SACoMaTiS 2008
International RILEM Conference
1-2 September 2008 Varenna (LC)
Como Lake - Italy
POLITECNICO DI MILANO
www.sacomatis.org
on Site Assessment of Concrete, Masonry and Timber Structures

EXPERIMENTAL VERIFICATION OF A VIBRATION-BASED DAMAGE IDENTIFICIATION METHOD IN A TIMBER STRUCTURE UTILISING NEURAL NETWORK ENSEMBLES

Ulrike Dackermann, Jianchun Li, Bijan Samali, Fook Choon Choi and Keith Crews

Centre for Built Infrastructure Research, Faculty of Engineering, University of Technology Sydney, NSW 2007, Australia

Abstract

Vibration-based damage identification methods utilise the abnormality in dynamic fingerprints of a structure to detect damage. Dynamic fingerprints can be extracted from time histories, frequency response functions, natural frequencies or modal strain energies. Damage occurring in a structure alters these dynamic fingerprints, and therefore they can be used as reliable tools to identify damage.

This paper presents an overview of a project that aims to identify structural damage by examining a variety of dynamic fingerprints. Artificial neural networks (ANNs) are developed to identify pattern changes associated with damage. Neural network ensemble techniques are adopted to fuse outcomes of individual network estimations and to provide a more accurate and reliable damage prediction.

In detail, a procedure is presented that utilises the damage index method, which is based on modal strain energy changes, to determine the location and the severity of single damage. Numerical models of timber beams inflicted with several types of damage are generated. A laboratory timber beam damaged at mid-span is experimentally tested and analysed. Damage is identified by neural network ensembles that use damage index values as input patterns. The networks are first trained with indices of numerical timber beams and then tested with data obtained from the laboratory timber beam.

Keywords

Damage Identification, Artificial Neural Network, Neural Network Ensemble, Structural Health Monitoring, Damage Index Method

1. INTRODUCTION

Timber structures are often exposed to harsh environmental and loading conditions, which, in the course of time, can result in rot, decay, insect attack, weathering and mechanical damage. These deteriorations may lead to a loss of structural integrity. To ensure the reliability of these structures and the safety of the public, health monitoring, condition assessment and safety evaluation is necessary. Various non-destructive testing (NDT) methods have been developed over the past two decades to provide accurate information on the condition of timber structures. Most of these techniques, however, are local methods, such as visual inspection, drill resistance, stress wave, ultrasonic, microwave or radiography. These methods require the damaged area to be known a priori in order to be economical, efficient and reliable.

Vibration-based damage identification techniques are global methods and are able to assess the condition of the entire structure. By examining changes in the dynamic characteristics of a structure, they are able to identify the damage. These techniques eventually reduce to some form of pattern recognition problem. Among various vibration-based techniques, the damage index method, which is based on changes in modal strain energy, is particularly promising and has successfully been used in many applications. This method, however, faces critical problems when applied in the field where many issues, such as incomplete data due to limited sensor arrays, measured noise and mode shape estimation errors, lead to unreliable and inaccurate damage identification [1 2 3 and 4].

ANNs are artificial intelligence that simulate the operation of the human brain. They are capable of learning, i.e. pattern recognition, and are robust in the presence of noise. When used in combination with vibrational damage identification techniques, the original methods can be greatly improved.

In this paper, authors present a robust and reliable procedure that identifies damage in a laboratory timber beam. The damage index method in combination with ANNs is used to identify the defects. First, networks are trained with indices of numerical timber beams and then the networks are tested with data obtained from the laboratory timber beam.

2. PROJECT OVERVIEW

The objective of this project is to develop a damage detection procedure which is suitable for field application. It will incorporate conditions, which are encountered in real field-testing, such as limit number of sensor arrays, measurement noise or incomplete data sets. The developed procedure will be non-destructive, global, robust and reliable.

A variety of measured data, in which structural dynamic characteristics are inherent, will be used to determine the existence, location and severity of damage. Such data are, for instance, time histories obtained from vibrations, frequency response functions, natural frequencies, mode shapes, damping ratios or modal strain energies. The vibrational parameters will individually be processed to identify damage utilising conventional damage detection methods in combination with ANNs. The fusion with neural network techniques will improve the conventional methods and overcome problems like noise interferences or incomplete data sets. The individual damage predictions will eventually be combined with a neural ensemble and a final, overall damage identification is produced. Thereby, the benefits of each individual type of vibrational parameters are used to its best and an artificial intelligence will give a final damage prediction.

3. DAMAGE INDEX METHOD

The damage index method was developed in 1992 by Stubbs, Kim & Topole [5]. It utilises the relative differences in modal strain energy before and after damage to identify defects.
The strain energy in a Bernoulli-Euler beam associated with a particular mode shape ϕ_i is calculated from

$$U_i = \frac{1}{2}\int_0^L EI\left(\phi_i''(x)\right)^2 dx \tag{1}$$

By subdividing the Euler-Bernoulli beam and associating the modal strain energy to an element j and relating the damaged* to the undamaged state, the so-called damage index β_{ij} is obtained from

$$\beta_{ij} = \frac{\int_j \left(\phi_i''^{*}(x)\right)^2 dx \int_0^L \left(\phi_i''(x)\right)^2 dx}{\int_j \left(\phi_i''(x)\right)^2 dx \int_0^L \left(\phi_i''^{*}(x)\right)^2 dx} \tag{2}$$

To establish a comparative basis for different modes, the damage index β_{ij} is transformed into the standard normal space and the normalised damage index Z_{ij} is calculated from

$$Z_{ij} = \frac{\beta_{ij} - \mu_{\beta ij}}{\sigma_{\beta ij}} \tag{3}$$

with $\mu_{\beta ij}$ being the mean and $\sigma_{\beta ij}$ -the standard deviation of the β_{ij} values for all j elements. Positive Z_{ij} values indicate the possibility of damage and can therefore be utilized to locate the defects. The estimation of the damage severity for an element j can be formulated by equation

$$\alpha_{ij} = 1 - \frac{1}{\beta_{ij}} \tag{4}$$

with α_{ij} being the severity estimator.

4. ARTIFICIAL NEURAL NETWORKS

Artificial neural networks (ANNs) are artificial intelligence, which were originally developed as a methodology for emulating the biology of the human brain. They consist of weighted interconnected neurons, which are arranged in sets of input, hidden and output layer. The neurons are weighted by an adjustable variable (weight) and offset by a constant (bias). The layers are linked by transfer functions. A key property of ANNs is the capability of learning, i.e. pattern recognition and classification. ANNs can be regarded as nonlinear mathematical functions that map a set of input variables pi (i = 1, 2 ... d) to a set of output variables ak (k = 1, 2 ... r) [6]. The weights and biases in the hidden layers are iteratively varied in order to move the network outputs closer to the targets. The circled illustration of Figure 1 shows the schematic model of a multi-layer feed-forward neural network, which is the most commonly used network in damage detection.

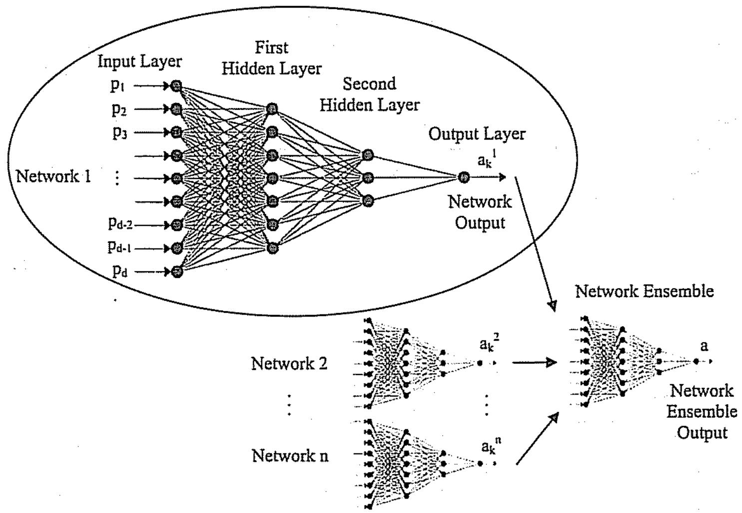


Figure 1: Feed-forward multi-layer neural network ensemble

The neural network ensemble was developed by Hansen & Salamon in 1990 [7]. It is a learning paradigm where a collection of neural networks is trained simultaneously for the same task [8]. First, each network in the ensemble is trained individually and then the outputs of each of the networks a_e ($e = 1, 2 \ldots n$) are combined to produce the ensemble output a. With the neural network ensemble approach the generalization ability of a neural network system can significantly be improved [9]. A neural network ensemble model is also shown in Figure 1.

5. METHODOLOGY

This paper presents a modal-based method that utilises the damage index values as input patterns for artificial neural networks to identify defects. The neural network ensemble approach is utilised in order to respect different characteristics of the damage index values and to consider the varying importance of individual modes. To consider real applications where no information on the structure is available, the networks are exclusively trained with patterns generated from numerical models. Damage of the experimental timber beam is identified by simulating the numerically trained networks ensemble.

Firstly, mode shapes are extracted by solving the eigenvalue problem of the numerical model or by direct measurements of the accelerometers from experimental testing. Real life issues regarding limited sensor arrays are incorporated by using a minimal number of measurement points. The cubic spline interpolation technique is adopted to reconstruct fine

mode shapes and to thereby improve the damage detection results. Secondly, from the identified mode shapes the damage index values Z_{ij} and α_{ij} are derived. Thirdly, sets of individual neural networks are trained to map the mode separated damage index values to the location and the severity of damage. Finally, a neural network ensemble is used to combine the outcomes of the individual networks and an overall damage prediction is obtained.

6. DAMAGE IDENTIFICATION PROCEDURE

6.1 Numerical model

A numerical model of a pin-pin supported timber beam with the dimensions of 45 mm by 90 mm by 4,500 mm is created using the finite element analysis package ANSYS (2005a). The cross-section is modelled with 20 elements across the height and 4 elements along the width. A division into 201 nodes in the longitudinal direction of the model is chosen in accordance with previous sensitivity studies undertaken by Choi [10]. The modulus of elasticity is set to12,196 N/mm^2, which is obtained from four-point bending tests of the actual timber that is used for the laboratory beam. Figure 2 depicts a model of the timber beam.

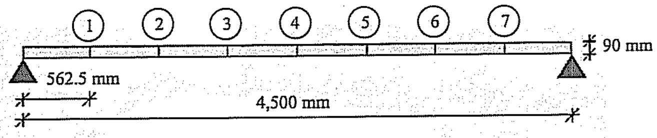


Figure 2: Finite element modelling of a pin-pin supported timber beam

Seven different damage locations with spacings of 562.5 mm (1/8th of the span length) are considered. The locations are denoted as 1, 2, 3, 4, 5, 6 and 7 as shown in Figure 2. For each of these locations five different damage severities, termed as extra light (XL), light (L), medium (M), severe (S) and extra severe (XS) are introduced, generating a total of 35 different damage cases. All inflicted damage are 45 mm in length (1 % of the total span length) and 9 mm, 18 mm, 27 mm, 36 mm and 45 mm in height. This corresponds to 27.1 %, 48.8 %, 65.7 %, 78.4 % and 87.5 % of loss of the second moment of area (I). Damage is modelled by rectangular openings from the soffit of the beam along the span length. A medium size damage is depicted in Figure 3.

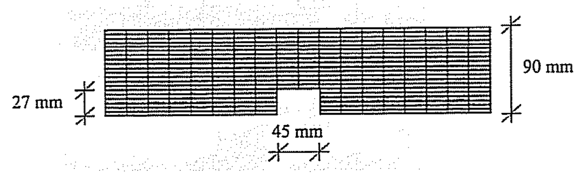


Figure 3: Finite element modelling of medium size damage (27 mm x 45 mm)

Using the modal analysis module in ANSYS, the first five flexural modes, with their corresponding natural frequencies, damping ratios and mass normalised mode shapes are extracted. To incorporate real life problems with limited sensor arrays, coordinates of the mode shape vectors are reduced from 201 data points to 9 data points, representing 9 measurement sensors. Subsequently, the mode shape vectors are reconstructed from 9 to 41 data points, utilising cubic spline interpolation techniques, in order to improve the damage identification results. By correlating the mode shape curvature vectors of the undamaged beam to those of the different damaged beams, the damage index values Z_{ij} and α_{ij} are determined following the procedure outlined in section 3.

6.2 Experimental model

Laboratory testing of a pin-pin supported timber beam is undertaken in the Structures Laboratory of the University of Technology, Sydney (UTS). The dimensions of the beam comply with the specifications of the numerical model. The experimental set up is displayed in Figure 4.

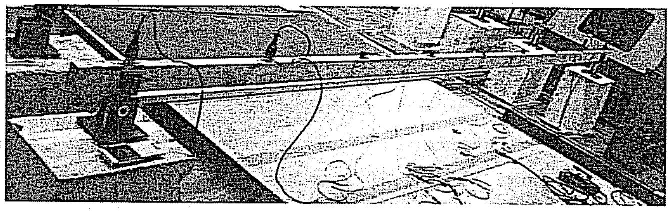


Figure 4: Experimental test set up

The timber beam is inflicted with three different severities (XL, M, XS) of single damage situated in the mid-span of the beam (damage location 4). The damage is introduced by saw cuts from the soffit of the beam, 45 mm in length and 9 mm, 27 mm and 45 mm, respectively, in height. The mid-span location is chosen as this is a node point of mode 2 and mode 4 and therefore most problematic for the damage index method. The medium size damage is displayed in Figure 5.

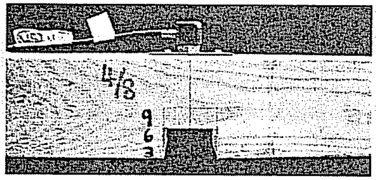


Figure 5: Experimental medium size damage (27 mm x 45 mm)

To obtain the modal parameters of the beam, experimental modal testing and analysis is performed. In modal testing, the beam is excited by an impact hammer and the acceleration responses are measured by nine equally spaced piezoelectric accelerometers. The signals of the hammer and the acceleration responses are first amplified by signal conditioners and then

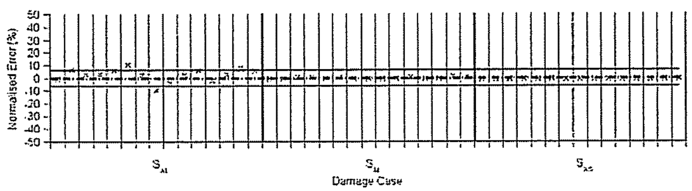
recorded by a data acquisition system. The sampling rate is set to 10,000 Hz for a frequency range of 5,000 Hz and 8,192 data points, thus giving a frequency resolution of 0.061 Hz per data point. The acquired time history data is transformed into the frequency domain and by performing modal analysis the modal parameters are determined. The identified first five flexural mode shapes are again reconstructed from 9 to 41 data points and the damage index values are derived as presented in section 3. The undamaged beam is tested 5 times and the different damage cases 3 times each. Thereby a total of 45 Z_{ij} and α_{ij} damage indices are generated (3 damage severities x 5 undamaged data sets x 3 damaged data sets).

6.3 Artificial neural network model

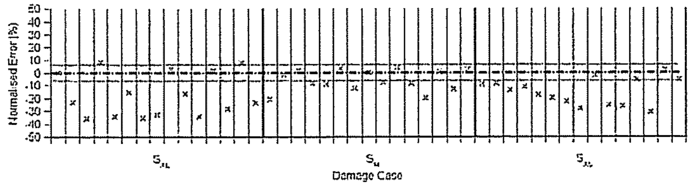
An ensemble of supervised feed-forward multi-layer neural networks is designed to identify the damage. The neural network ensemble is trained with numerical and tested with experimental data. The derived damage indices Z_{ij} and α_{ij} are utilised, respectively, as input patterns to the networks to estimate the location and severity of damage. First, the individual neural networks are trained with damage indices specific to individual modes. Then, the outcomes of the individual neural networks are combined in a neural network ensemble and an overall damage prediction is obtained. The individual neural networks comprise of an input layer with 41 nodes, representing the 41 data points of the damage indices; three hidden layers with 30, 20 and 10 nodes and one single node output layer estimating the location or the severity of the damage. The network ensemble is designed with 5 input nodes, which are the outputs of the 5 individual networks; three hidden layer of 7, 5, and 3 nodes and one output node estimating the damage location or severity. The transfer functions used are hyperbolic tangent sigmoid functions. Training is performed utilising the back-propagation conjugate gradient descent algorithm. The input data is divided into three sets; a training, a validation and a testing set. While the network adjusts its weight from the training samples, its performance is supervised utilising the validation set to avoid overfitting. The network training stops when the error of the validation set increases while the error of the training set still decreases, which is the point when the generalisation ability of the network is lost and overfitting occurs. The complete data set of 35 numerical samples is allocated for training. The experimental samples are divided into sets of 18 for validation and 27 for testing. The design and operation of all neural networks is performed with the software Alyuda NeuroIntelligence version 2.2 from Alyuda Research Inc.

7. RESULTS AND DISCUSSION

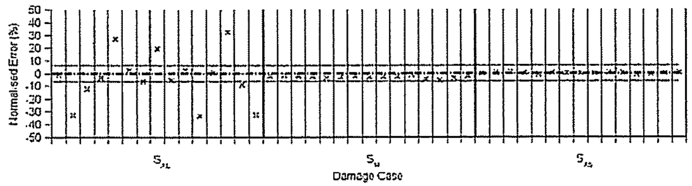
For each mode shape, individual neural networks are trained and simulated with damage index values to identify damage. The damage index Z_{ij} is utilised to determine the location of the damage and the damage index α_{ij} to estimate the damage severity. The networks are first trained with data obtained from the numerical timber beams and then tested with data from the laboratory beam. The outcomes of the individual networks that estimate the damage location of the laboratory timber beam are shown in Figure 6a to 6e. Note: Very similar outcomes are obtained from the networks trained to predict the damage severity.



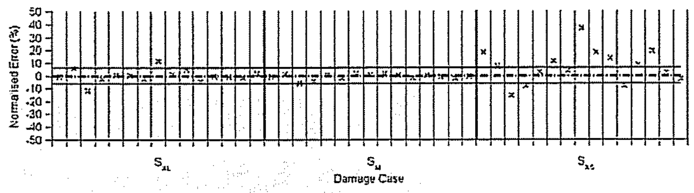
(a) Neural network outcomes to locate damage trained with Z_{ij} derived from mode 1



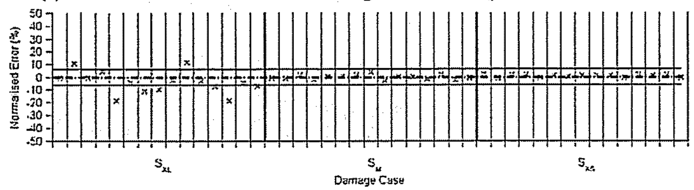
(b) Neural network outcomes to locate damage trained with Z_{ij} derived from mode 2



(c) Neural network outcomes to locate damage trained with Z_{ij} derived from mode 3



(d) Neural network outcomes to locate damage trained with Z_{ij} derived from mode 4



(e) Neural network outcomes to locate damage trained with Z_{ij} derived from mode 5

Figure 6: Individual neural network outcomes trained with Z_{ij} damage indices derived from (a) mode 1 to (e) mode 5 to estimate the damage location of the laboratory timber beam

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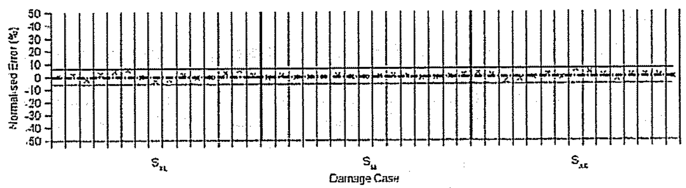
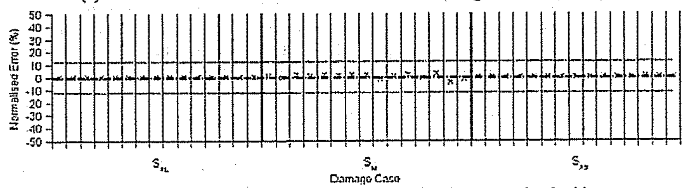
In the figures, the x-axis displays the 45 damage cases sorted by their severities (S_{XL}, S_M and S_{XS}). The y-axis represents the normalised error in prediction of damage location/severity, which is defined as $E_{norm}(d) = (T_d-O_d)/L_{max}$, where d is the damage case, T_d the target value of d, O_d the network output value of d and L_{max} the total length of the beam (here 4.5 m). The marked bandwidth around the 0 % error axis symbolises the area in which the network estimations must fall in order to correctly indicate the damage. Here the bandwidth ranges from -6.25 % to +6.25 % normalised error, representing the mid points in-between two damage locations.

It can be seen that the outcomes of the individual networks differ a lot. Many damage cases are incorrectly localised from the networks of mode 2 and mode 4. The reason for these misidentifications is that for mode 2 and mode 4 the mid-span of the beam is node point of flexural vibration and therefore, the damage cannot be identified correctly. For the networks of mode 1, mode 3 and mode 5, all medium and extra severe damage cases are situated in between the bandwidth. It can also be observed that many of the damage cases of extra light severity are wrongly located.

A final damage prediction based only on the outcomes of the individual networks is problematic as their damage estimations differ a lot. Likewise the importance of the individual modes varies. Therefore, a conclusive, intelligent fusion of the network outcomes is necessary to achieve reliable predictions. This is achieved by combining the outcomes of the individual neural networks in a neural network ensemble. Illustrated in Figure 7 are the final prediction outcomes of the neural network ensembles. It can be observed that all damage cases are eventually and correctly located and quantified. These outcomes show that the developed damage identification procedure is precise, robust and reliable and is capable of dealing with issues associated with node points, measurement noise and limited sensor availability.



(a) Neural network ensemble outcomes to locate damage trained with Z_{ij}



(b) Neural network ensemble outcomes to quantify damage trained with α_{ij}

Figure 7: Neural network ensemble outcomes trained with (a) Z_{ij} damage indices to locate damage and (b) α_{ij} damage indices to quantify damage

8. CONCLUSIONS

This paper presents a project that aims to develop a vibration-based method for damage identification in timber structures. The damage detection method is intended to be applicable in the field. Therefore, issues of real life testing, like limits on the number of sensor arrays or measurement noise, are incorporated. Defects can be detected by using a variety of dynamic characteristics in combination with neural network techniques.

In detail, a procedure is presented that utilises the damage index method, which is based on changes in modal strain energies, to detect defects. Neural network ensembles are trained to map damage index values, obtained from finite element models of timber beams, to the location and the severity of damage. A laboratory timber beam, inflicted with several types of damage, is dynamically tested and analysed. Damage in the experimental beam is identified by simulating the pre-trained neural network ensembles. The final predictions of the neural network ensembles correctly identify all damage locations and severities. These outcomes show that the developed damage detection procedure is reliable, robust and precise and that it is capable of dealing with issues of real life structures.

ACKNOWLEDGEMENTS

The authors wish to thank the Centre for Built Infrastructure Research (CBIR), Faculty of Engineering, University of Technology, Sydney (UTS) for supporting this project. Within the Faculty of Engineering, the authors wish to express their gratitude to the staff of UTS Structures Laboratory for their assistance in conducting the experimental works. Alyuda Research Inc. is gratefully acknowledged for providing a free copy of their Alyuda NeuroIntelligence software.

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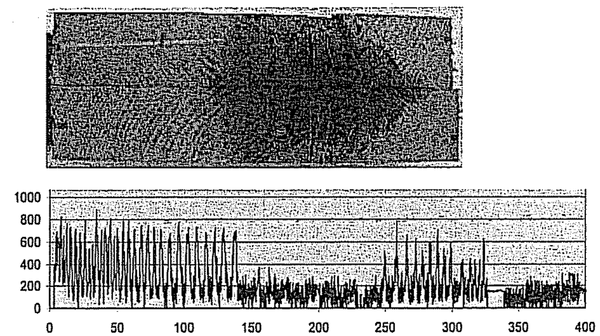
ON SITE ASSESSMENT OF TIMBER STRUCTURES

PART 2



Drilling profile describing decreased wood resistance caused by decay attack.
From 'Evaluation of wood density by means of distinct NDT'
M. Kotlinová, M. Kloiber, G. Vasconcelos, P.B. Lourenço and J. Branco