MULTISTAGE ARTIFICIAL NEURAL NETWORK IN STRUCTURAL DAMAGE DETECTION

GOH LYN DEE

A thesis submitted in fulfilment of the
requirements for the award of the degree of
Doctor of Philosophy (Civil Engineering)

Faculty of Civil Engineering
Universiti Teknologi Malaysia

JUNE 2015

This thesis is specially dedicated to
my beloved families and friends

ACKNOWLEDGEMENT

I am greatly indebted to my panel of supervisors, Prof Dr Azlan bin Ab. Rahman, Dr Norhisham bin Bakhary, and Assoc Prof. Baderul Hisham bin Ahmad, for their generous support, guidance, invaluable discussions, and responsibilities throughout the course of this study. Without their continued support and interests, this thesis would not have been the same as presented here.

Special thanks to the Ministry of Higher Education Malaysia (MOHE) and Universiti Teknologi MARA for supporting my PhD study. Special acknowledgement is also extended to the Eastern Pretech Sdn. Bhd. for supplying the prestressing strands for the study.

My sincere appreciation is also extended to all supporting staffs in the Structural Laboratory of Faculty of Civil Engineering, Universiti Teknologi Malaysia, for their help and assistance in various occasions in order to complete the study.

Last but not least, I am forever grateful to my family members, colleagues, and friends for their endless support, encouragement, prayers, and positive motivation throughout the PhD journey.

ABSTRACT

This study addressed two main current issues in the area of vibration-based damage detection. The first issue was the development of a pragmatic method for damage detection through the use of a limited number of measurements. A full set of measurements was required to establish the reliable result, especially when mode shape and frequency were used as indicators for damage detection. However, this condition is usually difficult to achieve in real-life applications. Hence, in this study, a multistage artificial neural network (ANN) was employed to predict the unmeasured data at all the unmeasured point locations to obtain full measurement before proceeding to damage detection. The accuracy and efficiency of the proposed method for damage detection was investigated. Furthermore, the sensitivity of the number of measurement points in the proposed method was also investigated through a parametric study. The second issue was the integration of the uncertainties into the proposed multistage ANN. The existence of uncertainties is inevitable in practical applications because of modelling and measurement errors. These uncertainties were incorporated into the multistage ANN through a probabilistic approach. The results were in the means of the probability of damage existence, which were computed using the Rosenblueth's point-estimate method. The results of this study evidenced that the multistage ANN was capable of predicting the unmeasured data at the unmeasured point locations, and subsequently, was successful in predicting the damage locations and severities. The incorporation of uncertainties into the multistage ANN further improved the proposed method. The results were supported through the demonstration of numerical examples and an experimental example of a prestressed concrete panel. It is concluded that the proposed method has great potential to overcome the issue of using a limited number of sensors in the vibration-based damaged detection field.

ABSTRAK

Kajian ini menangani dua isu utama semasa dalam bidang berasaskan getaran bagi mengesan kerosakan. Isu pertama adalah untuk membangunkan satu kaedah pragmatik yang menggunapakai bilangan data yang terhad bagi tujuan mengesan kerosakan. Biasanya, satu set lengkap pengukuran adalah diperlukan untuk memperoleh keputusan yang boleh dipercayai, terutamanya apabila bentuk mod dan frekuensi digunakan sebagai indikasi dalam pengesanan kerosakan. Walau bagaimanapun, keadaan ini biasanya sukar untuk dicapai dalam aplikasi peringkat yang sebenar. Oleh itu, dalam kajian ini, rangkaian neural tiruan terbilang (ANN) telah diguna untuk meramal data di titik lokasi di mana pengukuran tidak dilakukan bagi tujuan mendapatkan set ukuran lengkap sebelum prosedur mengesan kerosakan seterusnya dijalankan. Keberkesanan dan ketepatan kaedah mengesan kerosakan yang dicadangkan ini telah diselidik dalam kajian ini. Selain itu, satu kajian parametrik juga dilaksanakan bagi mengkaji sensitiviti bilangan data pengukuran dalam kaedah yang dicadangkan. Isu kedua adalah mengintegrasikan isu ketidaktentuan dalam ANN yang dicadangkan. Kewujudan ketidaktentuan ini tidak dapat dielakkan dalam aplikasi praktikal kerana wujudnya ketidaktepatan dalam prosedur permodelan dan dalam pengukuran yang dilakukan di lapangan. Ketidaktentuan yang wujud ini diambil kira dalam model ANN yang dicadangkan dengan menggunakan pendekatan kebarangkalian. Hasil daripada model ANN yang dicadang adalah dalam bentuk kebarangkalian berlakunya kerosakan, yang dikira menggunakan kaedah anggaran titik Rosenblueth. Hasil kajian ini telah membuktikan bahawa model ANN yang dicadangkan mampu untuk meramalkan data yang tidak ada pada titik lokasi yang proses pengukuran tidak dilakukan. Seterusnya, hasil kajian ini telah berjaya meramalkan lokasi dan tahap kerosakan yang berlaku, lebih-lebih lagi selepas faktor ketidaktentuan diambil kira dalam model ANN. Hasil kajian ini disokong melalui demonstrasi contoh berangka dan contoh eksperimen yang menggunakan panel konkrit prategasan. Kesimpulan yang boleh dibuat adalah kaedah yang dicadang dalam kajian ini mempunyai potensi yang besar untuk diguna bagi mengatasi isu penggunaan bilangan penderia yang terhad dalam bidang mengesan kerosakan berasaskan getaran.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

LIST OF SYMBOLS

c	-	damping matrix
m	-	mass matrix
k	-	stiffness matrix
$x(t)$	-	displacement
$\dot{x}(t)$	-	velocity
$\ddot{x}(t)$	-	acceleration
$\emptyset$	-	mode shape
λ	-	natural frequency
Φ	-	mode shape matrix
Λ	-	diagonal matrix
E	-	Young's modulus
F	-	flexibility matrix
μ	-	mean
σ	-	standard deviation
ρ	-	density
υ	-	Poisson ratio

LIST OF ABBREVIATIONS

ANN	-	Artificial Neural Network
ANN1	-	First Stage ANN
ANN2	-	Second Stage ANN
CGB	-	Conjugate Gradient with Powell-Beale Restarts
CGF	-	Fletcher-Reeves Conjugate Gradient
CGP	-	Polak-Ribiere Conjugate Gradient
CMIR	-	Condensed Model Identification and Recovery
COMAC	-	Co-ordinate Modal Assurance Criterion
COV	-	Coefficient of Variations
CS	-	Cubic Spline Interpolation
DOF	-	Degree of Freedom
FFT		Fast Fourier Transform
FPCOMAC	-	Flexibility Proportional Coordinate Modal Assurance Criterion
FRMAC	-	Flexibility Proportional Modal Assurance Criterion
FRF	-	Frequency Response Function
LM	-	Levenberg Marquart
LVDT	-	Linear Variable Differential Transducer
MAC	-	Modal Assurance Criterion
MSE	-	Mean Squared Error
MSF	-	Modal Scale Factor
PDE	-	Probability of Damage Existence
RP	-	Resilient Backpropagation
SCG	-	Scaled Conjugate Gradient
SEREP	-	System Equivalent Reduction Expansion Process
SDT	-	Structural Dynamic Tools
SHM	-	Structural Health Monitoring
SRF	-	Stiffness Reduction Factor

LIST OF APPENDICES

CHAPTER 1

INTRODUCTION

1.1 Introduction

Buildings, bridges, and other civil structures are built for the comfort of the growing community. The structures undergo deterioration due to factors such as aging, corrosion, load increments, unexpected environmental conditions, earthquakes, and normal wear and tear. The deterioration that causes the reduction of the structural integrity may result in catastrophic disasters. In addition, the owners and the authorities play an important role in ensuring the safety of the structures by conducting periodical inspection and maintenance to avoid incidents that may jeopardise public safety. Several disastrous incidents due to the failure of structural integrity have shown that an efficient periodical structural health monitoring is very important. For example, the collapse on 24 April 2013 of the Rana Plaza situated in Savar, 24 kilometres outside Dhaka in Bangladesh, claimed more than 1000 human lives and left 2500 others injured due to the ignorance of the authorities to take any precautionary steps after receiving reports of cracks in the eight-storey building (The New York Times, 2013). The sudden collapse of the I-35W Mississippi Bridge in Minnesota, United States, was another shocking incident that claimed 13 lives. The collapse of the bridge was caused by the failure of the main span of the deck truss. Another reported an incident that claimed 70 lives was the collapse in 2001 of the 116-year-old long steel truss bridge at Entre-os-Rios in Portugal connecting to Castelo de Paiva (BBC News, 2001). The collapse reportedly was caused by one of the deteriorated support pillars that gave way during a prolonged heavy rain.

The life of the structures can be prolonged, and their good health can be maintained by proper maintenance scheme. Periodical monitoring and maintenance should be carried out on a proper schedule as a preventive measure to ensure their fitness and any possibility of illnesses, if any should be identified. Without careful monitoring and maintenance, these structures can suffer complete failure, which may lead to loss of life and economic impact. Since the earliest study in 1970s, structural integrity has gained many interests, especially in the field of structural health monitoring (SHM). Farrar and Worden (2007) have provided a detailed literature on the studies of SHM.

In SHM, there are four categories for quantifying damages in structures: (1) damage detection; (2) damage location; (3) quantification of the degree of damage; and (4) estimation of the service remaining life. The conservative approach, which is based on visual inspection, is unable to reveal structural anomalies because many portions of the structure are not accessible to visual inspection (Kim and Bartkowicz, 2001). Besides, prior knowledge of the damage location is needed before the inspection can take place. Moreover, the conventional visual inspection requires subjective judgement from the inspector, which may lead to inconsistency in assessment result. Other than visual inspection, electrical impedance methods, such as the eddy current method, acoustic emission method, and ultrasonic method, also have disadvantages that limit their applications for damage detection. For example, the eddy current method requires considerable time for the scanning process, while the acoustic emission is only valid for a certain length of structure, and the ultrasonic method is not valid when there is an issue with free contact surface space for testing.

One technique that has gained the attention of the researchers and practitioners in the SHM field is the vibration-based damage detection. In the vibration-based damage detection, changes in the dynamic properties and modal parameters, which consist of frequencies, mode shapes, and modal dampings, are functions of the physical properties of the structure, such as mass, energy dissipation mechanisms, and stiffness. Therefore, changes in the physical properties cause the changes in the modal properties. The vibration parameters can be obtained from the results of dynamic (vibration) testing (Salawu, 1997). Furthermore, many studies have been conducted analysing the changes of modal data with the corresponding damage location and severity (Kosmatka and Ricles, 1999; Ren and Roeck, 2002; Yam *et al.*, 2003; Rucka and Wilde, 2006; Reynders *et al.*, 2007; Curadelli *et al.*, 2008; Ren and Sun, 2008; Vallabhaneni and Maity, 2011; Rahmatalla *et al.*, 2012; Zhou *et al.*, 2013). These studies concluded the modal parameters are feasible for damage detection.

However, most of the previous work in vibration-based damage detection is limited to numerical examples and small scale laboratory tests with small number of degree of freedom (DOF). In addition, one of the main issues that limits the application of this technology to real structures is its requirement of a large number of sensors for obtaining a complete measurement set. A complete measurement set obtained from the structural response is required for an accurate prediction of all possible damage locations and their severities. Nevertheless, a complete measurement set often involves a high number of measurement points. Reducing the number of measurement points may jeopardise the accuracy of the damage prediction. Important information may be missed out at the unmeasured point locations. It is a considerable challenge to obtain a complete measurement; consequently, the available number of sensors and the accessible locations for the engineers to assess the structure is limited. Therefore, many researchers have been looking for alternatives in extracting more informative data based on limited number of measurement points for damage identification (Yun and Bahng, 2000; Santos *et al.*, 2003; Carvalho *et al.*, 2007; Yang and Liu, 2007; Chen, 2008; Li *et al.*, 2008a; Rahmatalla *et al.*, 2012; Xu *et al.*, 2012). In the recent years, researchers have actively explored various methods in damage identification using incomplete measurements for damage detection. However, an effective method in dealing with a limited number of measurement points has yet to be encountered.

Among the many methods applied in vibration-based damage detection is the Artificial Neural Network (ANN). ANN has received considerable attention due to its capability in establishing both linear and non-linear relationships between vibration parameters (frequencies and mode shapes), damage locations, and severities. According to Vallabhaneni and Maity (2011), ANN is also a promising tool for detecting damages in large civil engineering structures as the data usually contain uncertainties and are often incomplete. Moreover, many studies have reported the potential of ANN vibration-based damage detection (Wu *et al.*, 1992; Pandey and Barai, 1995; Rhim and Lee, 1995; Zang and Imregun, 2001b; Suresh *et al.*, 2004; Efstathiades *et al.*, 2007; Caglar *et al.*, 2008; Bakhary *et al.*, 2010a; Gonzalez-Perez and Valdes-Gonzalez, 2011; Shu *et al.*, 2013). Therefore, this study dealt with the issue of the limited number of measurement in vibration-based damage detection. Furthermore, since ANN has been reliable in establishing a non-linear relationship between input and output parameters, this study employed ANN as the tool to predict the unmeasured mode shape points and to detect damages based on modal data.

1.2 Problem Statements

The accuracy of vibration-based damage detection depends on the amount of measurement points, whereby, a higher number of measurement points provides more accurate information for damage detection. This is due to the fact that more information can be extracted from a high number of measurement points. As damage can affect the structural performance, it is crucial to assess the condition of the structure as detailed as possible. Besides, a large structure means the amount of response must be recorded from a large number of locations. Using a number of measurement points that is too small may set the reliability and the accuracy of the damage assessment at stake. However, using a higher number of measurement points (sensors) to measure the data input will lead to higher measurement number in the analysis. Hence, the issue of long computational time and effort becomes a crucial factor in selecting the appropriate vibration-based method to assess damage in structures.

Long computational time and/or huge computation effort may reduce the efficiency in obtaining accurate results for damage detection. In the case of using a large number of measurement points in any analysis method, a huge number of DOFs are often involved in the analyses. Thus, this leads to a slow convergence in the analysis as more variables are involved in the calculations. In addition, a complex algorithm that is employed to achieve convergence in the analysis adds to a longer computation time, which increases in the computation effort. To overcome the issue of high measurement points and to avoid long computational time and effort, the recent research trend has switched to utilisation of only a limited number of measurement points for damage detection, i.e. low number of sensors. Furthermore, it is impossible to obtain a complete measurement set due to practical limitations, especially when the access is limited.

There are various methods introduced by researchers to enhance the quality of modal data based on limited measurements to ensure the reliability of the proposed vibration-based damage detection method. Some of the proposed methods are modal reduction and expansion methods, the substructural method, and model updating. In the expansion method, the modal data, for example, the mode shape data are expanded to match all the DOFs of the finite element model under consideration. On the other hand, the reduction method is used to reduce the large DOFs to suit the finite element model under consideration. Studies that have applied these methods were conducted by Law *et al.,* (2001), Au *et al.,* (2003), Kim and Cho (2006), Yang and Liu (2007), Li *et al.,* (2008b), Yin *et al.,* (2009), and Lam and Yin (2011). The findings show that these two methods are deceptive, especially when dealing with noisy measurements. In addition, some information is lost during the matrix expansion or reduction calculation process. In the substructural method, a large system of DOFs is divided into many smaller systems containing relatively smaller DOFs. The limitations of these methods are that the result is only valid for the chosen substructure of the overall structure and a large computational effort is required, especially when dealing with high number of DOF, as demonstrated by Xu (2006). Structural condition assessment through dynamic testing usually requires a comparison between the dynamic properties of the structure and the dynamic properties of a numerical model of the structure. Thus, in the model updating method (Carvalho *et al.*, 2007; Yuen, 2012), the finite element model is updated to match the measured modal properties to detect damages. The iterative process of model updating is very time consuming and requires high computational effort, thus limiting its practical application in the engineering industry, especially when time is a primary concern.

In the application of ANN, a high measurement number means a large ANN model is involved. When a large ANN model is involved, a large number of connections between neurons in between layers within the network are created. The high number of connections between neurons may jeopardise the training time and quality. At the same time, the computation effort may also increase enormously. This is one of the main issues highlighted by many researchers (Rhim and Lee, 1995; Chang *et al.*, 2000; Fang *et al.*, 2005; Bakhary *et al.*, 2010a). Even though computational effort mainly depends on the model size of the ANN and the learning algorithm used, the ANN can be executed rapidly and efficiently because of its simplicity, provided it is well trained and an appropriate learning algorithm is employed.

Due to the limitations of the existing methods described above, in this study a new and reliable method in dealing with the structural responses, especially when the incomplete measurement is involved, was proposed. This study proposed a new multistage ANN to overcome the issue of the limited number of measurements in damage detection. As the ANN is capable of establishing a non-linear relationship, it was utilised to predict the unmeasured structural responses at the unmeasured point locations at the unmeasured point locations to form a complete measurement for damage detection purposes. As there are a limited number of works that have investigated the appropriate learning algorithms applied in ANN, especially for the purpose of damage detection, this study provided an appropriate ANN learning algorithm by carrying out a sensitivity study on different ANN learning algorithms. The study was also extended to the study on the effects of the uncertainties to the damage detection because the existence of uncertainties affects the accuracy of the damage assessment results. The damage prediction result is no longer reliable if the measured data contain a high level of uncertainties. The uncertainties often exist due to the random noises, which are inevitable during the measurements and also due to modelling errors. Thus, to tackle this issue in this study, a probabilistic approach was considered to incorporate the uncertainties in the proposed multistage ANN.

1.3 Research Objectives

The objectives of this study are as follows:

i. To demonstrate the applicability of ANN for damage detection by investigating the performance of six different ANN learning algorithms for vibration-based damage detection.

ii. To develop a new multistage ANN model to predict the unmeasured modal data at the unmeasured points for vibration-based damage detection. A parametric study is carried out to investigate the effect of the total number of measurements points and the influence of different sensor topographic using the newly developed multistage ANN.

iii. To propose a probabilistic multistage ANN model to consider uncertainties in terms of modelling and measurement errors with a limited number of measurement points for vibration-based damage detection.

iv. To validate the proposed multistage ANN using the actual experimental data recorded from the constructed prestressed concrete panel in the laboratory.

1.4 Research Scope and Limitations

This research aimed to provide information about the structural responses at the unmeasured points to form a complete measurement data set. Subsequently the information on damage location and severity were obtained through the proposed multistage ANN, a non-model based method. The multistage ANN proposed in this study consisted of two stages: the first stage ANN was for predicting the unmeasured structural response, while the second stage ANN was for damage detection. The feasibility and the applicability of the proposed method were demonstrated through the numerical examples and one experimental example. Due to the large scope of the research, field work was not conducted in this study.

In development of ANN models, only one hidden layer of network was utilised. The activation functions utilised were tan-sig and purelin at the hidden and output layers, respectively. Since the learning algorithm is an important parameter in the ANN, hence a thorough sensitivity study of different learning algorithms was carried out. Only six learning algorithms, consisting of Levenberg Marquart, Resilient Backpropagation, Scaled Conjugate Gradient, Conjugate Gradient with Powell-Beale Restarts, Polak-Ribiere Conjugate Gradient, and Fletcher-Reeves Conjugate Gradient were considered in this study. Only one learning algorithm out of six considered was utilised for the remaining scope in this thesis. The learning algorithm was decided based on the generalisation performance and training time as described in Chapter 4. All ANN models were performed using the Neural Network Toolbox (Beale *et al.*, 1992) running on Matlab platform.

For the numerical examples in this study, a continuous two-span reinforced concrete slab was employed. A similar structure was used as an example for determining the appropriate learning algorithm in Chapter 4, the deterministic approach in Chapter 5, and the probabilistic approach in Chapter 6. The finite element model of the continuous slab was modelled using the Structural Dynamics Tools (SDT) (Balmes *et al.*, 2009). The material properties, such as the Young's modulus, concrete density and Poisson ratio used in the finite element model, were assumed. To train the ANN models, a set of 3000 training data was generated from the finite element model. The training data consisted of various damage cases from the finite element model. To create the damage in the designated location, the Young's modulus of the selected segments in the model is reduced from the original value. The range of the Young's modulus for the deterministic multistage ANN model was between $0.2\times E$ and $1.0\times E$. The range of the Young's modulus for the probabilistic multistage ANN model was between $0.2\times E$ and $1.7\times E$. The structural damage was characterised by a change in stiffness only, and therefore, the structural mass was assumed unchanged in this study. Structural damping is also excluded in this study. The structural responses are recorded from the modal domain, i.e. the modal frequencies and the mode shapes. They were utilised as the input into the

ANN models for damage detection. The first three natural frequencies and mode shapes were employed as the input into the ANN models in all numerical examples demonstrated in this study.

One prestressed concrete panel was cast for validation of the proposed method. The prestressed concrete panel contained only four numbers of prestressing strands without any untensioned reinforcement. Experimental modal testing was carried out to obtain the actual modal parameters of the panel on a series of static loadings. The vertical displacement data during the static load tests were also recorded. The finite element model of the prestressed concrete panel was prepared using the SDT. The material properties for the concrete such as Young's modulus and Poisson ratio were assumed while the concrete density was determined based on the actual dimensions and weight of the panel. The material properties for the prestressing strands were based on the manufacturer's data. Two different ANN models were developed to test the feasibility of the proposed method with both dynamic data (natural frequencies and mode shapes) and static data (displacement). In the verification work using multistage ANN models tested with dynamic data, the first four natural frequencies and mode shapes were employed as the ANN input. On the other hand, for the verification work using multistage ANN models tested with static displacement data, five vertical data were used as the input into the ANN.

1.5 Significance of the Research

As mentioned in subchapter 1.2, this study deals with the issues of utilisation of a limited number of measurement points for the purpose of reducing the computational time and effort, and the consideration of the effects of uncertainties in the vibration-based damaged detection using the newly developed multistage ANN. The ANN is composed of a large number of highly interconnected processing elements in order to solve a specific problem. ANN learns through a series of learning (training) whereby the architecture and the parameters within are determined beforehand. Even though the computational effort mainly depends on the model size of ANN and the learning algorithm used, ANN can be executed rapidly and efficiently because of its simplicity, provided it is well trained and appropriate learning algorithm is employed. The development of ANN with a better training algorithm and the development of technology that brings forward the improved hardware have contributed to the efficiently of the ANN in solving complex problems. Their ability to learn by example makes them very flexible and powerful. The efficiency of ANN to solve various complex problems in the field of vibration-based damage detection is proved in studies by Meruane and Mahu (2014), Shu *et al.* (2013), Min *et al.* (2012), Yan and Yuan (2010), Wang and He (2007), Xu and Humar (2006), Yuen and Lam (2006), Zhang and Friedrich (2003), and Loukas (2000). Once the ANN model is successfully trained, it could be executed to obtain the results in a relatively fast manner. Moreover, the multistage ANN developed in this study will also provide a beneficial solution in the damage detection procedures, whereby with the utilisation of only a limited number of measurement data, a complete measurement data could be obtained before the damage information is generated.

1.6 Organisation of the Thesis

The organisation of this thesis is as follows:

Chapter 1 presents the background of the study, the problem statements, the research objectives, the research scope and limitations, the significance of the study, and the outline of the thesis.

Chapter 2 presents a review of various methods in vibration-based damage detections. The advantages and disadvantages of each method are discussed. A focus on the application of ANN for damage detection is also provided in this chapter. The current issue of the application of a limited number of measurement points is also highlighted in the chapter.

Chapter 3 contains the detailed research methodology and the numerical model used in this study.

Chapter 4 presents the design of ANN. The sensitivity study of the ANN learning algorithms is presented. The performances of the ANN models are demonstrated in terms of the training time and generalisation performance.

Chapter 5 demonstrates the application of the multistage ANN in damage detection using deterministic data. Comparison studies of the multistage ANN to the existing methods were carried out. Parametric studies were conducted to investigate the effect of the number of measurement points and the different sensors placement.

Chapter 6 studies the application of the multistage ANN in consideration of uncertainties in damage detection. A parametric study was carried out to investigate the influence of the uncertainties to the multistage ANN.

Chapter 7 provides the details of the physical model used in this study, the experimental results, and the observations. The chapter also demonstrates the application of the multistage ANN through the experimental data. Besides, the deterministic and the probabilistic data obtained from the multistage in ANN were employed in the study.

Chapter 8 provides the conclusions and highlights the contributions of this study. Recommendations for future work are also presented.

REFERENCES

Abdo, M. A. B. (2012). Parametric Study Of Using Only Static Response In Structural Damage Detection. *Engineering Structures,* 34, 124-131.

Adeli, H. (2001). Neural Networks in Civil Engineering: 1989-2000. *Computer-Aided Civil and Infrastructure Engineering,* 16 (2), 126-142.

Adeli, H. and Hung, S. L. (1994). An Adaptive Conjugate Gradient Learning Algorithm For Efficient Training Of Neural Networks. *Applied Mathematics and Computation,* 62 (1)**,** 81-102.

Aggelis, D. G., Barkoula, N.-M., Matikas, T. E. and Paipetis, A. S. (2012). Acoustic Structural Health Monitoring of Composite Materials: Damage Identification and Evaluation in Cross Ply Laminates Using Acoustic Emission and Ultrasonics. *Composites Science and Technology,* 72 (10), 1127–1133.

Allbright, K., Parekh, K., Miller, R. and Baseheart, T. M. (1994). Modal Verification Of A Destructive Of A Damaged Prestressed Concrete Beam. *Experimental Mechanics*, 34 (4)**,** 389-396.

Allemang, R. J. (2003). The Modal Assurance Criterion – Twenty Years of Use and Abuse. *Sound and Vibration,* 37 (8), 14-23.

Alvandi, A. and Cremona, C. (2006). Assessment of Vibration-based Damage Identification Techniques. *Journal of Sound and Vibration*, 292 (1), 179-202.

Antonaci, P., Bruno, C. L. E., Gliozzi, A. S. and Scalerandi, M. (2010). Monitoring Evolution of Compressive Damage in Concrete With Linear and Nonlinear Ultrasonic Methods. *Cement and Concrete Research,* 40 (7), 1106–1113.

Au, F. T. K., Cheng, Y. S., Tham, L. G. and Bai, Z. Z. (2003). Structural Damage Detection Based On A Micro-Genetic Algorithm Using Incomplete And Noisy Modal Test Data. *Sound and Vibration,* 259 (5)**,** 1081-1094.

Avitabile, P. (2001). Experimental Modal Analysis. *Sound and Vibration,* 35 (1)**,** 20-31.

Bakhary, N., Hao, H. and Deeks, A. J. (2007). Damage Detection Using Artificial Neural Network With Consideration Of Uncertainties. *Engineering Structures,* 29 (11)**,** 2806-2815.

Bakhary, N., Hao, H. and Deeks, A. J. (2010a). Structure Damage Detection Using Neural Network With Multi-Stage Substructuring. *Advances in Structural Engineering* 13 (1)**,** 95-110.

Bakhary, N., Hao, H. and Deeks, A. J. (2010b). Substructuring Technique For Damage Detection Using Statistical Multi-Stage Artificial Neural Network. *Advances in Structural Engineering,* 13 (4)**,** 619-640.

Bakhtiari-Nejad, F., Rahai, A. and Esfandiari, A. (2005). A Structural Damage Detection Method Using Static Noisy Data. *Engineering Structures,* 27 (12)**,** 1784-1793.

Bakir, P. G., Reynders, E. and Roeck, G. D. (2007). Sensitivity-Based Finite Element Model Updating Using Constrained Optimization With A Trust Region Algorithm. *Journal of Sound and Vibration,* 305 (1)**,** 211–225.

Bakir, P. G., Reynders, E. and Roeck, G. D. (2008). An Improved Finite Element Model Updating Method By The Global Optimization Technique 'Coupled Local Minimizers'. *Computers & Structures,* 86 (11), 1339–1352.

Balmes, E., Basseville, M., Bourquin, F., Mevel, L., Nasser, H. and Treyssede, F. (2008). Merging Sensor Data From Multiple Temperature Scenarios For Vibration Monitoring Of Civil Structures. *Structual Health Monitoring,* 7 (2)**,** 129-142.

Balmes, E., Bianchi, J. and Leclere, J. (2009). *Structural Dynamics Toolbox 6.2 (for use with MATLAB*. Paris, France: SDTools.

Banan, M. R., Banan, M. R. and Hjelmstad, K. D. (1994a). Parameter Estimation Of Structures From Static Response. II: Numerical Simulation Studies. *Journal of Structural Engineering,* 120 (11)**,** 3259-3283.

Banan, M. R., Banan, M. R. and Hjelmstad, K. D. (1994b). Time-Domain Parameter Estimation Algorithm For Structures. I: Computational Aspects. *Journal of Structural Engineering,* 121 (3)**,** 424-434.

Banks, H. T., Inman, D. J., Leo, D. J. and Wang, Y. (1996). An Experimentally Validated Damage Detection Theory In Smart Structures. *Journal of Sound and Vibration,* 191 (5)**,** 748-779.

Banks, H. T., Joyner, M. L., Wincheski, B. and Winfree, W. P. (2002). Real Time Computational Algorithms for Eddy-Current-Based Damage Detection. *Inverse Problems,* 18 (3), 795–823.

Basseville, M., Abdelghani, M. and Benveniste, A. (2000). Subspace-Based Fault Detection Algorithms For Vibration Monitoring. *Automatica,* 36 (1)**,** 101-109.

Bayissa, W. L., Haritos, N. and Thelandersson, S. (2008). Vibration-based Structural Damage Identification Using Wavelet Transform. *Mechanical Systems and Signal Processing,* 22 (5), 1194–1215.

Beale, M., Hagan, M. T. and Demuth, H. B. (1992). *Neural Network Toolbox*. The Math Works.

Beck, J. L., Au, S. K. and Vanik, M. W. (2001). Monitoring Structural Health Using A Probabilistic Measure. *Computer-Aided Civil and Infrastructure Engineering,* 16 (1)**,** 1-11.

Beidou, D., Henglin, L. and Yongsheng, J. (2011). Finite Element Model Updating Based On Direct Optimization Technique. *Advanced Materials Research,* 163-167, 2804-2810.

Berman, A. and Nagy, E. J. (1983). Improvement Of A Large Analytical Model Using Test Data. *AIAA Journal,* 21 (8)**,** 1168-1173.

Bernal, D. and Gunes, B. (2002). Damage Localization In Output-Only Systems: A Flexibility Based Approach. *Proeedings of the International Modal Analysis Conference (IMAC) XX*. Los Angeles, California,

Bland, S. N. and Kapania, R. K. (2002). Damage Detection Of Plate Structures Using A Hybrid Genetic Sensitivity Approach. *9th AIAA/ISSMO Symposium and Exhibit on Multidisciplinary Analysis and Optimization.* Atlanta, GA.

Caglar, N., Elmas, M., Yaman, Z. D. and Saribiyik, M. (2008). Neural Networks in 3-Dimensional Dynamic Analysis of Reinforced Concrete Buildings. *Construction and Building Materials,* 22 (5), 788-800.

Cantwell, W. J. and Morton, J. (1985). Detection of Impact Damage in CFRP Laminates. *Composite Structures,* 3 (3), 241-257.

Cao, Q., Liu, D., He, Y., Zhou, J. and Codrington, J. (2012). Nondestructive and Quantitative Evaluation of Wire Rope Based on Radial Basis Function Neural Network Using Eddy Current Inspection. *NDT & E International,* 46, 7-13.

Carden, E. P. and Fanning, P. (2004). Vibration Based Condition Monitoring: A Review. *Structural Health Monitoring,* 3 (4)**,** 355-377.

Carpinteri, A. and Lacidogna, G. (2007). Damage Evaluation of Three Masonry Towers By Acoustic Emission. *Engineering Structures,* 29 (7), 1569–1579.

Carvalho, J., Datta, B. N., Gupta, A. and Lagadapati, M. (2007). A Direct Method For Model Updating With Incomplete Measured Data And Without Spurious Modes. *Mechanical Systems and Signal Processing,* 21 (7), 2715-2731.

Catbas, F. N., Ciloglu, S. K., Hasancebi, O., Grimmelsman, K. and Aktan, A. E. (2007). Limitations In Structural Identification Of Large Constructed Structures. *Journal of Structural Engineering,* 133 (8)**,** 1051-1066.

Cawley, P. and Adams, R. D. (1979). The Location of Defects in Structures From Measurements of Natural Frequencies. *Journal of Strain Analysis,* 14 (2)**,** 49-57.

Cerri, M. N. and Ruta, G. C. (2004). Detection Of Localised Damage In Plane Circular Arches By Frequency Data. *Journal of Sound and Vibration,* 270 (1), 39-59.

Chandrashekhar, M. and Ganguli, R. (2009a). Damage Assessment Of Structures With Uncertainty By Using Mode- Shape Curvatures And Fuzzy Logic. *Journal of Sound and Vibration,* 326 (3), 939–957.

Chandrashekhar, M. and Ganguli, R. (2009b). Uncertainty Handling In Structural Damage Detection Using Fuzzy Logic And Probabilistic Simulation. *Mechanical Systems and Signal Processing,* 23 (2)**,** 384–404.

Chang, C. C., Chang, T. Y. P., Xu, Y. G. and To, W. M. (2002). Selection Of Training Samples For Model Updating Using Neural Networks. *Journal of Sound and Vibration,* 249 (5)**,** 867-883.

Chang, C. C., Chang, T. Y. P., Xu, Y. G. and Wang, M. L. (2000). Structural Damage Detection Using An Iterative Neural Network. *Journal of Intelligent Material Systems and Structures,* 11 (1)**,** 32-42.

Chang, P. C., Flatau, A. and Liu, S. C. (2003). Review Paper: Health Monitoring of Civil Infrastructure. *Structural Health Monitoring,* 2 (3)**,** 257-267.

Chao, S. H., Loh, C. H. and Tseng, M. H. (2014). Structural Damage Assessment Using Output-Only Measurement: Localization And Quantification. *Journal of Intelligent Material Systems and Structures,* 25 (9), 1097–1106.

Charalambous, C. (1992). Conjugate Gradient Algorithm For Efficient Training Of Artificial Neural Networks. *In Circuits, Devices and Systems,* 139 (3)**,** 301-310.

Chen, H. G., Yan, Y. J. and Jiang, J. S. (2007). Vibration-Based Damage Detection In Composite Wingbox Structures By HHT. *Mechanical Systems and Signal Processing,* 21 (1)**,** 307–321.

Chen, H. P. (2008). Application Of Regularization Methods To Damage Detection In Large Scale Plane Frame Structures Using Incomplete Noisy Modal Data. *Engineering Structures,* 30 (11), 3219-3227.

Chen, X. Z., Zhu, H. P. and Chen, C. Y. (2005). Structural Damage Identification Using Test Static Data Based On Grey System Theory. *Journal of Zhejiang University (Science),* 6 (8)**,** 790-796.

Choubey, A., Sehgal, D. K. and Tandon, N. (2006). Finite Element Analysis Of Vessels To Study Changes In Natural Frequencies Due To Cracks. *International Journal of Pressure Vessels and Piping,* 86 (3)**,** 181–187.

Cigada, A., Caprioli, A., Redaelli, M. and Vanali, M. (2008). Vibration Testing At Meazza Stadium: Reliability Of Operational Modal Analysis To Health Monitoring Purposes. *Journal of Performance of Constructed Facilities,* 22 (4)**,** 228-337.

Coulibaly, P., Anctil, F. and Bobee, B. (2001). Multivariate Reservoir Inflow Forecasting Using Temporal Neural Networks. *Journal of Hydrologic Engineering,* 6 (5)**,** 367-376.

Curadelli, R. O., Riera, J. D., Abrosini, A. and Amani, M. G. (2008). Damage Detection By Means Of Structural Damping Identification. *Engineering Structures,* 30 (12)**,** 3497-3504.

Degala, S., Rizzo, P., Ramanathan, K. and Harries, K. A. (2009). Acoustic Emission Monitoring of CFRP Reinforced Concrete Slabs. *Construction and Building Materials*, 23 (5), 2016–2026.

Dimarogonas, A. D. (1996). Vibration Of Cracked Structures: A State Of The Art Review. *Engineering Fracture Mechanics,* 55 (5)**,** 831-857.

Doebling, S. W., Farrar, C. R. and Prime, M. B. (1998). A Summary Review of Vibration-Based Damage Identification Methods. *The Shock and Vibration Digest,* 30 (2)**,** 91-105.

Douka, E., Loutridis, S. and Trochidis, A. (2003). Crack Identification In Beams Using Wavelet Analysis. *International Journal of Solids and Structures,* 40 (13)**,** 3557-3569.

Dua, R., Watkins, S. E., Wunsch, D. C., Chandrashekhara, K. and Akhavan, F. (2001). Detection And Classification Of Impact-Induced Damage In Composite Plates Using Neural Networks. *International Joint Conference on Neural Networks*. 681-686.

Efstathiades, C., Baniotopoulos, C. C., Nazarko, P., Ziemianski, L. and Stavroulakis, G. E. (2007). Application Of Neural Networks For The Structural Health Monitoring In Curtain-Wall Systems. *Engineering Structures,* 29 (12)**,** 3475–3484.

El-Kassas, E. M. A., Mackie, R. I. and El-Sheikh, A. I. (2001). Using Neural Networks In Cold-Formed Steel Design. *Computers & Structures,* 79 (18)**,** 1687-1696.

Elshafey, A. A., Haddara, M. R. and Marzouk, H. (2010). Damage Detection In Offshore Structures Using Neural Networks. *Marine Structures,* 23 (1)**,** 131–145.

Esfandiari, A., Bakhtiari-Nejad, F., Sanayei, M. and Rahai, A. (2010). Structural Finite Element Model Updating Using Transfer Function Data. *Computer & Structures,* 88 (1)**,** 54-64.

Fan, W. and Qiao, P. (2011). Vibration-based Damage Identification Methods: A Review and Comparative Study. *Structual Health Monitoring,* 10 (1)**,** 83-111.

Fang, S. E. and Perera, R. (2009). Power Mode Shapes For Early Damage Detection In Linear Structures. *Journal of Sound and Vibration,* 324 (1), 40–56.

Fang, S. E. and Perera, R. (2011). Damage Identification By Response Surface Based Model Updating Using D-Optimal Design. *Mechanical Systems and Signal Processing,* 25 (2), 717–733.

Fang, S. E., Perera, R. and Roeck, G. D. (2008). Damage Identification Of A Reinforced Concrete Frame By Finite Element Model Updating Using Damage Parameterization. *Journal of Sound and Vibration,* 313 (3), 544–559.

Fang, X., Luo, H. and Tang, J. (2005). Structural Damage Detection Using Neural Network With Learning Rate Improvement. *Computers & Structures,* 83 (25)**,** 2150–2161.

Farrar, C. R., Doebling, S. W. and Nix, D. A. (2001). Vibration-based Structural Damage Identification. *Phil. Trans. R. Soc. Lond.,* 359 (1778), 131-149.

Farrar, C. R. and Worden, K. (2007). An Introduction To Structural Health Monitoring. *Mathematical, Physical And Engineering Sciences,* 365 (1851), 303-315.

Farrell, P. J. and Stewart, R. K. (2006). Comprehensive Study Of Tests For Normality And Symmetry: Extending The Spiegelhalter Test. *Journal of Statistical Computation and Simulation,* 76 (9)**,** 803-816.

Fletcher, R. and Reeves, C. M. (1964). Function Minimization By Conjugate Gradients. *The Computer Journal,* 7 (2)**,** 149-154.

Flood, I. and Kartam, N. (1994). Neural Networks In Civil Engineering. I: Principles And Understanding. *Computing in Civil Engineering,* 8 (2)**,** 131-148.

Friswell, M. I., Garvey, S. D. and Penny, J. E. T. (1995). Model Reduction Using Dynamic and Iterated IRS Techniques. *Journal of Sound and Vibration,* 186 (2)**,** 200-212.

Friswell, M. I. and Penny, J. E. T. (2002). Crack Modeling for Structural Health Monitoring *Structural Health Monitoring,* 1 (2)**,** 139–148.

Fritzen, C. P., Jennewein, D. and Kiefer, T. (1998). Damage Detection Based On Model Updating Methods. *Mechanical Systems and Signal Processing,* 12 (1)**,** 163-186.

Gangadharan, R., Mahapatra, D. R., Gopalakrishnan, S., Murthy, C. R. L. and M.R.Bhat (2009). On The Sensitivity Of Elastic Waves Due To Structural Damages: Time–Frequency Based Indexing Method. *Journal of Sound and Vibration,* 320 (4)**,** 915–941.

Gao, Y., Spencer, B. F. and Bernal, D. (2007). Experimental Verification Of The Flexibility-Based Damage Locating Vector Method. *Journal of Engineering Mechanics,* 133 (10)**,** 1043–1049.

Goller, B. and Schueller, G. I. (2011). Investigation Of Model Uncertainties In Bayesian Structural Model Updating *Journal of Sound and Vibration,* 330 (25)**,** 6122-6136.

Gonzalez-Perez, C. and Valdes-Gonzalez, J. (2011). Identification of Structural Damage in a Vehicular Bridge using Artificial Neural Networks. *Structual Health Monitoring,* 10 (1)**,** 33-48.

Graupe, D. (2007). *Principles Of Artificial Neural Networks*. (2nd): World Scientific.

Hadjileontiadisa, L. J. and Douka, E. (2007). Crack Detection In Plates Using Fractal Dimension. *Engineering Structures,* 29 (7), 1612–1625.

Hager, W. W. and Zhang, H. (2006). A Survey Of Nonlinear Conjugate Gradient Methods. *Pacific Journal of Optimization,* 2 (1)**,** 35-58.

Hamerly, G. and Elkan, C. (2003). Learning The k In k-means. *Advances in Neural Information Processing Systems.* 3, 281-288.

Hassiotis, S. (2000). Identification of Damage Using Natural Frequencies and Markov Parameters. *Computer & Structures,* 74 (3)**,** 365-373.

Hassiotis, S. and Jeong, G. D. (1993). Assessment of Structural Damage From Natural Frequency Measurements. *Computer & Structures,* 49 (4)**,** 679-691.

He, J. and Sallfors, G. (1994). An Optimal Point Estimate Method For Uncertainty Studies. *Applied Mathematical Modelling,* 18 (9)**,** 494-499.

Hensman, J., Worden, K., Eaton, M., Pullin, R., Holford, K. and Evans, S. (2011). Spatial Scanning For Anomaly Detection In Acoustic Emission Testing of An Aero Space Structure. *Mechanical Systems and Signal Processing,* 25 (7), 2462–2474.

Hera, A. and Hou, Z. (2004). Application Of Wavelet Approach For ASCE Structural Health Monitoring Benchmark Studies. *Journal of Engineering Mechanics*, 130 (1)**,** 96-104.

Hester, D. and Gonzalez, A. (2012). A Wavelet-Based Damage Detection Algorithm Based On Bridge Acceleration Response To A Vehicle. *Mechanical Systems and Signal Processing,* 28, 145–166.

Hjelmstad, K. D. and Shin, S. (1997). Damage Detection And Assessment Of Structures From Static Response. *Journal of Engineering Mechanics,* 123 (6)**,** 568-576.

Hong, J.-C., Kim, Y. Y., Lee, H. C. and Lee, Y. W. (2002). Damage Detection Using The Lipschitz Exponent Estimated By The Wavelet Transform: Applications To Vibration Modes Of A Beam. *International Journal of Solids and Structures,* 39 (7), 1803–1816.

Hou, Z., Noori, M. and Amand, R. S. (2000). Wavelet-Based Approach For Structural Damage Detection. *Journal of Engineering Mechanics,* 126 (7)**,** 677-683.

Hsu, T. Y. and Loh, C. H. (2012). A Frequency Response Function Change Method For Damage Localization And Quantification In A Shear Building Under

Ground Excitation. *Earthquake Engineering & Structural Dynamics.* 42 (5), 653-668.

Hu, J. and Liang, R. Y. (1993). An Integrated Approach To Detection Of Cracks Using Vibration Characteristics. *Journal of the Franklin Institute,* 330 (5)**,** 841–853.

Hu, S. L. J., Li, H. and Wang, S. (2007). Cross-Model Cross-Mode Method For Model Updating. *Mechanical Systems and Signal Processing,* 21 (4)**,** 1690-1703.

Hua, X. G., Ni, Y. Q., Chen, Z. Q. and Ko, J. M. (2009). Structural Damage Detection Of Cable-Stayed Bridges Using Changes In Cable Forces And Model Updating. *Journal of Structural Engineering,* 135 (9)**,** 1093–1106.

Huang, P., Zhang, G., Wu, Z., Cai, J. and Zhou, Z. (2006). Inspection of Defects in Conductive Multi-Layered Structures By An Eddy Current Scanning Technique: Simulation and Experiments. *NDT & E International,* 39 (7), 578–584.

Huang, Q., Gardoni, P. and Hurlebaus, S. (2012). A Probabilistic Damage Detection Approach Using Vibration-Based Nondestructive Testing. *Structural Safety,* 38, 11-21.

Huynh, D., He, J. and Tran, D. (2005). Damage Location Vector: A Non-destructive Structural Damage Detection Technique. *Computer & Structures,* 83 (28), 2353-2367.

Hwang, H. Y. and Kim, C. (2004). Damage Detection in Structures Using A Few Frequency Response Measurements. *Journal of Sound and Vibration,* 270 (1), 1-14.

Ismail, Z. (2012). Application Of Residuals From Regression Of Experimental Mode Shapes To Locate Multiple Crack Damage In A Simply Supported Reinforced Concrete Beam. *Measurement,* 45 (6) 1455–1461.

Ismail, Z. and Ong, Z. C. (2012). Honeycomb Damage Detection In A Reinforced Concrete Beam Using Frequency Mode Shape Regression. *Measurement,* 45 (5), 950–959.

Ismail, Z., Razak, H. A. and Rahman, A. G. A. (2006). Determination Of Damage Location In RC Beams Using Mode Shape Derivatives. *Engineering Structures,* 28 (11), 1566–1573.

Jaishi, B. and Ren, W. X. (2006). Damage Detection By Finite Element Model Updating Using Modal Flexibility Residual. *Journal of Sound and Vibration,* 290 (1), 369-387.

Jaishi, B. and Ren, W. X. (2007). Finite Element Model Updating Based On Eigenvalue And Strain Energy Residuals Using Multiobjective Optimisation Technique. *Mechanical Systems and Signal Processing*, 21 (5), 2295–2317.

Jeong, D. I. and Kim, Y. O. (2005). Rainfall-Runoff Models Using Artificial Neural Networks For Ensemble Streamflow Prediction *Hydrological Processes,* 19 (19)**,** 3819-3835.

Jeyasehar, C. A. and Sumangala, K. (2006). Damage Assessment Of Prestressed Concrete Beams Using Artificial Neural Network (ANN) Approach. *Computers & Structures,* 84 (26)**,** 1709–1718.

Jiang, S. F., Fu, C. and Zhang, C. (2011a). A Hybrid Data-Fusion System Using Modal Data And Probabilistic Neural Network For Damage Detection. *Advances in Engineering Software,* 42 (6)**,** 368-374.

Jiang, S. F., Zhang, C. M. and Jiang, S. (2011b). Two-Stage Structural Damage Detection Using Fuzzy Neural Networks And Data Fusion Techniques. *Expert Systems with Application,* 38 (1)**,** 511–519.

Jiang, X. and Mahadevan, S. (2008). Bayesian Probabilistic Inference for Nonparametric Damage Detection of Structures. *Journal of Engineering Mechanics,* 134 (10)**,** 820-831.

Jones, K. and Turcotte, J. (2002). Finite Element Model Updating Using Antiresonant Frequencies. *Journal of Sound and Vibration,* 252 (4)**,** 717-727.

Jones, T. S., Polansky, D. and Berger, H. (1988). Radiation Inspection Methods for Composites. *NDT International,* 21 (4)**,** 277-282.

Joubert, P.-Y., Vourc'h, E., Tassin, A. and Diraison, Y. L. (2010). Source Separation Techniques Applied to the Detection of Subsurface Defects in the Eddy Current NDT of Aeronautical Lap-Joints. *NDT & E International,* 43 (7), 606–614.

Kao, C. Y. and Hung, S. L. (2003). Detection Of Structural Damage Via Free Vibration Responses Generated By Approximating Artificial Neural Networks. *Computers & Structures,* 81 (28)**,** 2631–2644.

Kerschen, G., Worden, K., Vakakis, A. F. and Golinval, J. C. (2006). Past, Present And Future Of Nonlinear System Identification In Structural Dynamics. *Mechanical Systems and Signal Processing*, 20 (3)**,** 505-592.

Kesavan, A., Deivasigamani, M., John, S. and Herszberg, I. (2006). Damage Detection In T-Joint Composite Structures. *Composite Structures,* 75 (1)**,** 313–320.

Keye, S. (2006). Improving the Performance of Model-based Damage Detection Methods Through the Use of An Updated Analytical Model. *Aerospace Science and Technology,* 10 (3), 199-206.

Kim, H. and Cho, M. (2006). Two-Level Scheme for Selection of Primary Degrees of Freedom and Semi-Analytic Sensitivity Based on the Reduced System. *Computer Methods in Applied Mechanics and Engineering,* 195 (33), 4244–4268.

Kim, H. and Melhem, H. (2004). Damage Detection of Structures By Wavelet Analysis. *Engineering Structures,* 26 (3)**,** 347–362.

Kim, H. M. and Bartkowicz, T. J. (2001). An Experimental Study For Damage Detection Using A Hexagonal Truss. *Computers & Structures,* 79 (2), 173-182.

Kim, J. T., Ryu, Y. S., Cho, H. M. and Stubbs, N. (2003). Damage Identification In Beam-Type Structures: Frequency-Based Method Vs Mode-Shape-Based Method. *Engineering Structures*, 25 (1), 57–67.

Ko, J. M., Sun, Z. G. and Ni, Y. Q. (2002). Multi-Stage Identification Scheme For Detecting Damage In Cable-Stayed Kap Shui Mun Bridge. *Engineering Structures,* 24 (7)**,** 857–868.

Koh, C. G., Tee, K. F. and Quek, S. T. (2006). Condensed Model Identification And Recovery For Structural Damage Assessment. *Journal of Structural Engineering,* 132 (12)**,** 2018–2026.

Kosmatka, J. B. and Ricles, J. M. (1999). Damage Detection In Structures By Modal Vibration Characterization. *Journal of Structural Engineering,* 125 (12)**,** 1384–1392.

Kourehli, S. S., Amiri, G. G., Ghafory-Ashtiany, M. and Bagheri, A. (2013). Structural Damage Detection Based On Incomplete Modal Data Using Pattern Search Algorithm. *Journal of Vibration and Control*. 19 (6), 821-833.

Koutsovasilis, P. and Beitelschmidt, M. (2008). Comparison of Model Reduction Techniques for Large Mechanical Systems. *Multibody System Dynamics,* 20 (2)**,** 111–128.

Kreyszig, E. (1999). *Advanced Engineering Mathematics, 8th Edition*. (Eighth): John Wiley & Sons.

Kudva, J. N., Munir, N. and Tan, P. W. (1992). Damage Detection In Smart Structures Using Neural Networks And Finite-Element Analyses. *Smart Materials and Structures,* 1 (2)**,** 108-112.

Lam, H. F. and Ng, C. T. (2008). A Probabilistic Method For The Detection Of Obstructed Cracks Of Beam-Type Structures Using Spatial Wavelet Transform. *Probabilistic Engineering Mechanics,* 23 (2)**,** 237-245.

Lam, H. F. and Yin, T. (2011). Dynamic Reduction-Based Structural Damage Detection of Transmission Towers: Practical Issues and Experimental Verification. *Engineering Structures,* 33 (5), 1459–1478.

Lautour, O. R. D. and Omenzetter, O. (2009). Prediction Of Seismic-Induced Structural Damage Using Artificial Neural Networks. *Engineering Structures,* 31 (2)**,** 600-606.

Law, S. S., Chan, T. H. T. and Wu, D. (2001). Efficient Numerical Model For The Damage Detection Of Large Scale. *Engineering Structures*, 23 (5), 436-451.

Lee, D. T. L. and Yamamoto, A. (1994). Wavelet Analysis: Theory And Applications. *Hewlett Packard Journal*, 45, 44-52.

Lee, E. T. and Eun, H. C. (2008). Damage Detection Of Damaged Beam By Constrained Displacement Curvature. *Journal of Mechanical Science and Technology*, 22 (6)**,** 1111-1120.

Lee, J. (2009). Identification Of Multiple Cracks In A Beam Using Natural Frequencies. *Journal of Sound and Vibration,* 320 (3), 482–490.

Lee, J. J., Lee, J. W., Yi, J. H., Yun, C. B. and Jung, H. Y. (2005). Neural Networks-Based Damage Detection For Bridges Considering Errors In Baseline Finite Element Models. *Journal of Sound and Vibration*, 280 (3)**,** 555–578.

Lee, U. and Shin, J. (2002). A Frequency Response Function-based Structural Damage Identification Method. *Computer & Structures,* 80 (2), 117-132.

Lei, Y., Su, Y. and Shen, W. (2013). A Probabilistic Damage Identification Approach for Structures under Unknown Excitation and with Measurement Uncertainties. *Journal of Applied Mathematics,* Lenett, M. S., Hunt, V. J., Helmicki, A., Brown, D. L., Catbas, F. N. and Aktan, A. E. (1999). Condition Assessment of Commissioned Infrastructure Using Modal Analysis and Flexibility. *International Modal Analysis Conference*. Kissimmee, Florida, 1251-1259.

Lew, J. S. (2008). Reduction Of Uncertainty Effect On Damage Identification Using Feedback Control. *Journal of Sound and Vibration,* 318 (4)**,** 903-910.

Li, H. J., Liu, F. S. and Hu, S. L. J. (2008a). Employing Incomplete Complex Modes For Model Updating And Damage Detection Of Damped Structures. *Science in China Series E: Technological Sciences,* 51 (12)**,** 2254-2268.

Li, J., Law, S. S. and Ding, Y. (2012). Substructure Damage Identification Based On Response Reconstruction In Frequency Domain And Model Updating. *Engineering Structures,* 41, 270–284.

Li, J., Law, S. S. and Hao, H. (2013). Improved Damage Identification in Bridge Structures Subject to Moving Loads: Numerical and Experimental Studies. *International Journal of Mechanical Sciences,* 74, 99–111.

Li, J., Wang, J. and Hu, S. L. J. (2008b). Using Incomplete Modal Data For Damage Detection In Offshore Jacket Structures. *Ocean Engineering,* 35 (17), 1793-1799.

Li, P. (2011). Structural Damage Localization Using Probabilistic Neural Networks. *Mathematical and Computer Modelling,* 54 (3)**,** 965–969.

Li, X. Y. and Law, S. S. (2008). Damage Identification Of Structures Including System Uncertainties And Measurement Noise. *AIAA Journal,* 46 (1)**,** 263–276.

Li, X. Y. and Law, S. S. (2010). Adaptive Tikhonov Regularization For Damage Detection Based On Nonlinear Model Updating. *Mechanical Systems and Signal Processing,* 24 (6), 1646–1664.

Li, Z. X. and Yang, X. M. (2008). Damage Identification For Beams Using ANN Based On Statistical Property Of Structural Responses. *Computers & Structures,* 86 (1)**,** 64-71.

Liang, R. Y., Choy, F. K. and Hu, J. (1991). Detection of Cracks in Beam Structures Using Measurements of Natural Frequencies. *Journal of the Franklin Institute,* 328 (4)**,** 505-508.

Limongelli, M. P. (2010). Frequency Response Function Interpolation for Damage Detection Under Changing Environment. *Mechanical Systems and Signal Processing*, 24 (8)**,** 2898-2913.

Liu, S. W., Huang, J. H., Sung, J. C. and Lee, C. C. (2002). Detection Of Cracks Using Neural Networks And Computational Mechanics. *Comput. Methods Appl. Mech. Engrg.*, 191 (25)**,** 2831–2845.

Liu, X., Lieven, N. a. J. and Escamilla-Ambrosio, P. J. (2009). Frequency Response Function Shape-Based Methods For Structural Damage Localisation. *Mechanical Systems and Signal Processing*, 23 (4), 1243–1259.

Liu, Y. Y., Ju, Y. F., Duan, C. D. and Zhao, X. F. (2011). Structure Damage Diagnosis Using Neural Network And Feature Fusion. *Engineering Applications of Artificial Intelligence*, 24 (1)**,** 87–92.

Lopes, V., Park, G., Cudney, H. and Inman, D. J. (2000). Impedance-Based Structural Health Monitoring with Artificial Neural Networks. *Journal of Intelligent Material Systems and Structures*, 11 (3)**,** 206-214.

Lopez, I. and Sarigul-Klijn, N. (2010). A Review Of Uncertainty In Flight Vehicle Structural Damage Monitoring, Diagnosis And Control: Challenges And Opportunities. *Progress in Aerospace Sciences* 46 (7)**,** 247–273.

Loukas, Y. L. (2000). Artificial Neural Networks In Liquid Chromatography: Efficient And Improved Quantitative Structure–Retention Relationship Models. *Journal of Chromatography A*, 904 (2)**,** 119–129.

Loutridisa, S., Douka, E. and Trochidis, A. (2004). Crack Identification In Double-Cracked Beams Using Wavelet Analysis. *Journal of Sound and Vibration*, 277 (4), 1025–1039.

Lu, X. J. and Zhang, P. (2012). An Identification Method of Bridge Structural Damage Based on Fourier Transform and Neural Network in Electronic Information Engineering. *Advances in Mechanical and Electronic Engineering*, 351-356.

Lu, Y., Ye, L., Su, Z., Zhou, L. and Cheng, L. (2009). Artificial Neural Network (ANN)-Based Crack Identification In Aluminum Plates With Lamb Wave Signals. *Journal of Intelligent Material Systems and Structures*, 20 (1)**,** 39-49.

Lu, Z. R. and Law, S. S. (2006). Identification Of Prestress Force From Measured Structural Responses. *Mechanical Systems and Signal Processing*, 20 (8)**,** 2186–2199.

Luong, M. P. (1998). Fatigue Limit Evaluation of Metals Using an Infrared Thermographic Technique. *Mechanics of Materials,* 28 (1), 155–163.

Mahmoud, M. A. and Kiefa, M. a. A. (1999). Neural Network Solution Of The Inverse Vibration Problem. *NDT&E International,* 32 (2)**,** 91-99.

Maia, N. M. M., Silva, J. M. M. and Almas, E. a. M. (2003). Damage Detection In Structures: From Mode Shape To Frequency Response Function Methods. *Mechanical Systems and Signal Processing,* 17 (3)**,** 489–498.

Majumdar, A., Maiti, D. K. and Maity, D. (2012). Damage Assessment Of Truss Structures From Changes In Natural Frequencies Using Ant Colony Optimazation. *Applied Mathematics and Computation,* 218 (19), 9759-9772.

Mao, Z. and Todd, M. (2012). A Model For Quantifying Uncertainty In The Estimation Of Noise-Contaminated Measurements Of Transmissibility. *Mechanical Systems and Signal Processing,* 28, 470-481.

Marquart, D. W. (1963). An Algorithm For Least-squares Estimation Of Nonlinear Parameters. *Journal of the Society for Industrial & Applied Mathematics,* 11 (2)**,** 431-441.

Matsuoka, K. (1992). Noise Injection Into Inputs In Back-Propogation Learning. *IEEE Transactions on Systems, Man, and Cybernetics,* 22 (3)**,** 436-440.

Mazanoglu, K. and Sabuncu, M. (2012). A Frequency Based Algorithm For Identification Of Single And Double Cracked Beams Via A Statistical Approach Used In Experiment. *Mechanical Systems and Signal Processing,* 30, 168-185.

Mclaughlin, P. V., Mcassey, E. V. and Deitrich, R. C. (1980). Non-destructive Examination of Fibre Composite Structures By Thermal Field Techniques *NDT International,* 13 (2)**,** 56-62.

Meo, M. and Zumpano, G. (2005). On The Optimal Sensor Placement Techniques For A Bridge Structure. *Engineering Structures,* 27 (10), 1488-1497.

Merhjoo, M., Khaji, N., Moharrami, H. and Bahreininejad, A. (2008). Damage Detection Of Truss Bridge Joints Using Artificial Neural Networks. *Expert Systems with Application,* 35 (3)**,** 1122-1131.

Meruane, V. and Mahu, J. (2014). Real-Time Structural Damage Assessment Using Artificial Neural Networks and Antiresonant Frequencies. Shock and Vibration, In press.

Mevel, L., Hermans, L. and Auweraer, H. V. D. (1999). Application of A Subspace-based Fault Detection Method to Industrial Structures. *Mechanical Systems and Signal Processing,* 13 (6)**,** 823-838.

Michaels, J. E. and Michaels, T. E. (2005). Detection of Structural Damage From the Local Temporal Coherence of Diffuse Ultrasonic Signals. *IEEE Transactions on Ultrasonics, Ferroelectrics, and Frequency Control,* 52 (10)**,** 1769-1782.

Min, J., Park, S. and Yun, C. B. (2010). Impedance-based Structural Health Monitoring Using Neural Networks For Autonomous Frequency Range Selection. *Smart Materials and Structures,* 19 (12)**,** 125011.

Min, J., Park, S., Yun, C. B., Lee, C. G. and Lee, C. (2012). Impedance-based Structural Health Monitoring Incorporating Neural Network Technique For Identification Of Damage Type And Severity. *Engineering Structures,* 39, 210-220.

Moaveni, B. and Conte, J. P. (2009). Uncertainty And Sensitivity Analysis Of Damage Identification Results Obtained Using Finite Element Model Updating. *Computer-Aided Civil and Infrastructure Engineering,* 24 (5)**,** 320–334.

Mohan, S. C., Maiti, D. K. and Maity, D. (2013). Structural Damage Assessment Using FRF Employing Particle Swarm Optimization. *Applied Mathematics and Computation,* 219 (20)**,** 10387–10400.

Moller, M. F. (1993). A Scaled Conjugate Gradient Algorithm For Fast Supervised Learning. *Neural networks*, 6 (4)**,** 525-533.

Montalvao, D., Maia, N. M. M. and Ribeiro, A. M. R. (2006). A Review of Vibration-based Structural Health Monitoring with Special Emphasis on Composite Materials. *The Shock and Vibration Digest*, 38 (4)**,** 295-324.

Morassi, A. (2001). Identification Of A Crack In A Rod Based On Changes In A Pair Of Natural Frequencies. *Journal of Sound and Vibration,* 242 (4)**,** 577-596.

Mottershead, J. E. and Friswell, M. I. (1993). Model Updating in Structural Dynamics: A Survey. *Journal of Sound and Vibration,* 167 (2)**,** 347-375.

Mottershead, J. E., Link, M. and Friswell, M. (2011). The Sensitivity Method In Finite Element Model Updating: A Tutorial. *Mechanical Systems and Signal Processing*, 25 (7), 2275–2296.

Mthembu, L., Marwala, T., Friswell, M. and Adhikari, S. (2011). Model Selection In Finite Element Model Updating Using The Bayesian Evidence Statistic. *Mechanical Systems and Signal Processing*, 25 (7)**,** 2399–2412.

Mukhopadhyay, S., Lus, H., Hong, A. L. and Betti, R. (2012). Propagation Of Mode Shape Errors In Structural Identification. *Journal of Sound and Vibration*, 331 (17,) 3961–3975.

Mukkamala, S., Sung, A. H. and Abraham, A. (2004). Intrusion Detection Using An Ensemble Of Intelligent Paradigms. *Journal of Network and Computer Applications*, 28 (2)**,** 167-182.

Nair, A. and Cai, C. S. (2010). Acoustic Emission Monitoring of Bridges: Review And Case Studies. *Engineering Structures*, 32 (6), 1704-1714.

Nair, K. K. and Kiremidjian, A. S. (2007). Time Series Based Structural Damage Detection Algorithm Using Gaussian Mixtures Modeling. *Journal of Dynamic Systems, Measurement, and Control*, 129 (3), 285-293.

Ndambi, J. M., Vantomme, J. and Harri, K. (2002). Damage Assessment in Reinforced Concrete Beams Using Eigenfrequencies and Mode Shape Derivatives. *Engineering Structures*, 24 (4)**,** 501–515.

Negnevitsky, M. (2005). *Artificial Intelligence: A Guide To Intelligent Systems*. (Second): Pearson Education.

Ng, C. T., Veidt, M. and Lam, H. F. (2009). Guided Wave Damage Characterisation in Beams Utilising Probabilistic Optimisation. *Engineering Structures*, 31 (12)**,** 2842-2850.

Ni, Y. Q., Zhou, H. F., Chan, K. C. and Ko, J. M. (2008). Modal Flexibility Analysis of Cable-Stayed Ting Kau Bridge for Damage Identification. *Computer-Aided Civil and Infrastructure Engineering*, 23 (3)**,** 223–236.

Ni, Y. Q., Zhou, H. F. and Ko, J. M. (2009). Generalization Capability of Neural Network Models for Temperature-Frequency Correlation Using Monitoring Data. *Structural Engineering*, 135 (10)**,** 1290-1300.

Ni, Y. Q., Zhou, X. T. and Ko, J. M. (2006). Experimental Investigation Of Seismic Damage Identification Using PCA-Compressed Frequency Response Functions And Neural Networks. *Journal of Sound and Vibration*, 290 (1)**,** 242–263.

Oberholster, A. J. and Heyns, P. S. (2006). On-Line Fan Blade Damage Detection Using Neural Networks. *Mechanical Systems and Signal Processing,* 20 (1)**,** 78–93.

Okafor, A. C. and Dutta, A. (2000). Structural Damage Detection In Beams By Wavelet Transforms. *Smart Materials and Structures,* 9 (6), 906–917.

Ong, K. C. G., Wang, Z. and Maalej, M. (2008). Adaptive Magnitude Spectrum Algorithm For Hilbert–Huang Transform Based Frequency Identification. *Engineering Structures,* 30 (1)**,** 33–41.

Ooijevaar, T. H., Loendersloot, R., Warnet, L. L., Boer, A. D. and Akkerman, R. (2010). Vibration Based Structural Health Monitoring Of A Composite T-Beam. *Composite Structures,* 92 (9), 2007–2015.

Ovanesova, A. V. and Suarez, L. E. (2004). Applications Of Wavelet Transforms To Damage Detection In Frame Structures. *Engineering Structures,* 26 (1), 39–49.

Pan, D. G., Lei, S. S. and Wu, S. C. (2010). Two-Stage Damage Detection Method Using the Artificial Neural Networks and Genetic Algorithms. *Information Computing and Applications,* 6377, 325-332.

Pandey, A. K. and Biswas, M. (1994). Damage Detection in Structures Using Changes in Flexibility. *Journal of Sound and Vibration,* 169 (1)**,** 3-17.

Pandey, A. K., Biswas, M. and Samman, M. M. (1991). Damage Detection From Changes in Curvature Mode Shapes. *Journal of Sound and Vibration,* 145 (2)**,** 321–332.

Pandey, P. C. and Barai, S. V. (1995). Multilayer Perceptron In Damage Detection Of Bridge Structures. *Computers & Structures,* 54 (4)**,** 597-608.

Papadopoulos, L. and Garcia, E. (1998). Structural Damage Identification: A Probabilistic Approach. *AIAA Journal,* 36 (11)**,** 2137-2145.

Park, J. H., Kim, J. T., Hong, D. S., Ho, D. D. and Yi, J. H. (2009). Sequential Damage Detection Approaches For Beams Using Time-modal Features And Artificial Neural Networks. *Journal of Sound and Vibration,* 323 (1)**,** 451-474.

Park, N. G. and Park, Y. S. (2003). Damage Detection Using Spatially Incomplete Frequency Response Functions. *Mechanical Systems and Signal Processing,* 17 (3)**,** 519-532.

Parloo, E., Guillaume, P. and Overmeire, M. V. (2003). Damage Assessment Using Mode Shape Sensitivities. *Mechanical Systems and Signal Processing*, 17 (3)**,** 499–518.

Parloo, E., Vanlanduit, S., Guillaume, P. and Verboven, P. (2004). Increased Reliability Of Reference-Based Damage Identification Techniques By Using Output-Only Data. *Journal of Sound and Vibration*, 270 (4), 813–832.

Patil, D. P. and Maiti, S. K. (2003). Detection Of Multiple Cracks Using Frequency Measurements. *Engineering Fracture Mechanics*, 70 (12)**,** 1553–1572.

Perera, R. and Ruiz, A. (2008). A Multistage FE Updating Procedure For Damage Identification In Large-Scale Structures Based On Multiobjective Evolutionary Optimization. *Mechanical Systems and Signal Processing*, 22 (4), 970–991.

Piersol, A. and Paez, T. (2009). *Harris' Shock And Vibration Handbook*. (Sixth): McGraw-Hill.

Pines, D. and Salvino, L. (2006). Structural Health Monitoring Using Empirical Mode Decomposition And The Hilbert Phase. *Journal of Sound and Vibration*, 294 (1)**,** 97–124.

Portugal Bridge Collapse 'Kills 70'. (2001), *BBC News*.

Powell, M. J. D. (1977). Restart Procedures For The Conjugate Gradient Method. *Mathematical Programming*, 12 (1)**,** 241-254.

Priddy, K. L. and Keller, P. E. (2007). *Artificial Neural Networks: An Introduction*. New Delhi: Prentice-Hall of India.

Pye, C. J. and Adams, R. D. (1981). Detection of Damage in Fibre Reinforced Plastics Using Thermal Fields Generated During Resonant Vibration. *NDT International*, 14 (3)**,** 111-118.

Quek, S. T., Tran, V. A., Hou, X. Y. and Duan, W. H. (2009). Structural Damage Detection Using Enhanced Damage Locating Vector Method With Limited Wireless Sensors. *Journal of Sound and Vibration*, 328 (4)**,** 411-427.

Radzienski, M., Krawczuk, M. and Palacz, M. (2011). Improvement Of Damage Detection Methods Based On Experimental Modal Parameters. *Mechanical Systems and Signal Processing*, 25 (6)**,** 2169-2190.

Rahmatalla, S., Eun, H. C. and Lee, E. T. (2012). Damage Detection From The Variation Of Parameter Matrices Estimated By Incomplete FRF Data. *Smart Structures and Systems*, 9 (1)**,** 55-70.

Ratcliffe, C. P. (1997). Damage Detection Using A Modified Laplacian Operator On Mode Shape Data. *Journal of Sound and Vibration,* 204 (3)**,** 494-406.

Reddy, D. M. and Swarnamani, S. (2012). Damage Detection And Identification In Structures By Spatial Wavelet Based Approach. *International Journal of Applied Science and Engineering,* 10 (1)**,** 69-87.

Ren, W. X. and Roeck, G. D. (2002). Structural Damage Identification using Modal Data. II: Test Verification. *Structural Engineering,* 128 (1)**,** 96-104.

Ren, W. X. and Sun, Z. S. (2008). Structural Damage Identification By Using Wavelet Entropy. *Engineering Structures,* 30 (10), 2840–2849.

Report on Deadly Factory Collapse in Bangladesh Finds Widespread Blame. (2013, 22 May). *The New York Times*.

Reynders, E. and Roeck, G. D. (2010). A Local Flexibility Method for Vibration-Based Damage Localization and Quantification. *Journal of Sound and Vibration*, 329 (12), 2367–2383.

Reynders, E., Roeck, G. D., Bakir, P. G. and Sauvage, C. (2007). Damage Identification on the Tilff Bridge by Vibration Monitoring Using Optical Fiber Strain Sensors. *Engineering Mechanics,* 133 (2)**,** 185-193.

Rhim, J. and Lee, J. W. (1995). A Neural Network Approach For Damage Detection And Identification Of Structures. *Computational Mechanics*, 16 (6), 437-443.

Riedmiller, M. and Braun, H. (1993). A Direct Adaptive Method for Faster Backpropagation Learning: The RPROP Algorithm. *International Conference on Neural Networks* IEEE.

Rodríguez, R., Escobar, J. A. and Gómez, R. (2010). Damage Detection In Instrumented Structures Without Baseline Modal Parameters. *Engineering Structures,* 32 (6)**,** 1715-1722.

Rosell, A. and Persson, G. (2012). Finite Element Modelling of Closed Cracks in Eddy Current Testing. *International Journal of Fatigue,* 41, 30-38.

Rosenblueth, E. (1975). Point Estimates For Probability Moments. *Proceedings of the National Academy of Sciences,* 72 (10)**,** 3812-3814.

Rosenblueth, E. (1981). Two-point Estimates In Probabilities. *Applied Mathematical Modelling,* 5 (5)**,** 329-335.

Rucka, M. and Wilde, K. (2006). Application Of Continuous Wavelet Transform In Vibration Based Damage Detection Method For Beams And Plates. *Journal of Sound and Vibration*, 297 (3), 536–550.

Rucka, M. and Wilde, K. (2010). Neuro-Wavelet Damage Detection Technique In Beam, Plate And Shell Structures With Experimental Validation. *Journal of Theoretical and Applied Mechanics* 48 (3)**,** 579-604.

Ruotolo, R. and Surace, C. (1997). Damage Assessment Of Multiple Cracked Beams: Numerical Results And Experimental Validation *Journal of Sound and Vibration,* 206 (4)**,** 567–588.

Rytter, T. (1993). *Vibration Based Inspection of Civil Engineering Structure.* Ph.D., Aalborg University.

Sagiroglu, S., Besdok, E. and Erler, M. (2000). Control Chart Pattern Recognition Using Artificial Neural Networks. *Turkish Journal of Electrical Engineering and Computer Sciences,* 8 (2)**,** 137-147.

Sahin, M. and Shenoi, R. A. (2003). Quantification And Localisation Of Damage In Beam-Like Structures By Using Artificial Neural Networks With Experimental Validation. *Engineering Structures,* 25 (14)**,** 1785–1802.

Salawu, O. S. (1997). Detection Of Structural Damage Through Changes In Frequency: A Review. *Engineering Structures,* 19 (9)**,** 718-723.

Samanta, B. (2004). Gear Fault Detection Using Artificial Neural Networks And Support Vector Machines With Genetic Algorithms. *Mechanical Systems and Signal Processing,* 18 (3)**,** 625-644.

Sampaio, R. P. C., Maia, N. M. M. and Silva, J. M. M. (1999). Damage Detection Using the Frequency-Response-Function Curvature Method. *Journal of Sound and Vibration,* 226 (5)**,** 1029-1042.

Sanayei, M. and Nelson, R. B. (1986). Identification Of Structural Element Stiffnesses From Incomplete Static Test Data. *Rep. Soc. of Automotive Engrs. Tech. Paper Series.* Long Beach, California: Society of Automotive Engineers.

Sanayei, M. and Onipede, O. (1991). Damage Assessment Of Structures Using Static Test Data. *AIAA Journal,* 29 (7)**,** 1174-1179.

Sanayei, M. and Scampoli, S. F. (1991). Structural Element Stiffness Identification From Static Test Data. *Journal of Engineering Mechanics,* 117 (5)**,** 1021-1036.

Santiago, D. F. A. and Pederiva, R. (2002). Comparison Of Optimization Techniques Of Neural Networks Training For Faults Diagnostic Of Rotating Machinery. *Mecánica Computacional,* 21, 1912-1921.

Santos, J. V. A. D., Soares, C. M. M., Soares, C. A. M. and Maia, N. M. M. (2003). Structural Damage Identification: Influence of Model Incompleteness and Errors. *Composite Structures,* 62 (3), 303-313.

Saravanan, N., Siddabattuni, V. N. S. and Ramachandran, K. I. (2010). Fault Diagnosis Of Spur Bevel Gear Box Using Artificial Neural Network (ANN), And Proximal Support Vector Machine (PSVM). *Applied Soft Computing,* 10 (1)**,** 344-360.

Sazonov, E. and Klinkhachorn, P. (2005). Optimal Spatial Sampling Interval For Damage Detection By Curvature Or Strain Energy Mode Shapes. *Journal of Sound and Vibration,* 285 (4), 783–801.

Schwarz, B. and Richardson, M. (2003). Scaling Mode Shapes Obtained From Operating Data. *Sound and Vibration,* 37 (11)**,** 18-22.

Shah, A. A. and Ribakov, Y. (2009). Non-Linear Ultrasonic Evaluation of Damaged Concrete Based on Higher Order Harmonic Generation. *Materials & Design,* 30 (10), 4095–4102.

Shaheed, M. H. (2004). Performance Analysis Of 4 Types Of Conjugate Gradient Algorithms In The Nonlinear Dynamic Modelling Of A TRMS Using Feedforward Neural Networks. *IEEE International Conference on Systems, Man and Cybernetics*. 5985-5990.

Shi, Z. Y., Law, S. S. and Zhang, L. M. (1998). Structural Damage Localization From Modal Strain Energy Change. *Journal of Sound and Vibration,* 218 (5)**,** 714-733.

Shifrin, E. I. and Ruotolo, R. (1999). Natural Frequencies Of A Beam With An Arbitrary Number Of Cracks. *Journal of Sound and Vibration*, 222 (3)**,** 409–423.

Shu, J., Zhang, Z., Gonzalez, I. and R. Karoumi, R. (2013). The Application Of A Damage Detection Method Using Artificial Neural Network And Train-Induced Vibrations On A Simplified Railway Bridge Model. *Engineering Structures*, 52, 408-421.

Sivanandam, S. N., Sumathi, S. and Deepa, S. N. (2006). *Introduction To Neural Networks Using Matlab 6.0*. Tata McGraw-Hill.

Sohn, H., Farrar, C. R., Hemez, F. and Czarnecki, J. (2003). A review of structural health monitoring literature: 1996-2001. Los Alamos National Laboratory Report, LA-13976-MS.

Sohn, H. and Law, K. H. (1997). A Bayesian Probabilistic Approach for Structure Damage Detection. *Earthquake Engineering and Structural Dynamics,* 26 (12)**,** 1259-1281.

Soliman, M., Frangopol, D. M. and Kim, S. (2013). Probabilistic Optimum Inspection Planning Of Steel Bridges With Multiple Fatigue Sensitive Details. *Engineering Structures,* 49, 996-1006.

Sun, Z. and Chang, C. C. (2002). Structural Damage Assessment Based on Wavelet Packet Transform. *Journal of Structural Engineering,* 128 (10)**,** 1354–1361.

Sun, Z. and Chang, C. C. (2004). Statistical Wavelet-Based Method For Structural Health Monitoring. *Journal of Structural Engineering,* 130 (7)**,** 1055–1062.

Sung, S. H., Koo, K. Y. and Jung, H. J. (2014). Modal Flexibility-Based Damage Detection Of Cantilever Beam-Type Structures Using Baseline Modification. *Journal of Sound and Vibration*, 333 (18), 4123–4138.

Suresh, S., Omkar, S. N., Ganguli, R. and Mani, V. (2004). Identification Of Crack Location And Depth In A Cantilever Beam Using A Modular Neural Network Approach. *Smart Materials and Structures,* 13 (4)**,** 907-915.

Tee, K. F., Koh, C. G. and Quek, S. T. (2009). Numerical And Experimental Studies Of A Substructural Identification Strategy. *Structural Health Monitoring,* 8 (5)**,** 397-410.

Teughels, A., Maeck, J. and Roeck, G. D. (2002). Damage Assessment By FE Model Updating Using Damage Functions. *Computers & Structures,* 80 (25)**,** 1869–1879.

Teughels, A. and Roeck, G. D. (2004). Structural Damage Identification Of The Highway Bridge Z24 By FE Model Updating. *Journal of Sound and Vibration,* 278 (3)**,** 589–610.

Toksoy, T. and Aktan, A. E. (1994). Bridge-Condition Assessment by Modal Flexibility. *Experimental Mechanics,* 34 (3)**,** 271-278.

Tomaszewska, A. (2010). Influence Of Statistical Errors On Damage Detection Based On Structural Flexibility And Mode Shape Curvature. *Computers & Structures,* 88 (3)**,** 154–164.

Tsai, C. Y. and Lee, Y. H. (2011). The Parameters Effect On Performance In ANN For Hand Gesture Recognition System. *Expert Systems with Applications,* 38 (7)**,** 7980-7983.

Tsou, P. and Shen, M. H. (1994). Structural Damage Detection And Identification Using Neural Networks. *AIAA Journal*, 32 (1)**,** 176-183.

Tufte, E. R. (2001). *The Visual Display Of Quantitative Information Graphics* (Second Edition): Graphics Press USA.

Vallabhaneni, V. and Maity, D. (2011). Application Of Radial Basis Neural Network On Damage Assessment Of Structures. *Procedia Engineering*, 14, 3104-3110.

Wahab, M. M. A. and Roeck, G. D. (1999). Damage Detection In Bridges Using Modal Curvatures: Application To A Real Damage Scenario. *Journal of Sound and Vibration,* 226 (2)**,** 217-235.

Wahab, M. M. A., Roeck, G. D. and Peeters, B. (1999). Parameterization Of Damage In Reinforced Concrete Structures Using Model Updating. *Journal of Sound and Vibration,* 228 (4)**,** 717-730.

Wang, B. S. and He, Z. C. (2007). Crack Detection Of Arch Dam Using Statistical Neural Network Based On The Reductions Of Natural Frequencies. *Journal of Sound and Vibration*, 302 (4)**,** 1037-1047.

Wang, L., Beeson, D. and Wiggs, G. (2004). Efficient And Accurate Point Estimate Method For Moments And Probability Distribution Estimation. *10th AIAA/ISSMO Multidisciplinary Analysis and Optimization Conference*. Albany, New York, USA,

Wang, X., Hu, N., Fukunaga, H. and Yao, Z. H. (2001). Structural Damage Identification Using Static Test Data And Changes In Frequencies. *Engineering Structures*, 23 (6)**,** 610-621.

Wang, X., Yang, C., Wang, L. and Qiu, Z. (2014). Probabilistic Damage Identification Of Structures With Uncertainty Based On Dynamic Responses. *Acta Mechanica Solida Sinica,* 27 (2)**,** 172-180.

Wang, Z., Lin, R. M. and Lim, M. K. (1997). Structural Damage Detection Using Measured FRF Data. *Computer Methods in Applied Mechanics and Engineering*, 147 (1), 187-197.

Wang, Z. and Ong, K. C. G. (2010). Multivariate statistical approach to structural damage detection. *Journal of Engineering Mechanics,* 136 (1)**,** 12-22.

Weber, B., Paultre, P. and Proulx, J. (2009). Consistent Regularization Of Nonlinear Model Updating For Damage Identification. *Mechanical Systems and Signal Processing*, 23 (6), 1965–1985.

Weekes, B., Almond, D. P., Cawley, P. and Barden, T. (2012). Eddy-current Induced Thermography - Probability of Detection Study of Small Fatigue Cracks in Steel, Titanium and Nickel-based Superalloy. *NDT&E International,* 49, 47-56.

Weng, S., Xia, Y., Zhou, X. Q., Xu, Y. L. and Zhu, H. P. (2012). Inverse Substructure Method For Model Updating Of Structures. *Journal of Sound and Vibration,* 331 (25), 5449–5468.

Weng, S., Zhu, H. P., Xia, Y. and Mao, L. (2013). Damage Detection Using The Eigenparameter Decomposition Of Substructural Flexibility Matrix. *Mechanical Systems and Signal Processing*. 34 (1), 19-38.

Wilamowski, B. M. (2009). Neural Network Architectures And Learning Algorithms. *Industrial Electronics Magazine,* 3 (4)**,** 56-63.

Worden, K. and Dulieu-Barton, J. M. (2004). An Overview Of Intelligent Fault Detection In Systems And Structures. *Structual Health Monitoring,* 3 (1)**,** 85-98.

Wu, J. R. and Li, Q. S. (2006). Structural Parameter Identification And Damage Detection For A Steel Structure Using A Two-Stage Finite Element Model Updating Method. *Journal of Constructional Steel Research,* 62 (3), 231–239.

Wu, X., Ghaboussi, J. and Garret, J. H. (1992). Use Of Neural Networks In Detection Of Structural Damage. *Computers & Structures,* 42 (4)**,** 649-659.

Xia, Y., and Hao, H. (2003). Statistical Damage Identification Of Structures With Frequency Changes. *Journal of Sound and Vibration,* 263(4), 853-870.

Xia, Y., Hao, H., Brownjohn, J. M. W. and Xia, P. Q. (2002). Damage Identification Of Structures With Uncertain Frequency And Mode Shape Data. *Earthquake Engineering and Structural Dynamics,* 31 (5)**,** 1053-1066.

Xia, Y. and Lin, R. (2004). Improvement on the Iterated IRS Method for Structural Eigensolutions. *Journal of Sound and Vibration,* 270 (4), 713–727.

Xu, B. (2006). Neural Networks Based Structural Model Updating Methodology Using Spatially Incomplete Accelerations. *Advances in Natural Computation,* 361-370.

Xu, B., He, J., Rovekamp, R. and Dyke, S. J. (2012). Structural Parameters And Dynamic Loading Identification From Incomplete Measurements: Approach And Validation. *Mechanical Systems and Signal Processing,* 28, 244-257.

Xu, B., Wu, Z. S., Yokoyama, K., Harada, T. and Chen, G. (2005). A Soft Post-Earthquake Damage Identification Methodology Using Vibration Time Series. *Smart Materials and Structures,* 14 (3)**,** S116–S124.

Xu, H. and Humar, J. M. (2006). Damage Detection In A Girder Bridge By Artificial Neural Network Technique. *Computer-Aided Civil and Infrastructure Engineering,* 21 (6)**,** 450–464.

Xun, J. and Yan, S. (2008). A Revised Hilbert–Huang Transformation Based On The Neural Networks And Its Application In Vibration Signal Analysis Of A Deployable Structure. *Mechanical Systems and Signal Processing,* 22 (7)**,** 1705-1723.

Yam, L. H., Yan, Y. J. and Jiang, J. S. (2003). Vibration-Based Damage Detection For Composite Structures Using Wavelet Transform And Neural Network Identification. *Composite Structures,* 60 (4)**,** 403-412.

Yan, A. and Golinval, J. C. (2005). Structural Damage Localization by Combining Flexibility and Stiffness Methods. *Engineering Structures,* 27 (12), 1752–1761.

Yan, A. M. and Golinval, J. C. (2006). Null Subspace-Based Damage Detection Of Structures Using Vibration Measurements. *Mechanical Systems and Signal Processing,* 20 (3)**,** 611-626.

Yan, W. and Yuan, L. (2010). Damage Detection In Structural Systems Using A Hybrid Method Integrating EMI With ANN. *Power and Energy Engineering Conference (APPEEC)*. Asia Pacific, 1-4.

Yan, Y. J., Cheng, L., Wu, Z. Y. and Yam, L. H. (2007). Development in Vibration-based Structural Damage Detection Technique. *Mechanical Systems and Signal Processing,* 21 (5), 2198-2211.

Yang, Q. W. (2011). A New Damage Identification Method Based On Structural Flexibility Disassembly. *Journal of Vibration and Control,* 17 (7)**,** 1000-1008.

Yang, Q. W. and Liu, J. K. (2007). Structural Damage Identification Based On Residual Force Vector. *Journal of Sound and Vibration,* 305 (1)**,** 298-307.

Yang, Q. W. and Liu, J. W. (2009). Damage Identification By The Eigenparameter Decomposition Of Structural Flexibility Change. *Int. J. Numer. Meth. Engng* 78 (4), 444–459.

Yeih, W. and Huang, R. (1998). Detection of the Corrosion Damage in Reinforced Concrete Members By Ultrasonic Testing. *Cement and Concrete Research,* 28 (7)**,** 1071–1083.

Yeo, I., Shin, S., Lee, H. S. and Chang, S. P. (2000). Statistical Damage Assessment Of Framed Structures From Static Responses. *Journal of Engineering Mechanics,* 126 (4)**,** 414-421.

Yin, T., Lam, H. F., Chow, H. M. and Zhu, H. P. (2009). Dynamic Reduction-based Structural Damage Detection of Transmission Tower Utilizing Ambient Vibration Data. *Engineering Structures,* 31 (9), 2009-2019.

Yuen, K. V. (2012). Updating Large Models For Mechanical Systems Using Incomplete Modal Measurement. *Mechanical Systems and Signal Processing,* 28, 297–308.

Yuen, K. V. and Lam, H. F. (2006). On The Complexity Of Artificial Neural Networks For Smart Structures Monitoring. *Engineering Structures,* 28 (7)**,** 977–984.

Yun, C. B. and Bahng, E. Y. (2000). Substructural Identification Using Neural Networks. *Computers & Structures,* 77 (1)**,** 41-52.

Yun, C. B., Yi, J. H. and Bahng, E. Y. (2001). Joint Damage Assessment Of Framed Structures Using A Neural Networks Technique. *Engineering Structures,* 23 (5)**,** 425–435.

Yun, H. D., Choi, W. C. and Seo, S. Y. (2010). Acoustic Emission Activities And Damage Evaluation of Reinforced Concrete Beams Strengthened With CFRP Sheets. *NDT&E International,* 43 (7), 615–628.

Zang, C. and Imregun, M. (2001a). Combined Neural Network And Reduced FRF Techniques For Slight Damage Detection Using Measured Response Data. *Applied Mechanics,* 71 (8), 525-536.

Zang, C. and Imregun, M. (2001b). Structural Damage Detection Using Artificial Neural Networks And Measured FRF Data Reduced Via Principal Component Projection. *Journal of Sound and Vibration,* 242 (5)**,** 813-827.

Zhang, K., Li, H., Duan, Z. and S.S.Law (2011). A Probabilistic Damage Identification Approach for Structures with Uncertainties under Unknown Input. *Mechanical Systems and Signal Processing,* 25 (4)**,** 1126–1145.

Zhang, Q. W., Chang, T. Y. P. and Chang, C. C. (2001). Finite-Element Model Updating For The Kap Shui Mun Cable-Stayed Bridge. *Journal of Bridge Engineering,* 6 (4)**,** 285-293.

Zhang, Z. and Friedrich, K. (2003). Artificial Neural Networks Applied to Polymer Composites: A Review *Composites Science and Technology,* 63 (14)**,** 2029-2044.

Zhao, J., Ivan, J. N. and Dewolf, J. T. (1998). Structural Damage Detection Using Artificial Neural Networks. *Journal of Infrastructure Systems,* 4 (3)**,** 93-101.

Zhou, Q., Ning, Y., Zhou, Q., Luo, L. and Lei, J. (2013). Structural Damage Detection Method Based On Random Forests And Data Fusion. *Structual Health Monitoring,* 12 (1)**,** 48-58.

Zhu, H., Li, L. and He, X. Q. (2011). Damage Detection Method For Shear Buildings Using The Changes In The First Mode Shape Slopes. *Computers & Structures,* 89 (9), 733–743.

Zimmerman, D. C., Simmermacher, T. and Kaoukpp, M. (1995). Structural Damage Detection Using Frequency Response Functions. *SPIE The International Society For Optical Engineering*. 179-184.

Zou, Y., Tong, L. and Steven, G. P. (2000). Vibration-based Model-dependent Damage (Delamination) Identification and Health Monitoring for Composite Structures - A Review. *Journal of Sound and Vibration,* 230 (2)**,** 357-378.