MULTISTAGE ARTIFICIAL NEURAL NETWORK
IN STRUCTURAL DAMAGE DETECTION

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This thesis is specially dedicated to my beloved families and friends.
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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 menggunakan 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 pengesan 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. Keberkesanannya dan ketepatannya mengesan kerosakan yang dicadangkan ini telah diselidiki 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.
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<td>$c$</td>
<td>damping matrix</td>
<td></td>
</tr>
<tr>
<td>$m$</td>
<td>mass matrix</td>
<td></td>
</tr>
<tr>
<td>$k$</td>
<td>stiffness matrix</td>
<td></td>
</tr>
<tr>
<td>$x(t)$</td>
<td>displacement</td>
<td></td>
</tr>
<tr>
<td>$\dot{x}(t)$</td>
<td>velocity</td>
<td></td>
</tr>
<tr>
<td>$\ddot{x}(t)$</td>
<td>acceleration</td>
<td></td>
</tr>
<tr>
<td>$\Phi$</td>
<td>mode shape matrix</td>
<td></td>
</tr>
<tr>
<td>$\Lambda$</td>
<td>diagonal matrix</td>
<td></td>
</tr>
<tr>
<td>$E$</td>
<td>Young’s modulus</td>
<td></td>
</tr>
<tr>
<td>$F$</td>
<td>flexibility matrix</td>
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</tr>
<tr>
<td>$\mu$</td>
<td>mean</td>
<td></td>
</tr>
<tr>
<td>$\sigma$</td>
<td>standard deviation</td>
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<tr>
<td>$\rho$</td>
<td>density</td>
<td></td>
</tr>
<tr>
<td>$\nu$</td>
<td>Poisson ratio</td>
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# LIST OF ABBREVIATIONS

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

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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 efficiency 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


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


