The Use of Dynamic Data for the Structural Health Monitoring of Bridges

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SUMMARY

This paper gives a brief overview of the structural health monitoring process and then presents the results of work done on laboratory scale reinforced concrete bridge decks to illustrate some of the advantages and problems in using vibration data for structural health monitoring.

Ten 5m by 2.5m reinforced concrete bridge decks were incrementally loaded to failure. At each load increment a full modal survey was performed. Variations in natural frequency with level of damage were identified, but several problems were noted regarding the efficient identification of modal properties, the effect of indeterminate boundary conditions and the tracking of modes between different damage states. Finite element model updating was used to relate the changes in modal properties to stiffness changes in the decks, but this process was again limited due to the complexity of the deck structure and the need for prior knowledge of the damage location.

Finally, alternative signal processing techniques were applied to the frequency response function data, including principal component analysis and spectral distance measures. Although these approaches lack the physical meaning of modal parameters, they did prove to be a more efficient and robust method of comparing the vibration data. In particular, they are more suited to use in a real time active monitoring scheme than the modal methods.

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1. STRUCTURAL HEALTH MONITORING

1.1 Context

Road transport authorities worldwide have the responsibility of maintaining safe and efficient road networks. A key element of any road network is the bridge infrastructure, and bridge maintenance is becoming an increasingly important issue in most developed countries. Limitations on the budgets for bridge maintenance, rehabilitation and reconstruction have made comprehensive bridge management systems, and with them reliable condition assessment procedures, increasingly important. Although traditional periodic visual inspections provide economical means of condition assessment, they do tend to be highly subjective and may miss non-visible degradation.

In recent years, structural health monitoring (SHM) based on measured bridge response, has been suggested as a way to overcome some of the shortcomings of visual inspections. Ideally, the SHM system should be inexpensive, non-invasive (no bridge closure) and automated to avoid subjective operator differences.

1.2 The Structural Health Monitoring Process

The SHM process can be summarised by the so-called "data to decision cascade" and includes:

- Instrumentation and data collection,
- Data processing, data reduction and feature extraction
- Data storage
- Data interpretation, relating data to the structural condition
- Use of the data to make informed management decisions.

The implementation of the SHM process can be achieved using either a passive or active monitoring approach. Passive monitoring involves repeated, periodic inspections of the structure using a range of instrumentation and inspection methods. In this case the inspection team would be responsible for instrumentation and data collection, data processing and evaluation, and making bridge management decisions. The frequency of inspection would be determined by safety criteria and depends on the type, condition and location of bridge. In contrast, an active monitoring system is based on instrumentation that is permanently installed within the structure and uses a dedicated computer to log data continuously. The host computer processes and stores data in real time and makes decisions regarding bridge management actions. The work in this paper is aimed principally at active monitoring systems.

Comparing the active and passive approaches, the latter causes greater disruption to bridge operation, but is likely to provide more detailed survey results. In contrast, for the active approach the bridge is fully operational apart from when the instrumentation is installed, but the number of sensors is limited for it to be cost effective. This in turn reduces the information that can be gained from the SHM system and monitoring objectives must be set accordingly.

1.3 Vibration Data and Structural Health Monitoring

In theory, vibration data are ideally suited for use as the basis for a SHM system since they are cheap to collect and give a measure of the global behaviour from relatively few sensors. In particular, changes in stiffness associated with damage should lead to changes in modal parameters; a reduction in stiffness causing a reduction in natural frequency and a change in stiffness distribution causing a change in mode shape.

The traditional approach to using vibration data for either damage detection or SHM is to relate changes in the natural frequencies to changes in the stiffness of the system. This requires first the identification of the dynamic system (mode shapes and naturally frequencies) and then some form of model to relate changes in the modal parameters to damage in the structure. This latter step is usually achieved through finite element model updating in which a numerical eigensensitivity matrix is created and then used to update the FE stiffness matrix based on changes in the measured modal parameters.

1.4 Problems Using Vibration Data for Structural Health Monitoring

Although the approach outlined in the preceding section appears simple in principle, its effective implementation has proved remarkably elusive despite significant developments in both hardware and software. A key issue is the sensitivity of modal parameters to changes in the structural system. Often the changes are so small as to be masked by environmental effects. This is compounded by difficulties in obtaining reliable, robust modal estimates. A large number of measurement points are often required to identify mode shape data accurately and the curve fitting procedures for modal identification can be time consuming, unreliable and subjective. Furthermore, structural factors such as indeterminate support conditions and non-linearity may influence modal parameters. Some researchers have even questioned the validity of tracking modal changes when damage inevitably leads to different structural systems.

Therefore, recent research has focused on alternatives to the traditional system identification (SI) paradigm, considering novel data processing techniques such as statistical pattern recognition (SPR), artificial neural networks (ANN) and non-linear SI. This paper will use the results of laboratory studies on RC bridge decks to illustrate these issues and to consider different approaches to using vibration data that exploit the inherent benefits of vibration data whilst minimising the problems.

2. EXPERIMENTAL STUDIES

A series of pilot studies on reinforced concrete beam structures has shown that damage to reinforced concrete beams due to overloading leads to changes in the vibration characteristics that are measurable and repeatable. It has also been possible to relate these changes in modal parameters to changes in the physical system using FE model updating techniques. However, these studies have also shown that the cracking results in a significant non-linearity that makes accurate determination of the mode shapes and natural frequencies difficult.

This initial work was aimed at a practical system for bridges and so further tests have been carried out to see whether the results were applicable to more complicated bridge structures. A series of ten RC bridge decks of a generic beam and slab construction with transverse beams across the abutments (figure 1) were cast. Two different reinforcement arrangements were considered so that the influence of different failure mechanisms could be investigated; six decks had full shear reinforcement and were designated type A. The remaining four decks had minimal shear links and were designated type B.

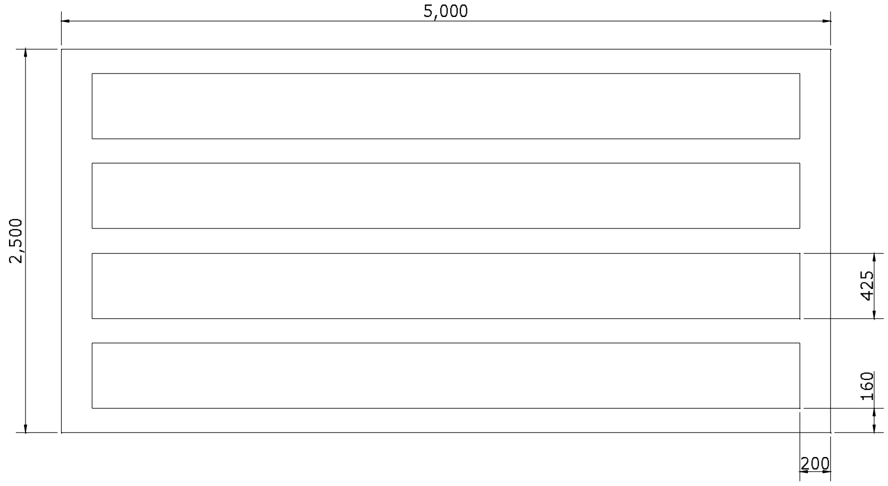

Figure 1: General arrangement drawing of model bridge decks

2.1 Testing Procedure

The testing procedure was similar to that for the beams in the earlier project. First, the natural frequencies and mode shapes of the decks were measured. To assess different excitation techniqeus, both an instrumented hammer and electromechanical shaker were used in the modal survey and the modal data were recorded at 45 points across the deck. Then the decks were incrementally loaded to failure, each load increment being ~ 50 kN. After each increment, the static load was removed and the modal survey repeated to determine the mode shapes and natural frequencies of the decks in the damaged state. Three loading arrangements were used to apply the static load. In the first, symmetrical, the central beam was loaded in 4 point bending. In the second, asymmetrical, the outer two beams on one side were loaded in four point bending. The third, HB, sought to replicate the vehicle load specified in BS5400. The loading arrangements and deck types are summarised in table 1.

Table 1: Summary of loading arrangements and deck types

Deck Number	Type	Loading	Ultimate Load
1	A	Symmetric	210*
2	A	Symmetric	345
3	A	Asymmetric	316
4	B	Asymmetric	180
5	B	Asymmetric	200
6	B	Symmetric	210
7	B	Symmetric	235
8	A	Symmetric	315
9	A	HB	337
10	A	HB	340

(* Deck 1 was not loaded to failure)

2.2 Modal Survey Results

The results from the modal surveys are summarised in figure 2, which shows the average reduction in natural frequency for the measured modes of selected decks. Although there is some repeatability between results for the symmetrically loaded type A decks, there is a significant scatter of results for the other cases. This scatter is even more marked when the individual modes are considered, figure 3. It was noted that tracking modes as the level of damage increased became difficult and subjective.

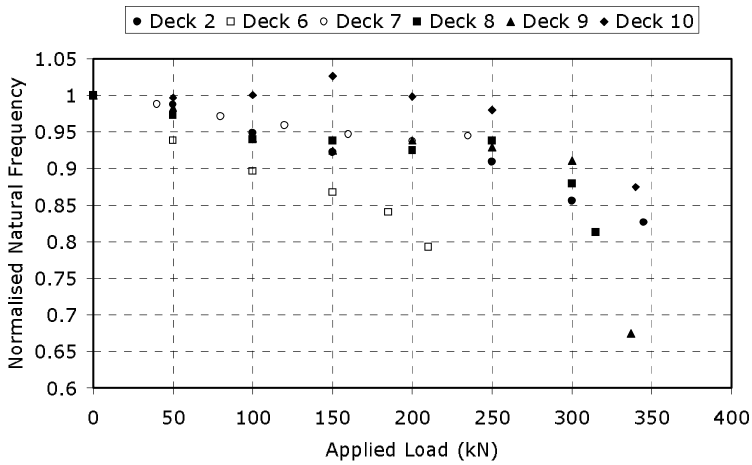

Figure 2: Average reductions in natural frequencies with damage (10 supports)

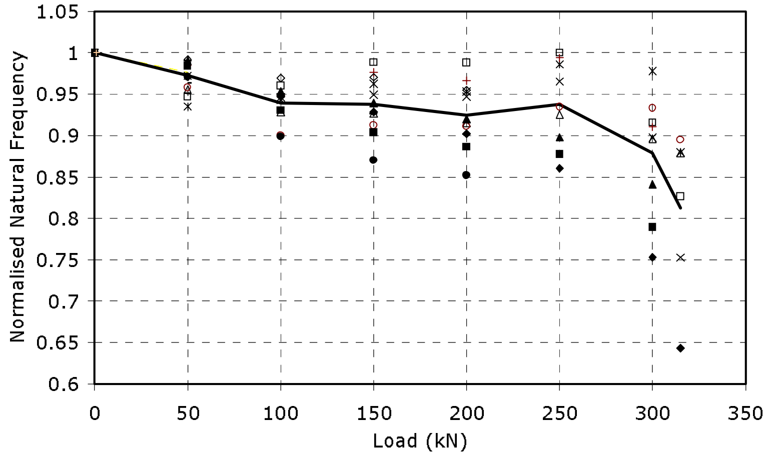

Figure 3: Variations in natural frequencies, Deck 8 (10 supports)

To investigate the effect of the indeterminate boundary conditions on these vibration characteristics, the modal surveys for some of the decks were repeated using a reduced, statically determinate bearing system with only three points of support. Typical results for these tests are shown in figures 4 & 5, and show more consistent trends, both between decks with the same type of loading and between decks with different reinforcement configurations.

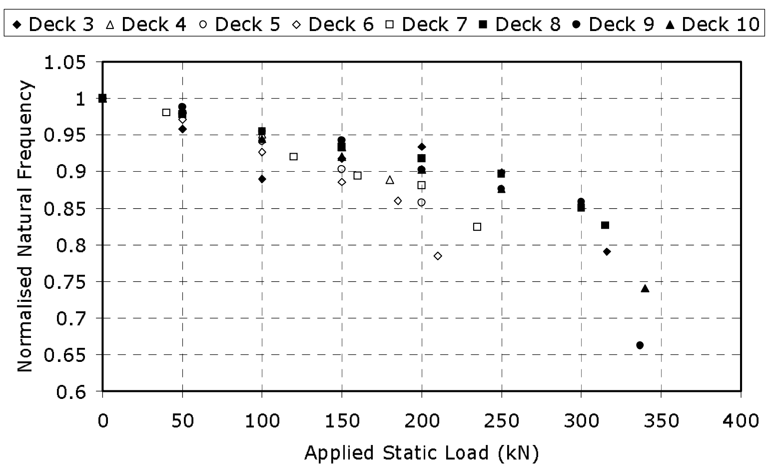

Figure 4: Average reductions in natural frequencies with damage (3 supports)

The results in figures 2-5 show that there is a significant reduction in natural frequency with damage, though this reduction is less clear for decks with indeterminate support conditions. The level of reduction is consistent with the earlier studies on beam structures and it is important to note that the average reduction in natural frequency of between 15 and 30 % at failure is larger than generally reported variation (5%) due to ambient effects. Although these results are encouraging from the point of view of using natural frequencies to monitor damage, as yet they have not been linked directly to a model of the structure. This is important to provide a structural explanation for the changes in natural frequency and to identify the location and severity of damage.

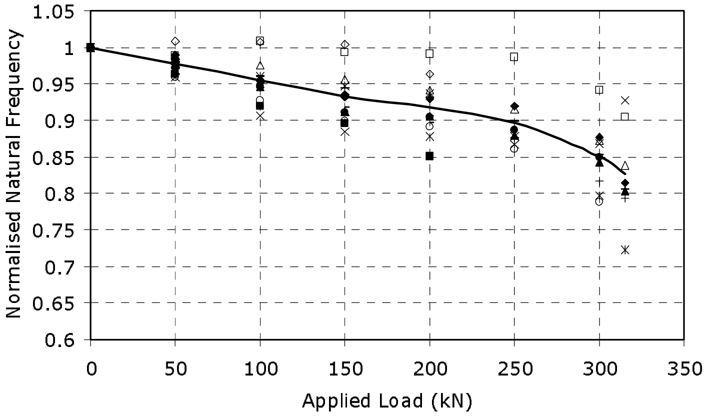

Figure 5: Variations in natural frequencies, Deck 8 (3 supports)

3. FINITE ELEMENT MODELLING

3.1 Model Updating - Outline Methodology

One approach for relating changes in the vibration characteristics to structural system changes is finite element (FE) model updating. This is a systematic method of fine-tuning a FE model based on the measured structural response. As vibration characteristics depend on the global mass and stiffness of a structure they are often used for model updating by constructing a sensitivity matrix relating changes in vibration characteristics to changes in selected model parameters. If natural frequencies are used for updating, then the relevant eigen-sensitivities can be obtained directly by differentiating the mass and stiffness matrices:

$$\frac{\partial \lambda_r}{\partial p_i} = \{\phi\}_r^T \frac{\partial [K]}{\partial p_i} \{\phi\}_r - \lambda_r \{\phi\}_r^T \frac{\partial [M]}{\partial p_i} \{\phi\}_r \tag{1}$$

and assembled into the sensitivity matrix $[A]$:

$$[A] = \begin{bmatrix} \frac{\partial \lambda_1}{\partial p_1} & \cdots & \frac{\partial \lambda_1}{\partial p_n} \\ \vdots & \ddots & \vdots \\ \frac{\partial \lambda_m}{\partial p_1} & \cdots & \frac{\partial \lambda_m}{\partial p_n} \end{bmatrix} \tag{2}$$

Here, λ_r and $\{\phi\}_r$ are the eigen-values and -vectors (natural frequencies and mode shapes), p_i are the updating parameters and $[M]$ and $[K]$ are the FE mass and stiffness matrices. Having obtained the eigen-sensitivity matrix, the FE model can be systematically fine tuned by adjusting the updating parameters as follows:

$$\{p\} = \{p\} + \{\Delta p\}, \qquad \{\Delta p\} = [A]^+ \{\Delta \lambda\} \tag{3}$$

where $\{\Delta\lambda\}$ is the difference between predicted and measured natural frequencies and $[A]^+$ is the pseudo-inverse of $[A]$.

The philosophy of FE model updating fits neatly with the damage detection problem. An updated model of the undamaged structure is first created, providing a calibrated datum. Vibration measurements from the damaged structure are then compared with predictions from the FE model and the updating method used to change the updating parameters to improve the correlation. If the updating parameters are chosen to be physically meaningful variables, e.g. local stiffness or loss of section, then these changes can be used to predict damage severity and location.

3.2 Application to Model Bridge Deck Data

In this project, a finite element model of the decks was created with the ANSYS package using 8 noded linear elastic brick elements (solid 45). These elements were chosen because they allowed the various cracked regions to be modelled simply by locally reducing the modulus of elasticity. They are also similar in shape to the ANSYS reinforced concrete element (solid 65) allowing the same mesh to be later used for more detailed modelling of the static load cases. As ANSYS does not allow the mass and stiffness matrices to be exported directly, a perturbation technique was used to obtain the eigen-value sensitivity matrix. This matrix was then used to successively update the model for each of the static load increments. Vibration data for both decks 8 and 9 were used, so that the effects of symmetric and asymmetric load arrangements could be studied. In both cases, a reduced set of updating parameters was chosen based on the modulus of elasticity in regions where cracking had been observed.

3.3 Model Updating – Results

The first point to note is that obtaining a calibrated model of the undamaged bridge decks represented a significant problem, principally because of the indeterminate bearing conditions discussed earlier. Identifying boundary conditions from the updating procedure does not work well as the change in stiffness is highly non-linear. In this work, an equivalent foundation including both vertical and torsional stiffness was defined at each abutment to overcome this problem.

Figures 6 and 7 show the normalised changes in modulus of elasticity for different regions of the deck as the level of static load is increased. Effectively, these represent the changes in stiffness due to localised cracking. This demonstrates that physically meaningful damage information can be extracted from the vibration data, but it does require prior knowledge of the failure mechanisms in order to simplify the updating procedure to a level that can be implemented practically. Even then, this updating process is cumbersome and is not a useful technique for use in an active monitoring scheme. It is therefore necessary to consider alternative signal processing techniques that can exploit the inherent information on structural condition embedded in the vibration measurements.

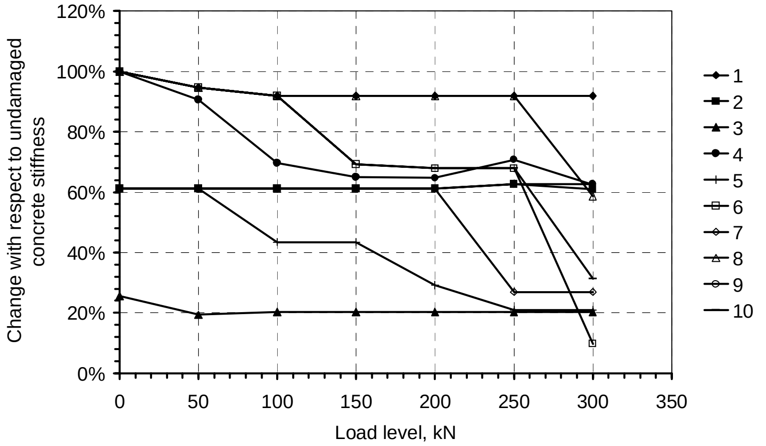

Figure 6: Summary of Material Changes from Finite Element Updating, Deck 8

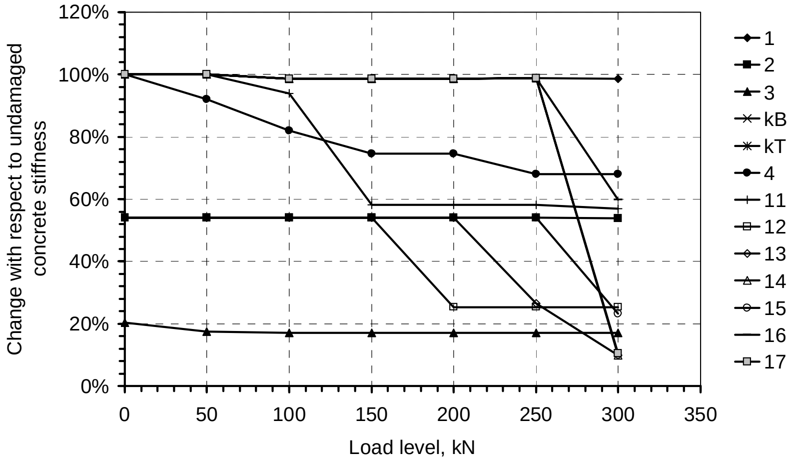

Figure 7: Summary of Material Changes from Finite Element Updating, Deck 9

4. STATISTICAL PATTERN RECOGNITION APPROACHES

4.1 Classification by Damage State Using Pricipal Component Analysis (PCA)

PCA is a powerful data reduction tool that allows large, complicated data sets to be represented by reduced feature vectors containing just a few elements (see for example Joliffe 1986). These techniques therefore have great potential in active monitoring systems where large data sets are collected in real time. They are also useful in pre-processing input data for artificial neural networks (ANNs) for solving classification problems (Bishop 1995). This technique has been applied for damage detection in Mechanical Engineering applications (Zang & Imregun 2001) and has been applied to the data from the model bridge decks.

First, the measured frequency response function data were reduced using PCA. Each FRF is treated as an n-dimensional vector, which can then be expressed in terms of a series of ortho-normal vectors obtained from the eigenvectors of the covariance matrix, $[\Sigma]$:

$$[\Sigma] = \sum_{i=1}^{N} \left(\frac{\{H_i(\omega)\} - \{\overline{H}(\omega)\}}{S(\omega)} \right)^T \left(\frac{\{H_i(\omega)\} - \{\overline{H}(\omega)\}}{S(\omega)} \right) \tag{4}$$

where $\{\overline{H}(\omega)\}$ is the mean of the N available RRF vectors and $\{S(\omega)\}$ is their standard deviation. If the eigenvectors of $[\Sigma]$ are given by $\{\sigma_j\}$, then the corresponding principal components z_{ij} for a given FRF $\{H_i(\omega)\}$ are given by:

$$z_{ij} = \{\sigma_j\}^T \left(\{R_i(\omega)\} - \{\overline{R}(\omega)\} \right) \tag{5}$$

The number of principal components used is data dependent, though it is typical to use as few as possible so that the feature vector has the least number of components. The number chosen is usually determined by considering the error in reconstructing the RRFs from the calculated principal component values:

$$E_j = \frac{\sum_{i=j+1}^{N} \lambda_i}{\sum_{i=1}^{N} \lambda_i} \tag{6}$$

where E_j is the error when using the first j principal components and λ_i is the ith eigenvalue of the covariance matrix. For this study, adequate reconstruction was obtained using the first 10 principal components.

An indication of the separation of damage states achieved through using PCA is given by figures 8 and 9, which show plots of the first against second principal components for decks 2 and 10. In these figures, data from each static load increment (i.e. damage state) are clearly seen to form clusters. The variation of other principal components with damage level is shown in figure 10, which again shows sharp differences between damage states. The principal components are well suited to form input vectors for a simple ANN and this has proved successful in similar applications (Haritos & Owen 2004, Owen et al 2002).

Although the classification technique illustrated here would seem to be a useful tool, it has one major drawback for Civil Engineering systems. The classification system essentially requires an a priori knowledge of the different damage states and an appropriate set of data for each one from which to calculate the PCs and train the ANN. This is quite possible in Mechanical Engineering applications where there may be many thousands of identical products, but is unlikely to be the case for bridge structures.

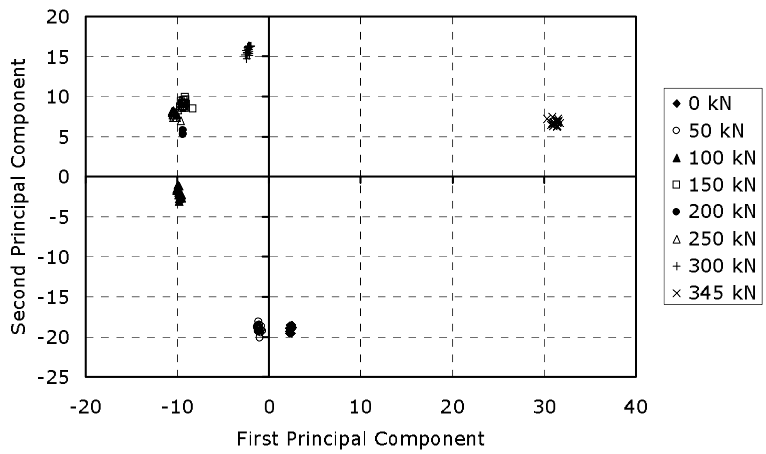

Figure 8: Plot of the first two principal components, Deck 2

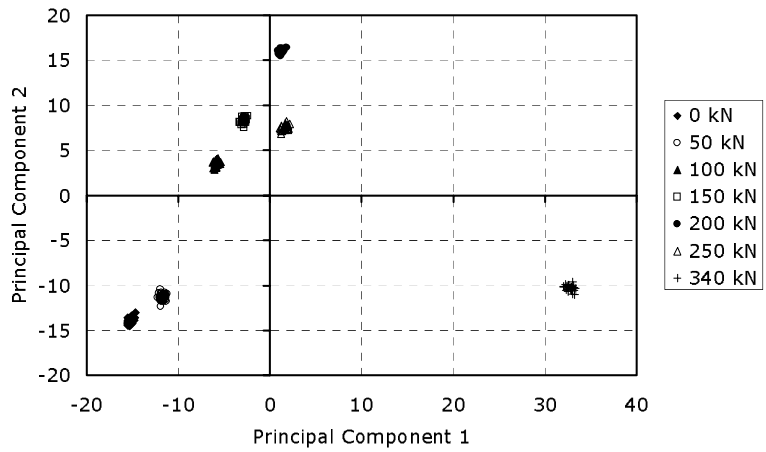

Figure 9: Plot of the first two principal components, Deck 10

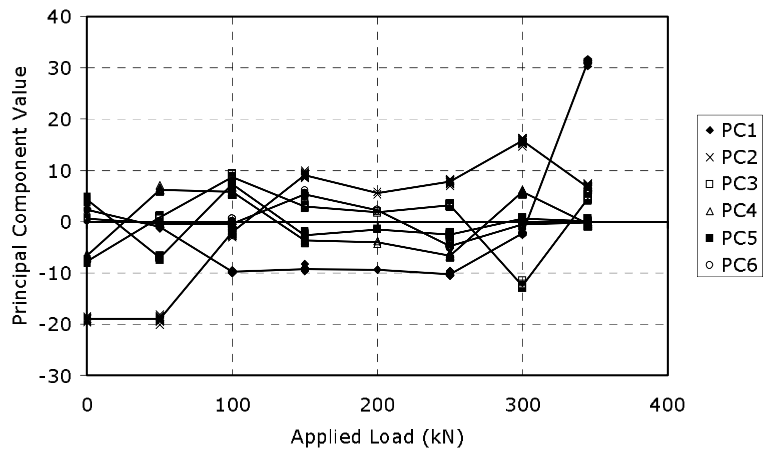

Figure 10: Variation of principal components with static load (damage), Deck 2

4.2 The Use of Spectral Distance Measures

The Cosh spectral distance (Trendafilova 2001) is a simple measure that can be used to compare two spectral quantities, such as the different FRFs from these tests. For this work, an average FRF was calculated for the undamaged state for each accelerometer location. Individual FRFs from each of the subsequent damage states were then compared with these averages using the following measure:

$$C\left(H,\overline{H}\right)=\frac{1}{2N}\sum_{j=1}^{N}\left[\frac{H\left(\omega_j\right)}{\overline{H}\left(\omega_j\right)}-\log\frac{H\left(\omega_j\right)}{\overline{H}\left(\omega_j\right)}+\frac{\overline{H}\left(\omega_j\right)}{H\left(\omega_j\right)}-\log\frac{\overline{H}\left(\omega_j\right)}{H\left(\omega_j\right)}-2\right] \qquad (7)$$

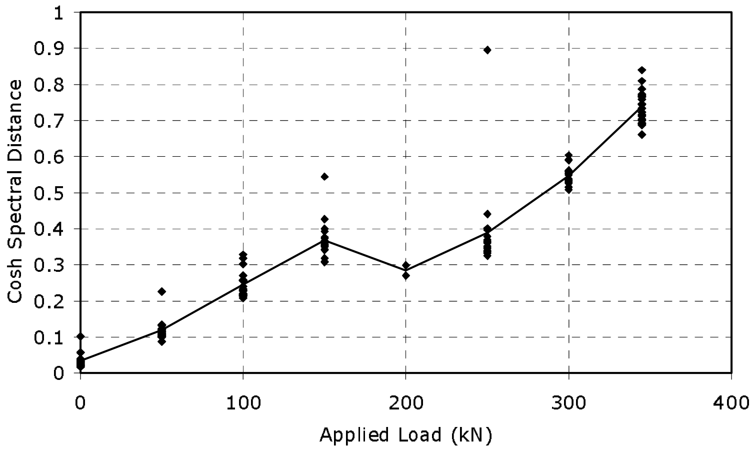

Figure 11: Variation of COSH spectral distance with static load (damage), Deck 2

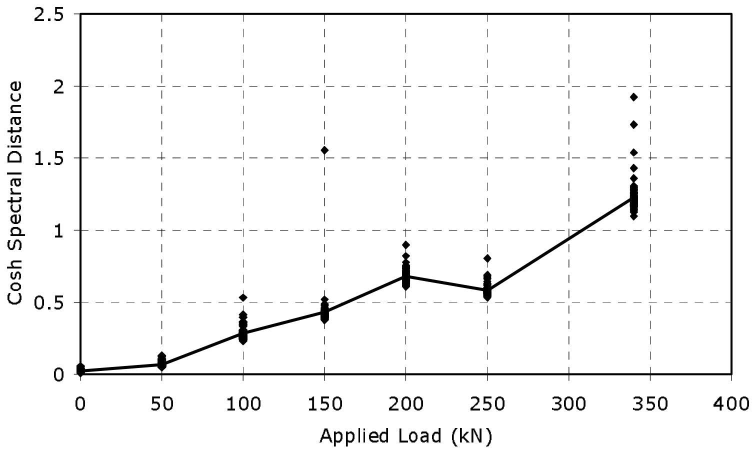

Figure 12: Variation of COSH spectral distance with static load (damage), Deck 10

The results for decks 2 and 10 are shown in figures 11 and 12 for one of the accelerometer locations. These figures both show a gradually increasing separation from the undamaged state, although there is a small reduction in separation in the middle of the damage regime. The importance of these figures is that they show that a simple distance measure allows comparison of the spectral data without a priori knowledge of the likely changes that might occur due to damage. The measures are simple to compute, meaning they are suitable for active monitoring approaches, and, although they do not yield structural information directly, crossing of an appropriate threshold can be used to trigger more detailed investigations.

5. CONCLUSIONS

The work outlined in this paper has confirmed previous studies that show vibration data do contain useful information about the integrity of a structure. Vibration data therefore represent a potential basis for SHM. However, this study has also highlighted some significant problems with their application.

First, identification of modal parameters for complicated bridge structures is still a subjective and not necessarily robust process. Furthermore, relating changes in modal parameters to changes in the structural system using model updating techniques is also a significant challenge. A priori knowledge of damage mechanisms and locations does simplify the process for bridge structures making estimates of damage possible. These issues, together with other factors discussed in the paper, suggest that extracting modal parameters is not the best method of exploiting the information in vibration data for real time SHM applications.

Statistical pattern recognition techniques do, however, show some promise as alternative data processing techniques for SHM. In particular, simple measures such as the COSH spectral distance provide an efficient way of identifying changes in vibration data that is well suited to active SHM systems. Appropriate thresholds applied to a restricted instrument set could then be used to trigger more detailed investigations.

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BIOGRAPHICAL NOTES

Dr J S Owen is a lecturer in the School of Civil Engineering at the University of Nottingham. His principal research interests are in structural dynamics, response of structures to wind and tubular structures.

Dr S R Pearson is a former PhD student in the School of Civil Engineering at the University of Nottingham, whose PhD research formed the basis for the work presented in this paper. He is now employed by AEA Technology, Rail.

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