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Baseline-Based Detection of Structural Changes: Drawbacks and an Alternative Approach

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Abstract

The present paper addresses the detection of structural changes using statistical learning methods with the objective of exposing the major limitations of defining baselines in which structural systems must be assumed unchanged. For this purpose, the data acquired during approximately two years in a cable-stayed bridge is used and was chosen since it comprises unchanged structural responses as well as measurements comprising changes imposed by creep and shrinkage.

In addition to the study of baseline-based detection, the present paper proposes a simple yet effective baseline-free approach relying auto-correlation functions. The effectiveness of the proposed strategy in clearly distinguishing between changed and unchanged structural responses was demonstrated using the same data set.

Keywords: *Structural Changes, Bridges, Neural Networks, Auto-Correlation.*

Introduction

Structural Health Monitoring (SHM) is generally defined as the development and implementation of strategies to detect structural changes [1]. A large number of these strategies is nowadays proposed in the literature and used in practical applications relying on statistical learning algorithms to obtain accurate and non-parametric descriptions of the monitored structural responses [2], [3].

Regardless of the algorithms underpinning their definition, these strategies rely almost exclusively on the assumption that the structural systems are healthy and remain unchanged during a certain period of time, which is named baseline or training period [1], [4]. The responses acquired during this period are in-putted into the statistical learning algorithms, which are trained and output a set of coefficients that are posteriorly used for predicting structural responses [5], [6].

Changes are then identified by comparing the errors associated with these predictions for two distinct periods: the baselines and posterior testing periods, which are associated with unknown structural conditions [1], [5]. These errors are generally named residuals and the comparison of their distributions, obtained from the baselines and testing subsets, is generally based on hypothesis testing [7], [8].

When the baselines are acquired from healthy and unchanged structural responses, the statistical learning algorithms learn the "regular" structural behaviour and can therefore outline future structural changes. However, this assumption may not always be met, especially for SHM applications comprising aged structural systems [2], [9]. If a baseline is defined during the occurrence of structural changes, chances are that the statistical learning algorithms will learn these changes as "regular" and thus will not be capable of identifying future ones.

The present paper aims at addressing this problem by conducting baseline-based and baseline-free detection of structural changes using the two statistical learning algorithms most reported in SHM literature: the multivariate linear regression (LR) [10], [11] and the multi-layer perceptron neural networks (MLP) [12], [13].

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In the present paper, section 1 provides a brief overview of the statistical methods used and section 2 aims at presenting the case study used herein. Section 3 aims at exposing the main limitations and hazards of using baseline-based detection while section 4 presents an alternative approach, which does not require the definition of baseline, as well as the evaluation and comparison of the two methods' performances. Afterwards, the main conclusions are drawn from the work described are presented.

1 Statistical learning algorithms

Multivariate linear regression (LR) is the most straightforward regression method reported in the SHM literature. Its formulation is based on the assumption that the structural response, denoted Y and referred to as "output", is linearly or near-linearly dependent on a set of action-related measured quantities, X, denoted as "input". Considering a vector of structural response data, Y, and a set of d action-related quantities (operational or environmental) acquired at the same n time-instants, X; a generic multivariate linear regression model, capable of explaining the changes observed in Y using the ones obtained from X, is generically represented in Figure 1a and can be defined as follows [14]

$$Y_{n.p} = U^{(0)}_{n.p} + X_{n.d}\, U_{d.p} + RE_{n.p} \tag{1}$$

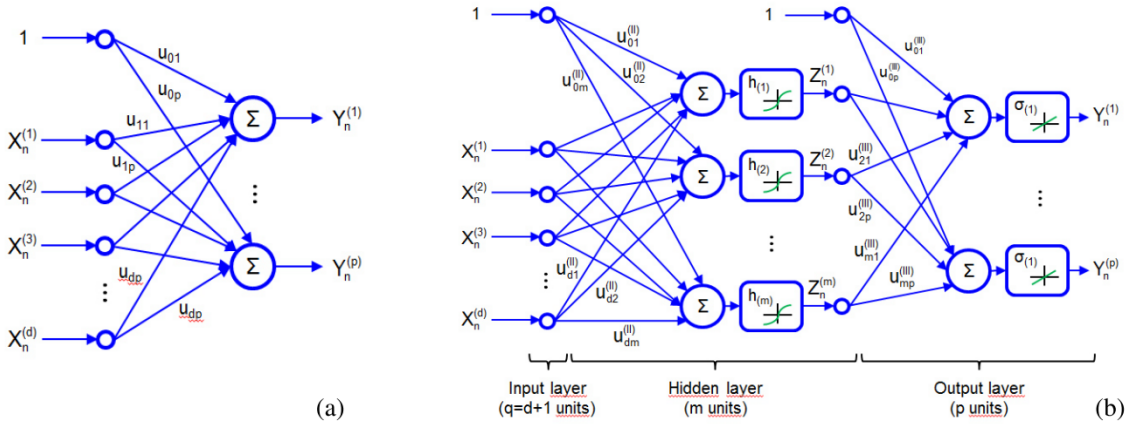


Figure 1: Graph representations of: (a) linear regression, (b) multi-layer perceptron.

where U is the vector of regression weights (or coefficients) and $U^{(0)}$ is the "bias" vector, which allows for any fixed offsets to be considered in the regression model. The detection of structural changes based on LR consists in finding the optimal set of coefficients U by minimizing the prediction's squared error and in evaluating the residuals' (RE) distributions.

The Multi-Layer Perceptron (MLP) comprising a single layer of hidden units (Figure 1b) and trained with the back-propagation algorithm is the most used method among those classified as "artificial neural networks" [14]. The mathematical model which describes the output variables, Y, in terms of the inputs X, can be defined as

$$\hat{Y}_{n.p} = Z_{n.m}\, U^{(III)}_{m.p} + RE_{n.p} = h\left(X_{n.q}\, U^{(II)}_{q.m}\right) U^{(III)}_{m.p} + RE_{n.p} \tag{2}$$

where $U^{(iii)}$ and $U^{(ii)}$ are the regression coefficients of the output and hidden layers, respectively. The function h allows the MLP to find non-linear relations among the input and output variables and is taken herein as in the majority of applications found in the literature as the hyperbolic tangent.

Unlike the LR, the problem of finding the optimal set of coefficients does not exhibit a unique and linear solution. Hence, this solution if found through the iterative back-propagation optimization technique based on gradient descent. Over-fitted solutions are obviated herein using

the early-stopping technique, while under-fitted solutions are avoided by defining a number of hidden units equal to the number of input variables. The effects of ill initialization are minimized by performing multiple repetitions of each training. As with the LR, the detection of structural changes based on MLP consists of finding the optimal set of coefficients, $U^{(ii)}$ and $U^{(iii)}$, and in evaluating the residuals' (RE) distributions. Additional information regarding the MLP can be found in [14], [15]

2 Case study – the Salgueiro Maia Bridge

The cable-stayed Salgueiro Maia Bridge is located in the Portuguese highroad A13, over the river Tagus, 70km upstream of Lisbon. The structural system is 570m long and partially suspended over a length of 489m by a single plane of seventy two stay-cables, eighteen in each of four semi-fans. Due to the high seismic risk of the region where the bridge was built, the superstructure is structurally independent from the infrastructure, which supports the first by means of fifty six high damping rubber bearings (HDRB), which provide a high level of seismic isolation.

The superstructure is symmetric and composed of a 570m long box girder deck monolithically connected to two pylons, which are 50m high (Figure 2a). The central suspended span is 246m long while the lateral counterweight spans are 78m and 42m long. The box girder section is 2.62m high and 27.7m wide, composed of a rectangular shape plus two cantilevers punctually supported by prefabricated concrete struts. The pylons are divided into a bottom part composed of a rectangular reinforced concrete section and a steel-concrete composite part comprising two concrete rectangles connected by steel elements which anchor the stay-cables. The seventy two stay cables are 31m to 131m long and exhibit vertical inclinations varying from 35º to 69º. Their cross sections vary from 55 to 73 strands and their anchoring devices are spaced by 6m on the deck and 1.2m on the pylons. Besides individual mono strand sheathing, the stay cables are protected by a global sheath of high density polyethylene.

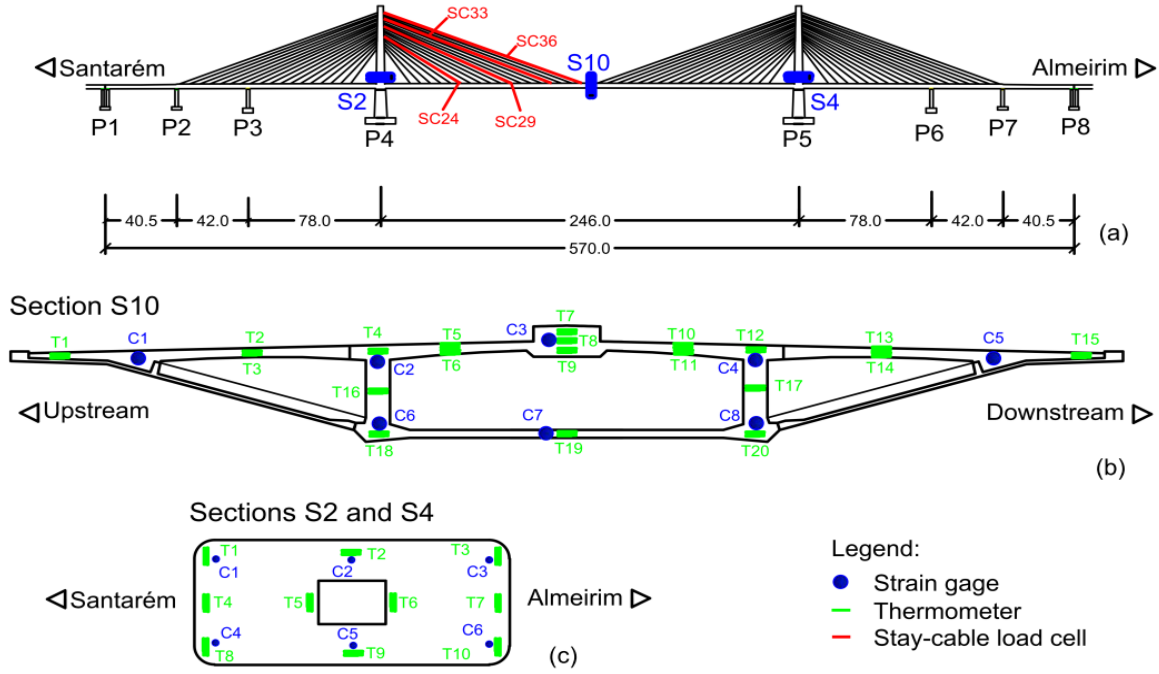


Figure 2: Salgueiro Maia Bridge: (a) overall view, (b) sensors on the deck and (c) sensors on the pylon.

During and immediately after the bridge's construction (from 1998 to 2000), an automatic monitoring system comprising more than two hundred sensors was deployed *in situ* with the objective of studying its behaviour and of controlling its safety in mid and long term. The sensorial

system comprises acoustic (vibrating wire) strain gages and embedded resistance thermometers (Figure 2b,c), a hydrostatic levelling system and stay-cables' load cells (4 per semi-fan).

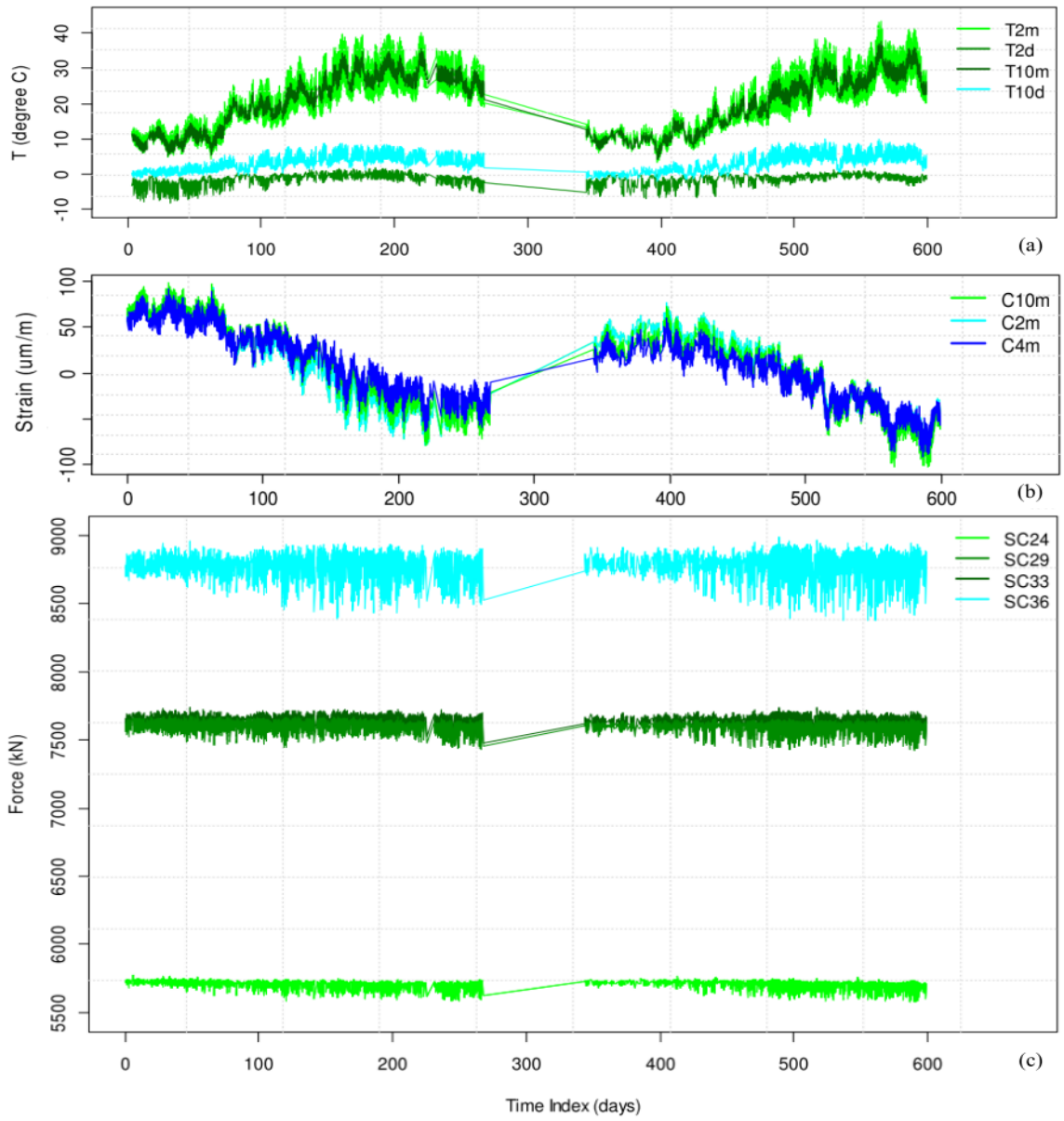


Figure 3: Time-series of: (a) average and differential temperatures, (b) average strain and (c) stay-cables' forces. Time index's null value defined at 0:00 of the 29th December 2004.

The data set used in the present paper was obtained from the thermometers and strain gages of sections S2, S4 and S10 as well as from the load-cells identified in Figure 4a. The location of the thermometers and strain gages in the three concrete cross-sections can be observed in Figure 4b,c. For each of these sections, the data used was fused without loss of structural relevant information into average strains: C2m, C4m and C10m (time-series shown in Figure 5b); as well as in average and differential temperatures: T2m, T10m, T2d and T10d (time-series shown in Figure 5a). The stay-cables' forces were used as obtained *in situ* and their time-series are shown in Figure 5c.

As it can be observed in Figure 5a,c, the temperatures and forces reveal important reversible variations which are directly correlated with the time of the year (time index's null value defined at

0:00 of the 29th December 2004). Nonetheless, their overall trend appears to be horizontal, thus suggesting that the structural system is not changing over time. Conversely, the strain measurements exhibit, in addition to the variations imposed by temperature, an irreversible downward trend generated by the structural changes imposed by creep and shrinkage.

3 Baseline-based detection of structural changes

The availability of one set of structural responses influenced only by the "regular" action of temperature (the four stay-cables' forces, SC24, SC29, SC33 and SC36 – see Figure 2a) and another influenced also by irreversible structural changes (average strain measurements, C2m, C4m and C10m) motivated the evaluation of the two learning methods concerning their ability to: (i) learn the "regular" behaviour (first set of responses) and to (ii) outline structural changes (second set of responses).

When using baselines to train the regression methods, the detection is based on comparing the distributions of the residuals obtained from the baselines and from the testing subsets. In the present paper, choice was made to carry out this comparison using a single-valued quantity, D, defined from the residuals interquartile intervals

$$D_i(B,T) = \frac{\max\left\{\left|Q^{(i,25,B)} - Q^{(i,25,T)}\right| ; \left|Q^{(i,75,B)} - Q^{(i,75,T)}\right|\right\}}{Q^{(i,75,B)} - Q^{(i,25,B)}} \quad ; \quad i = 1,...,p \tag{3}$$

where i is the index identifying each of the seven structural responses and $Q^{(i,25,B)}$ as well as $Q^{(i,75,B)}$ are the 25% and 75% quantiles obtained from the residuals of the baseline subset of sensor i. Similarly, $Q^{(i,25,T)}$ and $Q^{(i,75,T)}$ are the corresponding quantiles obtained for the testing subset. Since this indicator is based on interquartile intervals, its values must reflect changes in the residuals' distributions (not only on the expected value, but also in its variance, symmetry and flatness). Large values of D(B,T) indicate very dissimilar distributions between a baseline and the testing set, and thus the presence of structural changes, while small values suggest similarity between them, and thus unchanged behaviour. Hence, bearing in mind the effects influencing the stay-cables forces and average strains, an effective baseline-based detection algorithm must be capable of:

- generating small D(B,T) values for the stay-cables' forces (SC24, SC29, SC33 and SC36);
- generating high D(B,T) values for the three average strains (C2m, C4m and C10m).

To study the effectiveness of baseline-based detection, four distinct lengths of baseline data (shown in green colour in Figure 4) were used for training the LR and the MLP: (i) 300 days, (ii) 350 days, (iii) 400 days, (iv) 450 days. The time-series shown in Figure 4 illustrate the analysis conducted herein for the average strain on the deck, C10m, using the MLP neural network. From this figure it can be observed that the residuals' distributions, are highly influenced by the length of the chosen baseline.

The detection procedure exemplified in Figure 4 was repeated using the MLP method for the seven structural responses analysed. Its outcome is summarized in Figure 5, where it can be readily observed that the Dsc(B,T) values (obtained from the stay-cables) are low and not dependent on the baseline length. Conversely, the values of Dc(B,T) (obtained from the average strains) are much higher for small baseline lengths, thus leading to the conclusion that if the learning methods are trained with baselines comprising structural changes, they become ineffective in outlying future variations of identical nature.

The same analysis was conducted also using the multivariate linear regression and the results of this analysis along with those presented in Figure 6 are summarized in Figure 7 using Dc(B,T) and Dsc(B,T), which consist of the average D(B,T) obtained for the three average strains and for the four stay-cables' forces. From this figure it can be once again observed that if the learning methods are trained with unchanged structural responses (Figure 7b), their effectiveness is not dependent on the chosen baselines. However, if these methods are trained with structural responses comprising changes (Figure 7a), their effectiveness can be highly variable.

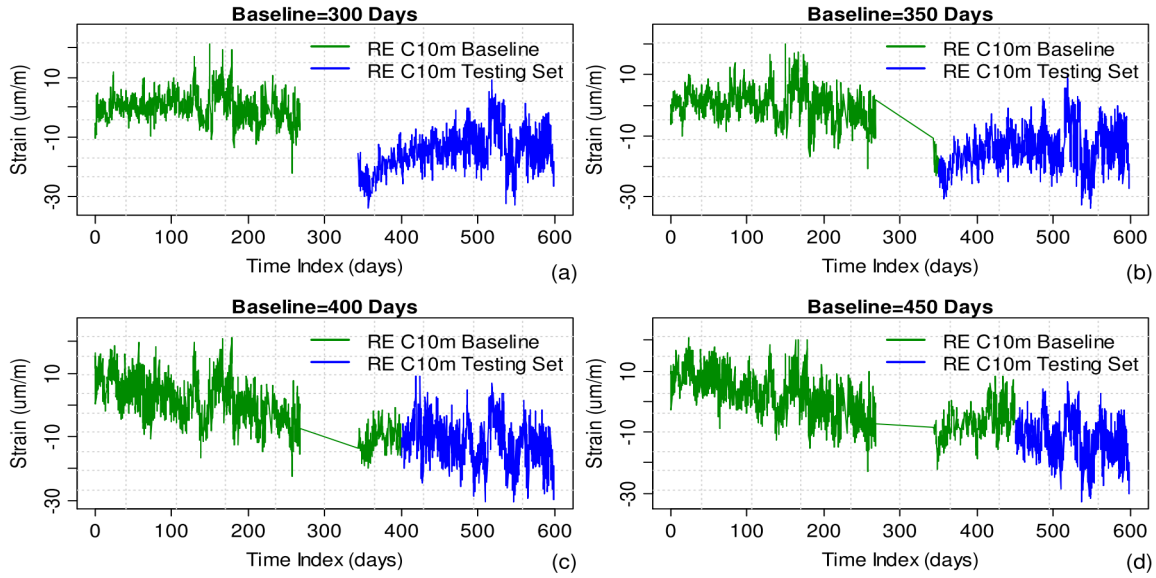


Figure 4: Time-series of residual errors obtained for C10m, considering four different baseline lengths: (a) 300 days, (b) 350 days, (c) 400 days, (d) 450 days.

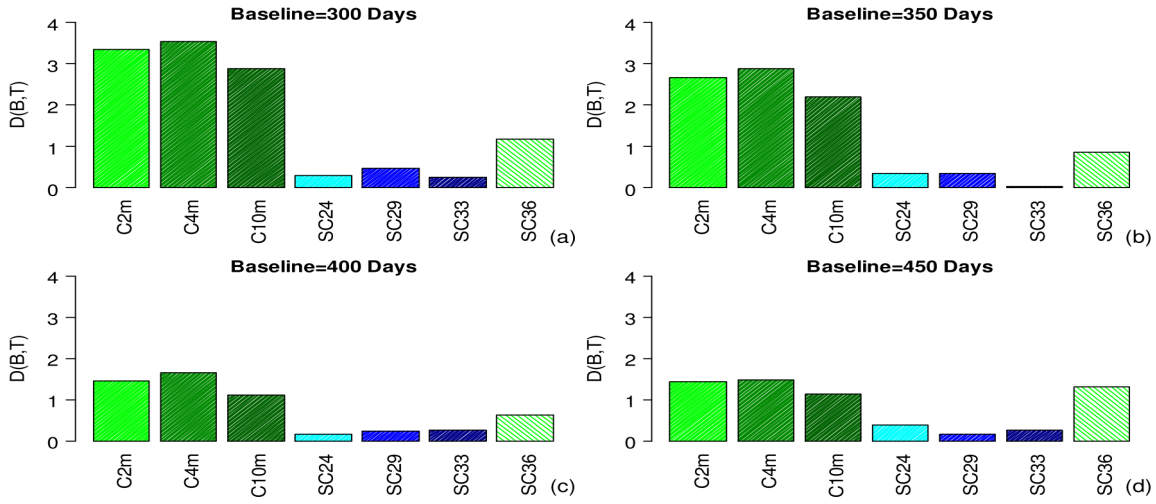


Figure 5: Bar-plots of the D(B,T) obtained using MLP-based normalization and four distinct baseline subsets lengths: (a) 300 days, (b) 350 days, (c) 400 days and (d) 450 days.

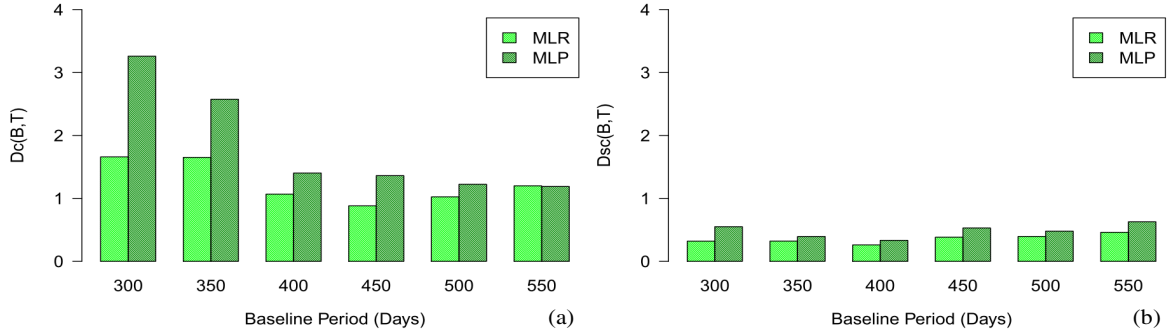


Figure 6: Average D(B,T) values for the four baselines: (a) Dc(B,T), (b) Dsc(B,T).

These results expose the main limitation of baseline-based SHM strategies: if no structural changes occur during the baseline period, the outcome of the detection can be relied on; however, if structural changes occur during this period, the estimation methods "learn" them as normal behaviour and are incapable of pointing them out in future data subsets. In this case, the premise in which baseline-based detection relies is not valid and SHM methods will suggest the non-existence of novelties when they might, in fact, exist.

4 Baseline-free alternative procedure

To avoid the hazards of having SHM strategies which might be unable to detect changes, a simple yet effective strategy is proposed herein. It consists of not drawing assumptions about the structural condition during an analysed monitoring period by using its entire length to train the statistical learning algorithms. Since no separation of the data is performed, no comparison between residuals' distributions can be carried out, and information obtained from one single time-series must be used for detecting structural changes. Herein, choice was made to use the concept of auto-correlation function along with the knowledge that random-like time-series exhibit null (or nearly null) auto-correlation [16]. Ideally, the residuals of the LR or of the MLP must exhibit this type of distributions since they are independent from the "regular" action of temperature. However, if any structural changes occur, the residuals' auto-correlations must be high, thus signalling the existence of structural changes.

The auto-correlation of a residuals' time-series is simply defined as [16]

$$AC_h(RE_n) = \gamma^2\left(RE_{n-h}^{(t)}; RE_{n-h}^{(t+h)}\right) / \sigma^2\left(RE_n^{(t)}\right) \quad (4)$$

where $RE^{(t)}$ and $RE^{(t+h)}$ are subsets of RE, each comprising n-h elements and starting, respectively, as instant t+h and t. The quantity σ^2 is the variance and γ the auto-covariance, defined as in [16]

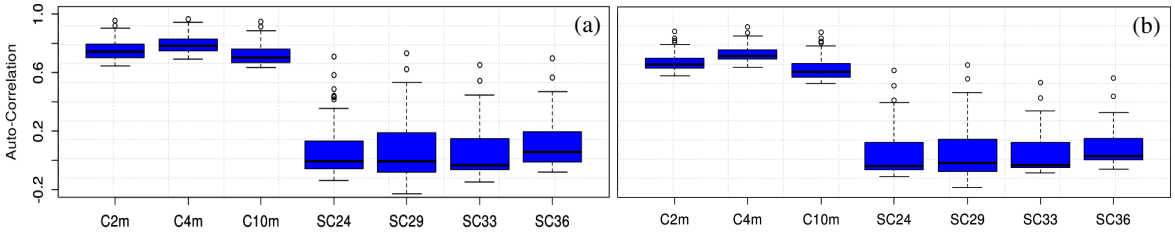


Figure 7: Box-and-whiskers plots of the ACF obtained from the residuals of: (a) LR and (b) MLP.

The auto-correlation function, ACF, can then be simply defined by varying the lag values, from 1 to a specified chosen value. To assess the effectiveness of the proposed baseline-free SHM strategy, the ACF were obtained for each of the 14 residuals' series (obtained from 7 sensors and 2 methods) and for h=1 to 100. The resulting ACF distributions are shown in the box-and-whiskers plots in Figure 7. As it can be observed, when applied under the proposed baseline-free strategy, both methods appear to be highly effective in distinguishing between changed and unchanged structural responses. To obtain a more accurate comparison, the ratio of the average ACF value computed for the strains and for the forces was obtained and resulted in 5.1 for the MLP and 4.6 for the LR. The higher this ratio, the more effective the method in distinguishing between changed and unchanged conditions. Hence, it can be concluded that the iterative nature of the MLP allow it to achieve higher performance in detecting structural changes under the proposed baseline-free approach.

Conclusions

In the present paper, the multivariate linear regression (LR) and the multi-layer perceptron neural network (MLP) were applied to a data set acquired from the Salgueiro Maia Bridge. This set

comprises structural responses describing changed and unchanged behaviour, which were analysed under baseline-based and baseline-free approaches.

The application conducted using baselines exposed an important limitation of this type of SHM strategies: if no structural changes occur during the baseline period, the outcome of the detection can be relied on; however, if structural changes occur during this period, the estimation methods "learn" them as normal behaviour and are incapable of pointing them out in future data subsets. In this case, the premise in which baseline-based detection relies is not valid and SHM methods will suggest the non-existence of novelties when they might, in fact, exist.

To overcome this disadvantage, a baseline-free approach was proposed and consists in analysing whether the statistical learning methods (LR and MLP) remove the auto-correlation from the time-series of structural responses acquired on site. This univariate statistical feature (auto-correlation) is not generally used to evaluate the outcome of SHM normalization. Nonetheless, it proved effective in distinguishing time-series influenced by structural changes from those influenced only by temperature. In addition, it was also observed that even if the relations between structural responses and temperatures are generally linear, the MLP outperformed the LR when applied under the proposed baseline-free methodology.

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