Structural Steel Plate Damage Detection using DFT Spectral Energy and Artificial Neural Network

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***Abstract*— In this paper, simple methods for crack identification in steel plates and their classification based on the frame based frequency domain features is presented. Based upon the boundary conditions and experimental modal analysis, two simple experimental methods are designed to measure the vibration at different positions of the steel plate. The plate is excited by an impulse signal and made to vibrate. The propagated vibration signals are then recorded. The signal is transformed into frequency domain by computing the Discrete Fourier Transformation (DFT). The frequency spectral bands are identified and the spectral energy is extracted as features. The condition of the steel plate namely healthy or faulty is associated with the extracted features to form a final feature vector. Two simple neural network models were developed, trained using Backpropagation (BP) and Radial Basis Function (RBF) algorithms. The results and the effectiveness of the system are validated through simulation.**

***Keywords*— Vibration Signal, Damage Detection, Experimental Modal Analysis, Discrete Fourier Transformation, Spectral Energy, Backpropagation, Radial Basis Function Network.**

I. INTRODUCTION

Health monitoring of vibrating structure in machines is an 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 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 (SHM) is an 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 with the aid of vibration signals. 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]. An unidentified damage in steel plates can degrade the lifespan of the product. To ensure long life, the condition of the steel plate needs to be monitored. Nondestructive vibration testing methods for damage identification gains more importance in the recent past.

In this work, two types of experimental arrangements are proposed based on the boundary conditions. The vibration signals are captured from the stainless steel plate in pre and post damage conditions. The vibration signal is transformed into frequency domain by computing the Discrete Fourier Transformation (DFT). The frequency spectral bands are identified and the spectral energies are extracted as features. These extracted features are then associated with the healthy or faulty condition of the steel plate. Multilayer Perceptron network model and Radial basis function network model are developed and the features are trained and tested. The results obtained are compared. This paper, is organized in the following subsections; the experimental design, feature extraction and the artificial neural networks for classification are explained in the corresponding subsections.

II. EXPERIMENTAL DESIGN AND DATA ACQUISITION

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. 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.

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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/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.

C. Experimental Setup

A clean 2B Stainless steel plate of length 60 cms, breadth 24 cms and thickness 0.12 cms 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. 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

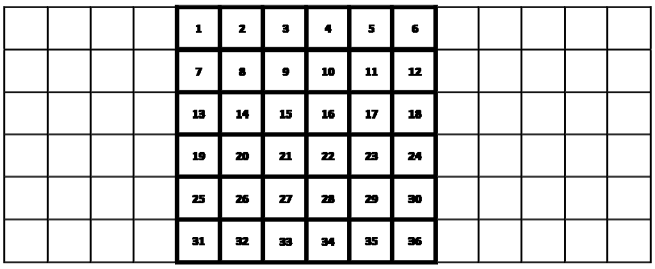

Fig.2 Grid formation of the steel structure

D. Test Setup 1.Case A

An aluminium 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.

E. 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.

F. 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 nondestructive 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) = $60\text{x}10^{-1} m$ and Thickness (h) = $1.2\text{x}10^{-2}$ m. The natural frequency can be computed [9] using the equation (2)

$$D = \frac{Eh^3}{12(1-\mu^2)} Nm \qquad (1)$$

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

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)

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

G. 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. The level of vibration at the nearest three nodal points is measured using the accelerometers.

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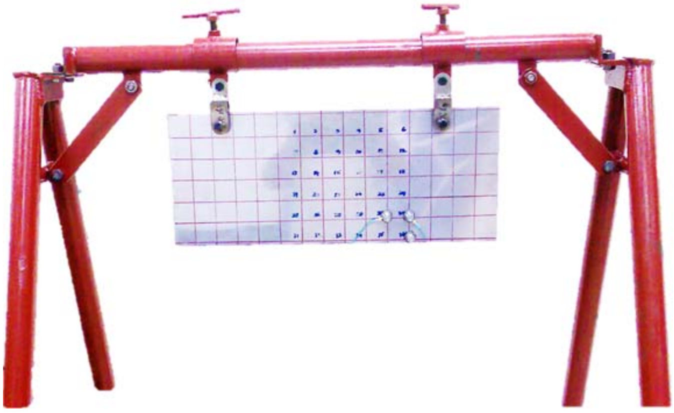

Fig.3b. Experimental Test Setup of Steel Plate Hinged one side

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 4 kHz. This procedure is executed in all the 36 cells and 10 such trials are applied during the healthy condition of the stainless steel plate.

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 from the steel plate during the fault condition is captured using the same procedure described above. 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.

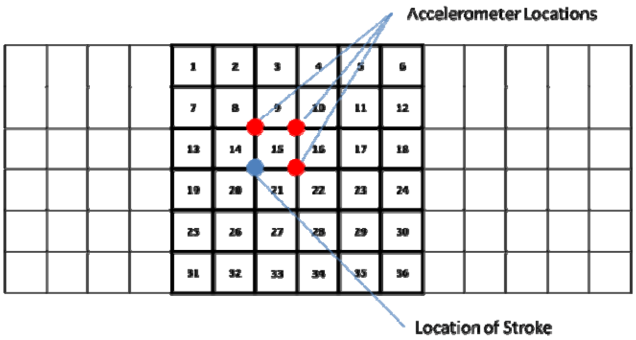

Fig.4.Location of Strike – Protocol 1

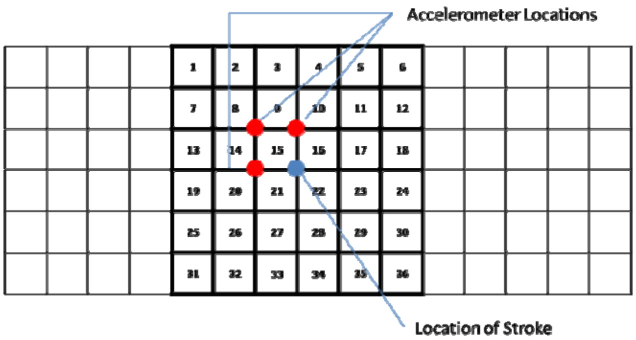

Fig.5.Location of Strike – Protocol 2

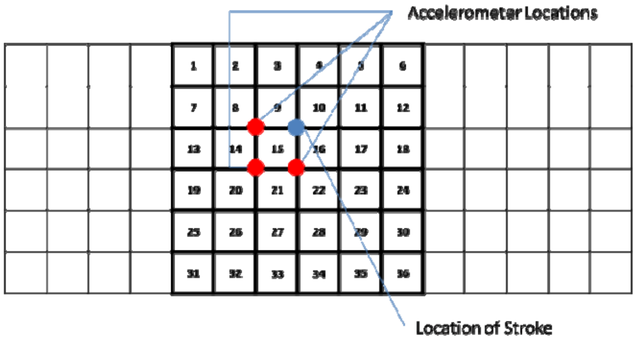

Fig.6.Location of Strike – Protocol 3

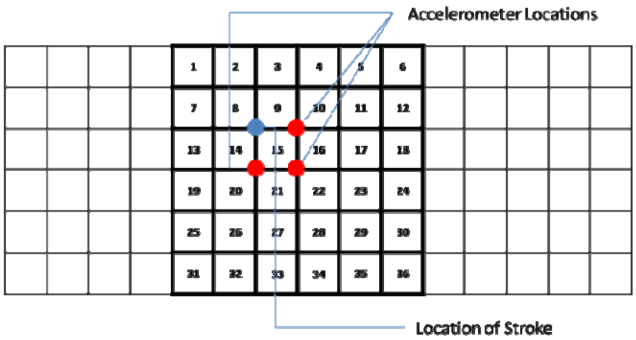

Fig.7.Location of Strike – Protocol 4

III. DATA PREPROCESSING

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 1 second before the occurrence of the peak and 14 seconds after the peak. The final length of clipped signal is 60000 samples at a sampling frequency of 4000 samples per second. The figure shows the clipped signal during the data analysis.

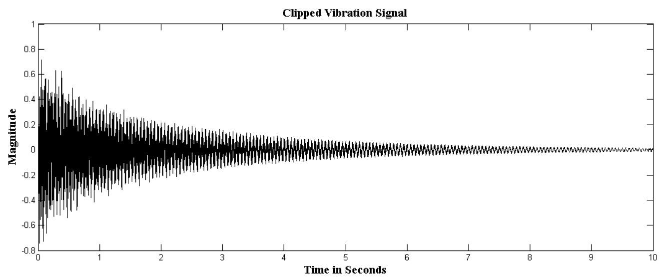

Fig.8.Typical Clipped Vibration Signal

IV. FEATURE EXTRACTION

A. Frequency Domain DFT Bands Feature Extraction

The vibration signal recorded represents the time information. To extract the frequency information, the signal is then transformed into frequency domain by computing the Discrete Fourier Transformation (DFT) using the Fast Fourier

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Transformation (FFT) algorithm for faster computation. The typical frequency spectrum of a vibration channel is shown in Figure 9. From the frequency spectrum, it is observed that the frequency components arise between a range of 0Hz - 250 Hz. The frequency spectrum of a vibration channel is depicted in Figure 9. The Spectral Energy bands are identified. The peak spectral energies are calculated. The frequency band with a threshold range of spectral energies above 0.2 times the peak spectral energy before and after the occurrence of the peak is considered. The frequency spectrum is grouped into band of frequencies as presented in the Table 1 and Table 2. 15 frequency bands are formed per each vibration signal in Case A that forms 45 final feature vectors. 18 frequency bands are formed per each vibration signal that makes 54 final feature vectors for Case B.

TABLE 1
DFT Frequency Band - CASE A SIMPLY SUPPORTED

Band No	Frequency Range
Band 1	4Hz - 9Hz
Band 2	14Hz - 20Hz
Band 3	23Hz - 27Hz
Band 4	32Hz - 38Hz
Band 5	42Hz - 49Hz
Band 6	59Hz - 70Hz
Band 7	84Hz - 95Hz
Band 8	96Hz -107Hz
Band 9	111Hz - 116Hz
Band 10	128Hz - 133Hz
Band 11	135Hz - 150Hz
Band 12	160Hz - 170Hz
Band 13	174Hz - 175Hz
Band 14	187Hz - 195Hz
Band 15	200Hz - 230Hz

TABLE 2
DFT Frequency Band - CASE B.HINGED FREE

Band No	Frequency Range
Band 1	6Hz - 11Hz
Band 2	15Hz - 19Hz
Band 3	22Hz - 28Hz
Band 4	35Hz - 49Hz
Band 5	52Hz - 58Hz
Band 6	65Hz -75Hz
Band 7	75Hz - 81Hz
Band 8	88Hz -101Hz
Band 9	101Hz - 114Hz
Band 10	114Hz - 127Hz
Band 11	130Hz - 144Hz
Band 12	144Hz - 152Hz
Band 13	153Hz - 166Hz
Band 14	166Hz - 176Hz
Band 15	180Hz - 202Hz
Band 16	204Hz - 223Hz
Band 17	228Hz – 238Hz
Band 18	238Hz – 250Hz

The frequency band is represented using the equation 3.

$$X = \sum_{i=1}^{N} x_1, x_2, x_3, \ldots, x_M \qquad (3)$$

where $i = 1,2,3,\ldots,M$

N = *length of each frequency band*

M = *number of frequency bands*

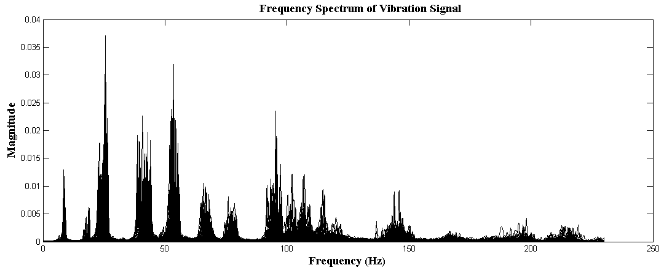

Fig 9 DFT Frequency Spectrum

V. DATA POST PROCESSING

The frequency band features extracted from the three vibration channels are associated with the condition of the steel plate. In Case A the 45 input features are associated to one target pattern. In Case B the 54 input features are associated to one target pattern. The feature matrix is rescaled to a definite range using a normalization criterion to improve speed and reduce complexity during classification. In this research work softmax normalization is used [18]. The data is then randomized and the training and testing database are formulated.

VI. CLASSIFICATION USING ARTIFICIAL NEURAL NETWORK

A. 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 [17]. Artificial Neural Networks (ANN) provides alternative form of computing that attempts to mimic the functionality of the brain. Two Neural network models Multi-layer Perceptron (MLP) and Radial Basis Function (RBF) are modelled and trained using the features extracted from the vibration signal.

B. Multilayer Perceptron Neural Network

A simple MLP neural network model is developed and trained using Backpropagation learning procedure in this work. The MLP network consists of 3 layers, with one input layer, one hidden layer and an output layer. The neural network model consists of an input layer with input neurons based on the number of DFT frequency band features extracted. It contains a hidden layer and an output layer associated to the target pattern. In the MLP neural network, the total mean squared error is backpropagated to the input neurons so that the weight vectors are adjusted to minimize the error gradient. A sum of 60 percent, 70 percent and 80 percent of the whole database is considered for training the neural network and 100 percent data is used to test the neural network. The 'newff' function with the 'trainlm' – Levenberg Marquertt learning method is used to train the neural network. The parameters used for training and the results of the mean epoch and

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classification accuracy are tabulated for Case A and Case B and shown in Table 3 and Table 4 respectively.

TABLE 3
MLP TRAINING RESULTS - SIMPLY SUPPORTED

Input Neurons : 45 Output Neurons : 1 Hidden Neurons : 25 Maximum Epoch : 150			Training Tolerance : 0.001 Testing Tolerance : 0.1 Testing Samples : 2880 Activation Function : Sigmoidal			
	Training Samples					
	60 % = 1728		70 % = 2015		80 % = 2304	
Trial	Mean Epoch	CR (%)	Mean Epoch	CR (%)	Mean Epoch	CR (%)
1	30	95.06	43	96.66	13	98.19
2	36	94.13	34	96.11	73	97.91
3	52	94.72	52	96.94	33	98.26
4	36	95.31	47	97.46	35	98.22
5	39	95.27	68	96.97	42	98.47
6	113	93.75	39	96.84	75	98.19
7	37	95.03	33	96.70	47	98.43
8	44	94.61	76	96.70	47	98.47
9	29	94.82	41	97.01	42	98.02
10	29	95.10	42	96.80	39	98.36
Mean	-	**94.78**	-	**96.82**	-	**98.25**

C. Radial Basis Function Network

The RBF Neural Network consists of three layers. The first layer being the input layer which contain the extracted features as input vectors. The condition of the steel plate corresponds to the output vector. The hidden neurons are computed using the radial basis function. The network is trained using the inbuilt radial basis neural network 'newrb' function present in MATLAB. The spread of the Gaussian distribution is derived experimentally. The network is trained using 60, 70 and 80 percent of samples and tested using 100 percent samples by simulation. The parameters used for training and the results of the hidden neurons and classification accuracy are tabulated for Case A and Case B are shown in Table 5 and Table 6 respectively.

V. RESULTS AND DISCUSSION

To evaluate the effectiveness of the network model, the confusion matrices for the MLP and RBF network are calculated. The MLP network model has the best sensitivity and specificity values as 99.72 percent and 99.79 percent for Case A and 99.93 percent sensitivity and 99.86 percent specificity for Case B. The RBF network model has the best sensitivity and specificity values as 98.99 percent and 90.01 percent for Case A and 99.24 percent sensitivity and 98.38 percent specificity for Case B. From the neural network training results presented in Tables 3 - 6, it is observed that the MLP network trained using DFT spectral energy features has a better classification accuracy compared to the RBF network model.

TABLE 4
MLP TRAINING RESULTS–HINGED FREE

Input Neurons : 54 Output Neurons : 1 Hidden Neurons : 25 Maximum Epoch : 100			Training Tolerance : 0.001 Testing Tolerance : 0.1 Testing Samples : 2880 Activation Function : Sigmoidal			
	Training Samples					
	60 % = 1728		70 % = 2015		80 % = 2304	
Trial	Mean Epoch	CR (%)	Mean Epoch	CR (%)	Mean Epoch	CR (%)
1	17	94.44	23	95.76	20	98.12
2	23	94.86	23	96.25	20	98.22
3	16	94.93	20	96.45	19	98.40
4	14	94.23	20	96.73	37	98.26
5	23	94.40	31	96.45	22	97.70
6	30	94.20	20	96.73	35	97.60
7	25	94.27	26	96.25	31	97.50
8	20	95.00	22	96.42	29	97.98
9	28	94.51	28	96.25	18	97.43
10	27	95.51	20	95.59	34	98.26
Mean	-	**96.46**	-	**96.28**	-	**97.95**

TABLE 5
RBF TRAINING RESULTS - SIMPLY SUPPORTED

Input Neurons Output Neurons		45 1	Testing Samples Training Goal Testing Goal		2880 0.01 0.1	
	60 % = 1728 samples		70 % = 2015 samples		80 % = 2304 samples	
Spread	HN	CR (%)	HN	CR (%)	HN	CR (%)
0.1	425	70.55	425	85.42	425	90.72

TABLE 6
RBF TRAINING RESULTS - HINGED FREE

Input Neurons Output Neurons		54 1	Testing Samples Training Goal Testing Goal		2880 0.01 0.1	
	60 % = 1728 samples		70 % = 2015 samples		80 % = 2304 samples	
Spread	HN	CR (%)	HN	CR (%)	HN	CR (%)
0.1	450	82.4	450	89.25	450	91.47

VI. CONCLUSION AND FUTURE WORK

This paper presented two simple experimental methods for the nondestructive vibration based damage detection. DFT spectral bands are identified and the spectral energies are extracted from the vibration signals. The features are associated with the condition of the steel plate to form the final feature matrix. Two neural network models are developed and trained using Backpropagation and Radial

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Basis Function algorithms. The results show that the identification and use of the DFT spectral energy band features contribute towards a better classification of the condition of the steel plate. Furthermore, RBF network can be effectively used in the diagnosis of condition of the steel plate.

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REFERENCES

[1] S.W.Doebling, C.R. Farrar and M.B. Prime (1998), *A summary review of vibration based damage identification methods*, The Shock and Vibration Digest 30(2), pp 91-105.

[2] Richardson MH (1980), *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.

[3] Tandon N, Nakra B C, *Vibration and acoustic monitoring technique for detection of defects in rolling element bearings a review*, Shock and Vibration Digest 1992, 24(3), pp 3-11.

[4] A.Dimarogonas, *Vibration Engineering*, West Publishes, St.Paul, Minesota, 1976.

[5] N.Anifantis, P.Rizos, A.Dimarogonas, *Identification of cracks by vibration analysis, American society of Mechanical Engineers*, Design Division Publications DE 7 (1985), pp 189-197.

[6] A.D.Adams, P.Cawley, *The location of defects in structures from measurements of natural frequencies*, Journal of Strain analysis 14 (1979) pp 49-57.

[7] William T. Thomson, *Theory of Vibration with Applications*, Fourth Edition, Nelson Thornes Ltd, 2003, pp 80-81.

[8] 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, Virginia Beach, VA, May 1-4, 2000, pp. 623-634

[9] Tom Irvine, "Natural Frequencies of Rectangular Plate Bending Modes", www.vibrationdata.com, July 1999.

[10] Ventsel, E and Krauthammer.T 2001, *Thin Plates and Shells Theory- Analysis and Applications*, Marcel Dekker, New York, pp 276 -278.

[11] Arthur W, Leissa, I, NASA SP-160, National Aeronautics and Space Administration, Washington D.C, 1969.

[12] Jain, A.K. *Fundamentals of Digital Image Processing*, Englewood Cliffs, NJ: Prentice-Hall, 1989.

[13] Eric Y.Lim, Andy C, C Tan, Bo-Suk Yang and Vladis Kosse, *Experimental Study on Condition Monitoring of Low Speed Bearings: Time Domain Analysis,* 5th Australian Congress on Applied Mechanics, ACAM 2007.

[14] Hajnayeb, S.E. Khadem and M.H. Moradi, *Design and Implementation of an automatic condition monitoring expert system for ball-bearing fault detection,* Journal of Industrial Lubrication and Tribology 2008.

[15] B.Zhang, G.Geogoulas, M.Orchad, A.Saxena, D.Brown, G.Vachtsevanos and S.Liang, *Rolling Element Bearing Feature Extraction and Anamaly Detection based on Vibration Monitoring,* 16th Mediterrenean Conference on Control and Automation Congress Centre, France, 2008.

[16] Sophocles J. Orfanidis, *Introduction to Signal Processing,* pg 7-10, Prentice Hall 1996.

[17] KL Priddy and PE Keller, Artificial Neural Networks – An Introduction, SPIE Press, 2005.

[18] S.N Sivanandam and Paulraj M, An Introduction to Artificial Neural Networks, Vikhas Publication , India, 2003.

[19] Simon Haykin, *Neural Networks- A Comprehensive Foundation,* Prentice Hall, 2002.