Proceedings of International Conference on Applications and Design in Mechanical Engineering (ICADME)
11 – 13 October 2009, Batu Ferringhi, Penang, MALAYSIA

Artificial Neural Network for the Classification of Steel Hollow pipe

[1]N mohamad, [1]Hafizawati, [1]R.A Siregar, [1]M.Hariharan and [1]Fauziah Mat
[1]School of Mechatronic Engineering,Blok A, Kompleks Pusat Pengajian Unimap,Jalan Arau-Kangar,02600 Jejawi Perlis,
hafizawati@unimap.edu.my, 019-4783806

***Abstract*-Within industry, piping is a very important system that used to convey fluid (liquid and gases) from one location to another. Steel pipe is one of the commonly type of pipe that has been used since before. Crack on pipe is one of the things that always happen on pipe due to transfer fluid. Non-destructive (NDT) testing is responsible to detect the damage on pipe to avoid from bursting. From this, the paper presents a NDT method to detect damage in pipe by using Artificial Intelligence Neural Network (ANN) to compare Frequency Response Function (FRF) derived from impact testing on intact and damage pipe. Carbon Steel pipe with different hollow through the pipe in free-free condition is considered as a specimen. A simple feedforward with multilayer backpropagation neural network models is developed for the recognition of intact and damage steel pipe. FRF data presented on variation of amplitude load vs. frequency wave depends on disposition features can be very useful in crack detection in pipelines knowing the frequencies. This indicates that the representation of intact and damage pipe by the frequency using Artificial Neural Network (ANN) is reasonably accurate. Experimental results demonstrate that the recognition rate of the proposed neural network models is about 91.48%.**

I. INTRODUCTION

Nowadays, non-destructive testing (NDT) methods are plentiful used for detection of cracks in machine and structural components but it becomes uneconomical for long beams and pipelines which are widely met in power plants, chemical plants and offshore oil installation, etc. There are many nondestructive testing methods available for crack detection such as visual examination die penetrates test, ultrasonic method, magnetic particle technique and X-ray method. Although in order to detect a crack by any of these methods, this makes the process tedious and time consuming. It’s because the whole component are requires scanning and the cost involved may make the application prohibitive. This has motivated development of alternative methods.

The methods based on vibration for detection of cracks can offer some advantages over the traditional methods [1]. It is well known that when a crack develops in a component it leads to changes in its vibration parameters, e.g. a reduction in the stiffness and increase in the damping [2]. Frequency based neural network is considered to be a potential candidate and a lot of efforts are now directed in this direction. The method can help to determine the healthy or damage component from the frequency wave collected from impact testing by impact hammer. From vibration, modal analysis can be used to determine the fundamental vibration modes shape and corresponding frequencies of the pipe. It is worth mentioning that, modal testing is has a potential to evolve the research in NDT. The frequencies at which vibration naturally occurs, dynamic response which the vibrating system assumes are properties of the system can be determined analytically using modal analysis. Dynamic response is one of the powerful ways of probing the behavior of a complex system and it’s observing how it responds to a force applied to it, especially the "indirect" effects that take place at different places or at other times than the force. This is a way of probing the direct and indirect relationships of cause and effect. In this context we are using the term force quite loosely to refer to any interaction with the system.

From Dynamic response, the frequency response function (FRF) is one of the easiest to obtain in real-time as it only requires a small number of sensors and in situ measurement is straightforward [3-4]. In such an approach, rather than using a validated reference model, the measured FRF from the intact and damaged structures will be used directly without resorting to the modeling procedure [5-6].

From this paper, we used the FRF as an input data to neural network training. By training FRF in neural network, its can classified the different hollow size through the pipe. An artificial neural network is an information processing system that has been developed as a generalization of mathematical model of human cognition (faculty of knowing). A neural network is a network of interconnection neurons, inspired from studies of the biological nervous system. The function of neural network is to produce an output pattern when presented with an input pattern. Neural networks approximate functions of arbitrary complexity using training data and it is trained to recognize the frequency responses of an intact structure as well as the frequency responses of the structure whose elements have varying degrees of damages [7].

The trained neural network will then have the capability of classified the different size of hollow through the pipe. This is the initial stage for detect crack in pipe. The most desirable feature of this approach is that it is able to know the properties of pipe without prior knowledge of the model of the structure. Instead of classified, information through a complicated reconstruction of the structure model, the pattern identification is realized through a trained network which does not involve heavy computation such as large scale finite element analysis. Therefore, a well-designed neural network is able to classified and learned of the different size of hollow through the pipe with the same condition. Clearly, Artificial Neural Network will train the network efficiently and perform the mapping correctly and give a percentage precisely.

II. SYSTEM OVERVIEW

A system flow of the experiment is shown in fig. 2. Before start the experiment, the experimental setup has been prepared. Carbon Steel pipe with 0.5m long, 2.5 inch diameter and 4 mm thickness are taken as a specimen have been test using impact testing by impact hammer and accelerometer. The distance considered between hammer and accelerometer is 20 cm and 30 cm with hollow in the middle for both damage pipes. The output signal had been analyzed using Picoscope 6 analyzer and software. Data has taken in time domain (Fast Fourier Transform) before convert to (Frequency Response Function) frequency domain. This FRF data has been used as a feature for input in neural network.

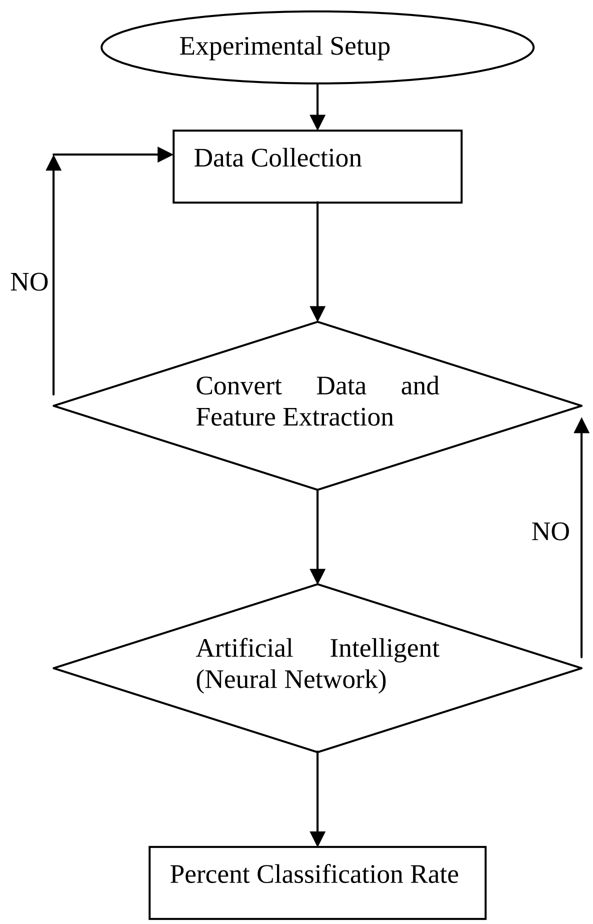

Fig. 2. System flow

III. IMPACT TESTING

Impact testing, or more accurately experimental impact test, is the field of measuring and analyzing the structural response of structures and or fluids when excited by an input. Impact hammer has been used as input (force) 25 cm from the accelerometer with straight line. Impact hammer was lightly tapped parallel with the accelerometer to produce a vibration on the specimen (structure). When the pipe is subjected to the strike, it is excited and vibrated according to the bandwidth of the impulse. From this, the response of the specimen can be determined. By determining the relationship between the forces imparted to a structure and the structure's response to those forces, the intact and damage pipe can be compare.

IV. EXPERIMENTAL SETUP

Simple free condition frame has been developed to hang the pipe in free-free condition. The pipe has suspended on a frame as a free-free condition using bungee cords to isolate it from the ground. Three type of pipe with different properties are taken as a specimen. The first specimen is intact pipe when the second and third specimen it has 5mm and 10mm hole in the middle. Accelerometer (Type 4374, Bruel & Kjaer, Denmark) with a mass of 0.65 g has fixed on the top of the specimens using wax. Impact testing from vibration technique is used to produce vibration signal and received by accelerometer for analysis. The output signal obtained from accelerometer and impact hammer has analyzed using a PicoScope 6 analyzer. Time domain data from this analyzer was converting to frequency domain as Frequency Response Function (FRF).

There are many tools available for performing vibration analysis and testing. The Frequency Response Function (FRF) is a particular tool. Frequency response function based damage identification requires inputs from only a few sensors located on the structure [8]. A FRF is a transfer function, expressed in the frequency domain and a complex functions, with real and imaginary components. They may also be represented in terms of magnitude and phase. Kim (2003) developed an online structural damage identification which identifies the damage and determines it extent from the frequency responses of a damaged structure [9].

Fig. 3. Experimental Setup

A FRF expresses the structural response to an applied force as a function of frequency. The response may be given in terms of displacement, velocity, or acceleration. Furthermore, the response parameter may appear in the numerator or denominator of the transfer function. In this experiment, Apparent Mass FRF (force/acceleration) has been used as an input to neural network and it's have converted from Fast Fourier Transform (FFT) manually. The FRF data was produced by divided the amplitude of force from impact hammer with the amplitude of acceleration from accelerometer. The FRF data shows a good different between the intact and damage pipe. 2032 first data was taken from this FRF and used as input weight in the training neural network. Figure 4 and 5 show the FFT of three different specimen and Figure 6 show the FRF of the intact and damage pipe (with hole in the middle of pipe). By a statistical analysis, we have founded some different from intact and damage pipe. In figure 6, it shows that the different signal with intact and damage pipe in range 0.5 Hz to 1 Hz. From the circle in figure 6, the signal from both damage pipes is dropped.

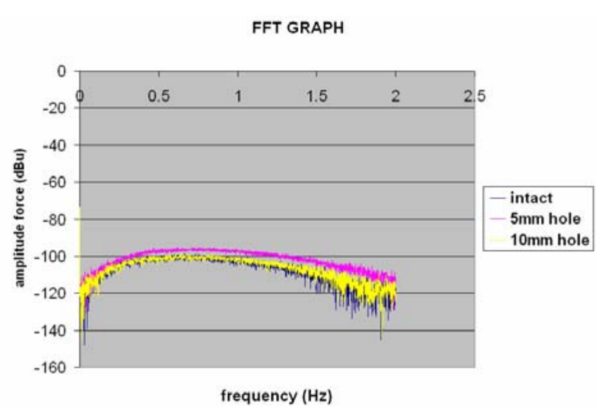

Fig. 4. Amplitude Force FFT Graph

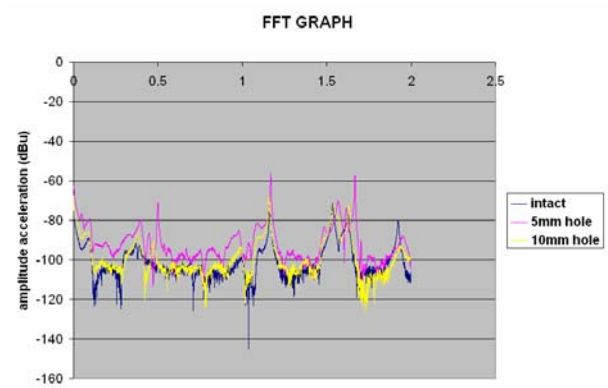

Fig. 5. Amplitude Acceleration FFT Graph

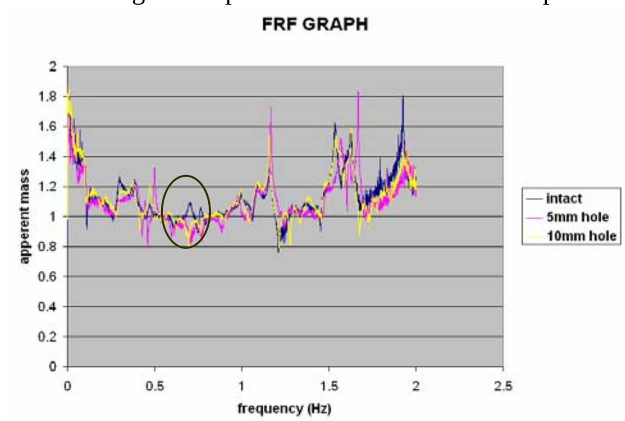

Fig. 6. FRF Graph

V. NEURAL NETWORK

Artificial neural networks provide a general, non-linear parameterized mapping between a set of inputs and a set of outputs. A network with three layers of weights and sigmoidal activation functions can approximate any smooth mapping and such a type will also be used here. A typical supervised feed-forward multi-layer neural network, known as a Back Propagation (BP) neural network, is schematically illustrated in Figure 1.

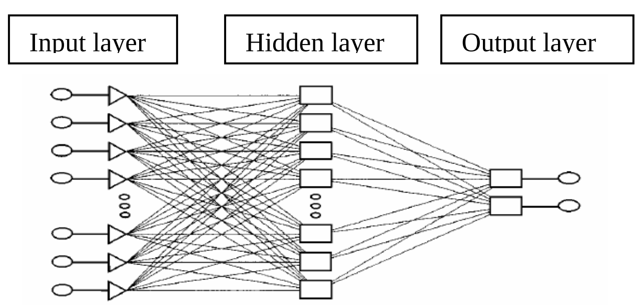

Fig. 1. Typical BP neural network for damage detection.

VI. NEURAL NETWORK CLASSIFIER

Artificial Neural Network (ANN) provides alternative form of computing that attempts to mimic the functionality of the brain [10]. A simple neural network model is developed for sign recognition using the features FRF features. The Neural Network architecture has three layers consisting of an input layer, one hidden layer and an output layer.

To classify the different type of pipe, a simple neural network model using error back propagation is developed. The neural network model has 2032 input neurons and 3 output neurons. It also has one hidden layer with 125 hidden neurons. The initial weights for the neural network are normalized between 0 and 1 and randomized. The performance of the network model is determined using different sets of initial weights. The mean squared error tolerance is fixed as 0.001 for the network. The learning rate and momentum factor are chosen as 0.02 and 0.9 respectively.

This network is trained by the conventional back propagation procedure with momentum and adaptive learning rate. 45 samples weight are used for training the neural network and tested with 2032 input weight. The network is trained with five trial sets of weights.

The training results for the networks namely the classification rate average, time average and epoch average are shown in Table 1. From the table, it shows that the average classification rate for different pipe is 91.47% that have 36.960 second with 312.27 epochs respectively.

Table. 1. Classification Rate

Trial no	Classification Rate (%)	Time (s)	Number of Epoch
1	91.67	37.74	322.65
2	92.22	36.12	305.18
3	90.61	35.70	303.00
4	90.22	36.65	313.50
5	92.67	38.60	317.03
Average	91.48	36.960	312.27

Table. 2. Neural Network Classifier Table

Neural Network Classifier	
Number of input neurons	2032
Number of Hidden Neurons	125
Number of output neuron	3
Activation Function	Binary sigmoid
Learning Rate	0.2
Momentum Factor	0.9
Training Tolerance	0.001
Testing Tolerance	0.2
Number of samples used for training	45
No. samples used for testing	45

VII. CONCLUSION

This paper presents a NDT method to detect the damage in a pipe using FRF and ANN. The overall accuracy of the proposed method is 91.48%. It shows the effectiveness of the proposed method in detecting damage in pipe. In the future work, it is proposed to develop other feature extraction and classification algorithm to improve the accuracy of the system.

REFERRENCE

[1] B. P. NANDWANA? and S. K. MAITI; Modelling of vibration of beam in presence of inclined edge or internal crack for its possible detection based on frequency measurement. Indian Institute of Technology, Bombay 400 076, India

[2] Adams, R. D., Walton, D., Flitcroft, J. E. and Short, D., Vibration testing as a nondestructive test tool for composite materials. *Composite Reliability, ASTM STP*, 1975, 580, 159-175.

[3] Heylen W, Lammens S. FRAC: a consistent way of comparing frequency response functions. In: *Proceedings of conference on identification in engineering systems, 1996.*

[4] Schulz MJ, Naser AS, Pai PF, Chung J. Locating structural damage using frequency response reference functions. *J Intell Mater Syst Struct 1998*;9:899–905.

[5] Tsou P, Shen M-HH. Structural damage detection and identification using neural network. In: *Proceedings of the 34th AIAA/ASME/ASCE/AHS/ASC structures, structure dynamics, and material conference. Washington, DC: AIAA; 1993*. p. 3551–60.

[6] Luo H, Hanagud S. Dynamic learning rate neural network training and composite structural damage detection. *AIAA J 1997;35(9):*1522–7.

[7]. Zang, C. and Imregun, M., Combined neural network and reduced FRF techniques for slight damage detection using measured response data. *Arch. Appl. Mech., 2001*, 71, 525–536.

[8] Ajay Kesavan: Embedded Intelligence in Structural Health Monitoring Using Artificial Neural Networks *Mechanical & Manufacturing Engineering Melbourne, Victoria, Australia.RMIT University August 2006.*

[9] Kim, HY 2003, 'Vibration-based Damage Identification using Reconstructed FRFs in Composite Structures', Journal of Sound and Vibration, vol.259, no.5, pp.1131-1146.

[10]X. Fang a, H. Luo b, J. Tang a,*. Structural damage detection using neural network with learning rate improvement Department of Mechanical Engineering, *The University of Connecticut, 191 Auditorium Road, Unit 3139, Storrs, CT 06269, USA b GE Global Research Center, 1 Research Circle, Niskayuna,* NY 12309, USA