of features with better discriminating capability and choice of classifier model with better prediction capability produces promising classification results.

1) Outlier identification and removal: Outliers are referred to as the data which are inconsistent with the rest of the data in the dataset. The outlier present in the dataset when unidentified distorts the mean and variance which further leads to poor classification results. Outliers can be identified by visualizing the data distribution.

Outliers are removed from the dataset using five point summary method [11]. A total of 116 samples were removed as outliers from the original dataset leaving 2764 samples.

C. Data normalization and randomization

The dataset derived from the features does not follow a uniform data distribution. Normalization is a preprocessing technique widely employed in applications whose input variables are rescaled. Data normalization quickens the training time of the classifiers since all the feature vectors fall under the same scale. The softmax normalization technique is used in this work. The dataset can be nonlinearly transformed using the sigmoidal function shown in (7) where the data is distributed between the range of $[0.1 \text{ to } 0.9]$ or the hyperbolic tangent function shown in (7) where the dataset is rescaled between $[-0.9 \text{ to } +0.9]$. The softmax normalization technique rescales the data by computing the mean and standard deviation. It also reduces the influences of outliers if present in the dataset. [12] [13].

$$C = \left(\frac{S_{ij} - \mu_i}{\sigma_i}\right) \tag{6}$$

$$S_{ij} = \frac{1}{1 + e^{-(t)}} \tag{7}$$

where C = Normalized data,

S_{ij} = Destabilized input data of i^{th} row and j^{th} column,

μ_i = Mean of the i^{th} column of destabilized input data and

σ_i = Standard deviation of the i^{th} column of destabilized input data.

In this work, the dataset are normalized using sigmoidal activation function.

1) Output labeling: Classifiers with supervised learning are often fed with the input output mapping for training the model. The input feature vectors are associated with the corresponding class with a numerical value. The type of target output representation is problem specific and depends on the classification problem. In this research work, the target output (condition of the steel plate) is classified as either normal or fault. To represent the normal condition of the steel plate, the input features are mapped to '0.1' and to represent the fault condition in the steel plate, the input features are mapped to '0.9'. The target output can be depicted in binary values either logistic sigmoidal function $[0.1 \text{ to } 0.9]$ or hyperbolic tangent function $[-0.9 \text{ to } +0.9]$ [12].

D. Feature reduction / dimensionality reduction

Data with large dimensionality increases the complexity of sampling the space. The dimensionality of the data is adjusted before applying the pattern recognition algorithms for classification. The relationship between the number of features and the number of samples is the key area in effective classifier design. The number of features directly affects the performance of the classifier / classification system. For efficient classifier design the salient features that carry dominant information must to be identified.

The principal components are computed by covariance method using the eigenvector analysis [12] [14]. The feature vector is transformed to a higher dimension by computing the principal components. The principal components (PCs) are calculated using correlation matrix method. The required number of principal components is identified using size of variance. In this research work, the required numbers of PCs are calculated by a rule of thumb by computing the variances. The number of identified principal components is sorted in ascending order according to the variance and then the principal components whose variances greater than 0.7 are retained and are used for modeling the classifier. From the 12 frame energy based features 8 principal component features were identified.

IV. 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 [15]. Artificial Neural Network (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.

A feed-forward neural network is modeled and trained using the extracted feature vectors. The neural network training parameters such as activation function, learning rate, and momentum factor are optimally chosen during the training of the network.

Split sample testing or the hold out method is the supervised training procedure, where the dataset is randomly separated into two sets namely training and testing. The training set is used to train the network, while the testing set is used to validate the network for generalization error [12].

In this work, a similar method of split sample testing method is used, where the dataset is randomly divided into training sets of 60%, 70% and 80%. The complete dataset (100%) which includes training data and unseen data is used to validate the performance measure of the trained network.

During the validation of the trained neural network, the actual output is compared across the desired output with a testing tolerance. In this work, the '*threshold and margin criterion*' devised by Scott E. Falhman [16] is considered. In this method the output classes: class1 and class2 are associated to 0.1 and 0.9 respectively. The threshold value is set in such a way that, the output values of the simulated network lying between 0 to 0.3 is considered as 0.1 (class1) and output values lying between 0.7 to 0.9 is considered to be 0.9 (class2). The target output values above 0.3 and below 0.7 are considered 'marginal' and are not considered as correct during training. The neural network training results are testing using this method and are tabulated.

A. Feed-forward neural network

The feed-forward neural 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 in the hidden layer are allocated experimentally. The hidden neurons contribute towards the weighted connections of the neural network.

The feed-forward neural network is modeled for the simply supported experiment method based on the features extracted from the vibration signals and subsequently trained using Levenberg Marquardt Back Propagation algorithm. The 'trainlm' function available in MATLAB neural network toolbox is used to model, train and simulate the neural network. The neural network models are trained using 60%, 70% and 80% samples of the database and tested against the complete database. The trained neural networks are validated across the testing samples which include unseen inputs by the trained network. The network is tested with normal method and proposed falhman testing method.

The feed-forward neural network modeled in this work use hyperbolic tangent and logistic sigmoid activation functions appropriately. A lower value of the learning rate between 0.1 to 0.3 is used to avoid oscillations during the learning of the network. The momentum constant is chosen a higher value so as to avoid the network getting caught during the local minima. In the feed-forward neural network model, the momentum constant is chosen to be between 0.8 to 0.9. The number of hidden neurons is chosen in a trial and error basis.

The trained neural networks are validated with the testing samples which include unseen inputs by the trained network. The network is tested with falhman testing method. The results are tabulated in Table I and II respectively.

V. RESULTS AND DISCUSSION

The feed-forward neural network model is trained by adjusting the training parameters listed in Table I. The neural network model was trained for 5 trials, each trial containing 25 iterations.

The mean classification accuracy, sensitivity, specificity and number of epochs of the 5 trials are calculated and the results are tabulated in Table II.

The performance of the trained network model is validated by calculating the true positives, true negatives, false positives and false negatives.

The minimum and maximum classification accuracy are obtained as 93.00% (60 percent samples) and 95.26% (80 percent samples) respectively. The minimum and maximum sensitivity are obtained as 92.18% (60 percent samples) and 94.30% (80 percent samples) respectively. The minimum and maximum specificity are obtained as 93.82% (60 percent samples) and 96.22% (80 percent samples) respectively. The minimum and maximum number of epoches are obtained as 116 (60 percent samples) and 152 (80 percent samples) respectively.

TABLE I. FRRD-FORWARD NEURAL NETWORK TRAINING PARAMETES

Neural Network Training Parameters	Input Neurons	8
	Hidden Neurons	23
	Output Neurons	1
	Total number of weighted connections	207
	Activation Function : Hidden neuron	Tansig
	Activation Function : Output neuron	Tansig
	Learning Rate	0.1
	Momentum Factor	0.9
	Training Tolerance	0.01
	Testing Tolerance	0.1
	Testing Samples	2764

TABLE II. MEAN CLASSIFICATION RESULTS USING FALHMAN TESTING

	No. of Training Samples	**60%**	**70%**	**80%**
Neural Network Results	**Classification Accuracy**	93.00	94.80	95.26
	Sensitivity	92.18	93.79	94.30
	Specificity	93.82	95.81	96.22
	Number of Epoches	106	118	152

The results show that 80 percent data samples produce better results compared to 60 percent and 70 percent samples. Though the larger the number of samples, the more the complexity and weighted connections of the network.

VI. CONCLUSION

In this work, an experimental method was developed based on the non-destructive testing and experimental modal analysis. Feature extraction algorithms using frame energy based statistical time domain signal processing methods were developed to extract the features from the vibration signals. Data preparation methods were developed to formulate the feature vectors for classifier models. A feed-forward neural network model was modeled to classify the condition of the steel structure using the features extracted from the vibration signals. The Network model shows promising results.

ACKNOWLEDGMENT

The authors would like to thank Y.Bhg.Kol.Prof Dato' Dr. Khamarudin b. Hussin, Vice Chancellor, University Malaysia Perlis for his constant encouragement. The authors express their profound gratitude to Universiti Malaysia Perlis and the Ministry of Higher Studies, Malaysia. This study was conducted at University Malaysia Perlis.

REFERENCES

[1]. Kolakowski, P, "Structural health monitoring - A review with the emphasis on low-frequency methods", Engineering Transactions, 55, 3, 239-275, 2007.
[2]. S.W.Doebling, C.R. Farrar and M.B. Prime, "A summary review of vibration based damage identification methods", The Shock and Vibration Digest 30(2), pp 91-105, 1998.
[3]. Richardson MH, "Detection of damage in structures from changes in their dynamic (modal) properties – a survey", NUREG/CR-1931, U.S. Nuclear Regulatory Commission, Washington, District of Calumbia, 1980.
[4]. Tandon N, Nakra B C, "Vibration and acoustic monitoring technique for detection of defects in rolling element bearings a review", Shock and Vibration Digest, 24(3), pp 3-11, 1992.
[5]. Dimarogonas, A,"Vibration Engineering", West Publishes, St.Paul, Minesota,1976.
[6]. Anifantis N, Rizos P, Dimarogonas A, "Identification of cracks by vibration analysis", American society of Mechanical Engineers, Design Division Publications DE 7., pp 189-197, 1985.
[7]. Cawley, P., & Adams, A. D.,"The location of defects in structures from measurements of natural frequencies", Journal of Strain Analysis", Vol 14, No 2. (1979) pp 49-57, 1979.
[8]. Shen, M.H, Pierre C, "Natural modes of Bernoulli Euler beams with symmetric cracks", Journal of Sound and Vibration 138, pp 115-134, 1990.
[9]. Ahlin, K., & Brandt, A.. "Experimental modal analysis in practice", Saven Edu Tech AB, Taby, Sweden, 2001.
[10]. Lebold, M., McClintic, K., Campbell, R., Byington, C. & Maynard, K.,"Review of vibration analysis methods for gearbox diagnostics and prognostics", Proceedings of the 54th Meeting of the Society for Machinery Failure Prevention Technology, pp. 623-634, 2000.
[11]. Laurikkala, J., Juhola, M., & Kentala, E.,"Informal identification of outliers in medical data". Proceedings of a workshop at the 14th European Conference on Artificial Intelligence (ECAI-2000), pp. 20–24, Berlin, Germany, 2000.
[12]. Priddy, K. L., & Keller, P. E., "Artificial neural networks - An Introduction", Tutorial Texts in Optical Engineering, Volume TT68, SPIE Press, 2005.
[13]. Bishop, C. M., "Neural networks for pattern recognition", Oxford University Press, 1995.
[14]. Haykin, S., "Neural networks and learning machines", Third Edition, Prentice Hall, 2009.
[15]. S.N Sivanandam and Paulraj M, "An Introduction to Artificial Neural Networks", Vikhas Publication , India, 2003.
[16]. Falhman, S. E., "An empirical study of learning speed in backpropagation Networks", CMU-CS-88-162, 1998.