

**VIBRATION BASED DAMAGE DETECTION USING ARTIFICIAL
NEURAL NETWORK**

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ABSTRACT

This thesis presents the study on the application of Artificial Neural Network (ANN) in vibration based damage detection. Vibration parameters such as frequencies and mode shapes are used as the input variables, while the location and damage severity are used as the output. Sensitivity study on the effects of different backpropagation training algorithms on ANN prediction and training performance is studied. In addition, a parametric study on the effect of different input variables is also carried out. A numerical model of two-span reinforced concrete slab and a numerical model of steel frame are used as examples in the study. These structures are analyzed using modal analysis to finite element model to observe the behaviour of modal parameters. The results show that ANN is capable in detecting damage and predict the damage severity.

ABSTRAK

Kajian ini membicarakan aplikasi Artificial Neural Network (ANN) dalam menegesan kerosakan struktur berdasarkan kaedah gegaran. Parameter gegaran (*vibration parameters*) seperti frekuensi asli (*natural frequency*) dan bentuk mode (*mode shape*) telah digunakan sebagai input manakala lokasi kerosakan dan tahap kerosakan struktur merupakan output yang diramal dalam aplikasi ANN. Dalam kajian kepekaan latihan algoritma (*training algorithm*) yang dijalankan, kesan kepelbagaian latihan algoritma terhadap prestasi latihan dan ramalan telah dikaji dan dibincangkan. Tambahan pula, kajian parametrik bagi menyiasat kesan kepelbagaian input terhadap prestasi ANN turut dijalankan. Semua kajian di atas adalah berdasarkan model matematik bagi struktur papak konkrit (*concrete slab*) dan struktur kerangka besi (*steel frame*). Sifat-sifat modal parameter bagi struktur-struktur berkenaan adalah didapati daripada analisis modal ke atas model-model *finite element*. Daripada keputusan kajian, ANN berupaya mengesan dan meramal tahap kerosakan struktur secara berkesan.

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LIST OF ABBREVIATIONS

ANN	-	Artificial Neural Network
COMAC	-	Coordinate Modal Assurance Criterion (COMAC)
FEM	-	Finite Element Model
FRF	-	Frequencies Respond Functions
Logsig	-	Log-Sigmoid
MAC	-	Modal Assurance Criterion
MLP	-	Multi-Layer Perceptron
MSE	-	Min Square Error
Purelin	-	Linear
SHM	-	Structural Health Management
SOM	-	Self Organising Maps
SRF	-	Stiffness Reduction Factor
Tansig	-	Tangent-Sigmoid

LIST OF SYMBOLS

$[A]$	-	Damaged mode shape
$[A']$	-	Normalised mode shape
A_k	-	Hessian matrix
$[B]$	-	Original undamaged mode shape
β_k	-	Update value for Scaled Conjugate Gradient algorithm
$[C]$	-	Vector of damping
ΔX	-	Weight change for Resilient Backpropagation algorithm
dX_{prev}	-	Previous change to the weight or bias
$\frac{dperf}{dx}$	-	Gradient in transfer function
\mathbf{e}	-	Network error vector
E	-	Young Modulus
$\{f(t)\}$	-	Vector of input forces
gX	-	Gradient in Resilient Backpropagation algorithm
\mathbf{J}	-	Jacobian matrix that contains the first derivatives
$[K]$	-	Stiffness matrices
λ_{jk}	-	j^{th} Mode frequency at k^{th} cases
lr	-	Learning rate
$[M]$	-	Vector of mass
mc	-	Momentum and learning rate adjustment
$\{\phi_i\}$	-	i^{th} Mode shape
ϕ_{jk}	-	j^{th} normalised mode displacement at k^{th} cases
P	-	Mass Density
(P_0)	-	Steepest descent direction
p_R	-	R^{th} Input for neuron's transfer function

SRF_{nk}	-	SRF for segment at k^{th} cases
ν	-	Poisson Ratio
ω_i	-	i^{th} Modal circular frequency
$w_{1,R}$	-	R^{th} Weight in transfer function
$\{\ddot{\mathbf{X}}\}$	-	Vector of acceleration
$\{\dot{\mathbf{X}}\}$	-	Vector of velocity
$\{\mathbf{X}(t)\}$	-	Vector of displacement

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CHAPTER 1

INTRODUCTION

According to Farrar and Worden (2007), damage can be defined as alterations introduced into a system that adversely affects its current or future performance. Damage in structure or buildings is generally induced by long-term wear and tear, environmental effects, corrosion damage, fatigue, cyclic loading and design faults and poor workmanship during construction stage.

It is also noted that many people generally do not emphasize the importance of structural health work of the buildings. The continuous neglect and no remedial actions taken have made the structures ultimately not fit for use. Therefore, structural damage has caused economic loss, humiliation on the owner and endangering public's lives. In Malaysia, roof collapses in stadium, leakages in the parliament house and government offices, closure of important buildings and highways like Martrade building and MRRII due to structural defects and etc has become part of the citizen lives.

As a result, there has been a growing awareness among the building owners to consider damage detection and assessment be done on their buildings. This indicates that there is a need for a reliable damage evaluation technique or structural health monitoring technique to assess the damaged state of the surviving structures.

Structural health monitoring can be described as the process of monitoring the condition of a structure and detection of damage occurring in the structure over time. (Catbas et al., 2008). Structural health monitoring (SHM) has been practiced in various industries including aerospace, manufacturing and more recently civil engineering infrastructure. SHM involves many challenges consisting of identifying the damage and its location, evaluating the severity of the damage, testing of the structure, data acquisition and interpretation, modelling and simulation, statistical analysis and ultimately estimating the remaining service life of the structure. Conventionally, structural damage detection or structural health monitoring is done based on visual inspection and ultrasonic testing. However, these methods involved a lot of judgments from experienced technician. This may contribute to inconsistency in determining the deterioration level of the damage in structure. Moreover, those methods require the location of the damage to be known in advance, before visual inspection take place. However, this may not be possible as not all damaged part of structural members can be detected with naked eyes or ultrasonic equipments due to accessibility problem.

According to Kiremidjian et al. (1997), it is important to have rapid and reliable structural health assessment techniques especially in areas where natural disasters were frequent. Among the available monitoring techniques, structural dynamics approach is one of the most interesting assessment techniques for evaluation of structural damage.

The earliest study by Cawley and Adams (1979) suggested that dynamics parameters such as natural frequencies and mode shapes can be applied in detecting structural damage. This is because the modal parameters are functions of structural properties like mass, stiffness and damping properties. So any degradation of the structural properties will cause the modal parameters like natural frequencies mode shapes and etc. to change (Richardson, 1997). According to Bakhary (2008), combinations of global and local vibration based data enable unique identification of complex damage states and damage locations. With the graphical comparisons of relative changes in mode shapes damage location and damage existence can be detected. (Doebling et al., 1998). Nevertheless, many other approaches have been investigated or are still being developed to identify damage from vibration properties.

Among these approaches, the method that does not require detailed knowledge of the vulnerable parts or the failure modes of the structure can process unexpected failure patterns better (Bakhary, 2008). Therefore, Artificial Neural Networks (ANN) method has been suggested by many researchers due to its capability in prediction of damage location and severity from modal parameters. There are several studies indicating the applicability of ANN in damage detection. The early works in application of ANN in damage detection was initiated by Wu et al. (1992). In the study, neural networks were trained to recognize and predict the condition of a 3 storey frame in damage and undamaged states under earthquake effects. Reduction in the members' stiffness was used as damage indicator in the research. Here, results obtained from these trained neural networks generally showed the good capability of ANN in identifying the location and magnitude of damage (reduction in stiffness) in the structure. Pandey and Barai (1995), demonstrated the suitability of backpropagation ANNs in detecting damage in steel truss bridge by just measuring the structural responds at a few locations. Zhao et.al. (1998), further investigated the ANNs damage detections with parameters like static displacements, natural frequencies, mode shapes, and other parameters based on mode shapes. It is demonstrated that ANNs can generally detect damage using those structural response parameters. Ni et al. (2002) demonstrated the hierarchical use of neural networks in damage detection of large-scale structures like bridges and buildings.

Kao and Hung (2003), demonstrated ANNs ability to identify damage and undamaged state of the structure using numerical and experimental examples of large structure. In Bakhary (2006), it has been demonstrated that ANN are able to predict damage with good accuracy if trained with combinations of parameters like natural frequencies and mode shapes of higher mode. These studies also highlighted the importance of considering noise effect if experimental data are used. Bakhary et al. (2007) concluded that noise effect of the experimental data can be reduced by the introduction of statistical method. Bakhary (2008) again proved that ANN is able to detect damage in structure. In the study, it also successfully demonstrated that sub-structuring methods can be used to detect damage in ANN application. Haryanto et al. (2009) again demonstrated the applicability of ANN in structural damage detection by utilizing the structural static parameters i.e deflection and strain.

Many more studies have demonstrated ANN model as a promising tool for detecting structural damage based on dynamic properties.

1.1. Problem Statement

Due to limitations of conventional non-destructive technique, as mentioned earlier, damage detection is an inverse process, thus, damages will be identified from vibration parameters such as frequencies and mode shapes. Modal parameters like mode shapes and natural frequencies can be derived from the structural dynamics's equation of motion as:

$$[\mathbf{M}] \{\ddot{\mathbf{X}}\} + [\mathbf{C}] \{\dot{\mathbf{X}}\} + [\mathbf{K}] \{\mathbf{X}(t)\} = \{\mathbf{f}(t)\} \quad (1.1)$$

where natural frequencies and mode shape can be determine from structural parameters like mass, stiffness and elasticity. Here, Matrices calculations are involved as the structures are of multiple degrees of freedom. To detect damage inverse calculation is needed where the structural parameters are determined from vibration parameters such as natural frequencies and mode shapes. However, in practice, this inverse process involved a complicated process. Therefore, Artificial Neural Network (ANN) is suggested to identify the damage in the structure and this method is proven effective by many researchers. The advantages of using ANN to detect damage on structure include the generalisation capability of ANN in detecting structural damage correctly despite being trained with incomplete data. However in most applications of ANN, there were no detailed studies in terms of the effect of different algorithm to ANN prediction performance. Thus, in this study, the performance of ANN in damage detection using different training algorithm is compared. Moreover, a parametric study to determine the effect of different combination of input variables to damage detection performance is also conducted.

1.2. Objectives of Research

The objectives of the study are:

- To demonstrate the suitability of frequency & mode shape in structural damage detection.
- To investigate the applicability of modal parameter for damage detection.
- To study the effect on performance and training time for different ANN backpropagation training algorithm.

1.3. Scope of Research

This study will involve:

- Numerical modeling of slab and frame structure using SAP2000
- Build, train, validate and test the ANN models to detect damage.
- Analysis of the effect on performance and training time for 5 different ANN backpropagation training algorithms.

1.4. Significance

The result of the research will be the innovation to a better damage detection method by utilizing ANN in assessing structural damage location. One of the major advantages of using ANN is that, once trained, the relationship between modal parameters and damage location and severity can be established. Hence, by using the modal parameters the damage location and severity can be predicted. Moreover, through this study a suitable algorithm for damage detection would be suggested.

1.5. Structure of the Study

The presentation of this study is accordance to the chapters as follows:

- Chapter 1 Introduction

This chapter presents a brief background of the importance of structural health monitoring, application of Artificial Neural Networks in structural damage detection, scope and objectives of the study, significance of the studies and the thesis outline.

- Chapter 2 Literature Review

This chapter presents the literature review and theoretical background of the study. Various types of Structural Health Monitoring techniques, Artificial Neural Network application and the various types of structural responses that could be used for damage detection are discussed here.

- Chapter 3 Methodology

This chapter discussed the methodology adopted in the SAP 2000 finite element modelling and the applications of Matlab's Artificial Neural Network Toolbox 6 of this research.

- Chapter 4 Results and Analysis

This chapter discusses the analysis and results obtained from the ANNs predictions. Also, the effects of different back propagation training are also reviewed here.

- Chapter 5 Conclusion and Recommendations

This chapter presents a summary of the work done and its outcomes. Subsequently, conclusions are formed for the work conducted in this research and followed by some recommendations for future work.