

## **ANOMALY DETECTION ON A CONCRETE ARCH DAM: EXPLORING THE INFLUENCE OF TRAINING PERIODS**

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### **Abstract**

*The condition monitoring of civil engineering structures involves systematic assessment of their performance and integrity, which may decrease over time due to external actions and material degradation. Therefore, the early detection of structural changes is essential to guarantee well-planned management of the structure's operation and to perform timely interventions when needed.*

*To detect damage or ongoing processes of deterioration, techniques such as visual inspections, non-destructive testing and continuous data-based structural health monitoring (SHM) can be used. In the case of the latter, key properties can be tracked, initially to build data-bases and subsequently to create damage sensitive features that can support the identification of statistical anomalies. The approach most used in SHM for the detection of anomalies is based on the comparison between new data and data previously recorded during a period when the structure is thought to be in a perfectly healthy state (known as training period).*

*In this context, this work takes advantage of the combination of numerically simulated damage with real experimental data obtained from the continuous monitoring of a concrete dam, to explore the relation between the length of the training period, the intensity of the simulated damages and the ability of statistical tools to detect these anomalies. Additionally, the impact of including damaged-state data in the training period is explored.*

**Keywords:** Structural Health Monitoring (SHM), Data Normalization, Anomaly Detection, Dam Monitoring.

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## 1 INTRODUCTION

The core idea behind Structural Health Monitoring (SHM) systems is to gather experimental data during a structure's regular operation, which can be utilized to create a baseline reference model of its behavior. As the structure continues to operate, new data is compared to this reference model, and any discrepancies are interpreted as potential signs of new or abnormal behavior, possibly indicating structural damage. This approach can encounter significant obstacles when the structure operates in a changing environment, and the reference model only represents a specific range of external conditions. In such cases, measurements taken under undamaged conditions but within different environmental states might be incorrectly identified as deviations and perceived as structural degradation. However, this issue can be addressed by ensuring the inclusion of a sufficient amount of data across various operational and environmental conditions to build the reference model, followed by the use of processing techniques that allow the prediction of the structure's behavior and subsequent mitigation of external effects through the calculation of residuals obtained from the difference between measured and predicted behavior.

In this context, this work takes advantage of previously developed studies addressing the dynamic behaviour of a concrete dam to explore the potentiality of residuals resulting from the difference between measured and predicted data. More precisely, the length of the training period needed to build robust control charts is studied using three different prediction methods: Multiple Linear Regressions (MLR), Neural Networks (NN) and the Minimum Mean Square Error estimator (MMSE). Moreover, control charts are used to detect damage with increasing intensity and the effect of considering data containing simulated damages in the training period is analyzed.

## 2 BEHAVIOUR PREDICTION AND ANOMALY DETECTION

In the context of Structural Health Monitoring and the minimization of environmental and operational effects, there are several methods that can be trained using experimental data and then used to predict the behaviour of a structure. Among them, Multiple Linear Regression (MLR) models are commonly used, due to their simplicity and good applicability. These models allow to perform data prediction using independent variables associated with the external factors affecting the structure behaviour [1]. In the case of dam monitoring, these factors are generally considered to be reversible and elastic effects, such as the hydrostatic pressure on the dam's upstream face, normally indirectly considered through the variation of the level of water in the reservoir, and the effects resulting from temperature variations; as well as irreversible and inelastic effects, such as concrete hardening, which are idealized as a function of time. The temperature effect can be modelled either as a linear combination of sinusoidal functions depending only on the year's day (Hydrostatic-Season-Time approach - HST), or the actual temperature measurements obtained on site can be used (Hydrostatic-Temperature-Time approach - HTT) [2] [3].

Recently, other types of models have been used, based on machine learning algorithms with high performance in pattern recognition tasks, also considering independent variables as inputs. For instance, neural network (NN) models can adjust "weights" to learn patterns in the data through an iterative process during a training period and then be used to predict new data. Parallely to the case of MLR, NN models can also follow either an HST or an HTT approach(es). Besides the two types of prediction models mentioned, based on the use of independent variables related to the external factors affecting structural behaviour, when considering multivariable datasets with enough redundancy, which is typically the case with dynamic monitoring, a subset of the observations can be estimated using the remaining varia-

bles. For this, the linear estimator proposed by J. Kulla [4] (Minimum Mean Square Error estimator - MMSE) can be used, considering the minimization of the mean square error between the observed and the estimated data as optimization goal.

In addition to data prediction, which is then used to minimize the effects of environmental and operational conditions on monitoring features through the calculation of residuals, statistical tools are used to detect anomalies laying in the data. In this work, multivariate  $T^2$ -Hotelling control-charts are used, together with an upper control limit (UCL) equal to the 95<sup>th</sup> percentile of the  $T^2$ -statistic computed in the training period.

### 3 STRUCTURE UNDER ANALYSIS

The Baixo Sabor is a concrete arch dam that spans the Sabor River in the north of Portugal. The structure presents a double-curvature arch which stands 123 meters tall and stretches 505 meters along the crest. The arch is composed of 32 concrete blocks, separated by vertical contraction joints, and includes horizontal inspection galleries where a dynamic monitoring system is installed. This system comprises three digitizers, a central computer for data storage, GPS antennas to ensure synchronization between different measurement channels, and 20 uniaxial accelerometers arranged radially as shown in the left part of Fig. 1. The monitoring system is designed to continuously record acceleration time-series at a sampling rate of 50 Hz for 30 minutes at all instrumented points, thereby producing 48 sets of time series per instrumented point each day.

Since 2015 the modal properties of the dam (natural frequencies, damping ratios and mode shapes) are being continuously tracked, resorting to an automated operational modal analysis procedure that combines the SSI-Cov method [5] [6] with an hierarchical clustering algorithm [7] [8]. In this work, the first five vibration modes of the dam are considered through 3-hour averages of the natural frequencies identified during the first three years of monitoring, therefore focusing on the analysis of measured from 01/12/2015 to 30/11/2018.

However, since the dam was recently built, and based on monitoring data, it is not expected to present signs of degradation. Therefore, previous works addressed the topic of damage development and its numerical simulation through different mechanisms and location [9]. In this work, the occurrence of damage in the central part of the dam was considered, as presented on the right side of Fig. 1, resorting to reductions in the value of the concrete elasticity modulus.

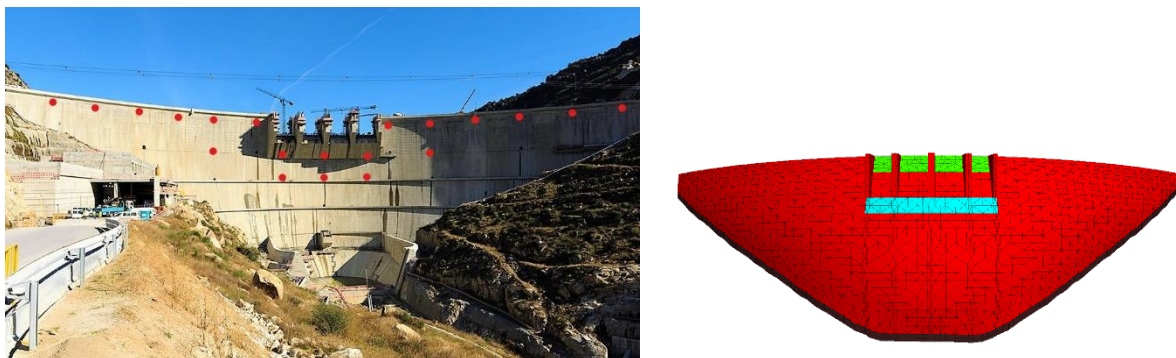


Fig. 1. On the left: Baixo Sabor dam (downstream view) and locations of the accelerometers installed within the dam. On the right: numerical model of the dam showing the simulated damage.

#### 4 DATA NORMALIZATION AND ANOMALY DETECTION

Previous works [10], analyzed the ability of MLR, NN and MMSE models to minimize the effects of environmental and operational conditions on natural frequencies, with the whole set of models presenting satisfactory results. For MLR and NN models, both HST and HTT approaches were considered, using moving averages of air temperature values in the second case, to account for concrete thermal inertia, producing slightly better results. For this, the first two years of monitoring were considered as training period, while the third year was used for validation. In **Fig. 2** the histograms of the residuals obtained after the application of the best model obtained for the first three vibration modes are presented. Bell-like shapes with average values close to zero are obtained in the three cases, indicating a good removal of systematic external influence.

In this work, a step forward aims to build robust control charts, based on the residuals previously obtained and to use them to study their ability on anomaly detection. In this sense, the residuals obtained from the application of MMSE estimator were used to build the control chart presented in **Fig. 3**. The first two years of data were used as training period, both to train the MMSE model and the control chart. Therefore, the third year is used for validation, considering residuals obtained solely on prediction, that were not part of the training sample, which is prone to produce artificial anomalies if the minimization model is not working well. Nevertheless, analyzing **Fig. 3** it can be concluded that this is not the case, since only 1.1% of outliers are observed in the validation period, well below the 5% threshold defined by the UCL (represented in red). Each point corresponds to 1 day.

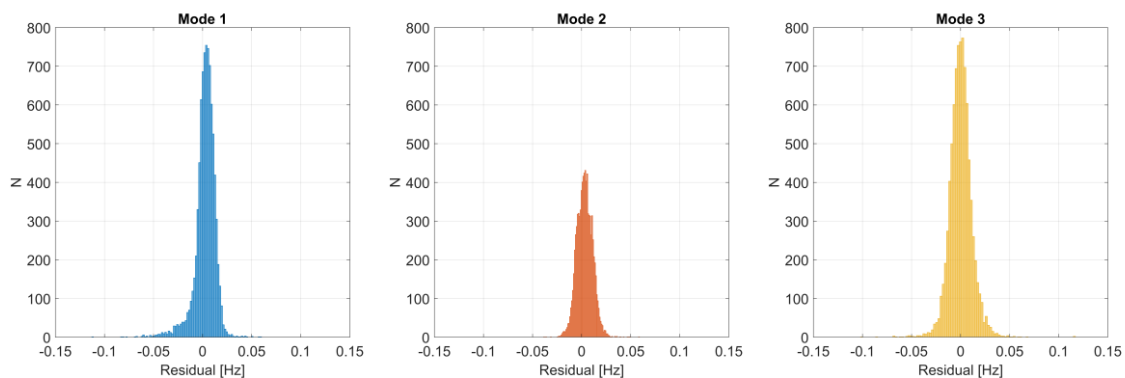


Fig. 2. Histograms of residuals for the first three modes.

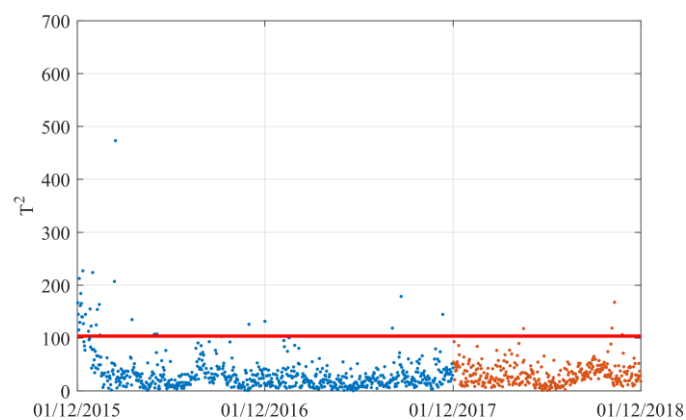


Fig. 3. Control chart using the residuals obtained from the application of the MMSE estimator. A training period of two years (blue) and a validation period of one year (orange) are used. The UCL is represented by the red horizontal line.

Though it was possible to build a robust control chart, with a low percentage of outliers above the UCL during the validation period, two years of data were used for training, which in determined contexts can be considered a long period. In this sense, a study was performed involving the length of the training period used both for the minimization of external factors and to build the control chart, which was the same in all tested scenarios. Training periods with lengths varying from 1 month to 2 years were tested, and the percentage of points above the UCL during the validation period was analyzed. Three models were used for data prediction, consisting of the MLR-HTT, the NN-HTT and the MMSE. The results obtained are presented in **Fig. 4**.

As expected, a large number of points above the UCL is obtained when short training periods are used, indicating that a minimum length is needed for the model to fully characterize the variability of the data. On the one hand, it can be noticed that acceptable results with about 10% of points above the UCL are achieved by the three models for training periods as short as 12 months, corresponding to a full seasonal cycle. On the other hand, it should be noted that the MMSE reaches the 5% limit with a training period of only 8 months. Additionally, for larger periods, the NN model presents better results than the MLR.

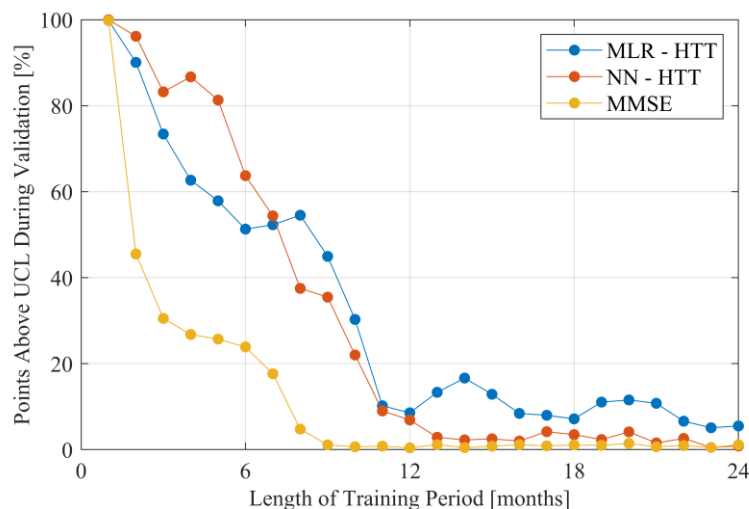


Fig. 4. Effect of the length of the training period on the number of points above the UCL in the control chart during the validation period.

After the definition of reliable control charts, damages were introduced in the experimental data through the manipulation of natural frequencies. The numerical model was used to determine the frequency shifts produced by the damage simulated, for increasing levels of damage. These frequency shifts, with different values for each mode, were considered as sudden damage occurring on the first day of the third year of monitoring. Average frequency shifts of  $-0.079\%$  were considered for the lower level of damage considered, while the higher level used average frequency shifts of  $-0.507\%$  [9].

**Fig. 5** presents the control chart obtained using residuals from the MMSE estimator and 2 years of training. The third year is used for validation (healthy - orange) and then repeated for increasing levels of damage (yellow, purple and green). It can be concluded that for the specific damage addressed, the first intensity level is not detected, while the second and third levels produce a high level of outliers (above 70%), that suggest the occurrence of an anomaly.

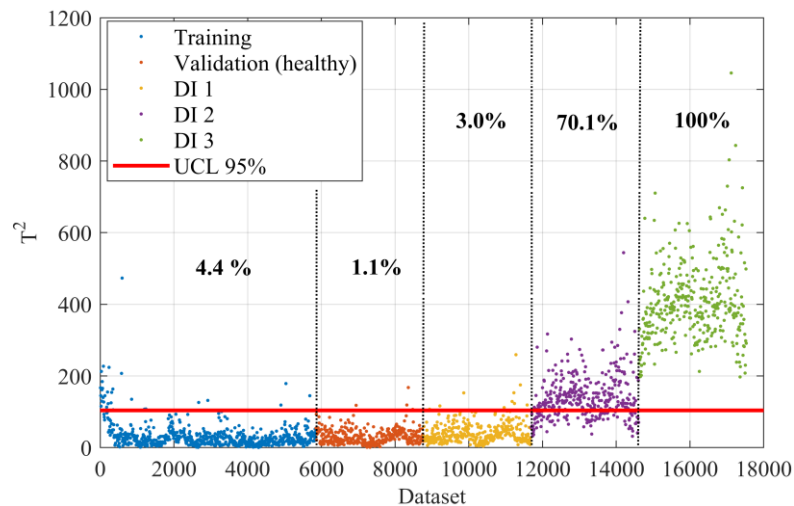


Fig. 5. Control chart using the residuals obtained from the application of the MMSE estimator. Damages considering 10% (DI 1), 30% (DI 2) and 50% (DI 3) reduction of the elasticity modulus of selected elements were introduced in the data represented, respectively, in yellow, purple and green. For each scenario the percentage of points above the UCL is represented in bold.

Finally, since the moment damage occurs, or starts developing, is not known, the effect of mistakenly considering damaged data in the training of the models is tested.

For this, the MMSE estimator together with a sudden damage is considered once again. The second level of intensity (purple) is used, for which around 70% of points above the UCL were observed when the training consisted only of healthy data. The quantity of data corresponding to a damaged state that were used in the training of the models was gradually increased from 1 day to 3 months. For each case, the percentage of points above the UCL during validation was analyzed and its variation with the increase of damaged data in the training is presented in **Fig. 6**.

As the number of points in the training corresponding to a damaged state increase, the UCL changes and the number of points above it decreases. It can be mentioned that, with only 30 days of damaged data used in the training, about half the outliers disappear, and that in the case of 90 days, only 10% of outliers are observed, which could not be enough to define an anomaly.

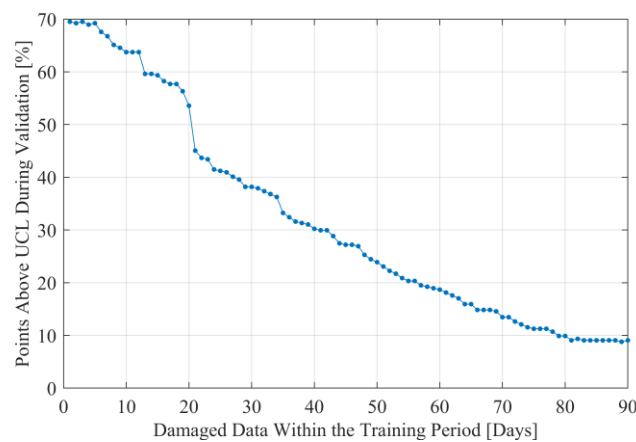


Fig. 6. Variation of the percentage of points above the UCL during validation, with an increasing number of damaged data used in the training (MMSE estimator). Damage level 2 is used.

## 5 CONCLUSIONS

In this study, three different methodologies were employed to mitigate the influence of environmental and operational conditions on natural frequencies. Each method produced stable control charts when a considerably large training period was used, and acceptable results when using at least one year of training. Notably, the residuals derived from the application of the Minimum Mean Square Error estimator required the least amount of training time, highlighting its efficiency and potential for practical implementation.

The detection of anomalies due to the simulated damage was successfully achieved using control charts, validating the effectiveness of this approach in identifying structural irregularities. However, it was observed that incorporating even a short period of damaged data into the training of the model significantly impaired the control chart's ability to detect anomalies. This finding, though expected, emphasizes the importance of maintaining the integrity of the training dataset to ensure accurate anomaly detection, through continuous adaptation of the analysis instead of relying on a simple control chart.

Looking ahead, future research will explore the impact of different types of damage and the possible connection between frequency shifts correlation and each model effectiveness. Additionally, a gradual progression of damages, rather than sudden occurrences, will be studied, as well as a methodology to detect the inclusion of anomalies in the training. This will provide a more comprehensive understanding of these model's capabilities and limitations, ultimately enhancing the reliability and applicability of Structural Health Monitoring systems in real-world scenarios.

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