Available online at www.easdprocedia.org
EASD Procedia EURODYN (2020) 1195-1204

EURODYN 2020
XI International Conference on Structural Dynamics
M. Papadrakakis, M. Fragiadakis, C. Papadimitriou (eds.)
Athens, Greece, 23–26 November 2020

# REDUCTION OF TEMPERATURE EFFECTS FOR BRIDGE HEALTH MONITORING

**Viet Ha Nguyen**[1], **Tanja Kebig**[1], **Jean-Claude Golinval**[2], **Stefan Maas**[1]

[1] University of Luxembourg
6 Rue Richard Coudenhove-Kalergi, Luxembourg 1359
e-mail: vietha.nguyen@uni.lu; tanja.kebig@uni.lu; stefan.maas@uni.lu

[2] University of Liege
9 Allée de la Découverte, Quartier Polytech 1, 4000 Liège 1
e-mail: JC.Golinval@uliege.be

**Keywords:** temperature compensation, damage detection, eigenfrequency, bridge, Principal Component Analysis

**Abstract.** *Structural health monitoring of concrete bridges can be achieved by tracking static load-testing results or dynamic properties as for example eigenfrequencies. Deviations from a healthy reference state can be used as damage indicators and even more, help to localize zones of stiffness reduction, i.e. cracking. However, outdoor temperature effects also lead to changes of monitored physical characteristics in the same order of magnitude as damage. Hence, temperature effects need to be removed prior to any condition analysis. The present paper presents a new two-step approach by applying physical compensation first, before using a statistical method based of Principal Component Analysis (PCA) or more exactly on principal vectors and singular values. This technique is here applied to eigenfrequencies, first of a new bridge without damage, but with extreme temperature variation due to thick asphalt layer and special bearing constraints, thus showing strong sensitivity along seasonal temperatures in the intact state. The second object is the Z24 Bridge in Switzerland, which is well documented in literature and where artificial damage was applied prior to demolition. The proposed techniques allow removing noise and temperature effects in a coherent and efficient way. The corrected measurement data can then be used in subsequent steps for its definite purpose, i.e. detection and localization of damage for instance by updating a numerical finite element model which allows assessing a stiffness loss.*


doi: 10.47964/1120.9096.19343

# 1 INTRODUCTION

Damage diagnosis in civil engineering systems is often based on static or/and dynamic measurements, which allow to detect, localize and quantify stiffness reduction going along with concrete cracking. For instance, for bridge structures, static displacement or strain measurements are typically done along the length at defined positions for a known test-loading in regular time intervals. Alternatively, modal properties like eigenfrequencies, modeshapes, modal masses or damping values can be measured and tracked. However, both static and dynamic characteristics can show high sensitivity to temperature variations, which show important influence on asphalt-, soil- and bearing-stiffness. Variations of the measured characteristics due to temperature can be typically in the same order of magnitude than those caused by real damage. Therefore, prior to further analysis, compensation of measured data regarding temperature effects is mandatory. Furthermore, tests should be performed in similar conditions due to other non-linearities of concrete bridges, e.g. the level of excitation (force, load) either without temperature gradients or local differences in the structure. In real application, bridge temperature cannot be fully controlled due to day-night and seasonal changes, why compensation algorithms are so fundamental prior to further comparison and damage analysis. Lloyd et al. [1] used the bootstrap for temperature compensation of measured frequencies and displacements to assess bending and shear stiffness of a concrete bridge. Temperature and operational effects were removed by Magalhães et al. [2] through multiple linear regression analysis for damage detection in an arch bridge. Cury et al. [3] normalized data of a PSC box girder bridge by a prediction law using non-linear regression based on neural networks.

After temperature compensation, the measured data can be analyzed to evaluate a bridge's current condition. For example, repeating measured static displacements at many points along the length of bridge can be directly taken to draw the deflection line in [4]. Several researchers fit responses of a finite element model to real measured data [5, 6, 7]. The fitting between numerical and experimental characteristics gives good insight to a structure's behavior. But temperature effects must be removed from the raw measurements prior to their use as input for model updating. Schommer et al. [8] compensated static displacement measurements with a 3D finite element model of a prestressed concrete bridge. In the present paper, the same compensation with subsequent noise removal by PCA is applied for eigenfrequencies for two real bridges. Considerable reductions of the scatter are achieved and corrected data may later either be used for direct analysis or for further processing like the mentioned model updating. Finally, a yes-no indicator based on novelty-index is presented and applied to the two bridges with very good results.

# 2 TEMPERATURE COMPENSATION AND NOISE ELIMINATION

Two subsequent steps are used here for removal of temperature and noise effects: the first consists in shifting the measured characteristics to a reference temperature along a previously identified physical line, while the second step is based on a statistical mathematics with Singular Value Decomposition (SVD) for general noise removal.

## 2.1 Physical temperature compensation

Nguyen et al. [4] proposed a technique for temperature compensation and applied it to static displacement data. It is based on the projection of measured data along a measured regression line, identified within data from the intact state. Figure 1 illustrates how a set of data A (e.g. eigenfrequency $f$) from the healthy state of the structure changes versus temperature $t°$. Measurements for other states, possibly in different ranges of temperature, can be traced back to a reference temperature and compared to the intact state. The comparison is based on linear dependency of the measured quantity $f$ versus temperature, which is more or less true, as can be seen in two examples below. Hence, first data are measured at different temperatures in the reference state. Then a linear regression line is determined by its equation's terms; a corresponding standard-deviation $\sigma$ with respect to this line is also assessed. Once they are known, different sets of data A, B, C can be projected with the slope of the regression line to the reference temperature $t_1$, referred here as $A_1$, $B_1$, $C_1$. Thus, temperature effects can be reduced based on a physical measured line.

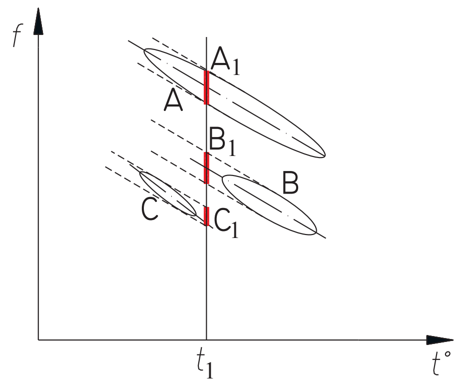


Figure 1: Temperature compensation by data projection

## 2.2 Principal Component Analysis and Novelty Index

It is known from statistics that Principal Component Analysis (PCA) can be used to remove environmental effects and noise [9]. The Singular Value Decomposition (SVD) of an observation matrix $\mathbf{X}$ containing $m$ records of $N$ time samples (e.g. displacements or eigenfrequencies versus time) determines principal vectors and singular values of $\mathbf{X}_{m\times N}$:

$$\mathbf{X} = \mathbf{USV}^T \tag{1}$$

where matrices $\mathbf{U}_{m\times m}$ and $\mathbf{V}_{N\times N}$ are orthogonal; the diagonal matrix $\mathbf{S}_{m\times N}$ contains in decreasing order non-negative singular values while $\mathbf{U}$ contains column-wise corresponding principal vectors.

When the observation matrix $\mathbf{X}$ contains for instance $m$ eigenfrequencies after temperature compensation, the first singular value in $\mathbf{S}$ is typically by far larger than subsequent singular values. Hence, there is only a unique dominant singular value and only one principal vector $\mathbf{U}_1$ in $\mathbf{U}$ has to be considered for reconstruction of the data in order to remove noise:

$$\mathbf{X}_{reconstructed} = \mathbf{U}_1\mathbf{U}_1^T\mathbf{X} \tag{2}$$

By doing so, PCA can be used as additional filter for data processing to clean it from environmental noise.

Furthermore, Novelty Index ($NI$) proposed by YAN et al. in [9] can be used as a damage index, in form of a red-green light index. $NI$ sizes up the error of the reconstructed data from the initial observation data through Euclidean norm (Eq. 3) or Mahalanobis norm (Eq. 4):

$$\mathbf{E} = \mathbf{X} - \mathbf{X}_{reconstructed}; \quad NI_k^{Eucl} = \sqrt{\mathbf{E}_k^{\mathrm{T}}\,\mathbf{E}_k} \tag{3}$$

$$NI_k^{Maha} = \sqrt{\mathbf{E}_k^{\mathrm{T}}\mathrm{cov}(\mathbf{X})^{-1}\mathbf{E}_k} \tag{4}$$

where $\mathrm{cov}(\mathbf{X}) = \mathbf{X}\,\mathbf{X}^{\mathrm{T}}$ is the covariance matrix of the features.

Then an actual state can be assessed by two indicators: 1) ratio between the mean values of this actual state and the reference state $\overline{NI}_{actual}/\ \overline{NI}_{reference}$; 2) a statistical threshold as outlier limit e.g. $\overline{NI}_{reference} + 3\sigma$ that $\sigma$ is the standard deviation of *NI* in the reference (intact) state. A ratio close to unit together a low outlier limit can be assumed no change or damage (i.e. green light); otherwise, statistical relevant changes are very probable (i.e. red light).

## 3 ANALYSIS

An application of the physical temperature compensation algorithm was presented in [4] with static displacements, which require as reference long-term monitoring without environmental effects and noise. The present work examines eigenfrequencies as characteristic dynamic properties of structure. For bridge systems, the combination of physical and statistical PCA-based temperature compensation can be beneficial as shown below.

First a new composite bridge without damage but with extreme temperature sensitivity is analyzed. Second, an older bridge subjected to multiple artificial damage steps will be dealt with. The data matrix **X** is here frequencies vs. temperature is processed here with the mentioned 2-step procedure. From the reference i.e. initial/ undamaged state, full range of temperature variation is known and a regression line is calculated, i.e. eigenfrequencies $f_i$ versus concrete temperature $t°$. Data from actual measurements are projected with the identified slope of the regression-line to a chosen reference temperature, which is close to the average temperature. The subsequent PCA procedure according to Eq. (2) is also based on the same reference period. For both bridges, the first singular value of matrix **S** is by far larger than the others and occupies more than 95% of the total energy. So only the first principal vector of the reference period $\mathbf{U}_1^{reference}$ is taken into account for data reconstruction.

### 3.1 Bridge in Useldange, Luxembourg

In 2006 a new bridge was built in Useldange, Luxembourg and then monitored during 4 years. The steel-concrete composite bridge has a very thick asphalt layer, that's why its eigenfrequencies strongly depend on the temperature, e.g. up to 7‰ per °*C* for $f_1$ [10].

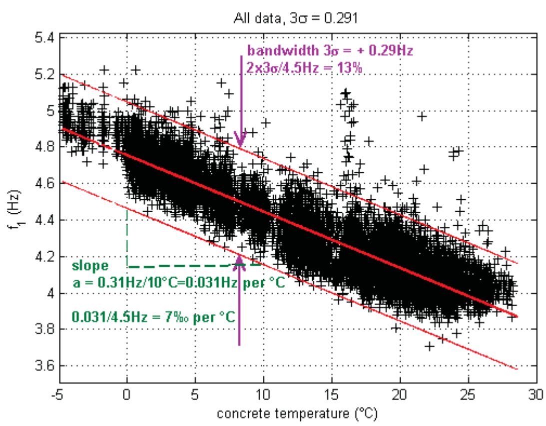


Figure 2: First eigenfrequency $f_1$ vs. concrete $t°$ for Useldange bridge (Luxembourg - ambient excitation)

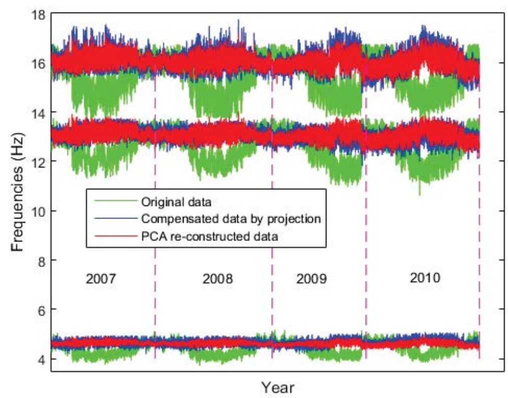


Figure 3: Eigenfrequencies monitored during 4 years- Useldange bridge

Figure 2 show the first eigenfrequency measured from ambient excitation with its regression line. It has an important slope and a quite large scatter of 13%, determined here as 3 times of standard deviation $\sigma$. In Figure 3, the data-sets are simply superposed versus time: three classes of data are: original (raw) data in green, data after the physical compensation in blue and statistical reconstructed data by PCA in red. The original data in green show clearly the seasonal behavior: low stiffness with low frequencies in summer and vice-versa in winter. This behavior is significantly attenuated after the physical temperature compensation and even more after PCA-filtering.

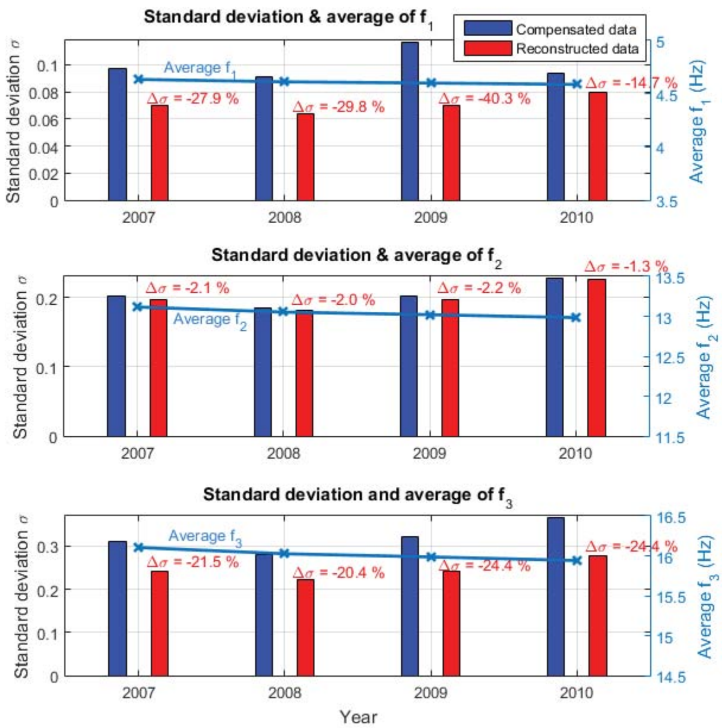


Figure 4: Comparison before and after PCA-filtering for Useldange Bridge

As reported in Figure 4 especially for modes 1 and 3, PCA-filtering reduces the standard deviation $\sigma$ by approximatively 25% in average even after physical temperature compensation. Also in Figure 4, the mean frequencies are indicated in light blue solid lines with mark "×" referring to the right ordinate axis. It should be noted that for this new bridge without damage, all eigenfrequencies show slight reductions over the first years, which fit well to other studies and other bridges [10], thus confirming the quality of the 2-step compensation.

### 3.2 Bridge Z24, Switzerland

The Z24-bridge has been studied in several works by Peeters, Teughels, Reynders et al. [11-13]. The bridge was monitored during 1 year and then demolished after about 40 days of testing with progressive damage. Vibration analysis was performed by Peeters et al. [11] together with the measurement of temperature. In Figures 5 and 6, only positive temperatures were selected to avoid freezing periods, where this Z24-Bridge showed quite different behavior.

In Figure 5, the measured eigenfrequencies of 4 modes are plotted against concrete deck temperature. Teughels et al. [12] stated that the first mode is pure bending; while the third and the fourth are coupled bending-torsion modes. They all show decreasing frequencies with increasing temperatures. In contrast, the second is a transversal mode and increases slightly with temperature. Significant differences are noticeable especially for the damaged state, which is shown by red dots.

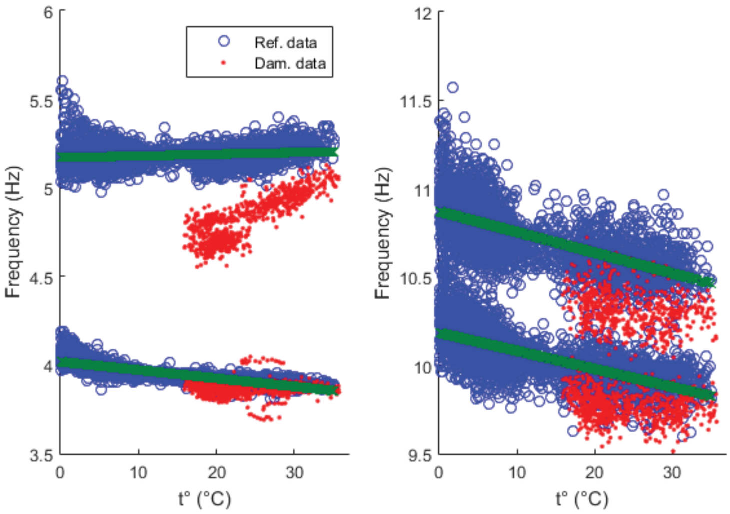


Figure 5: Identified frequencies vs. structural temperature
o - *reference state;* • - *damaged state;*
xxx - *regression line of the reference data*

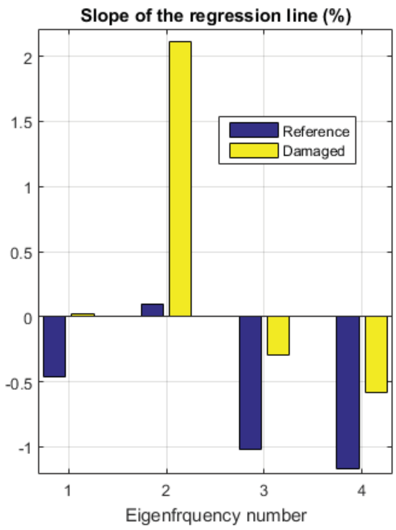


Figure 6: Slopes of the regression lines for the reference and damaged states

Figure 6 highlights the slopes of the regression lines for the reference and the damaged states for each mode. The frequencies $f_1$, $f_3$, $f_4$ show negative gradients whose magnitude decreases with damage. Only $f_2$ has opposite sign and increases considerably in the damaged state. These are individual characteristics and must be measured at site, i.e. today cannot be ad-hoc simulated.

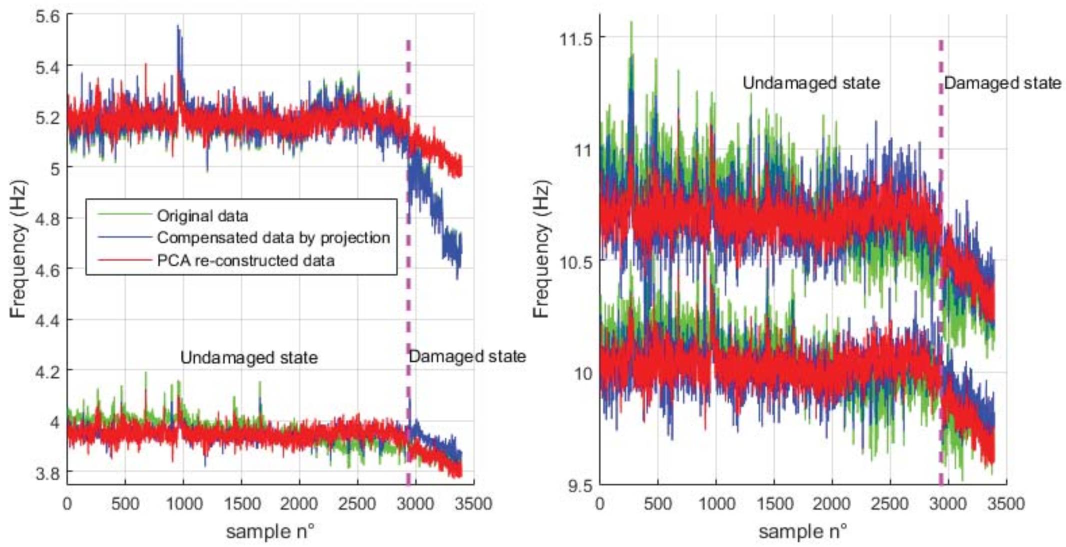


Figure 7: Evolvement of eigenfrequencies during the monitored period

To carry out the physical temperature compensation, all data are projected according to the scheme in Figure 1 to a reference temperature, which is chosen here at medium value $t_{ref} = 20°C$. A PCA-reconstruction step is also performed then the three families of data are presented in Figure 7. Only samples that all the modes could be identified are collected in the observation matrix, in total about 3400 samples. The dashed vertical line separates the intact from the damaged state of the bridge.

For better comparison, eigenfrequencies are analyzed in several small blocks of 150 samples. The scatter of data does not notably differ during the processing and is not presented here. The averaged values of eigenfrequencies are shown on the left of Figure 8, while on the right the relative difference by mean values of each block from the reference state within any family of data is deployed. These results reveal clearly that in the undamaged/reference state, $\Delta f_i$ can vary up to 2%, but less than 0.5% after the physical temperature compensation. PCA helps additionally a little bit to decrease variation. After introduction of artificial damage, the reduction of eigenfrequencies is much better observed by the proposed compensation procedures. Such processing ensures visibly reliability and thus facilitates comparison between different measurements. Schommer et al. [8] used static deformation data after physical temperature compensation for model-updating and so achieved very good results.

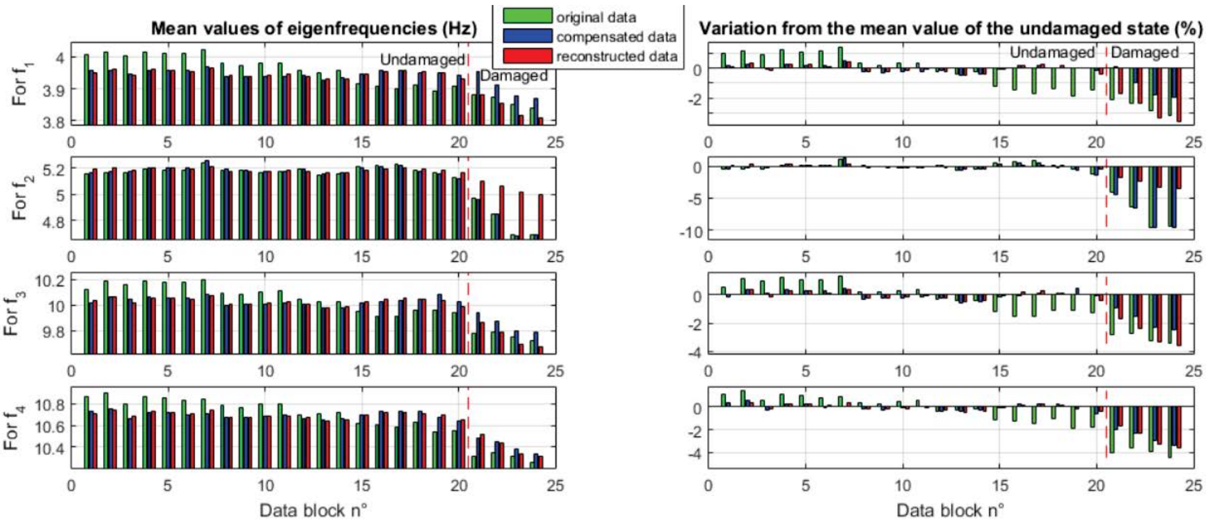


Figure 8: Averaged $f_i$ and $\Delta f_i$ assessed for each of the 3 families of data

The proficiency of the temperature compensation for damage detection can also be assessed by Novelty Index *NI*, as proposed by Yan et al. [9]. Both initial raw data **X** and compensated data - $\mathbf{X}_{reconstructed}$ are used to compute *NI*. Figures 9-10 shows *NI* versus time (or sample number) accordingly to Euclidean and Mahalanobis norms. In each figure, the top image presents the indexes from the original or raw data while the bottom image following to the physical and PCA compensation. Every chart is split into 2 parts, reference and damage states separated around sample n° 2900. An outlier limit is set for instance at $\overline{NI}_{reference} + 3\sigma$. Each state is characterized by its mean value and overshoot counting the percentage of indexes overpassing the outlier limit. By means of Euclidean norm, the ratio between the mean values of the damaged vs. the reference state $\overline{NI}/\overline{NI}_r$ weighs 1.9 by the raw data and 2.8 by the compensated data, with overshoot of 16.2% and 41.6% respectively. As for Mahalanobis norm, the ratio is 1.5 with the raw data and doubled to 3.2 after the 2-step compensation, while overshoot grows from 0.6% to 46.6% respectively. So in term of overshoot by the raw data, there is a clear distinction between the two norms but they give quite equivalent outcome based on the compensated data. This confirms the performance and its stability of the proposed compensation technique.

## 4 CONCLUSIONS

Damage leads to micro-cracking or cracking of concrete and therefore to stiffness loss, which can be detected for instance by reduction of eigenfrequencies. But the stiffness of asphalt, bearing pads and subsoil can also be affected by environmental factors, which cause also important perturbation for eigenfrequencies. Hence if eigenfrequencies are used as input for detection, it is necessary to separate temperature from damage effects.

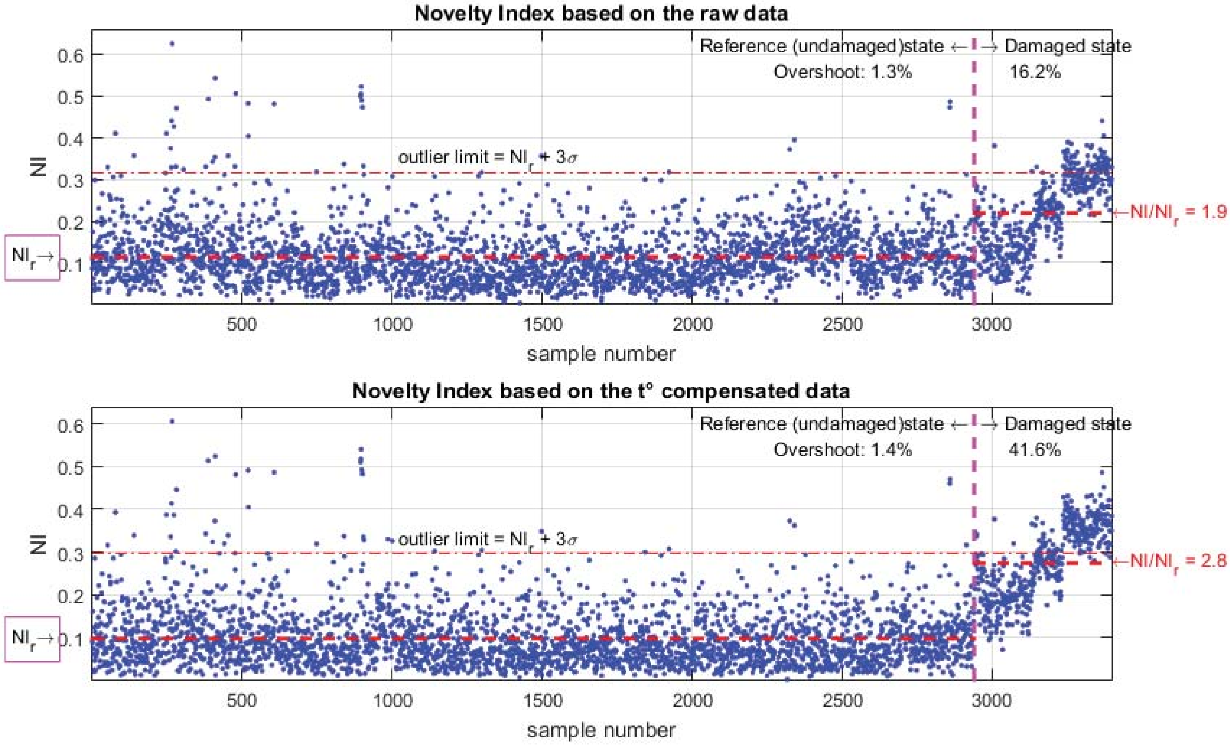


Figure 9: Damage detection by Novelty Index – Euclidean norm, Z24 bridge

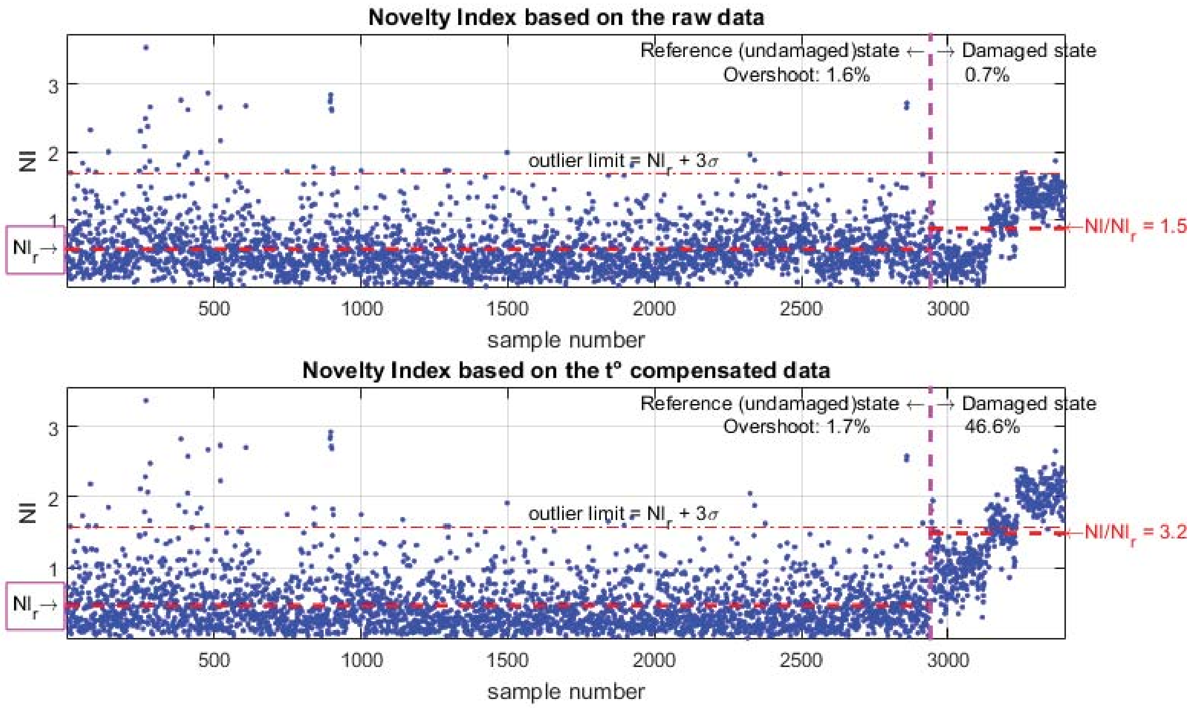


Figure 10: Damage detection by Novelty Index – Mahalonobis norm, Z24 bridge

The present paper does not propose a new damage index, but focuses directly on eigenfrequencies identified from vibrational tests. A two-step procedure is proposed based on measured physical sensitivity and on de-noising by PCA. The technique's efficiency could be proved by its application to two real bridges.

## REFERENCES


[1] Lloyd, G.M., Wang, M.L., Wang, X. (2004), Thermomechanical analysis of long-term global modal and local deformation measurement of the Kishwaukee Bridge using the bootstrap, Earthquake engineering and engineering vibration, 05, 3(1), pp.107-115.

[2] Magalhães, F., Cunha, A. A.M.F., De Sa Caetano, E. (2012), Vibration based structural health monitoring of an arch bridge: From automated OMA to damage detection, Mechanical Systems and Signal Processing 28, DOI: 10.1016/j.ymssp.2011.06.011.

[3] Cury, A., Cremona, C., Dumoulin, J. (2012), Long-term monitoring of a PSC box girder bridge: Operational modal analysis, data normalization and structural modification assessment, Mechanical Systems and Signal Processing, Volume 33, pp. 13-37.

[4] Nguyen V. H., Schommer S., Maas S., Zürbes A. (2016), Static load testing with temperature compensation for structural health monitoring of bridges, Engineering Structures 127, pp. 700-718.

[5] Huth, O., Feltrin G., Maeck J., Kilic N. and Motavalli M. (2005), Damage Identification Using Modal Data: Experiences on a Prestressed Concrete Bridge, Journal of Structural Engineering, Volume 131 Issue 12.

[6] Reynders, E., De Roeck G., Bakir, P. G. and Sauvage, C. (2007), Damage Identification on the Tilft Bridge by Vibration Monitoring Using Optical Fiber Strain Sensors, Journal of Engineering Mechanics, Volume 133 Issue 2.

[7] Reynders, E., De Roeck G. (2010), A local flexibility method for vibration-based damage localization and quantification, Journal of sound and vibration, Volume 329, Issue 12, pp. 2367-2383.

[8] Schommer S., Nguyen V. H., Maas S., Zuerbes A. (2017), Model updating for structural health monitoring using static and dynamic measurements, X International Conference on Structural Dynamics, EURODYN 2017, Procedia Engineering.

[9] Yan, A. M., Kerschen, G., De Boe, P., Golinva, J.-C. (2005), Structural damage diagnosis under varying environmental conditions, Part I, Mechanical Systems and Signal Processing 19, pp. 847-880.

[10] Nguyen, V. H., Mahowald, J., Schommer, S., Maas, S. (2017), A study of temperature and aging effects on eigenfrequencies of concrete bridges for health monitoring, Engineering, Volume 9, No.5, 2017.

[11] Peeters, B., Maeck, J., De Roeck, G. (2010), Dynamic Monitoring Of The Z24-Bridge: Separating Temperature Effects From Damage, Proceeding of the European COST F3 Conference on System Identification and Structural Health Monitoring, pp. 377-386.

[12] Teughels, A., De Roeck, G. (2003), Structural damage identification of the highway bridge Z24 by FE model updating, Journal of Sound and Vibration 278, pp. 589-610.

[13] Reynders E. , Wursten G. and De Roeck G. (2014), Output-only structural health monitoring in changing environmental conditions by means of nonlinear system identification, Structural Health Monitoring, 13(1):82-93.