Classifying Turbomachinery Blade Mode Shapes Using Artificial Neural Networks

Ismail Abubakar, Hamid Mehrabi, Reg Morton

Abstract—Currently, extensive signal analysis is performed in order to evaluate structural health of turbomachinery blades. This approach is affected by constraints of time and the availability of qualified personnel. Thus, new approaches to blade dynamics identification that provide faster and more accurate results are sought after. Generally, modal analysis is employed in acquiring dynamic properties of a vibrating turbomachinery blade and is widely adopted in condition monitoring of blades. The analysis provides useful information on the different modes of vibration and natural frequencies by exploring different shapes that can be taken up during vibration since all mode shapes have their corresponding natural frequencies. Experimental modal testing and finite element analysis are the traditional methods used to evaluate mode shapes with limited application to real live scenario to facilitate a robust condition monitoring scheme. For a real time mode shape evaluation, rapid evaluation and low computational cost is required and traditional techniques are unsuitable. In this study, artificial neural network is developed to evaluate the mode shape of a lab scale rotating blade assembly by using result from finite element modal analysis as training data. The network performance evaluation shows that artificial neural network (ANN) is capable of mapping the correlation between natural frequencies and mode shapes. This is achieved without the need of extensive signal analysis. The approach offers advantage from the perspective that the network is able to classify mode shapes and can be employed in real time including simplicity in implementation and accuracy of the prediction. The work paves the way for further development of robust condition monitoring system that incorporates real time mode shape evaluation.

Keywords—Modal analysis, artificial neural network, mode shape, natural frequencies, pattern recognition.

I. INTRODUCTION

MODAL analysis is generally employed in acquiring dynamic response of a vibrating component and are widely used in condition monitoring of turbomachinery blades [1]. The analysis provides useful information by exploring various mode shapes that a vibrating blade can take up during operation since mode shapes have their corresponding natural frequencies.

Currently, in modal analysis of turbo machinery blades, extensive data analysis is performed to acquire mode shapes in real time. This approach is affected by constraints of time and the availability of qualified personnel. As such, new approaches for mode shapes identification that provide faster and accurate results which can describe to a non-technical expert how a blade is behaving in real time graphical form are pursued. In turbomachines, a variety of machine learning algorithms have been employed for prognostic and diagnostic

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analysis of various components. Basically the machine learning method is related to making class of the pattern from raw data and generates expert systems for some tasks [2]. Also, an autonomous orbit pattern recognition using deep learning method on shaft orbit shape images is put forward in [3].

Considering that each natural frequency produces a unique mode shape, a pattern recognition algorithm is devised in this study to provide information on the mode shape of an operating blade and therefore help facilitate blade condition monitoring tasks. There are therefore two key objectives for the work reported in this study. The first objective is to carry out a finite element analysis simulation study to obtain natural frequencies and mode shapes of a small scale laboratory blade. The second objective is to develop a nomenclature for mode shape classification and further train a neural network to recognise these mode shapes based on frequencies supplied to the network.

A. Computational Modal Analysis

The sketch of blade assembly used in this study is presented in Fig. 1. Each of the blades and the hub assembly are made of structural steel. Considering that only the parameters of a single blade are usually measured instantaneously in turbo blades signal analysis and that the blades are identical and symmetrical, using a single blade from the whole assembly would suffice for the simulation. However, the analysis is carried out using two different software packages – Solidworks and Nastran. There are two reasons to this. Firstly, the results obtained from each software will be used to validate the other. Secondly, this will make provision for more data to be used in training the network since accuracy of the network is dependent on the amount of data used to train the network.

B. Simulation Results

For the simulation, the material properties used are:
- Young's modulus: 210 GPa
- Poisson's ratio: 0.28
- Density: 7700 kgm^{-3}

The material properties were assigned to the blade and constrained as it is on the assembly of Fig. 1 and the simulation study was carried out similar to that reported in [4]. The first five modes were extracted and the results are presented in Fig. 2.

A second simulation was run on Nastran Software in the same manner as the one described above. The mode shapes extracted are similar to those obtained in Solidworks. Table I provides a summary of the modes and frequencies obtained
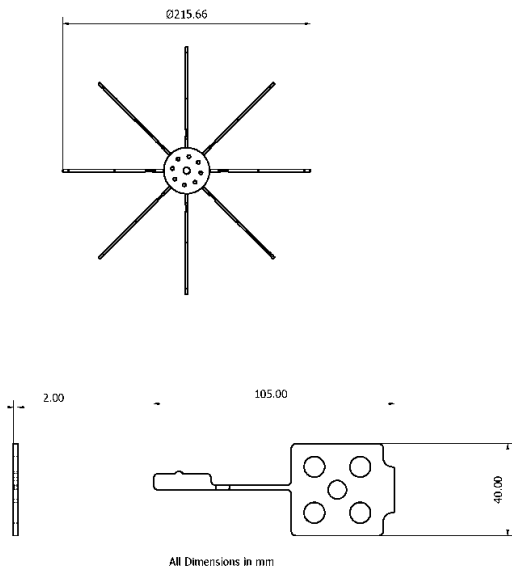
from the two software.
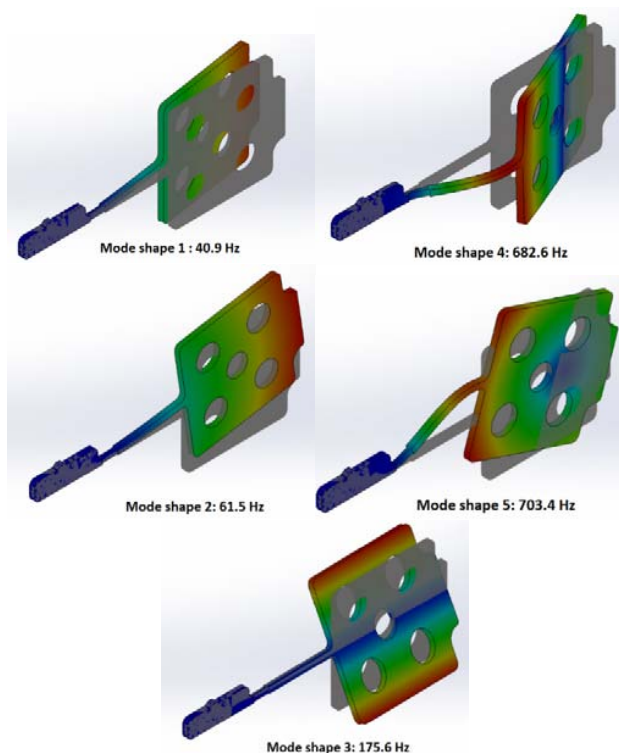

Fig. 1 Blade assembly profile

Fig. 2 First five modes obtained from finite element modal analysis

The results presented in Table I show that the values extracted from the two different software are in good agreement.

II. MODE SHAPE NOMENCLATURE FOR PATTERN RECOGNITION

When inputs are to be classified into N different classes, the target vectors have N elements. For each target vector, one

element is 1 and the others are 0 [5]. The mode shape obtained from the modal analysis simulation is the first five modes. Hence there are five different classes that the network aims to recognise. Table II summarises frequencies and their corresponding mode shapes in conjunction with the nomenclature adopted for training ANN pattern recognition model.

TABLE I
SINGLE BLADE MODAL ANALYSIS DATA OBTAINED FROM SOLIDWORKS AND NASTRAN

Mode	Frequency - Hz (Solidworks)	Frequency - Hz (Nastran)
1	40.9	40.5
2	61.5	61.4
3	175.64	165.3
4	682.6	677.3
5	703.4	700.1

TABLE II
ACER SINGLE BLADE DATA

Mode	Frequency - Hz (Solidworks)	Frequency – Hz (Nastran)	Mode shape nomenclature				
1	40.9	40.5	1	0	0	0	0
2	61.5	61.4	0	1	0	0	0
3	175.6	165.3	0	0	1	0	0
4	682.6	677.3	0	0	0	1	0
5	703.4	700.1	0	0	0	0	1

A. Network Architecture

A multilayer feed forward pattern recognition network is used to train the data in Table II. This type of network consists of interconnected processing neurons working together to solve a specific task as illustrated in Fig. 3. The first layer is referred to as the input layer and it receives frequency value into the network as input. The next layer is the hidden layer that has connection with the input layer and also connected to the output layer as illustrated in the figure. The output layer provides output from the network corresponding to a mode shape nomenclature. A properly trained feedforward neural network can be used to solve problems involving nonlinear and complex input to output mapping.

B. ANN Training

The training commenced from the input layer and to the hidden layer in which the resulting error between the predicted and target values is propagated backwards from the output layer to hidden layer and back to the input layer. By doing so, the values of the weights and biases are updated continuously until a minimum error is achieved. One of the major problems in training a neural network is the issue of obtaining optimum weights and biases that can guarantee an optimum network performance. For this reason, Genetic Algorithm was implemented in the training process to facilitate acquiring optimum weights and biases so that mode shapes can be predicted with a high degree of accuracy. By incorporating genetic algorithm (GA) to the neural network, an effective training method is attained following the procedure (Fig. 4):

i.   Separate data into inputs and outputs
ii.   Randomly divide data into training, validation and testing

iii. Configure network: Assign number of neurons to the hidden layer, learning rate, training algorithm, transfer functions and epochs
iv. Run GA iteratively with defined generations,

chromosomes, mutation rate, cross over and selection to find the best fitness value using mean squared error (MSE) to determine the best fitness value and pass it to the network as the optimum weight and bias.
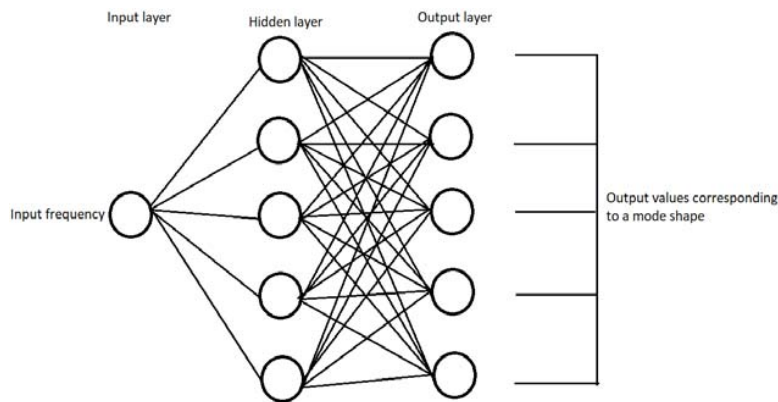

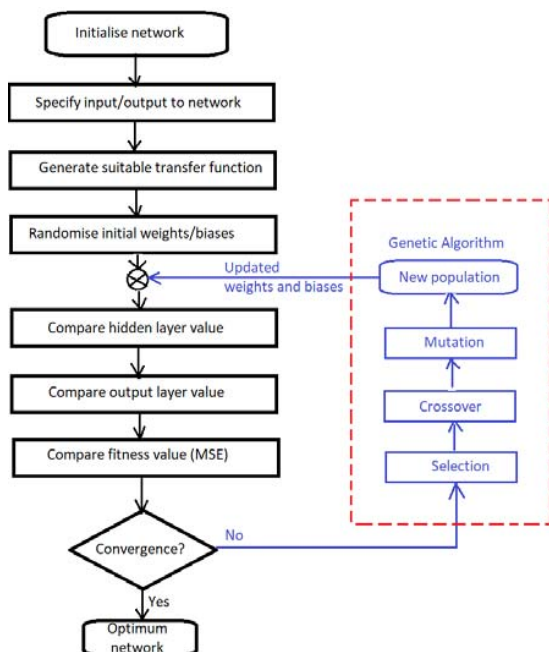Fig. 3 Neural Network architecture for mode shape recognition

Fig. 4 Loop of GA optimising ANN training

C. Results and Discussion

The confusion matrix in Fig. 5 analyses the network's response by showing the final network errors.

The rows of the confusion matrix correspond to what the ANN predicted and the columns correspond to the known truth (target class). The cells along the diagonal (the green boxes) are a representation of how many times the trained data were correctly classified. The cells that are not on the diagonal (the red boxes) correspond to incorrectly classified observations. Each cell shows the number of observations in conjunction with the percentage of the total number of observations. From the matrix produced in Fig. 5, it can be

seen that the network was able to accurately classify all the modes.

Fig. 5 Confusion Matrix

The model was able to map input frequencies (Hz) to their corresponding nomenclature associated with mode shapes. Following the results obtained, there is an evidence of using ANN to identify the vibratory mode of a turbo machine blade in operation without the need for extensive signal processing and computational time currently incurred in most scenarios. In addition, the nomenclature proposed for mode shape pattern recognition is suitable to interpret mode shape in real time and can be easily adapted to a graphical plot. Finally, in order to implement the algorithm in real time, it is important to collect training data from the turbomachine blade which it would serve. In other words, the algorithm is application specific

III. CONCLUSION

The study in this paper presents mode shape classification of a small blade assembly using machine learning. The network performance evaluation shows that the ANN employed is capable of identifying the existing correlation between natural frequencies and mode shapes. This is achieved without the need of extensive signal analysis. This method is applicable to recognise mode shapes of a vibrating turbo blade assembly at resonance frequencies where modal data have been acquired and used to train the network. The solution presented in this work offers high advantage from the view that the network is able to classify mode shapes and can be employed in real time including simplicity in implementation and accuracy of the prediction. Future work will consider an extensive experimentation using experimental modal testing to and therefore increase the training datasets. Also, alternative machine learning approach will be explored.

ACKNOWLEDGMENTS

REFERENCES

[1] Oberholster, A. J. & Heyns, P. S., 2009. Online condition monitoring of axial floe turbomachinery blades using rotor-axial Eulerian laser Doppler vibrometry. *Mechanical Systems and Signal Processing,* 23(5), pp. 1634-1643.

[2] Duda O, R., Hart, P. E. & Stork, D. G., 2012. *Pattern classification.* 2nd ed. s.l.:John Wiley & Sons.

[3] Jeong, H., Park, S., Woo, S. & Lee, S., 2016. Rotating Machinery Diagnostics using Deep Learning on Orbit Plot Images. *Procedia Manufacturing,* Volume 5, p. 1107–1118.

[4] Pickering, T. M., 2014. *Methods for Validation of a Turbomachinery Rotor blade Tip Timing System.* Master Thesis ed. Virginia: Virginia Polytechnic Institute and State University.

[5] Mathworks, 2019. *Classify Patterns with a Shallow Neural Network.* (Online) Available at: https://www.mathworks.com/help/deeplearning/gs/classify-patterns-with-a-neural-network.html (Accessed 25 July 2019).