

**DAMAGE IDENTIFICATION OF A BRIDGE COMPONENT USING
MODEL UPDATING AND ARTIFICIAL NEURAL NETWORK
TECHNIQUES BASED ON FREQUENCY RESPONSE FUNCTIONS**

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of the requirements of
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CERTIFICATE OF ORIGINAL AUTHORSHIP

I certify that the work in this thesis has not previously been submitted for a degree nor has it been submitted as part of requirements for a degree except as part of the collaborative doctoral degree and/or fully acknowledged within the text.

I also certify that the thesis has been written by me. Any help that I have received in my research work and the preparation of the thesis itself has been acknowledged. In addition, I certify that all information sources and literature used are indicated in the thesis.

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Abstract

Many civil engineering structures worldwide are now or will soon be approaching the end of their design lives. In New South Wales (NSW), Australia, a joint study conducted by the Sydney Morning Herald and the University of Technology, Sydney (UTS) suggested that across two-thirds of NSW councils needed more than \$340 million to bring their timber and concrete bridges up to a satisfactory condition. The American Society of Civil Engineers reported that 56,007 of the 614,387 bridges in the United States were found to be structurally deficient in 2016. Further, there was a recorded average of 188 million trips across structurally deficient bridges each day. One of the most important factors for budget prioritisation for asset maintenance is the condition assessment of structural assets. Austroads reported that the Roads and Maritime Services (RMS) in NSW maintains 5,500 structures in their Bridge Asset Management System. However, they are typically only able to inspect their timber bridges once per year and their other bridges every two years due to budgetary constraints. Further, the most commonly used method for bridge inspection is visual inspection, which is generally unable to identify subsurface damage.

In the past couple of decades, structural health monitoring (SHM) has gained increasing attention as a monitoring system that is able to observe the structural characteristics of a bridge over time. SHM systems have been implemented on in-situ bridges world-wide. However, there are a limited number of publications that show clear and useful interpretations of the information collected from these systems. Meanwhile, damage identification methods that have been proposed and demonstrated in a laboratory environment are often implemented on structures that are much simpler than in-situ bridges.

This thesis aims to reduce the gap between the damage identification methods developed in the laboratory environment and their implementation on in-situ structures by proposing two novel damage identification methods. The first method is based on finite element (FE) model updating, and the second method is based on artificial neural networks (ANNs). Both methods utilise frequency response functions (FRFs), which can be directly measured from the structure and provide an abundance of information. These methods are demonstrated on two jack arch specimens, which are replicates of a structural component of the Sydney Harbour Bridge.

The FRF sensitivity method for model updating is investigated in this thesis to estimate the location and severity of damage in a structure. One of the main challenges in model updating is that a FE model typically contains many more degrees of freedom (DOFs) than the number of DOFs that are measured from a physical structure. One way to address this issue is by reducing the FE model DOFs to the measured DOFs. The drawback of this approach is that important information of the FE mode shapes can be lost. Another approach is to expand the measured DOFs to the FE model DOFs. However, this can significantly increase the computational cost of the model updating procedure. In this study, the FE model is reduced to a linkage model using the System Equivalent Reduction Expansion Process (SEREP). Then, the measured mode shapes are expanded to the linkage model using its mass and stiffness matrices. Based on the expanded mode shapes, interpolated FRFs are synthesised, and the FRF sensitivity method for model updating is applied. The updating parameters are used to form a damage index to estimate the location and severity of damage. The results from the study show that the method is capable of estimating the location and severity of the cracks that are visually identified on the specimen.

In the context of vibration-based damage identification, researchers have used ANNs to detect damage in a structure. In some of these studies, principal component analysis (PCA) was used to reduce the dimensionality of FRFs, turning them into principal component (PC) scores and making them more practical to be used as inputs into ANNs. These researchers demonstrated that ANNs are capable of identifying trained and non-trained damage cases. However, few of these studies elaborated on how the PC scores of the non-trained cases can be obtained when they have no involvement in the calculation of the PCs that are used to transform the FRFs into PC scores. This important feature is explored, as the non-trained cases should have no involvement in the calculation of the PCs or in the ANN learning process. Further this methodology is applied to the jack arch specimen, which simulates a realistic structural component of a bridge where the inflicted damage is small, resulting in minimal changes in the FRF. The results from this study show that the PCs calculated from the FRFs of the trained cases can be used to calculate the PC scores of the non-trained cases, and that these PC scores are compatible with the ANNs that are learned with the trained cases. Further, this method is applicable to the jack arch specimen, and should be tested on in-situ structures in future works.

The main contributions to the body of knowledge in this thesis revolve around applying damage identification methods that have been demonstrated on simplified laboratory models in the past to more realistic applications. The jack arch specimens used in this study replicate a structural component of the Sydney Harbour Bridge. The complex geometry of the jack arch specimens means that these structures require solid elements to be modelled accurately. This will invariably mean that the FE model will contain far more DOFs than the DOFs that can realistically be measured from the physical structure. The proposed linkage modelling technique is able to mitigate this issue. Additionally, when training ANNs to identify damage, it is impractical for all possible damage scenarios to be incorporated in the calculation of the PCs that are used to transform the FRFs into PC scores. Hence, this study investigates techniques to obtain PC scores of damage cases that have no involvement in the calculation of the PCs.

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Conference Papers

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