Structural health monitoring of the Z-24 bridge in presence of environmental changes using modal analysis

Gunther Steenackers, Patrick Guillaume

Vrije Universiteit Brussel (VUB)
Department of Mechanical Engineering (WERK)
Acoustics and Vibration Research Group (AVRG)
Pleinlaan 2, B-1050 Brussels, Belgium
gunther.steenackers@vub.ac.be
www.avrg.vub.ac.be

ABSTRACT

Modal analysis is a technique that can be used to detect damage in civil structures. This paper starts from the hypothesis that occurring damage will manifest itself under the form of a change in dynamic behavior of the investigated structure. Vibrational and environmental measurements performed on the Z-24 bridge are available to investigate this hypothesis. The measured data are processed and sequential modal analyses are performed. The evolution of the bridge modes as a function of time are tracked, together with the measured environmental conditions such as temperatures. A correlation is made between the variations in temperatures and the resulting resonant frequency variations. The aim of the paper is to investigate if it is possible to distinguish changes in modal parameters due to damage from changes caused by temperature or other environmental variations.

1 INTRODUCTION

There is a great interest in techniques that make it possible to guard civil engineering structures, in particular to detect structural damage at a stage as early as possible. One of the most promising approaches makes use of the hypothesis that occurring damage will manifest itself through a change in dynamic behavior of the structure under investigation. One can ask oneself how these change in dynamic behavior can be detected and interpreted in a correct and practical manner. It is obvious to derive experimental system models, among other things to make use of the modal analysis approach. A change in dynamic behavior of the structure will be detected as a variation of the modal parameters characterizing the structure.

There can be a lot of reasons giving cause for a change of the estimated modal system model, for instance estimation errors or environmental influences (temperature, moisture, wind speed). This requires on the one hand that the utilized model estimation techniques have to be as robust as possible but on the other hand that the uncertainty associated with the model estimation must be described explicitly, such that it can be detected when these changes will be significantly important. A next step consists in distinguishing modal parameter changes caused by structural damage from changes due to environmental variations.

It will be investigated if the proposed methods for parameter estimation can be automated in a practical manner. To investigate the proposed methods one will make use of industrial measurement data from the Swiss Z-24 bridge. On this bridge, multiple vibration measurements were performed in combination the measurement of data in different environmental conditions (different temperature variation during different seasons). Civil engineering structures are subject to loads, vibrations and changing environmental conditions. Damage detection at an early stage makes it possible to plan maintenance and minimizes the cost and time when the structure is non-operational.
2 DESCRIPTION OF THE Z24 BRIDGE

The Z24 bridge was an overpass of the national highway A1 between Bern and Zurich, Switzerland. It was a classical post-tensioned concrete box girder bridge with a main span of 30 m and two side spans of 14 m (fig.1). Both abutments consisted of three concrete columns connected with concrete hinges to the girder. Both intermediate supports were concrete piers clamped into the girder (ref. [1]). Part of the data assembled was made public as a civil engineering benchmark for comparing the performance of various system identification techniques (ref. [2]). The benchmark data consists of 9 patches with a total of 99 measurements including 3 reference measurements that were common to all patches. Data was sampled at 100 Hz while the anti-aliasing filter was set to 30 Hz: The ambient excitation sources on the bridge were wind, traffic on the highway and pedestrians part of the test crew. Each channel measured 65536 samples, resulting in a measurement time of 10 min 55 s for each patch. For the input–output testing, two shakers were used. One was placed on a side span, the other at mid-span. The input signal was white noise between 3 and 30 Hz: The acquisition parameters were the same as during the ambient tests. More information about the bridge and the actual testing can be found in ref. [3].

3 ENVIRONMENTAL MONITORING SYSTEM

Civil engineering constructions are exposed to environmental influences. These influences give cause to variations in dynamic properties which can disguise variations due to structural damage. Because of that, environmental parameters and vibrations are being measured, aiming at identifying the dynamic properties of the examined structure. To identify the operational vibrations and thus identifying the dynamic behavior of the Z24 bridge, 16 accelerometers were spread across the structure. It is known that a change in temperature has an important effect on the dynamic behavior of a structure. As a result, temperature sensors were placed on strategically important positions (asphalt layer, bottom soil layer, piers). Also sensors for measuring air humidity and temperature, wind direction and speed were installed. The presence of rain and traffic under the bridge were also measured.

The environmental monitoring system, installed on the Z24 bridge, consists of, among other things (ref. [3]):

- 16 accelerometers
- 6 soil temperature sensors
- 24 bridge temperature sensors in 3 sections
- 1 air temperature sensor

The positions of the accelerometers and temperature sensors are visible on figure 2.
The EMS measurements are carried out on an hourly basis. The environmental parameters are being measured before and after the vibration measurements. The acceleration time histories are stored in 8 segments of in total 11 minutes durations with a sample frequency of 100 Hz. All data is stored as ascii-files. The measurement period spans the period between November 11th 1997 and September 10th 1998. During 9 months, these time signals were measured every hour. All measured data (6 Gbytes) was stored on 10 cd-roms and needed to be processed. More information on the Z-25 environmental monitoring system can be found in ref. [3].

4 OPERATIONAL MODAL ANALYSIS

Operational modal analysis has become a valid alternative for structures where a classic input-output test would be difficult if not impossible to conduct. In practice, one is often confronted with non-stationary ambient excitation sources (e.g., wind, traffic, waves, etc.). For a great deal of mechanical structures, the determination of modal models from classic input-output forced vibration tests may prove to be a difficult, if not impossible, task at least with standard testing material.

For instance, civil structures (e.g., bridges, buildings, off-shore platforms, etc.) and machinery, in operating conditions, are excited by unmeasurable ambient excitation sources (e.g., traffic, wind, waves, etc.). If an artificial excitation device is used, the presence of all other non-measured forces that act upon the structure (ambient excitation) will lead to a deterioration of the quality of the classic input-output model derived from the data.

Since in-operation analysis deals with output-only data, all excitation forces (including those which are hard or impossible to measure) are taken into account. On the other hand, the use of ambient excitation sources is cheap and freely available. The modeling of output only data, obtained from naturally excited structures, is particularly interesting because the test structure remains in its normal in-operation condition during the test. This can be considered as an advantage, since the condition of the test structure during a laboratory forced-vibration test often differs significantly from the structures real in-operation working conditions.

5 MEASUREMENT PROCESSING AND AUTOMATION OF THE PROCEDURE

5.1 Description of the successive processing steps

1. The measured accelerations and environmental values are stored as ascii-files on 10 cd roms. The cd’s contain more than 5500 files that need to be processed in one way or another. As a consequence, an automation of the processing procedure is necessary.

2. Since the input forces are not known, an operational modal analysis needs to be carried out on the basis of auto- and crosspower spectra. These power spectra must be calculated before an operational modal analysis can be carried out.

3. Once the estimated poles are known for all measurements, one wishes to track the evolution of a certain eigenfrequency mode as a function of time.

4. On the basis of the estimated poles one wishes to establish a relation between the value of the resonance frequency of a certain mode and the different temperature values measured across the structure.
5.2 Saturation of the measurement results

When analyzing the measured vibrational data, a problem came to rise with respect to the dynamic range of the measured amplitude levels. Saturated time blocks occurred, probably caused by heavy traffic in the vicinity of the Z24 bridge. From previous research (ref. [4], [5] and [6]), it is known that heavy traffic can alter the dynamic behavior of "lightweight" bridges by smearing out spectral peaks caused by added vehicle mass. After all, mass change causes a change in resonance frequencies. This phenomenon can lead to concealing certain structural changes. By removing the saturated time blocks, the vibrational behavior will not be influenced by heavy traffic and the accuracy of the estimated poles will increase.

![Figure 3: saturated (lower) and non-saturated (upper) measured time signal](image)

The saturated periods are clearly visible on figure 3 on the lower time sequence while the upper time sequence shows no saturated time blocks. Because this phenomenon could have an important effect on further processing of the data and the pole estimation procedure, the saturated periods need to be removed from the time histories to be processed.

The following actions for removing saturated time sequences are performed on the measured time data:

- The time histories are subdivided into blocks that are examined on the presence of saturation periods.
- For each block, all time histories are checked simultaneously on the presence of saturation periods.
- If at least one signal has saturated periods, all corresponding time periods are removed from all time histories (all measurement channels)
- The number of remaining unsaturated time sequences determines the number of averages that can be used in the spectral processing of the data. The smaller the number of unsaturated periods, the smaller the number of averages.

5.3 Automated calculation of the spectra

Using a Hanning window can lead to an overestimation of the damping value of a mode because the peak will be smeared out. This can be avoided by increasing the block size and decreasing the systematic error of using a Hanning window (ref. [7]). The drawback is a smaller number of possible block averages and thus the uncertainty on the measurements will increase.

A possible work-around for this problem is using auto- and crosscorrelation functions. The correlation functions can be decomposed into exponential functions. For considering only the stable system poles (decreasing exponential part of the function), one must apply an exponential window. Using an exponential window will introduce additional damping but can be compensated in calculations because the exponential decay is known. The auto- and crosspower spectra are calculated from the correlation functions by means of a Fast Fourier Transform. Because of the enormous amount of data to be processed, a procedure was written in "Matlab" for the automated calculation of the auto- and crosspower functions, based on the measured time signals.
5.4 Maximum likelihood identification

In ref. [8] a frequency-domain Maximum Likelihood estimator was proposed for the identification of modal parameters from input-output FRF measurements. It was shown in ref. [9] that a similar approach can be used for the estimation of modal parameters from crosspower functions of response measurements. During the Maximum Likelihood estimation process, uncertainty information, under the form of \( \text{var}\{S_{yy}(\omega_f)\} \) is taken into account. This way, more weight is set upon measurements with a high signal-to-noise ratio (low uncertainty) than on measurements with a low signal-to-noise ratio (high uncertainty).

Taking noise information into account usually leads to more accurate estimation results. The uncertainty on the measurements can be derived by means of several approaches depending on the nature of the data (input-output or output-only, stationary or non-stationary signals. Another important reason for making use of the Maximum Likelihood estimator is the fact that this is an iterative estimator that does not uses a stabilisation diagram, unlike those available in most commercial software packages. This means that the Maximum Likelihood estimator is suitable for implementing an automated procedure for the pole estimation and identification step in the used procedure.

6 TRACKING THE EVOLUTION OF THE MODES

From the set of estimated modes in previous operational modal analysis pole estimation, using the Maximum Likelihood estimator, it is the intention to track the interesting modes and their evolution during the complete measurement period. The interesting modes are those that are clearly detected and present during the complete measurement period.

Despite small frequency shifts in time, the following first 5 modes are systematically detected and estimated in successive analysis procedures (table 1). Similar estimation results can be found in ref. [2].
<table>
<thead>
<tr>
<th>Mode nr.</th>
<th>Frequency (Hz)</th>
<th>Type</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>3.9</td>
<td>Vertical bending</td>
</tr>
<tr>
<td>2</td>
<td>5.1</td>
<td>Transverse bending</td>
</tr>
<tr>
<td>3</td>
<td>9.9</td>
<td>Vertical bending and torsion</td>
</tr>
<tr>
<td>4</td>
<td>10.5</td>
<td>Vertical bending and torsion</td>
</tr>
<tr>
<td>5</td>
<td>12.7</td>
<td>Vertical bending</td>
</tr>
</tbody>
</table>

Table 1: Description of the Z24 bridge modes

The reason why one wants to follow or track the evolution of these modes as a function of time or temperature is because of damage detection possibilities. In a later stadium, a number of damage scenarios were executed on the Z24 bridge. Finally, a relation between evolution of a mode and certain measured temperature changes needs to be formulated. A possible correlation approach, based on regression analysis, will be explained in a later section of this paper.

A possible approach to track these modes is implemented and developed with the commercially available "Matlab" software package. A number of program stacks were written to capture and follow the evolution of a mode on the basis of frequency and damping values. To make post-processing in "Matlab" possible, the frequency and damping values of the estimated poles were exported to ascii-files. This makes a batch processing of the enormous amount of available measurement data possible.

In "Matlab" the tracking procedure of the modes can be described as follows:

- Each file, created from each separate modal analysis, is to be read in "Matlab". Each file contains frequency and damping values of all poles of one analysis.
- Initially, one chooses the frequency and damping value of the first correct mode as a reference from the first available analysis (eg. 3.97 Hz and 4.74% modal damping for mode n°1).
- All frequency and damping values from the processed analysis are sorted and the difference with the reference values are calculated.
- If the pole with the smallest frequency difference is also the one with the smallest damping value difference with respect to the reference pole, this pole will be considered as the pole in the processed analysis that corresponds best with the reference pole. This is not necessarily the correct pole that one wishes to find.
- If the pole with the smallest frequency difference is different from the pole with the smallest damping difference, one will consider the first two poles in the sorted matrix. If the frequency variation of the second sorted pole is smaller than 3 times the frequency difference of the first sorted pole, both poles qualify for the correct pole. If the damping value difference of the second pole is smaller than the damping difference of the first pole, than the second sorted pole will be considered as the best pole corresponding with the reference pole in the processed analysis.
- If the frequency difference of this pole with respect to the reference value is less than 0.1 Hz, than this pole is considered as a good representation for the reference pole (reference mode to be tracked). The frequency and damping values of this chosen pole will now be considered as the new reference frequency and damping values for the next analysis to be processed. If the frequency difference of this pole with respect to the reference value is more than 0.1 Hz, than this pole will NOT be considered as representative of the reference mode. This pole will be neglected and the average of the last 100 frequency and damping values will be defined as the new reference frequency and damping values. If there aren’t 100 representative poles yet available, one uses the initial reference values.
- In case there’s no representative pole found in a certain analysis, the initial reference value will be stored for this analysis in order to keep the processed time scaling (processed number of analysis) the same as the original time scaling. For each analysis one knows exactly at what time this data was measured.

As a result of the proposed procedure, the following figure 5 shows the tracked evolution of mode n°1 as a function of time (fig.5a) and as a function of temperature “$T/W/C^{1}$” (fig.5b). In figure 5b there is a clear trend noticeable, that will be discussed in detail in the next chapter.
When tracking the evolution of mode $n^o2$ with the proposed procedure, one finds the results visualized in figure 6a. The tracking is executed in chronological order: the measurements took place first in winter and afterwards during spring and summer season. The evolution of mode $n^o2$ is nicely tracked up to 7°C. From 0°C the tracking goes wrong and there is probably another mode selected as representative mode. Once there’s a wrong mode selected, the algorithm has difficulties with selecting again a good representative for the reference mode because the reference mode also changes in time. Instead, mode $n^o2$ was correctly tracked when the evolution of the mode was tracked in anti-chronological order. First the measurements in the summer and afterwards in the winter were considered for tracking purposes. The result is shown in figure 6b. The chronological order of processing the measured data plays a role in the proposed algorithm.

7 CORRELATION BETWEEN FREQUENCY AND TEMPERATURE

7.1 Introduction

When one uses vibration measurements as a health monitoring tool to constantly observe the condition of civil engineering structures, the following question arises. How to distinguish abnormal changes of the dynamic behavior from normal changes? Normal changes are caused by varying environmental conditions like humidity, wind and temperature. Temperature can have an effect on the boundary conditions (frozen soil) and the Young’s modulus of the construction material of the bridge (change of stiffness). On the other hand, abnormal changes due to damage are caused by a stiffness loss or a mass variation on a certain position on the bridge.
It is obvious that normal changes are not allowed to generate an alarm in the health monitoring system. Abnormal changes on the other hand can endanger the safety of the structure. This section tries to give an answer on the question if it is possible to distinguish the effect of environmental changes on the dynamic behavior of the structure from damage effects. Within the framework of the European “SIMCES” project (ref. [3]), the Swiss Z24 bridge is permanently observed during 10 months. Afterwards, the bridge was artificially damaged which makes it an excellent test object to investigate the effect of occurring damage.

It is obvious to consider the modal parameters as indicators for the dynamic behavior of the structure. For instance, a loss in stiffness is observed as a decrease of the natural frequencies. A realistic monitoring system must be able to estimate the modal parameters on the basis of output-only data (operational modal analysis). It is not possible to artificially excite the bridge with a known force while traffic crosses the bridge. That is why the traffic under the bridge can be used as ambient excitation force. This excitation force is in most cases not known.

7.2 Regression Analysis

Figures 5 and 6 show the evolution of the first and second natural frequency as a function of measured temperature. The exact positions of the temperature sensors are visible on figure 2. The relation between temperature and resonance frequency can be approximated by two straight lines crossing each other around 0°C (bilinear relation). During colder periods (frosty weather), the bridge stiffness will vary from the bridge stiffness in warm periods. During a warm period, the asphalt layer will not play a significant role but during a cold period this layer will add much more stiffness to the structure. A stiffness change will cause a variation of the natural frequencies.

The most common way to find a model for this relation is applying a linear regression: a linear relation between resonance frequency and one or more measured temperatures at a certain point of time is given by a least squares approximation. Because a linear relation is assumed, one chooses to take into account only these periods where the asphalt does not play a significant role. It would be difficult to draw conclusions if damage is occurring during cold periods because for these time periods the frequency changes are much larger. As seen on figures 5a and 6a, a large range of frequency estimates is present around -2°C. It is very unlikely that a frequency change caused by damage would be detectable outside this frequency interval. A possible linear regression approach could be to only consider the positive temperatures because damage events are much more difficult to detect with negative temperatures (frosty weather). Another problem with linear regression approach is the fact that the thermic behavior of the bridge is not taken into account. As seen on figure 11, time shifts are detected between temperatures measured on various locations. This is explained by the thermic inertia of the asphalt and concrete layers. A linear regression approach will not take these phenomena into account.

7.3 Linear regression analysis

One wants to find a linear relationship between the resonance frequency of the estimated mode and one or more measured temperature values.

Assume a linear relation of the form:

\[ y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \ldots + \beta_p x_p + \epsilon \]  

(1)

with frequency \( y \), measured temperature sensor \( i \) \( (x_i) \), temperature regression coefficients \( (\beta_i) \) and residual error \( (\epsilon) \)

In matrix notation (1) is written as (ref. [10]):

\[ Y = X\beta + \epsilon \]  

(2)

with \( Y \ (n \times 1) \) vector of frequency observations, \( \beta \ a \ (p \times 1) \) vector of parameters,
\[ X = \begin{pmatrix} 1 & x_{11} & \cdots & x_{p1} \\ 1 & x_{12} & \cdots & x_{p2} \\ \vdots & \vdots & \ddots & \vdots \\ 1 & x_{1n} & \cdots & x_{pn} \end{pmatrix} \]  

(3)

with \( X \in \mathbb{R}^{n \times (p+1)} \) temperature model matrix and \( e \in \mathbb{R}^{(n \times 1)} \) residual error vector of random variables with each element \( e_i \) is normally distributed with mean value zero.

A least squares approximation \( \hat{\beta} \) of \( \beta \) is given by:

\[ \hat{\beta} = (X^T X)^{-1} X^T Y = X^+ Y \]  

(4)

with \( X^+ \) the pseudo-inverse of temperature model matrix \( X \).

A criterion to examine how good the correlation is between the calculated linear fit and the measured points is defined by the correlation coefficient:

\[ R = \sqrt{1 - \frac{RSS}{SYY}} \]  

(5)

with

\[ RSS = \hat{e}^T \hat{e} = (Y - X \beta)^T (Y - X \beta) \]  

(6)

\[ SYY = \sum_{i} y_i^2 - \left( \frac{\sum_{i} y_i}{n} \right)^2 \]  

(7)

\[ \sigma_{error} = \sqrt{\frac{1}{n} \sum_{i} e_i^2} = \sqrt{\frac{RSS}{n}} \]  

(8)

with \( 'RSS' \) the residual sum of squares, \( 'SYY' \) the corrected sum of squares of y-values and \( \sigma_{error} \) the error standard deviation.

The correlation coefficient \( R \) is representative to what extent the regression error \( e \) is reduced by the knowledge of the \( x \)-values. If \( x \) and \( y \) (thus frequency and temperature) are hardly correlated, the correlation coefficient drops to zero.

### 7.4 Non-linear regression analysis

The linear regression approach, described in 7.3, can be extended to a non-linear regression approach by modifying the elements of the regression matrix (3). For instance, if one wishes to use a polynomial order 3 for the resonance frequency regression as a function of 2 temperature sensor measurements, regression matrix \( X \) must be modified to (9):

\[ X = \begin{pmatrix} 1 & T_{11} & T_{21} & T_{11}^2 & T_{21}^2 & T_{11}T_{21} & T_{11}^3 & T_{21}^3 & T_{11}T_{21}^2 \end{pmatrix} \]  

(9)

with \( T_{ij} \) measurement \( j \) of temperature sensor \( i \).

To evaluate to what extent a frequency variation is explained by temperature variation, it is possible to use the error standard deviation (\( \sigma_{error} \)) and the correlation coefficient (\( R \)). This coefficient describes how good a change in one parameter is explained by a change in another one. The ”best” relationship between two or more parameters is found for small \( \sigma_{error} \) and a high \( R \) values.
7.5 Regression results

When taking all (22 working) temperature sensor measurements into account for calculating a linear regression between resonance frequency and temperature measurements, the following values for regression coefficient and error standard deviation are found when considering the full (positive and negative) temperature range:

<table>
<thead>
<tr>
<th>Regression Type</th>
<th>Temperatures</th>
<th>R (%)</th>
<th>(\sigma_{\text{error}})</th>
</tr>
</thead>
<tbody>
<tr>
<td>linear static</td>
<td>22</td>
<td>79.5</td>
<td>0.037</td>
</tr>
</tbody>
</table>

Table 2: Linear regression results

Taking into account 22 temperature sensors is not sensible because the bridge temperatures are to some extent correlated with each other. From the absolute value of the regression coefficients, one can derive to what extent each temperature measurement is correlated with the resonance frequency. The temperature with the highest absolute coefficient value will be the most correlated with the frequency (fig.7).

![Figure 7: Absolute value of temperature regression coefficients](image)

When one considers only the highest 2 regression coefficients, temperature sensors 'TW C' and 'TP2', a new linear regression gives the following results:

<table>
<thead>
<tr>
<th>Regression Type</th>
<th>Temperatures</th>
<th>R (%)</th>
<th>(\sigma_{\text{error}})</th>
</tr>
</thead>
<tbody>
<tr>
<td>linear static</td>
<td>TWC, TP2</td>
<td>75.0</td>
<td>0.039</td>
</tr>
</tbody>
</table>

Table 3: Linear regression results (cont’d)

Correlation coefficient \(R\) has decreased and \(\sigma\) is a little bit increased. This result is the compromise between the number of parameters that one wishes to take into account and the resulting effect on the correlation.

On figure 8 one recognizes the surface that describes the linear regression and it cuts all measurement points in 2 regions. For the lower temperatures (lower than 0°C) the linear regression is less representative (worse linear fit) for the measurement points.

The equation of the calculated linear regression is:

\[
\text{Frequency} = 4.023 - 0.004 \times TWC1 - 0.002 \times TP2
\]
Figure 8: Linear regression of mode $n^1$ as a function of 2 temperatures \('TW'C1' and \('TP'2'\)

From (10) one concludes that temperature \('TW'C1'\) describes the frequency course better than temperature \('TP'2'\) because the respective coefficient is higher in absolute value. If temperatures \('TW'C1'\) and \('TP'2'\) are highly correlated with each other than the course of the resonance frequency can be described enough accurately by temperature \('TW'C1'\) only. When calculating a linear regression between these two temperatures, one finds the following equation (11):

$$TP2 = 1.193 + 1.064 \times TW'C1$$  \hspace{1cm} (11)

One finds a correlation coefficient \(R\) of 96\% between \('TW'C1'\) and \('TP'2'\). When calculating a linear regression between resonance frequency and only one temperature \('TW'C1'\), one finds:

<table>
<thead>
<tr>
<th>Regression</th>
<th>Type</th>
<th>Temperatures</th>
<th>R (%)</th>
<th>$\sigma_{error}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>linear</td>
<td>static</td>
<td>TW'C1</td>
<td>75.0</td>
<td>0.041</td>
</tr>
</tbody>
</table>

Table 4: Linear regression results (cont’d)

When comparing this result with the values found for a linear regression taking into account 2 temperatures, one notices that the correlation coefficient remains unchanged and $\sigma$ increased very little. From these results, one can conclude that taking into account only one temperature sensor \('TW'C1'\) is sufficiently representative for describing the course of resonance frequency of mode $n^1$.

From figures 5b and 6b it is clear that for the low (negative) temperature values there is a non-linear relation between the resonance frequency and temperature. That is why a non-linear regression will describe the correlation between the resonance frequency and temperature in a more realistic, more accurate way than a linear regression. This goes together with a higher expected correlation coefficient value. One assumes a regression polynomial of order 3 will be high enough to calculate an accurate regression model, taking into account that for higher polynomial orders oscillations could occur due to instability. Applying a non-linear regression leads to the following results:

<table>
<thead>
<tr>
<th>Regression</th>
<th>Type</th>
<th>Temperatures</th>
<th>R (%)</th>
<th>$\sigma_{error}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>non-linear</td>
<td>static</td>
<td>TW'C1, TP2</td>
<td>78.0</td>
<td>0.037</td>
</tr>
</tbody>
</table>

Table 5: Non-linear regression results
One can conclude that the correlation coefficient value \( R \) has increased from 75\% (linear regression) to 78\% (non-linear regression) and \( \sigma \) has decreased from 0.041 to 0.037. Also note the fact that \( R \) still is 1\% lower than with a linear regression approach taking into account all (22) temperature sensors. As a consequence one can conclude that the most accurate correlation between resonance and frequency is obtained by taking into account all working temperature sensors. Considering only one or two temperature sensors, there will always be frequency changes that can only to a certain extent be explained by a variation in one or both temperature measurements. The error variance remains unchanged when taking into account all temperature measurements.

![Figure 9: Non-linear regression of mode n°1 as a function of 2 temperature sensors](image)

![Figure 10: Non-linear regression of mode n°1 as a function of 2 temperature sensors (3D plot)](image)

The surface, visualized on figure 10, is the surface that describes the non-linear regression of the first resonance frequency as a function of two temperature sensors ‘TW C1’ and ‘TP2’ with a regression polynomial order 3. From the strong bending of the surface one can derive that the regression approximated model is only valid in the region of the measurement points. It is only in this region that the regression surface describes the measurement points very accurately. Comparing figure 9 with figure 8 it is clear that the evolution of the resonance frequency for negative temperatures is described much better by a third order regression polynomial than a linear regression (polynomial order 1).

A problem with the regression models used up till now is the fact that the thermic dynamics of the bridge structure are not taken into account. On figure 11 phase shifts are detectable between different temperature sensor measurements. This is caused by the thermic inertia of the asphalt and concrete layers. As a consequence, one must try to use regression models take into account the dynamic behavior of the civil engineering structure, in contrast with the previously used static regression models that only model a relationship between simultaneously measured data.

If it were possible to model the dynamic behavior in the previously applied regression models by taking into account the temperature measurements on previous points of time, a higher value of the correlation coefficient would be expected. This is possible by modifying regression matrix \( X \) (9) in the manner of adding columns with temperature observations shifted down over a certain number of rows (past temperature measurements taken into account). The number of rows shifted down depends on the time delay that one wants to take into account.
Figure 11: Temperature variation as a function of time for warm (left) and cold (right) period

In the case of modifying the nonlinear regression model for mode n°1 as a function of two temperature sensors ‘TWC1’ and ‘TP2’ (9), adding temperature measurements $TW_{C1,i-1}$, $TP_{2,i-1}$, $TW_{C1,i-2}$ and $TP_{2,i-2}$ on time steps $i-1$ and $i-2$ means adding four columns of which the first two must shift down 1 row (time $i-1$) and the last two must shift down 2 rows (time $i-2$). This way, temperature measurements with a desired time delay can be taken into account.

Taking into account time delays up to 24 hours, the regression equation becomes:

$$f = \beta_0 + \beta_1 T_{1,i} + \beta_2 T_{2,i} + \beta_3 T_{1,i}^2 + \beta_4 T_{2,i}^2 + \beta_5 T_{1,i} T_{2,i} + \beta_6 T_{1,i}^3 + \beta_7 T_{2,i}^3 + \beta_8 T_{1,i} T_{2,i}^2 + \beta_9 T_{1,i}^2 T_{2,i} + \beta_{10} T_{1,i-1} + \ldots + \beta_{33} T_{1,i-24} + \beta_{34} T_{2,i-1} + \ldots + \beta_{57} T_{2,i-24}$$

(12)

The updated dynamic regression model, using two temperature sensor data sets, leads the following results (table 6):

<table>
<thead>
<tr>
<th>Regression</th>
<th>Type</th>
<th>Temperatures</th>
<th>$R$ (%)</th>
<th>$\sigma_{error}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>non-linear</td>
<td>static</td>
<td>$TW_{C1}, TP_2$</td>
<td>78.0</td>
<td>0.037</td>
</tr>
<tr>
<td>non-linear</td>
<td>dynamic</td>
<td>$TW_{C1}, TP_2$</td>
<td>79.0</td>
<td>0.037</td>
</tr>
</tbody>
</table>

Table 6: Static and dynamic non-linear regression results

There can be observed that, by taking into account the past, the gain in correlation coefficient is 1% and the standard deviation remains unchanged. Up till now, the highest correlation coefficient value $R$ is found for a static linear regression model, using all 22 temperature sensor data at only one point of time. Next, when taking into account past temperature measurements, the new correlation coefficient value becomes:

<table>
<thead>
<tr>
<th>Regression</th>
<th>Type</th>
<th>Temperatures</th>
<th>$R$ (%)</th>
<th>$\sigma_{error}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>linear</td>
<td>static</td>
<td>22</td>
<td>79.5</td>
<td>0.037</td>
</tr>
<tr>
<td>linear</td>
<td>dynamic</td>
<td>22</td>
<td>83.0</td>
<td>0.036</td>
</tr>
<tr>
<td>non-linear</td>
<td>static</td>
<td>$TW_{C1}, TP_2$</td>
<td>78.0</td>
<td>0.037</td>
</tr>
<tr>
<td>non-linear</td>
<td>dynamic</td>
<td>$TW_{C1}, TP_2$</td>
<td>79.0</td>
<td>0.037</td>
</tr>
</tbody>
</table>

Table 7: Comparing linear and non-linear static and dynamic regression results

There can be observed that, by taking into account the past, the gain in linear correlation coefficient is 3.5% and the standard deviation decreases. All calculated results can be summarized in table 9. Using a non-linear regression model with two temperature
Figure 12: Frequency evolution (measurement and model) as a function of time

<table>
<thead>
<tr>
<th>Regression</th>
<th>Type</th>
<th>Temperatures</th>
<th>R (%)</th>
<th>$\sigma_{error}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>linear</td>
<td>static</td>
<td>all</td>
<td>79.5</td>
<td>0.037</td>
</tr>
<tr>
<td>linear</td>
<td>dynamic</td>
<td>all</td>
<td>83</td>
<td>0.036</td>
</tr>
</tbody>
</table>

Table 8: Static and dynamic regression results

sensor measurements taken into account, results in a tracking of the frequency as a function of time, shown in figure 12.

<table>
<thead>
<tr>
<th>Regression</th>
<th>Type</th>
<th>Temperatures</th>
<th>R (%)</th>
<th>$\sigma_{error}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>linear</td>
<td>static</td>
<td>22</td>
<td>79.5</td>
<td>0.037</td>
</tr>
<tr>
<td>linear</td>
<td>dynamic</td>
<td>22</td>
<td>83</td>
<td>0.036</td>
</tr>
<tr>
<td>linear</td>
<td>static</td>
<td>TWC1, TP2</td>
<td>75</td>
<td>0.039</td>
</tr>
<tr>
<td>linear</td>
<td>static</td>
<td>TWC1</td>
<td>75</td>
<td>0.041</td>
</tr>
<tr>
<td>non-linear</td>
<td>static</td>
<td>TWC1, TP2</td>
<td>78</td>
<td>0.037</td>
</tr>
<tr>
<td>non-linear</td>
<td>dynamic</td>
<td>TWC1, TP2</td>
<td>79</td>
<td>0.037</td>
</tr>
</tbody>
</table>

Table 9: Summary of regression results

8 DAMAGE DETECTION

8.1 Progressive damage tests

The final weeks of the measurement program have resulted in available measurements that contain a number of operational measurements during which a certain number of successive progressive damage tests are performed on the Z24 bridge. These damage scenarios are aiming at the measurement registration and can help to check whether occurring structural damage can be separated from environmental effects on the measurements. A detailed description of the progressive damage tests can be found in ref. [3] and [11].

On figure 13 one can notice that the resonance frequency of the investigated mode gradually decreases during the successive damage tests. In order to explain this frequency decrease, one has to look at the bridge parameters that have an immediate influence on the resonance frequency: mass and stiffness. If part of the structure is damaged, the bridge mass will obviously decrease and the resonance frequency will increase. A stiffness change during damage tests is less obvious and needs to be investigated for each damage scenario individually. Figure 13 shows mainly a decrease of frequency which indicates that a stiffness effect will be dominant.
Other damage tests include a cutting of the bridge internal connection cables that will result in a stiffness and frequency decrease.

8.2 Confidence intervals

A possible statistical approach for damage detection can be in formulating a confidence interval (ref. [12]). The measurements including the damage tests should be situated outside the defined confidence interval. When calculating the 95% confidence intervals of the residual errors, these are equal to the confidence intervals of the resonance frequencies because it is assumed that there is no error on the temperature measurements. The residual error is the difference between \( f - \hat{f} \) with \( \hat{f} = X\beta \) or in other words: the difference between estimated resonance frequencies and the frequencies calculated from the regression model.

Initially one calculates the confidence interval on the basis of the complete temperature range. This involves that all measurement points are taken into account for the calculation of the residual errors. Visualizing the progressive damage measurement points together with the calculated confidence interval on figure 15, one notices that a big part of the measurements with occurring damage are situated within the confidence interval boundaries. This due to the fact that positive as well as negative temperature measurement values are taken into account for the calculation of the confidence interval. On figure 9 one notices that there is a wide dispersion of measurement points for temperatures lower than 10\(^\circ\)C with a wide confidence interval range as a consequence.

From ref. [11] one can read that the progressive damage tests are executed during summertime. The confidence intervals for temperatures above 10\(^\circ\)C are overestimated as a result of noisy measurements at temperatures below 10\(^\circ\)C. To avoid this problem, one can consider only measurements with a temperature above 10\(^\circ\)C for the calculation of the confidence interval. On figure 16 one notices that a lot of measurements are now located outside the calculated confidence interval. This means that damage detection is better and faster detectable when calculating a confidence interval based on only temperature measurements above 10\(^\circ\)C.

For regression analysis, the confidence interval is calculated based on residual errors. This includes the hypothesis that the estimated frequency error is the same for the full temperature range. It is possible that the frequency error for negative temperatures is higher than for positive temperatures. This could be the explanation for the higher variance at low temperature range with an overestimated confidence interval for measurement points above 10\(^\circ\)C as result.
A proposed procedure to avoid this problem is calculating the confidence interval for small temperature intervals. If repeated for the full temperature range, one obtains a more accurate confidence interval that takes into account the temperature dependance of the measurement error. A proposed interval width of 2°C is used for calculations and the resulting confidence interval is plotted on figure 17.

It is demonstrated that the influence of outliers will have a non-negligible effect on the standard deviation values which causes a whimsical confidence interval. A different way of calculating a confidence interval can be done by using the interquartile range (iqr) value. The iqr-value \([12]\) calculates the difference between the 75% and 25% percentiles of the estimated frequency values. The iqr-value gives a more robust estimation for the data variance because the lower and upper 25% of data values are not taken into account thus outliers will have a smaller influence on the confidence interval width. A comparison of both confidence intervals and respective width is plotted on figure 18.

When comparing both confidence intervals, one notices that the interval based on standard deviation calculation is wider than iqr-based confidence interval. The explanation for this behavior is the fact that the iqr-value does not take into the presence of outliers.
Comparison of the three calculated confidence intervals in the temperature region where damage takes place (temperatures above 10°C) results in figure 19.

From figure 19 one can conclude that the three confidence intervals are almost coinciding and occurring damage can in fact be detected by calculating a confidence interval and determining whether there are measurement points located outside the calculated confidence interval. If this is the case, one can actually say with good certitude that a case of damage is taking place on the investigated civil engineering structure.

9 CONCLUSIONS

This document describes an automated procedure dealing with damage detection on civil engineering constructions by making use of the modal analysis approach. Before further analysis is possible, the measured time data needs to be cleared from saturated time periods in order to have pole estimations as accurate as possible. After completing the automated operational analysis procedure estimating the system poles with a Maximum Likelihood estimator, the evolution of the resonance frequencies is tracked as a function of time. A ”Matlab” procedure is suggested and tested on selecting the corresponding poles in different successive analysis files.

The tracking of a mode as a function of time makes it possible to apply different regression models to find a relationship between the estimated poles and the temperatures, measured on various locations of the bridge during constant time intervals. The regression of the first resonance frequency can be described most accurately by using a linear regression model, taking into account all temperature sensor measurements. This regression model also takes into account the thermic inertia of the bridge by also considering temperature measurements of the past couple of hours. Modelling the thermic inertia leads to a better regression model with a higher correlation coefficient. The best compromise is found in a regression polynomial order 3, taking into account two temperature sensors.

As a consequence, calculating a regression model makes it possible on the basis of the residual errors to define and calculate confidence intervals, within 95 % of all measurements are situated. When neglecting negative temperature values or calculating the
confidence interval based on small temperature intervals, one can conclude that the confidence interval becomes less wide for the higher positive temperature region. This is explained by the fact that it is assumed that the uncertainty on the measurements is constant. For the negative temperature values the measurement uncertainty is higher. If we take also the negative temperature values into account, the calculated confidence interval is overestimated. This can be avoided by considering only the positive temperature values or calculating the confidence interval for positive and negative temperature values, based on very small temperature regions. Since all damage scenarios are carried out during summertime and for these temperature values the dispersion of the measurement points is small, the “damage” measurement points are situated outside the confidence interval while frequency variations caused by temperature variations lie within the interval. As a result, one can conclude that applying a confidence interval can be used as a practical tool to detect occurring damage.

ACKNOWLEDGEMENTS

This research has been sponsored by the Flemish Institute for the Improvement of the Scientific and Technological Research in Industry (IWT), the Fund for Scientific Research - Flanders (FWO) Belgium. The authors also acknowledge the Flemish government (GOA-Optimech) and the research council of the Vrije Universiteit Brussel (OZR) for their funding.

REFERENCES


