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A METHODOLOGY FOR STRUCTURAL BEHAVIOUR CHARACTERIZATION OF COMPLEX INFRASTRUCTURES UNDER THE EFFECT OF TEMPERATURE: THE 25 ABRIL BRIDGE AS A CASE STUDY




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ABSTRACT

The challenge of early damage detection of large complex structures with high dimensional features is a determinant factor for structural health monitoring (SHM). The current technological advances contribute to the optimization of the data analysis, aiming to make Machine learning (ML) strategies more popular due to their capacity to estimate the structural behaviour based on the measurements gathered by the SHM systems. In this sense, this work proposes a new methodology based on neural networks (NN) for the prediction of structural behaviour applied to the 25 de Abril bridge in Lisbon, Portugal, based on data gathered by the SHM system. Environmental loads are considered to characterize the observed pattern of the structural response, and, in this sense, identify new trends or variations of patterns for future observations.

Keywords: Monitoring, structural behaviour, Ponte 25 de Abril, Artificial neural networks, Pattern recognition.

1. INTRODUCTION

Structural damage is intrinsic to civil engineering structures and has the tendency to propagate due to environmental or mechanical factors. In [1], the authors, considering this premise, define damage as a change in an structural system that affects the current or future performance concerning both structural safety and serviceability. Thus, while damage occurrence implies a structural novelty, a novelty may not necessarily imply damage that compromises the structural performance. Likewise, damage does not always indicate a complete failure, but only a comparative deterioration of the system functionality [2]. The monitoring of a structure to detect novelties and assess its life cycle consists of a powerful tool for damage assessment and performance evaluation of engineering structures. The process involves the observation and evaluation of a structure over time using periodically sampled measurements from a sensing system. Several civil engineering structures have been provided with structural health monitoring (SHM) systems in the last decades, and, according to [3], those systems are envisaged to ensure structural and operational safety using real-time information about anomalies in loading and response at an early stage.

SHM techniques can follow inverse or forward approaches for detecting damage. The former ones, also called model updating, are based on the fitting of analytical or numerical responses to experimental data to infer structural quantities that cannot be directly measured. Forward SHM approaches, instead, rely on pattern recognition techniques for extracting sensitive information from data acquired on-site [4]. Forward approaches, also called data-driven approaches, do not require the development of numerical or analytical models to be fitted with in situ data. Instead, these techniques aim at extracting sensitive information from the measured time series using statistical learning methods [5]. Because SHM systems are operated in harsh and noisy environments, the occurrence of abnormal data is inevitable and the large variation in extracted features from massive SHM data could cause conventional novelty detection techniques to perform poorly [6].

Structural damage identification based on changes in the structural response of the structures has been practiced qualitatively for decades since the time tap testing for fault detection became common (e.g., on train wheels). Intelligent monitoring systems that can allow structures to operate at the margin of safety without involving long periods of inspection, the advances in various branches of technology, such as sensing instrumentation, signal acquisition, and transmission, data processing and analysis, numerical simulation, and modelling, has allowed developing strategies that profit from the technological precision to accurately evaluate the structural health of civil structures using real-time monitored data [7].

Plenteous improvements in computational power and advancements in chip and sensor technology have enabled the use of Machine Learning (ML) techniques in engineering applications. ML techniques are focused on the development of intelligent algorithms capable of acquiring knowledge automatically from the available data with the objective of providing machines with a human-like ability to learn [2]. With recent technological advances, a relatively large number of sensors and sensor networks can now measure large volumes of response data. In this sense, data-driven ML techniques have been proposed by different authors to assess the global health condition of host infrastructures [2], [6], [8], [9] [10] and [11]. The powerful capability of ML and pattern recognition (PR) techniques to extract information and develop predictive models from large data became predominant approaches for SHM to learn the complex interrelation among influencing factors, thus performing predictions without the need for empirical models.

The present study proposes a structural characterization through the use of a neural network model in order to define a reference threshold for novelty identification. The case study is the 25 de Abril bridge over the Tagus River in Lisbon, Portugal, which is monitored by an SHM system capable of measuring different physical quantities corresponding to fast loads such as traffic, slow loads such as temperatures, and structural responses such as stresses. The prediction model was built with static data, provided by the Portuguese National Laboratory of Civil Engineering (LNEC), gathered by the SHM system installed in the bridge, considering five years of data with an hourly frequency of measurements. Only semi static loads were taken into account for the proposed analysis.

2. THEORETICAL BACKGROUND

The transition from traditional methods to ML represented an improvement in (i) damage-sensitive feature extraction from the monitored response, (ii) modelling the structural responses, and (iii) classifying the extracted features of civil structures. In [12], the authors state that SHM is a multilevel and multi-faced method dealing with data acquisition to decision process from single and multiple sources, to have a more robust and confident decision, multiple sensors are installed in the structure to be monitored, thus, data fusion becomes an indispensable step. ML-based approaches applied to SHM data require extracting damage-sensitive features that later will be used as the input of the ML model.

Two main SHM approaches for response modelling of structures based on ML models are cited by the authors in [13]. The protective approach refers to the case when damage-sensitive features are used to identify impending failure that led to altering the use of the system to avoid catastrophic failure. The predictive approach, instead, is applied to the cases in which trends in data are identified to predict when the damage will reach a critical level. In this case, cost-effective maintenance planning is needed, and ML strategies are useful. To identify such patterns, the learning process through the implementation of algorithms is proposed. Such a process can follow supervised, unsupervised learning [13] or, lately discussed by the academic field, self-supervised learning [14].

Within the supervised learning applications in civil SHM, it is common to use simulations to generate databases with multiple likely damage scenarios. Artificial neural networks (ANN) in this sense, had called the attention of the scientific community since the 1990s. A Neural Network (NN) computes a function of the inputs by propagating the computed values from the input neurons to the output neurons using different weights as an intermediate parameter [15]. According to the same author, the specific architecture of multilayer neural networks, known as feed-forward networks, assumes that all nodes in one layer are connected to those of the next layer, and the input layer transmits the data to the output layer going through a set of hidden layers that perform computations that are not visible to the user, but that can refine the weights between neurons over many input-output pairs to provide more accurate predictions. If a NN contains p_k units in each of its k layers, then the (column) vector representations of these outputs, denoted by h_k have dimensionalities $p_{k}.$

The weights of the connections between the input layer and the first hidden layer are contained in a matrix W_1 with size d_{p1} whereas the weights between the r^{th} hidden layer and the

$(r+1)^{th}$ hidden layer are denoted by the $p_r \times p_{r+1}$ matrix denoted by W_r. If the output layer contains *o* nodes, then the final matrix W_{k+1} is of size $p_k o$. The *d*-dimensional input vector $\bar{x}$ is transformed into the outputs using the following recursive equations, where Φ denote the activation function:

$$\bar{\mathbf{h}}_1 = \boldsymbol{\Phi}(\mathbf{W}_1^{\mathrm{T}}\bar{\mathbf{x}}) \tag{1}$$

$$\bar{\mathbf{h}}_{\mathbf{p+1}} = \boldsymbol{\Phi}\left(\mathbf{W}_{\mathbf{p+1}}^{\mathrm{T}}\bar{\mathbf{h}}_{\mathbf{p}}\right)\forall\mathbf{p} \in [\mathbf{1}, \dots, \mathbf{k}-\mathbf{1}] \tag{2}$$

$$\bar{\mathbf{o}} = \boldsymbol{\Phi}(\mathbf{W}_{\mathbf{k+1}}^{\mathrm{T}}\bar{\mathbf{h}}_{\mathbf{k}}) \tag{3}$$

while equation (1) is the one for the transition from the input to the hidden layer, equation (2) is the one to pass from the hidden to the hidden layer and equation (3) is the one from the hidden to the output layer. NN are known to theoretically be powerful enough to approximate any function. However, to avoid overfitting and ensure generalization, a careful architecture and learning process are needed even when large amounts of data are available [15].

In civil engineering structures, changes in the environmental conditions lead to changes in the structural behaviour. These changes can be equal or greater than the ones that occurred by damage and it is fundamental to interpret them to prevent undesirable consequences [16]. Response measurements (e.g., stresses) taken from bridges comprise the effects of several types of loads including vehicle traffic and ambient conditions. According to [17], and considering the former statement, an important step in measurement interpretation is to characterize the influence of the individual load components on the collected measurements. Long-term monitoring studies have illustrated that daily and seasonal temperature variations have a great influence on the structural response of bridges and can induce changes in modal parameters that can be interpreted as a false indication of damage when applying vibration-based damage detection algorithms[18]. In [19] the authors observed that temperature-induced stresses on long-span bridges create responses that are very difficult to model due to unexpectedly high levels of stress. In [20] the authors, considering at the beginning that the daily periodic air temperature change causes the characteristic global thermal deformation of a long-span cable-stayed bridge, proposed a damage-sensitive feature extraction method through ARIMA models from GPS measurements of those deformations, assuming that they have sensitivity to changes in the global structural properties. The design of methodologies to improve damage identification including environmental and operational conditions is an area of active research interest, motivated by the fact that new designs in civil, aeronautics and astronautics include the use of more complex structures subjected to variable environmental and operational conditions that need to be assessed [21].

Despite the design and maintenance codes and methodologies available, civil structures deteriorate over time, and structural health is affected by operational and environmental factors, including normal load conditions, and current and future environmental hazards during the lifetime [22]. All these factors are variables with uncertainties, and to warrant the safety and serviceability of the structure, reliable structural health assessment and continued monitoring is essential.

3. CASE STUDY

The case study chosen for application of the proposed methodology is the suspended 25 de Abril Bridge located in the estuary of the Tagus River connecting the cities of Lisbon and Almada, Portugal. The bridge has a total length of 2277.5m, with three suspended spans: the central suspended span of 1012.9m and the two laterals suspended spans of 483.4m each. The North access is made through a prestressed concrete viaduct comprising 13 spans while the South span is made by a railway tunnel and road access. The bridge deck consists in a suspended rigid beam with 1344 vertical hangers that are suspended by four principal cables supported at piers P2 and P5 and at pylons P3 and P4. The cross-section of the deck's stiffening truss supports, at the upper chord level, six car lanes, and at the lower chord level, a double electrified track railway. The structural monitoring system comprises eight types of sensors able to acquire data that would allow the characterization of the structural behaviour of the bridge and the imposed loads, such as traffic and environmental loads [23].

The statistical features obtained from all quantities measured on the bridge consist of hourly maximum and minimum values, hourly medians, and hourly quartiles. The median values assume particular importance since they are expected to smooth the extreme values introduced by the effect of traffic and other fast effects, thus reflecting slow effects that can be analyzed with higher precision, such as temperature. The data acquired continuously on the 25 de Abril Bridge reflects numerous effects generated by the simultaneous loads acting on the structure.

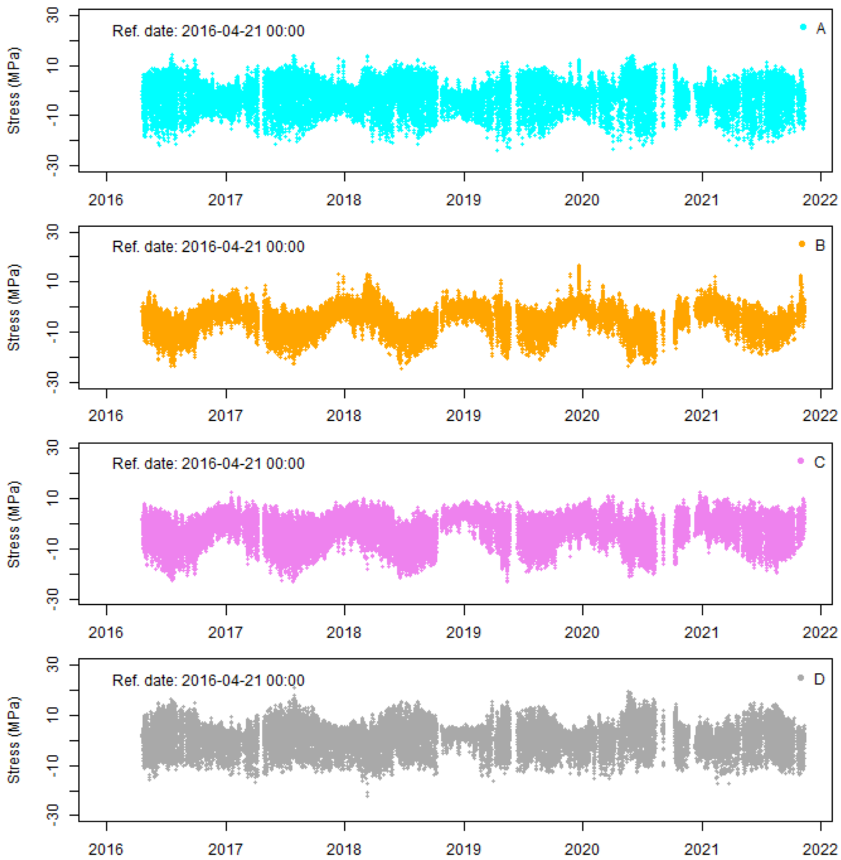

Figure 1. Relative stresses gathered by the strain gauges at the mid span of the rigid beam

Regarding the structural responses currently monitored on the 25 de Abril Bridge, 88 points of measurement of relative structural stresses in the rigid beam and in the towers are obtained using full bridges of strain gauges which, similarly to measurements with a strain gauge, measure strain variations caused by structural stresses (see Figure 1). The monitoring system installed on the 25 de Abril Bridge also measures the environmental loads of temperature and wind.

For SHM purposes, those data are divided into two subgroups: the imposed loads and the structural responses. The information extraction strategy applied in the bridge is based on obtaining from the time series at certain predefined time intervals: (i) static structural response that can be directly and precisely correlated with the loads imposed on the structure, and (ii) vibration information such as natural frequencies and their corresponding damping ratios and mode shapes. The proposed methodology was applied to the statistical features extracted from the time series corresponding to a period of five years from the mid-span section of the rigid beam (see Figure 2).

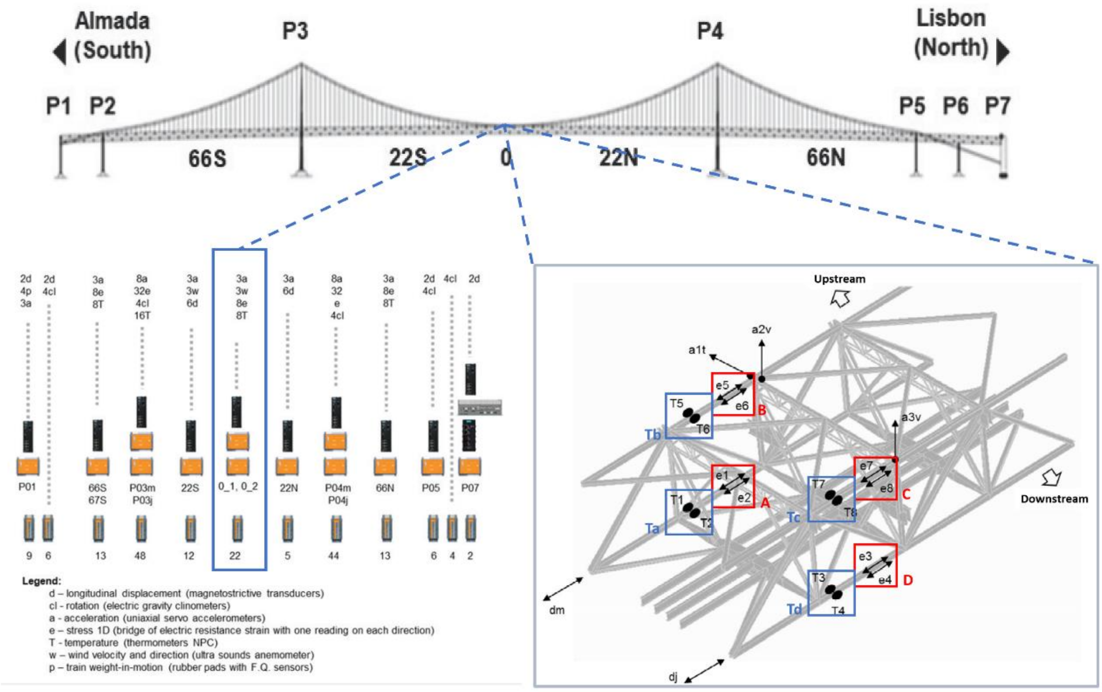

Figure 2. SHM system installed in Section 0 at the mid-span of the rigid beam [24]

As has been the case since construction, the structural temperature is measured using electrical resistance thermometers, while the wind is measured using two three-dimensional ultrasonic anemometers. At the mid-span, both wind and temperature loads are measured, as well as stresses and accelerations.

For the purpose of this study, stresses are the structural response considered and temperatures are the environmental loads, due to the greater correlation in comparison with the other physical quantities measured at the mid-span of the rigid beam. A five-year monitoring period from 20/04/2016 to 09/11/2021 with hourly measurements is used.

4. PROPOSED METHODOLOGY

Real-time monitoring can be effective to control safety and facilitate decision-making regarding interventions in the monitored structure. However, real-time diagnosis is usually sensitive to environmental and operational effects. In this sense, acquired data need to be processed so novelty detection and localization techniques can be employed. In this paper, a methodology to process and characterize the structural behaviour through monitored data gathered from the sensing system is proposed. Based on the data acquired from the SHM system of the bridge, a prediction model is built. Interpretations about the structural behaviour of the structure analyzed are inferred from the model itself and from the residual analysis from the model, which describes everything that was not explained by the prediction model.

Moving average and the corresponding standard deviation of the residuals are proposed in order to define a pattern behaviour smoothed from the intrinsic randomness of the readings (see Figure 3).

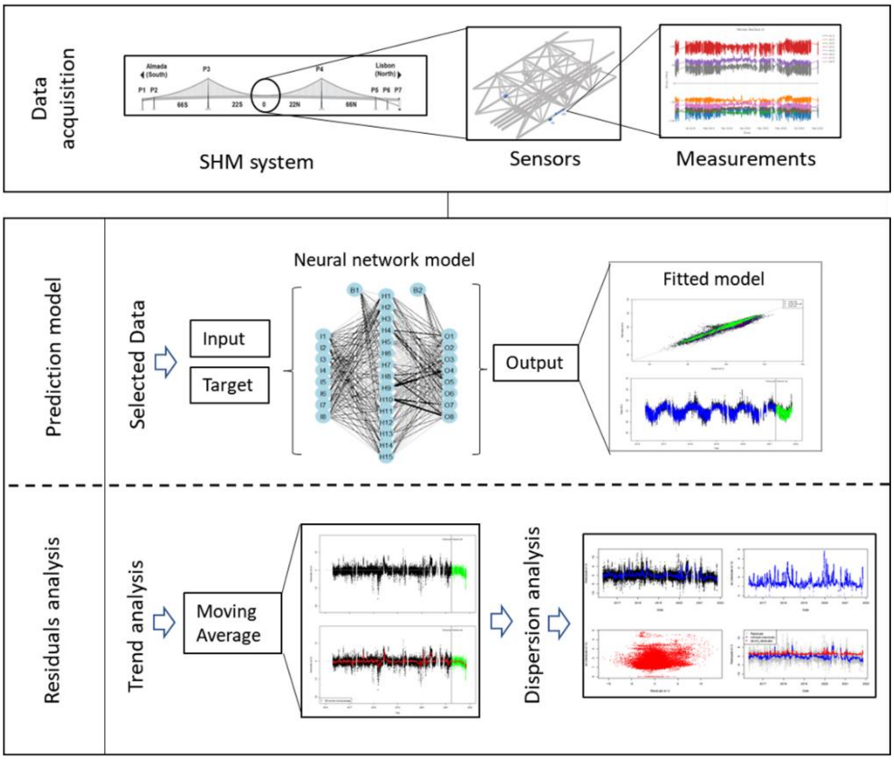

Figure 3. Steps of the proposed methodology

4.1 Prediction model

This step can follow two approaches: the inverse, the so-called model-based, or the forward, also known as a data-driven approach. The proposed methodology follows a data-driven approach. This approach does not require the development of numerical or analytical models to be fitted with in situ data; instead, it is based on the discipline of machine learning or, often more specifically, the pattern recognition aspects of machine learning. The idea is that one can learn relationships from data. In the context of SHM, this means that one can learn to assign a damage state, novelty or class to a given measurement vector from the structure or system of interest. ML methods had been used to deal with uncertainty problems within the context of damage detection and identification. Among the different ML applications in structural engineering in the last decade, the preference for artificial neural networks as a supervised method for learning, recognition, and perception process over time is considerable [25].

As discussed in the previous section, the fully connected architecture of the NN makes the predictions more efficient and robust, especially when we are treating data influenced by environmental and operational loads. Input data for the network should be selected according to the objectives of the analysis, in this case, the temperatures. Learning data must be divided into three subsets: the training, the cross-validation, and the testing sets.

The training subset is used to build the learning model, the NN might use different hyperparameters for the learning rate, and the same subset may be trying to build the models in multiple ways, in order to allow the estimation of the relative accuracy of different algorithm settings and chose the best one. The cross-validation subset is used for model selection and parameter tuning in order to test the accuracy of the model. According to [15] the best choice of each combination of parameters is determined in this part. The cross-validation subset should be viewed as a strategic solution to find the NN with adequate generalization capacity allowing to avoid overfitting. Finally, the testing subset is used to test the accuracy of the final (tuned) model at the end of the process. In cases of complex and large available data sets, the biggest percentage must be dedicated to training and cross-validation subsets.

The mean squared error (MSE) is proposed to be used in this step in order to determine the average loss of the observed data; the deviation from the observed data with the predicted data can assess the quality of the NN model. The MSE is defined as,

$$\mathrm{MSE} = \frac{1}{\mathrm{n}} \sum_{\mathrm{i}=1}^{\mathrm{n}} (\mathrm{x_i} - \hat{\mathrm{x}})^2 \tag{4}$$

where x_i describe the observed values and $\hat{x}$ the predicted values.

The set of random variables that remains after the outcome of the model, known as residuals, carry the residual variances of the predictions, where is possible to detect variations that can denote a novelty in the structural behaviour. Therefore, a threshold definition based on a residual's analysis is proposed herein.

4.2 Analysis of the residuals

Statistical approaches are proposed to characterize the residuals of the NN model. In order to reduce the intrinsic randomness of the data, a moving average control is proposed to treat the residuals (r) and detect, more clearly, any variation in its trend. A moving average (MA) control chart is a type of memory control chart based on an unweighted moving average and it is defined as:

$$\mathrm{MA} = \frac{r_i + r_{i-1} + \cdots + r_{i-w+1}}{w} = \frac{\sum_{j=i-w+1}^{i} r_j}{w}, i \geq w \quad (5)$$

where w is the width of the moving average at time j. For periods $i < w$, we do not have w observations to calculate a moving average of width w. For these periods, the average of all observations up to period i defines the moving average. Considering that the measurement frequency is hourly, four different MA of size 6, 12, 24 and 168 corresponding to a quarter, a half, an entire day, and a week are proposed to be used.

In order to describe the dispersion of the data, the standard deviation of the MA is presented in order to know how much the residuals vary or how disperse they are around the arithmetic mean, it is defined as:

$$\mathrm{sd} = \sqrt{\frac{1}{w} \sum_{j=i-w+1}^{n} (\mathrm{MA}_i - \overline{\mathrm{MA}}_{j \text{ to } i})^2} \quad (6)$$

With all the measurements collected, it is possible to proceed with the analysis and detection of variations that could be referential for the characterization of the structural behaviour.

5. RESULTS

In this section, the results of the application of the proposed methodology to characterize the structural behaviour of the 25 de Abril Bridge are described. Section 0 in the mid-span (see Figure 2) of the rigid deck is instrumented with eight strain gauges, two per chord, that measure the relative stresses and eight thermometers, two per chord, to measure temperatures, as can be seen in Figure 4. In order to obtain comparable results for the final characterization, the absolute mean value of each pair of sensors, (i.e. strain gauges and thermometers) was calculated and used as the value corresponding of each of the chords of the rigid beam, being A, B, C and D the average value of the stresses corresponding to each chord of the beam and Ta, Tb, Tc and Td the average value of the temperatures measured at each chord of the beam, as can be seen in Figure 4.

In this sense, A, B, C, and D are considered the structural responses (stresses [MPa]), and Ta, Tb, Tc, and Td the environmental loads (temperatures [°C]). Considering that the greater correlation between the stresses and temperatures among all the physical quantities measured at the mid-span was proven by a correlation analysis previously carried out, both were considered as the selected features for the prediction model.

Following the proposed methodology, a NN was the ML model chosen for the prediction process. It was trained in R [26] using the function *nnet* [25]. Input values correspond to the environmental loads: the temperatures, that are used to predict the stresses, the resulting outcome of the model, and the structural response to the imposed loads. Hidden values were defined based on the input dimensionality, due to the complex relationship between input-output and the large size data set (see Figure 5).

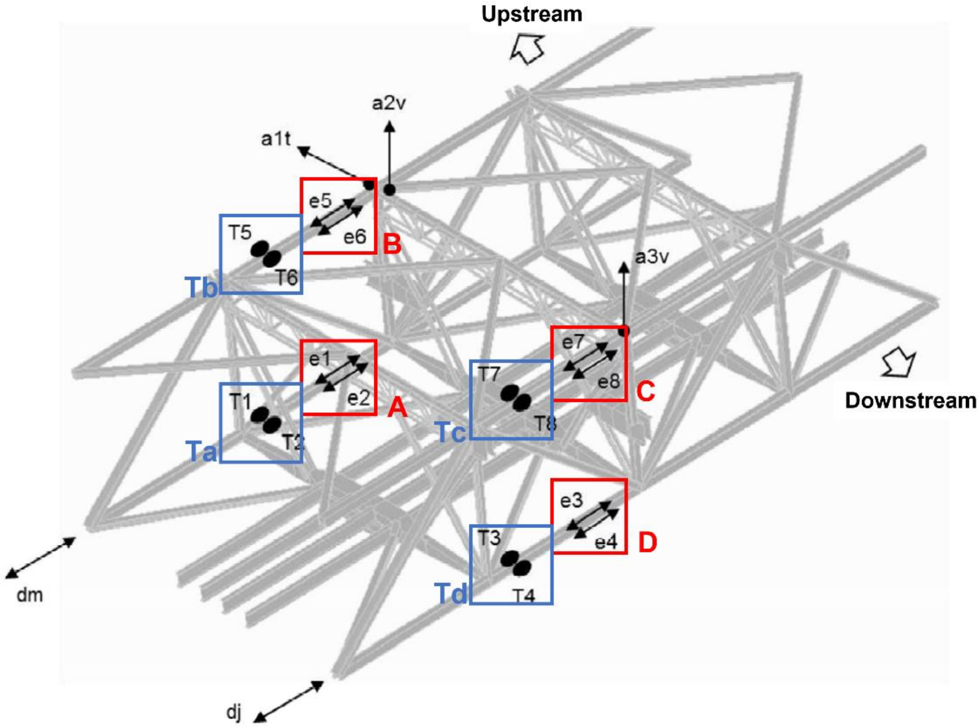

Figure 4. Location of the sensors at the rigid beam

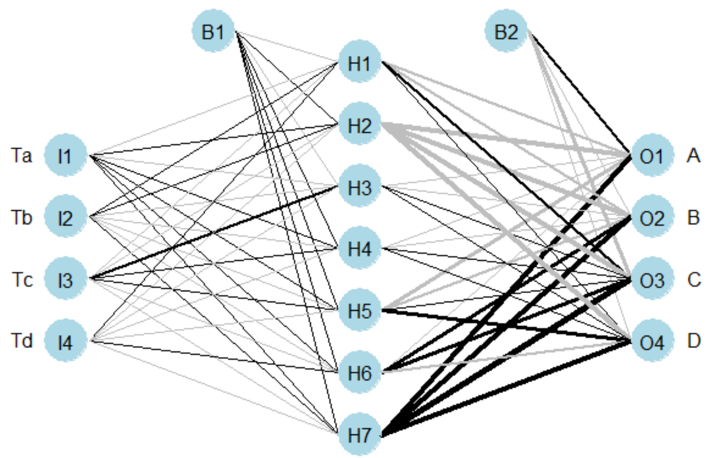

Figure 5. Resulting neural network where: (I) input variables, (B) bias associated with the node, (H) hidden values, and (O) outcome variables

The learning set was divided in three subsets: the training, the cross validation and the testing sets. The best repetition corresponding to the one with less errors for the cross-validation set was programmed to be identified among the iterations in order to ensure a better capacity for generalisation. To evaluate the quality of representation of the model, the MSE was calculated. The value for the training set is 4.60MPa, for the cross-validation, it is 4.43MPa and for the testing set it is 4.90MPa. Being all in the same range, Figure 6 shows the accuracy of the model representation.

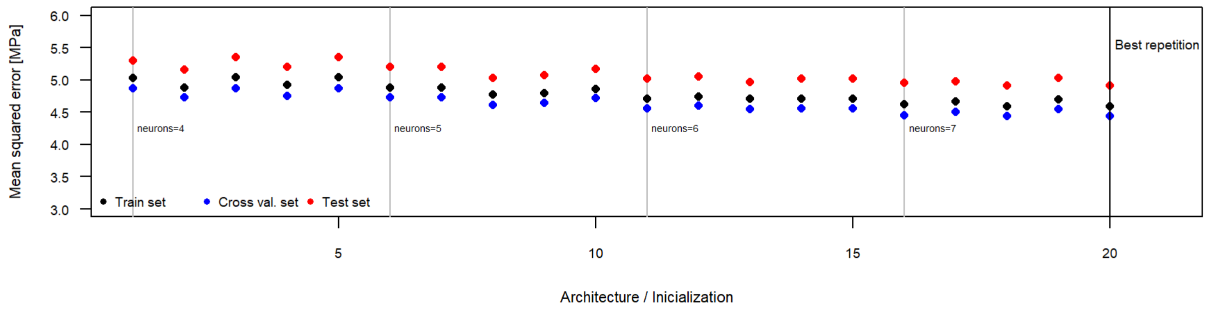

Figure 6. MSE values for each subset of the learning set

After validating the performance of the model, it is possible to perform the predictions of the observed structural behaviour and the proposed residual analysis, in order to check the possible variations and characterize the behaviour of the structure.

The learning data period was established to be represented by 90% of the model outcome, while the prediction period was the remaining 10%. The learning data period was then divided in three subsets: 80% dedicated to the training set, 15% to the cross-validation and 5% to the testing set.

Figure 7 shows in the top graph, the model results for target B as a reference, the time serie is divided by a line, biggest portion at left corresponds to the learning set and smaller one at right corresponds to the prediction set. It is possible to see the good fitting of the model values with the observed values represented in black on the same graph.

In the bottom graph of Figure 7, the residuals corresponding to the same target B are shown. In red, the residual's roll mean period of 7 days is represented, overlapping the residuals without a moving average application in black. Residuals values are close to zero as expected and the standard deviation described in blue, allows to confirm that neither an increase or a decrease of the dispersion, nor a significant change in the variability were identified.

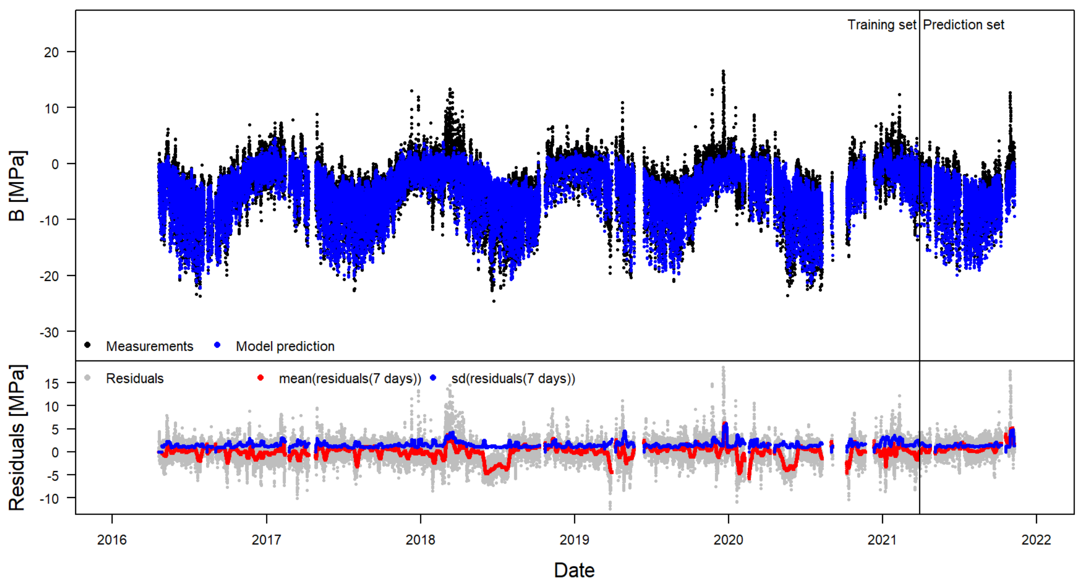

Figure 7. Model prediction for target B and residuals of target B

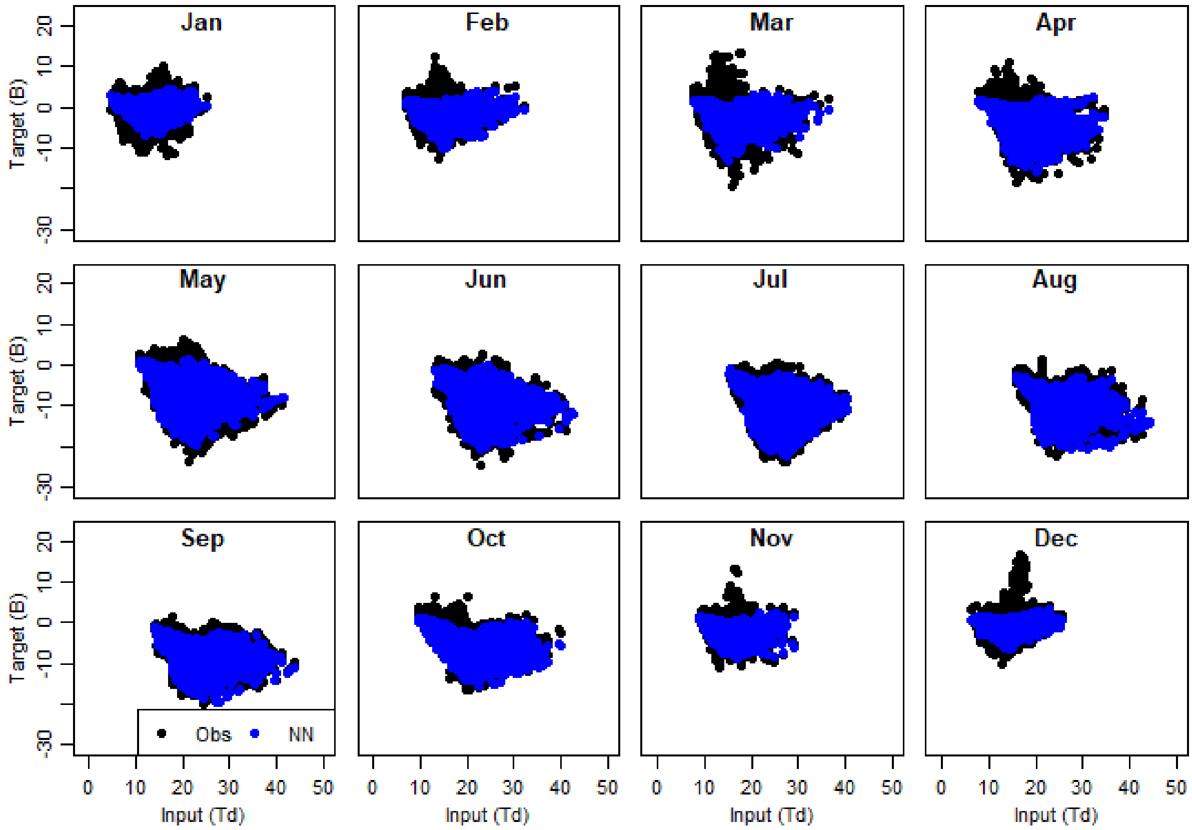

Figure 8. Correlation plots between target B and input Td

The identification of the variation pattern of the structural response to environmental loads allows, through a detailed analysis of the predictions and residuals resulting from the model, to characterize the structural behaviour of the bridge and established a reference state for future analyses or novelty detection. By comparison, the residuals mean roll of 7 days with the corresponding standard deviation, has a low dispersion, given that all the data points are close to zero, thus allowing to establish it as a precise baseline to use as a reference for future analyses.

Figure 8 show the good correlation among the stresses (target of the prediction model) with the temperatures (input of the prediction model) of target B and input Td as referential validating in this way the accuracy of the model along the time period under study.

6. FINAL REMARKS

This paper presented a new methodology based on neural networks (NN) for the prediction of structural behaviour on the 25 de Abril bridge in Lisbon, Portugal. NN was applied to static data corresponding to five years of hourly measurements gathered from the SHM system installed at the mid-span section bridge.

Results showed the good performance of the learning algorithm to characterize the structural behaviour. The residual analysis, the moving average, and the statistical measurements aimed at characterizing the behaviour pattern of the bridge, for both, observed and residual values, reducing the intrinsic randomness and allowing to review the information that was not described by the model predictions. With this analysis, it was possible to conclude that the proposed methodology can work as an effective strategy for the definition of an accurate baseline and reference indicators for further novelty detection analysis and characterization of complex critical infrastructures. In order to validate the robustness of the methodology and assess the evolution of the predicted responses in regard of the proposed inputs is recommended to perform a sensitivity analysis as further task.

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