Damage Detection of Concrete Slab Bridges

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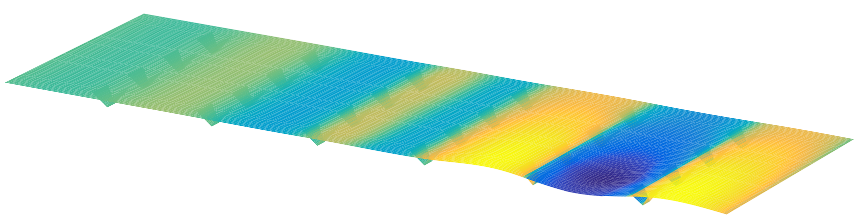

Dear reader, this literature review is taken from my thesis, the course was cancelled in my year but my supervisor was kind enough to sign me up for the literature review part of the course as I write my thesis.

1 Introduction

The probability of a bridge to fail increases over time until it is no longer considered safe for use. Maintenance of a bridge is typically carried out when something goes wrong or according to a preventative maintenance schedule based on expert knowledge, neither approach making the best use of limited maintenance resources. The Nanfang'ao bridge collapse in Taiwan on 1 October 2019 in which 6 people were killed and 12 were injured is a recent example of the importance of maintainence of civil infrastructure. The bridge was only twenty years old.

Sensors can provide real-time information without the delay or cost of a manual maintenance check. How can we detect damage on a no-prestress no-postension concrete slab bridge? This question is the topic of this thesis. In order to answer this question we must first answer the question of how can we collect sensor data for the purpose of damage detection? Only then can we answer the question of how can we detect damage in the acquired data. Related but less central questions include: how does the installed sensor configuration affect the ability to detect damage, and how could such a damage detection system be installed for the purpose of real-time structural health monitoring (SHM)?

In order to classify data as coming from either a damaged or healthy bridge it is of course necessary to have sensor data corresponding to both the damaged and healthy state of the bridge, otherwise we could not evaluate the accuracy of the classification techniques applied. Due to the fact that bridges are expensive structures, it is unsurprisingly not permitted in the general case to apply damage to a bridge. The use of finite element (FE) software allows us to create a simulation of a bridge to which damage can be applied. Sensor data can be collected from the FE simulation for the purpose of damage classification.

OpenSees (The Open System for Earthquake Engineering Simulation) is an open-source FE software package that anyone with a Windows, macOS or Linux machine, and an internet connection, can download and install. Depending on open-source rather than proprietary FE software enables users to explore, extend, or reproduce this research without having to acquire an expensive proprietary licence. All sensor data that is used for damage detection in this thesis is generated with the open-source program OpenSees.

A finite element model (FEM) is a model of a structure in software. All models are wrong but some are useful [1]. The sensor data that is generated with FE software will be different from sensor data collected from a real bridge, due to environmental and operational effects. However the simulated sensor data should be close enough to real data to provide confidence that the damage detection applied can also work with real sensor data, while acknowleding that some additional work would likely be needed to tune the anaysis techniques once real sensor data is available. It is thus necessary to validate the FE model and simulated sensor data in order to provide confidence in the damage detection methods applied to the data.

A FEM of the no-prestress no-postension concrete slab bridge, bridge 705, in Amsterdam was available at TNO (Netherlands Organisation for Applied Scientific Research) for the proprietary FE software package Diana. This FEM was previously validated against measurements from an experimental campaign. The existence of a validated FEM for bridge 705 allows the FEM for OpenSees to be validated by comparing responses under the same loading conditions in the two models. Sensor data collected with OpenSees is also compared directly to the measurements from static load tests in the experimental campaign.

An important environmental effect to consider is that of temperature. When a structure is heated up it will expand and when it cools down it will contract. In a structure such as a bridge where movement is constrained at the piers and abutments, forces will build up due to the thermal expansion/contraction and the bridge will deform. The effect of temperature and pier settlement (which is one of the considered damage scenarios) are validated by comparison of the responses generated under those conditions to the responses recorded in the FE software package AxisVM. AxisVM provides a graphical user interface (GUI) which allows for the simple visual verification of the built model, and the application of thermal loading or pier settlement is as easy as clicking a few buttons.

Once the FE model is validated additional steps are still necessary in order to combine responses generated via FE simulation under different loading conditions into a time series of responses under moving traffic. These time series are the data that will be used for damage detection, thus validating their correctness is paramount. To accomplish this a comparison will be made between a time series of measurements from the experimental campaign, where a truck was driven across bridge 705, and a time series of the simulated sensor data of the same truck moving across bridge 705.

SHM is a term used to describe a range of systems implemented for the purpose of assisting and informing about the "fitness of purpose" of a structure. A major part of any SHM system has to be geared towards long term evaluation of what is the "normal" of "healthy" state of the system [2]. This is because environmental effects such as temperature can affect the response of the structure enough to signal a departure from the structure's healthy state.

Evaluation of a SHM system for bridges requires that the SHM system has been installed prior to the occurence of damage. However for the economical decision of installing a long-term SHM system to be taken, someone needs to be convinced of the potential value of the system, somewhat of a catch 22. Thus research is largely based on numerical simulations of bridges, in which case environmental and operational effects are typically missing in the analysis, or damage is applied to a bridge before it is decommissioned, in which case the bridge is not under operational load. For these reasons any SHM system that is installed will likely be used in combination with operator expertise to prioritise maintenance or damage investigation, as the SHM system's long-term accuracy is evaluated and the system improved. According to [3], while a SHM system should be capable of a minimal amount of damage assessment the more likely scenario is that an additional investigation is triggered by the system.

A decision support system for bridge maintenance is a software system that provides the user of the system with information on the current state of a bridge. The provided information should enable the operator of the system to make a more informed decision about when and/or where maintenance should be carried out. The provided information can include real-time sensor data and an analysis thereof. Intelligence augmentation, where human experise is augmented by artifical intelligence (AI) techniques is a natural step in the development of fully automated AI-based systems. An example of this step in development is the car company Tesla's "auto-pilot" for self-driving on highways which is only a step in the direction to full self-driving but has shown enough value to be produced and will allow for the collection of huge amounts of data for the future improvement of the system. While AI can extend human's cognition with computational processing capacity, humans can at this point still offer a more holistic, intuitive approach in decision making [4].

Extensibility is a measure of the ability to extend software without accessing existing code to edit or copy it [5]. The research in this thesis is not just reproduceable but also extensible. This is achieved by not depending on expensive proprietary software, by "lifting" parameters to the boundaries of the system, and by publishing a system of composable functions that present the problem domain at a high-level of abstraction. After reading this thesis the large amount of work that went into data collection will become clear. It is my sincere hope to facilitate further research in the area of damage detection of concrete slab bridges and to prevent any duplication of effort. Any interested party should be able to download this work and swiftly move to the application of damage detection methods.

This thesis continues with an overview of the existing literature on damage detection and structural health monitoring of civil infrastructure, with a focus on bridges. Then additional motivational and theoretical background information is presented. The methods section describes the generation of sensor data via an extensible data collection system that combines data from many FE simulations, describes the inputs and outputs of the data collection system, and outlines the damage detection experiments on the generated data. In the results section the generated data and results of experiments on that data will be inspected and finally a conclusion of the work and results is presented.

2 Literature Review

The goal of this Section is to summarise the existing body of work related to the subject area of this thesis. This Section thus outlines the existing work on damage identification and SHM of civil infrastructure, with a particular focus on bridges. While the amount of literature related to SHM is vast with numerous book written on the topic, the literature related to SHM of bridges is a little smaller, and the focus on concrete slab bridges smaller again. In particular there seems to be mush more research on SHM of expensive bridges such as the Sydney Harbour Bridge (SHB) rather than less expensive but numerous concrete slab bridges. The literature is vast therefore a complete literature review is not presented but the papers that are visited are believed to be representative. A brief description is presented of each relevant paper along with a criticism of the research. This literature review is structured in two primary components, first research into damage detection of SHM is presented, followed by a review of practical considerations such as environmental noise and lessons learned from SHM installations.

2.1 Damage Detection

Much of the early research into damage identification of civil infrastructure is based on identifying modal properties, detecting damage by classifying changes in natural frequency or mode shape. Model-updating methods are based on having a model available and attempt to minimize the error between the model and real measurements by modifying model parameters with an optimization algorithm, in order to determine the state of the structure. Research into damage detection has over the years turned to the use of machine learning, in particular unsupervised learning which does not require a model. This Subsection will review some of the different methods of damage detection and finish with a review of machine learning-based damage detection.

Damage was applied to the I-40 bridge, a 130m girder bridge over the Rio Grande river, before it's demolition, and data recorded from ambient vibration tests. The damage was intended to simulate fatigue cracking and was inflicted with torch cuts in a girder. In the fourth and most severe damage state the web of the girder contained a 1.8 m cut and the flange was completely cut through. In [6] it is noted that changes in dynamic properties were only observed in the fourth damage state. Furthermore, changes of similar magnitude were observed from repeated ambient vibration tests on the undamaged structure.

In [7] introduced the use of the curvature of mode shapes which is obtained by differentiating the displacement mode shape twice. Changes in the curvature of the mode shape are localized to the damage and furthermore the absolute difference of the curvature mode shapes of the damaged and undamaged structures increase with damage severity [8]. However the [7] study was on a computer model of a beam, and did not consider robustness to noise.

In [9] changes in mode shapes, from the same I-40 experimental data, were shown to be statistically different from the undamaged state for all damage states, however the analysis could not discriminate whether the source of the change was structural damage. The damage in the fourth damage state was localized, however at this point the bridge was sagging by 2cm at the damage location, and according [10] the bridge would have collapsed under a live load.

In [11] changes in natural frequency and mode shapes from numerical simulations are used to determine the location and the extent of damage on a rigid frame and then to assess the safety of the structure. However this paper highlights two issues common in the literature. Modal parameters corresponding to a baseline or "healthy" state are required, and robustness to noise is not addressed in the work. The requirement of "baseline" data is not a fatal flaw and could be addressed in a number of ways: 1) the baseline state comes from sensor measurements taken for newly built structures, 2) existing structures could be monitored for *any* changes after sensor installation, not knowing whether the structure was already damaged or not, 3) a FEM is used to generate an approximation of the baseline state. The robustness to noise is a more crucial problem because civil structures will be subjected to environmental factors such as temperature changes and ambient vibration. In the research [11] it simply states "the existence of noise in the data processing should be addressed".

The 64m concrete Dogna bridge in Italy was built in 1978 and suffered from a strong flood in 2003. In 2008, prior to demolition, an experimental campaign was carried out where six damage configurations were applied to the bridge in the form of notches cut with a hydraulic saw. In [12] changes in modal curvature were succesfully used to identify the location of the damage. However the dynamic tests were all carried out under similar environmental conditions, thus the robustness to noise was not investigated.

In concrete structures with reinforcing steel bars, the bars are tensioned such that the concrete remains in compression. Once the steel bars have corroded and failed the concrete bridge is liable to collapse. However the stiffness of the bridge is mostly contributed by the concrete, the corrosion of the steel has little influence on the dynamics, until the reinforcing steel bars and bridge have failed [13].

In [14] a model-updating approach is applied which minimizes the difference in mode shapes. This approach was validated on the Z24 highway bridge in Switzerland, which is a 58m pre-stressed concrete bridge. The damage scenario considered was the lowering of one of the supporting piers (originally at a height of 44m) by 95mm. In this study only a single damage scenario was considered and environmental effects such as temperature which could represent a false positive damage scenario were not considered.

Model-updating approaches compare measurement data with responses from an analytical model and attempt to minimize the difference by updating model parameters. One problem with optimization algorithms used to update model parameters is that they may find a local rather than a global optimum. Evolutionary algorithms are good candidates for such problems and in [15] the particle swarm optimization algorithm is used as a model-updating approach using vibration data. The approach was experimentally verified against data from a 129m railway viaduct.

Health monitoring based on an analytical model imposes a challenge because an analytical model is required and the necessary data for building an analytical model is not always available. This is because civil infrastucture is not always built precisely to the original design, due to changes in orders or due to on-site construction constraints. Moreover, in the case of concrete, uniform material properties are not guaranteed.

A Bayesian probabilistic approach was applied in a laboratory test to a reinforced-concrete bridge column [16], this method compared the relative damage probabilites of different damage events based on data from vibration tests. The method has the potential advantage of not requiring an accurate analytical model, yet the study was only on a single column of a bridge and it was a laboratory experiment that did not account for environmental noise.

2.1.1 Machine Learning

Machine learning can broadly be split into two variants, supervised and unsupervised learning. Supervised learning methods map inputs to outputs based on previously given input-output pairs known as labeled training data. Thus for damage detection, supervised learning methods require the existence of data corresponding to damage states, which is unlikely in the case of expensive civil infrastructure such as bridges. Unsupervised learning methods attempt to find previously unknown patterns in data set without pre-existing labels. One-class classification is a form of outlier detection that can be considered a special case of supervised-learning, where only one class of training data is present in the training data.

In [17] a number of damage identification experiments were applied that attempted to identify damage on an aircraft wing. The study showed damage localization and assessment to be possible with machine learning methods however the experiments were in a controlled laboratory setting without any environmental factors present. In the same paper it is argued that "damage prediction cannot be addressed by machine learning methods in general".

In [10] a FEM of the 214m Clifton suspension bridge in Bristol, England is used to generate data corresponding to healthy and damaged states, namely damage to the girders. Environmental factors were considered by heating one side of the model by 30 °C. In order to generalize the classification problem, data was generated by simulating a vehicle moving at 3 different speeds. The vehicle was simulated using 2 concentrated loads, one per axle. Features were extracted from simulated vibration data and given as input to two unsupervised neural networks. The better-performing of the two was DIGNET [18] with a damage detection rate of 70%.

An ANN is used to detect damage from dynamic responses from a FEM of a railway bridge in [19]. To accomplish this an ANN is trained on past acceleration responses from the healthy bridge and then used to predict future values, the difference between predicted and measured data are used as a damage indicator. While prediction of subsequent acceleration data was possible, the loading applied is a much simplified case in contrast to a highway bridge that may have multiple lanes of traffic, in the research the loading applied was a single heavy vehicle (a train). Furthermore the authors suggest further work regarding the effect of environmental and operational effects.

The Sydney Harbour Bridge is a steel-reinforced concrete bridge built in 1932. The SHB consists of 800 jack arches in longitudinal direction. In an experimental campaign each jack arch was fitted with 3 accelerometers. It was known that one of the arches was cracked. Two very interesting papers applied damage detection to acceleration data collected from the sensors on the SHB. Both of these papers, unlike any of the works discussed so far, make use of structural information of the bridge.

[20] uses the idea that if an arch on the SHB is healthy then accelerometers would move together, if there is a crack then they would move differently. An SVM was trained using labeled data from features combining data from sets of 3 accelerometers on an arch. A one-class SVM (OCSVM) which is an unsupervised variant of the SVM that is trained only on the healthy data,

was also tested. The supervised variant achieved an accuracy of approximately 0.97 and the unsupervised approximately 0.71. In [21] an algorithm is suggested to improve selection of the Gaussian model parameter of the OCSVM, which improved damage detection accuracy on the same SHB data set.

Two methods were applied in [22] using the idea that similar substructures should behave similarly. k-means clustering was applied to the features collected from each arch. k-means clustering with k=2 and only considering 6 arches, including one known damaged arch, a cluster was formed containing primarily features from the damaged joint. This method did not perform well when the amount of arches considered was increased to 71. The other method applied in [22] considered a "joint representative", a feature that is the mean of the features from one arch. Then a pairwise map was created using the euclidean distance between each pair of joint representatives. This method detected the known damaged arch, another arch with a known faulty sensor and a third arch with unknown damaged state.

2.2 Practical Considerations

2.2.1 Noise

Any structural health monitoring system that is deployed on a real-life structure must consider the environmental and operational effects that will affect the responses of the bridge. Temperature changes the stiffness properties of a bridge deck resulting in different responses throught a day or year, and noise from traffic on another lane will also make damage identification more difficult.

A regression analysis was applied to acceleration data from the Alamosa Canyon Bridge in New Mexico in [23]. The natural frequency varied approximately 5% during the 24 hour interval when measurements were taken and the frequency was well correlated with temperature. Measured temperatures exceeded 45 and the eastern and western sides of the bridge showed a large temperature gradient, because the bridge is oriented north to south. In [24] a linear relationship is shown between the 1st and 2nd eigenfrequencies of the Z24 bridge in Zwitzerland and temperature above 0, and a separate linear relationship with temperature below 0. The bilinear relationship was related to the presence of the asphalt on the bridge. In [25] a number of model are proposed to show the relationship between natural frequency and temperature, these included a bilinear model and 4th polynomial order models with and without cross terms, all models performed well.

An integrated machine learning algorithm, combining techniques including PCA, is presented in [26] for separating the individual components of the deflection signal into componenets with separate frequencies. When the noise level was under 10%, each component (temperature, live load, structural damage) was succesfully separated based on data from a computer model of a long-span bridge. A linear relationship between temperature and deflection was assumed. Temperature was decomposed into two sinusoidal components, daily and annual. An auto-associative neural network is employed for separating the effect of damage in extracted features from responses caused by environmental variations of the system [27]. However the experiment was on a numerical simulation of a hard drive, and a laboratory test on a spring-mass system. The authors admit that several issues are to be addressed before the approach can be used on real structures.

2.2.2 Faulty Sensor

In any deployed SHM system the possibility that a sensor has developed a fault and that the received signal is incorrect must be considered, in the work on the SHB [22] one of the sensors was faulty, which was detected as damage. Damaged sensors can be detected via sensor data reconstruction. In this approach sensor data is reconstructed based on spatial and temporal correlations among the sensor network. If there are discrepancies between the measurement data and reconstructed data then the sensor may be faulty. Spatial correlations are used to reconstruct sensor data via PCA [28], minimum mean square error estimation [29], and support vector regression [30]. A recurrent neural network (RNN) was used that includes both spatial and past temporal data [31]. More recently in 2019 a bidirectional RNN includes more information by considering spatial and both past and future temporal correlations [32]. This method outperformed a number of existing methods on their test set, however the test data was from numerical simulation of an unvalidated model.

2.2.3 Deployments

A few bridges that had a SHM system deployed in real life have already been visited in this literature review. In the majority of these cases the bridge being researched was scheduled to be demolished [6, 12, 14], which enabled different damages to be applied to the bridge in the period prior to demolition. The SHB however had sensors installed on lane 7 in 2014 and they were still in use in 2016 [22]. In this Subsection we will examine a few

SHM deployments on bridges around the world.

A number of SHMS systems were deployed to monitor distinct behaviours on bridges in Kentucky. From 2005 - 2011 a system was deployed to monitor impact damage from over-height vehicles to the eastbound I-64 bridge and to identify the vehicles [33]. Vehicles were recorded by ultrasonic height sensors and video cameras, accelerometers and strain gauges compared impact to responses from sensors on a second bridge. One of the drawbacks that led to the system being decommissioned was the cost of replacement of the data acquisition system (once due to vandalism and once due to lightning strike) and time the system was down. Two SHM systems were deployed in Kentucky on bridges over the Ohio river, a barge impact detection system on the US 41 bridge and a crack growth monitoring system on the I-275 bridge [34]. The barge impact detection system (2006 - 2015) was pooly configured. Threshold limits were set based on [35] and did not detect an impact that was less than 0.25 times the set threshold. Data transfer was also sporadic due to a change in communication protocol by the cellular provider. The crack detection system consisted of a vibrating wire micro crack meter transmitting data to a server by cell modem every 10 minutes and data is viewable via a website. This was a succesful low cost installation which began in 2012, and was still operational in 2018 and through it additional costly repairs were deemed unecessary.

A number of SHM systems have been installed on bridges in Sweden. According to [36] many communities are responsible for the maintenance of their own bridges, but new constructions are dependent on political decisions that delay projects, thus a SHM system is deployed to provide confidence in the health of an old structure and the safety of users. The 9 x 78 m span New Arsta Railway Bridge highlights a number of proactical issues relating to the SHM system installed during construction in 2003 [37]. Data collection was interrupted due to interruption in power delivery and internet connectivity, water damage to the data logger due to freezing of a drainage hole, and damage to sensors including "violent treatment after the installation like hitting the sensors with heavy re-bars". In [38] a distributed fiber optic based SHM system was installed on the 950 m steel-beam concrete-deck Gotaalv bridge between Gothenburg and Hisingen. In an on-site crack test, the SHM system detected 4 of 7 cracks. The system is designed to operate for 15 years however it's effectiveness in reality remains to be seen.

2.3 Summary

The trend in damage detection is to employ machine learning, with particular use of unsupervised methods such as the OCSVM because they do not require having a model available. Feature extraction is arguably the most important and difficult step in ML-based health monitoring [17]. Much of the existing research suggests promising results but in a simulated or laboratory setting, and does not consider the difficulties that environmental or operational effects provide. Two works that succesfully detected apriori known damage on the SHB combined machine learning techniques with knowledge about the behaviour of the structure, in these works data from multiple sensors was compared.

{TODO: more on: anomaly detection. SHM installations in Hong Kong, and anomaly detection of non-bridge structures e.g. levees.}

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