INCREASING ROBUSTNESS OF CRITICAL INFRASTRUCTURES ASSESSMENT USING ARTIFICIAL INTELLIGENCE AND STRUCTURAL MONITORING

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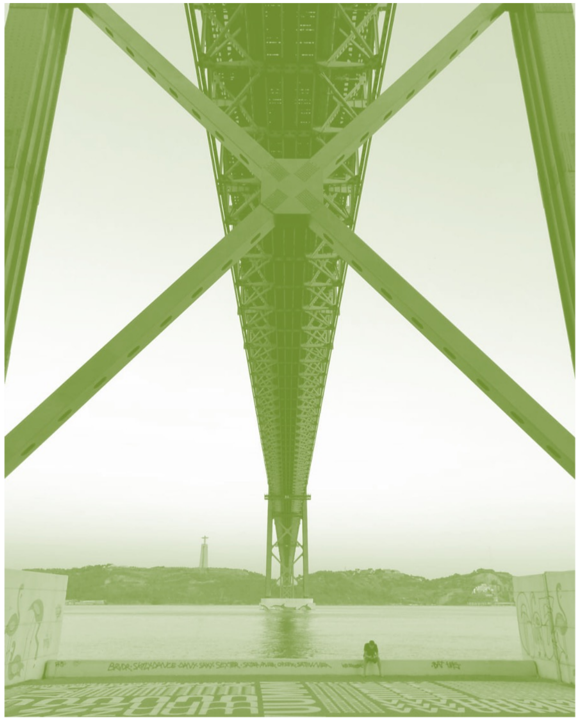


- Milestones
- Main objectives
- Thesis workflow/outline
- State of art – Structural Health Monitoring
- Case study
- Structural behaviour characterization and novelty identification of complex structures based on machine learning models. A data-driven methodology for model validation and threshold definition
- Characterization of relative movements between blocks observed in a concrete dam and thresholds definition for novelty identification based on machine learning models
- Improving traditional approach for structural behaviour analysis of bridges through LSTM models. Application to the 25 de Abril Bridge
- Ongoing work
- Chronogram of activities

Milestones

I. Increase the **sensitivity of damage identification** methods (reduce false negatives);

II. Increase the **robustness of damage identification** methods (reduce false positives);

III. Contribute to the **standardization of the SHM systems**;

IV. Provide stakeholders with **automated procedures** for safety assessment and decision-making based on predictive analysis of the structural condition;

V. Contribute to the achievement of **real-time damage identification** in practical applications of critical infrastructures.

Main objectives

Milestones

1. Apply the newest Machine Learning paradigms to SHM data acquired continuously onsite, namely EM and DL;
2. Assess the methods with the best performance considering site conditions, structural complexity and singularity, actions, hazards and sensorial limitations;

→ Milestones: I, II, IV, V

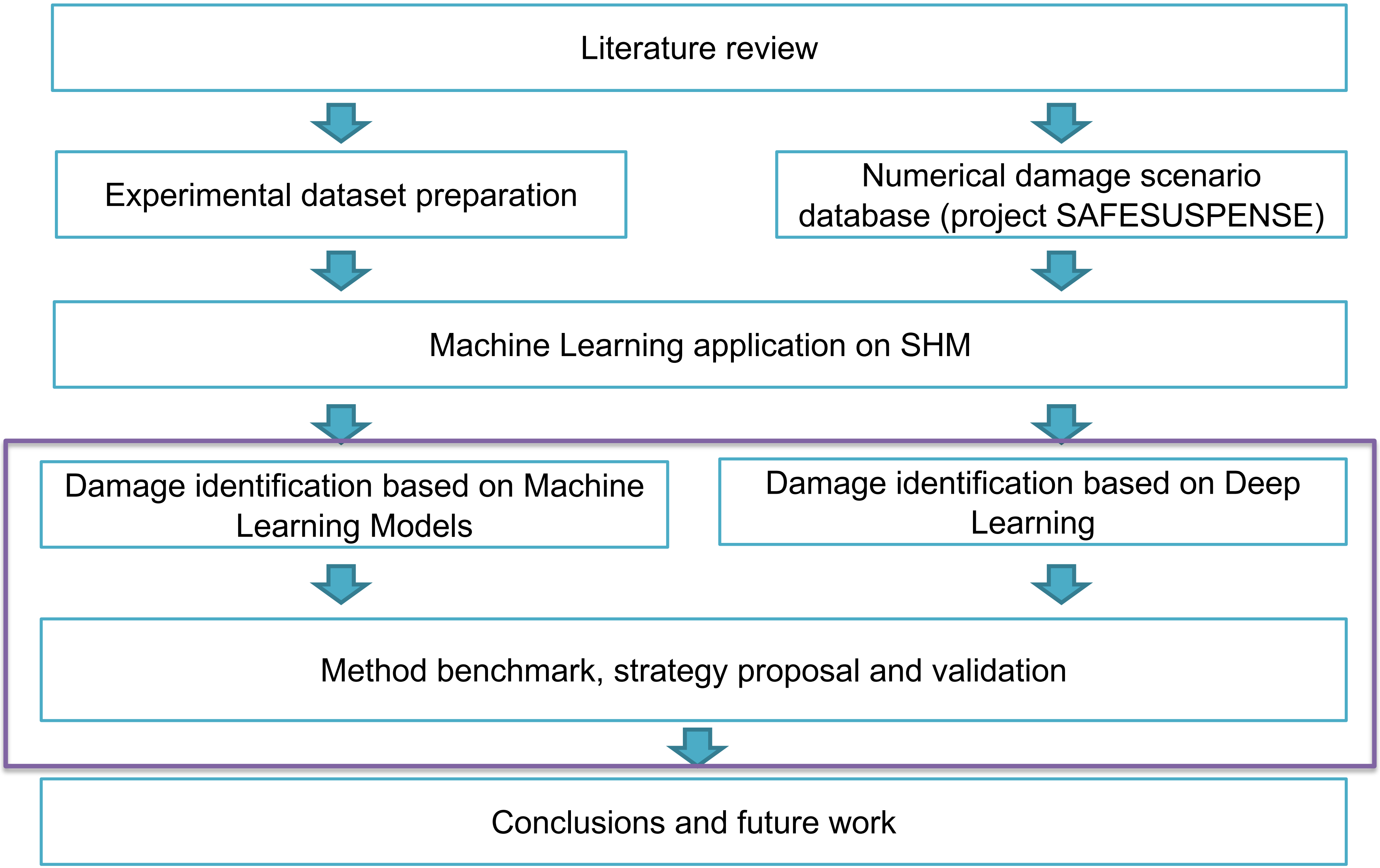
3. Analyse raw SHM data acquired on site:
   - instead of features, which must be defined beforehand and are usually case- and objective-dependent;
   - without the need to separate effects from different actions/hazards;
4. Use only structural response data, thus avoiding the need to characterize complex actions acting in large structural systems (temperature, wind, traffic);

→ Milestones: III, IV

5. Define the best SHM strategy based on the new SHM-ML paradigms;
6. Benchmark against the most common strategies used nowadays;

→ Milestones: I - V

Thesis workflow / outline



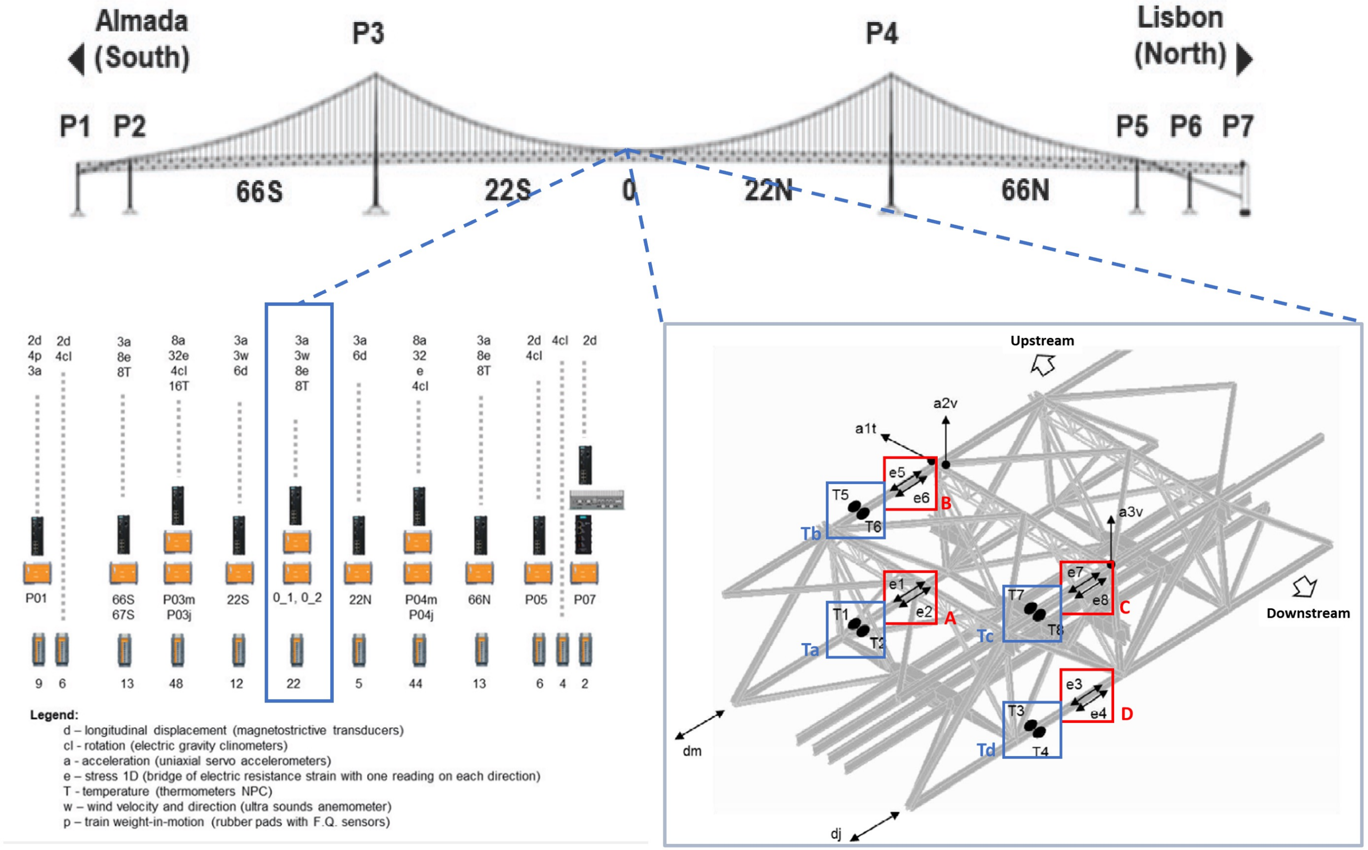
Structural behaviour characterization and novelty identification based on machine learning models.

Through the comparison between the observed values and predicted outcomes from the **Machine Learning models** is possible to identify new trends or variations of patterns for future observations:

- for the **characterization and prediction of the structural behaviour** based on the main loads

A methodology and a respective sensitivity analysis is proposed in order to:

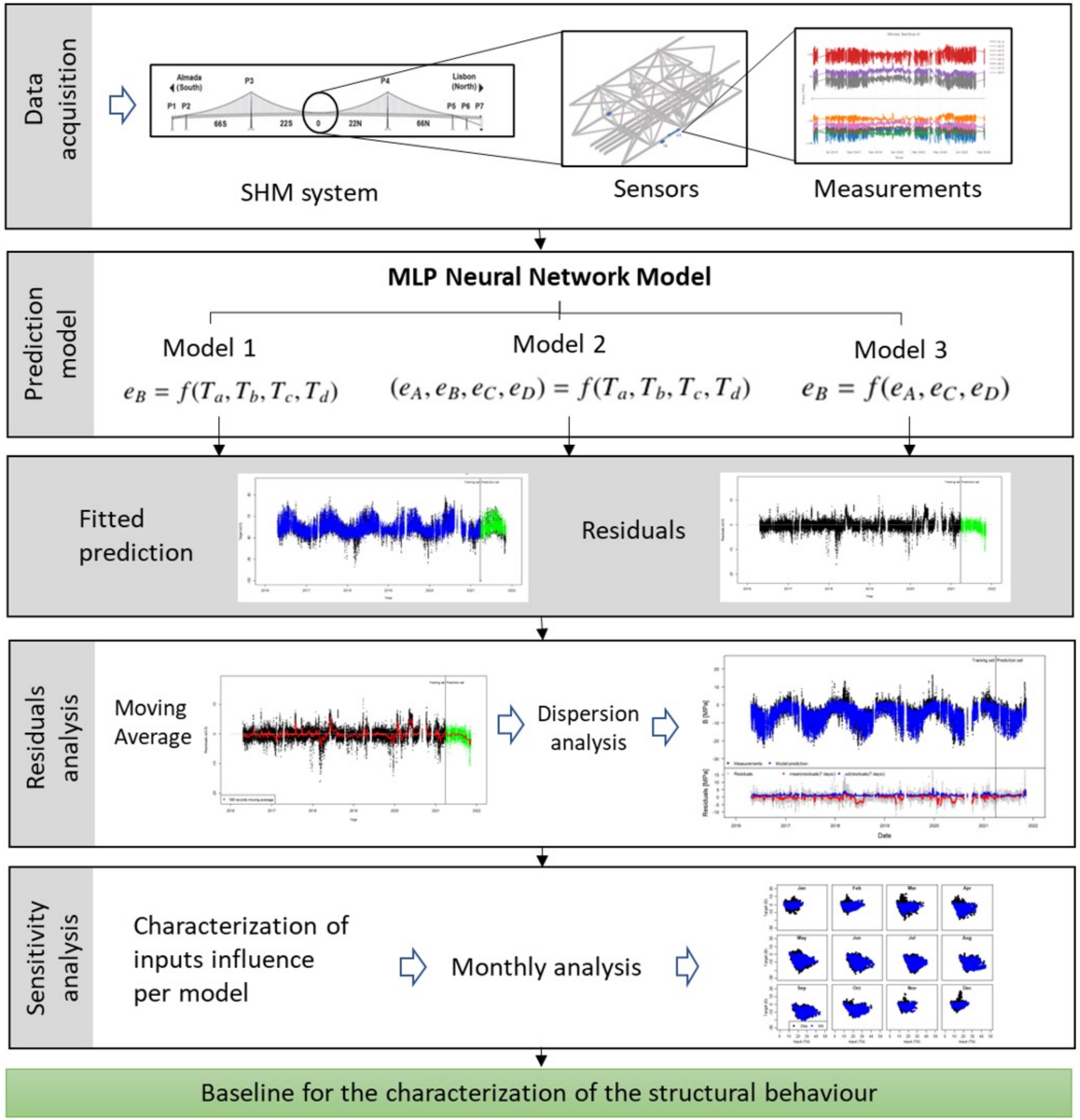
- to define an accurate **baseline of the structural behaviour** based on monitored data.



Section 0, located at the mid-span in the rigid beam was the section selected for this study, being:

- The stresses, considered as structural responses and,
- The temperatures of the environmental loads

Methodology



Prediction model

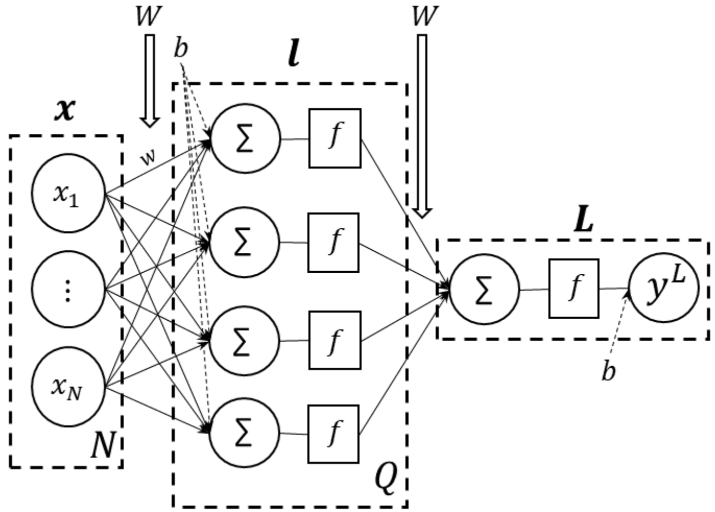
It is proposed to develop three different prediction models that relate:

(i) the structural responses (R), one by time in order to evaluate each response in function of the main loads (L) ,

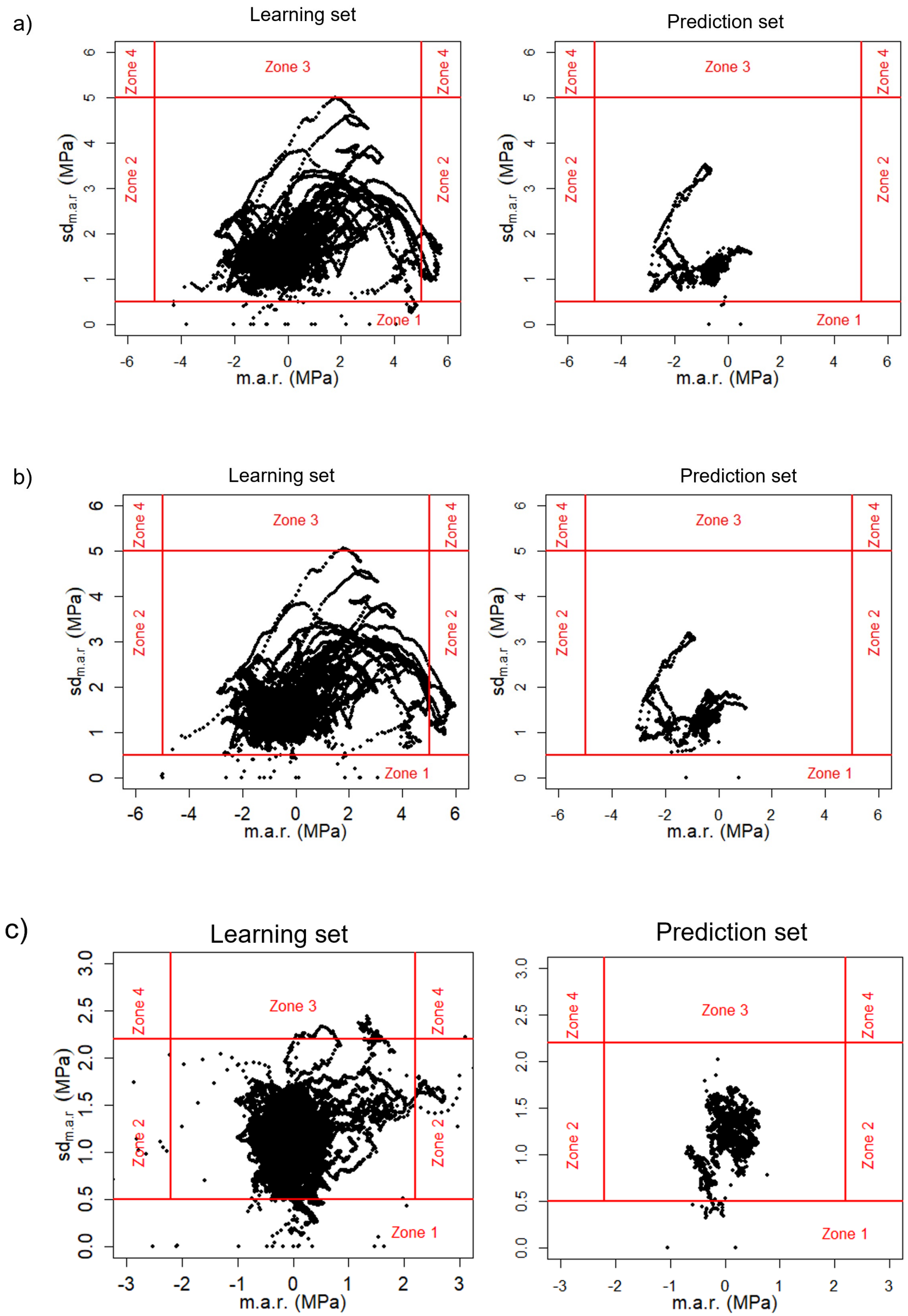
(ii) several structural responses in function of the main loads and

(iii) structural responses in function of other structural responses in the section.

Designation	Model: $Output = f(Input)$
Model 1	$R_1 = f(L_1, \ldots, L_n)$
Model 2	$(R_1, \ldots, R_n) = f(L_1, \ldots, L_n)$
Model 3	$R_1 = f(R_2, \ldots, R_n)$



Multilayer Perceptron Neural Network was chosen because of its proven efficiency in the pattern recognition and novelty identification.



- Correlation plots of $sdm.a.r.$ and the $m.a.r.$ for Models 1 and 2 are proposed in order to identify novelty candidates.
- For clearest interpretability, each correlation plot was discretized by zones based on the percentiles of the $m.a.r.$ and $sdm.a.r..$

Final Remarks

- Regarding the quality of representation, both models showed good results, pointing to the **good performance of the neural network**. The residual analysis results also showed a low dispersion in the mean weekly evolution of the residuals with no signs of unusual values. The performance of Model 3 was also adequate, given the good correlation among its quantities.
- **MLP neural network models showed great ability of generalisation** considering the dataset size and complexity.
- Resulting outcomes **allow to stablish an accurate baseline for the characterization of the structural behaviour** that can be used as referential for future works.

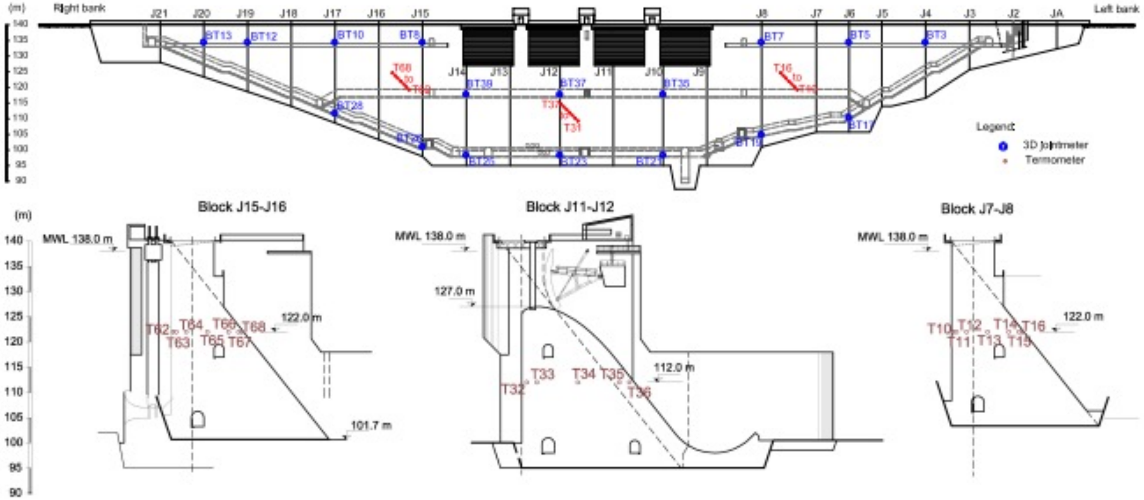
Characterization of relative movements between blocks observed in a concrete dam and thresholds definition for novelty identification based on machine learning models

Mata, J.; Miranda, F.; Antunes, A.; Romão, X.; Pedro Santos, J. Characterization of Relative Movements between Blocks Observed in a Concrete Dam and Definition of Thresholds for Novelty Identification Based on Machine Learning Models. *Water* **2023**, *15*, 297. https://doi.org/10.3390/w15020297

The proposed threshold definition related to novelty identification, which considers the evolution of the records over time and the simultaneity of the structural responses was applied to interpret the relative movements between blocks measured hourly in **a concrete dam under exploitation**.

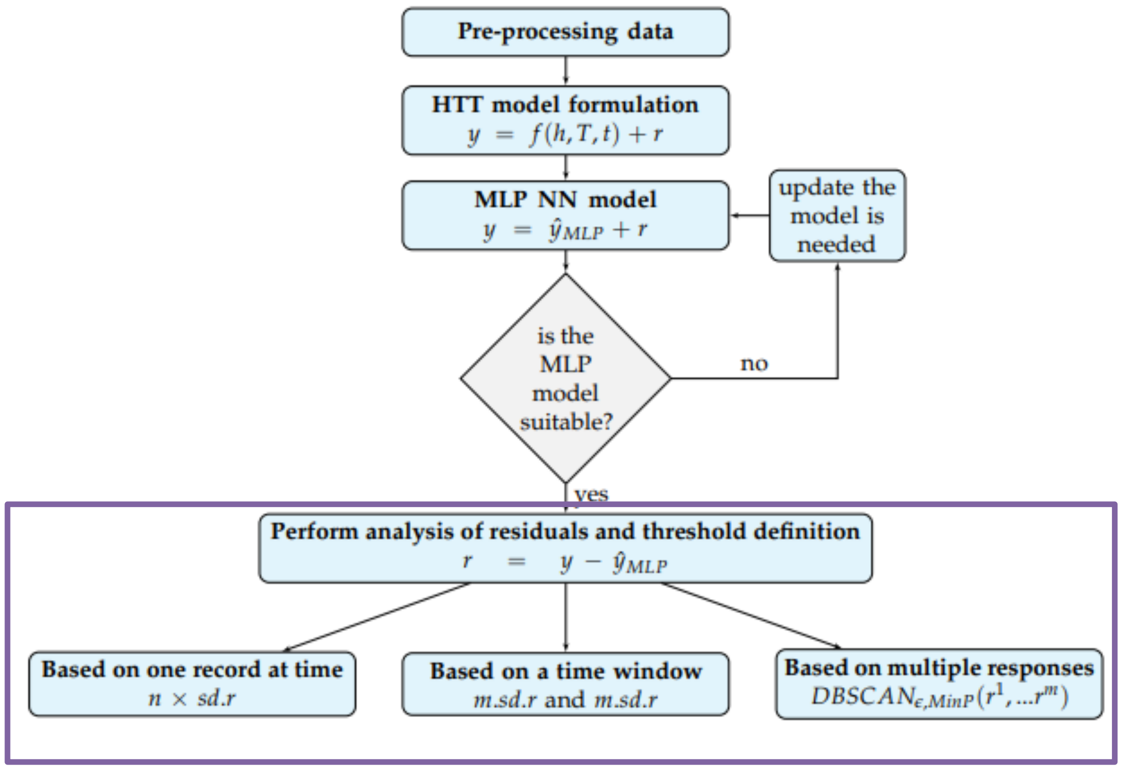
Data set

The Feiticeiro dam comprises a concrete gravity dam with an overflow-controlled spillway and a downstream stilling basin.

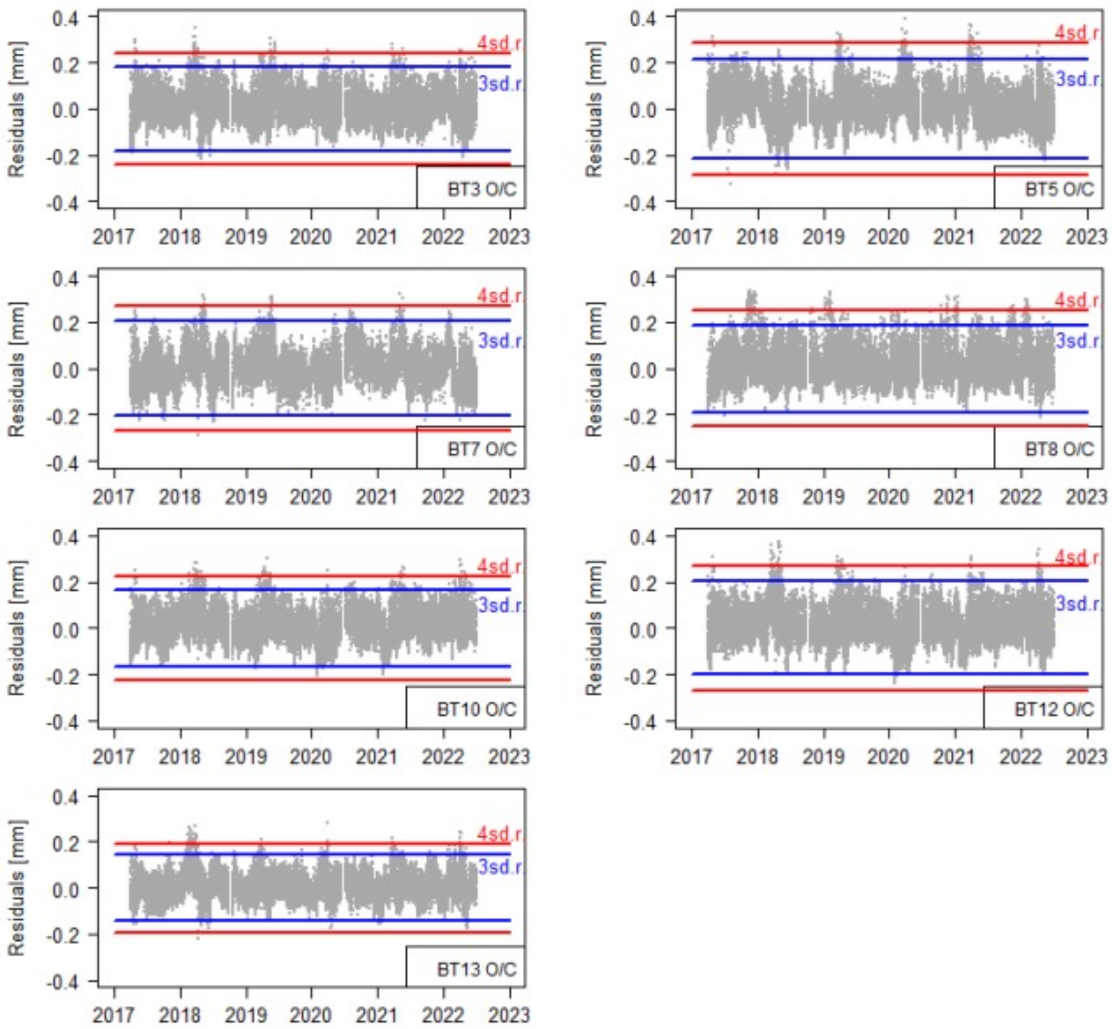


Thermometers (in red) and 3D jointmeters (in blue) included in the automated monitoring system.

Methodology



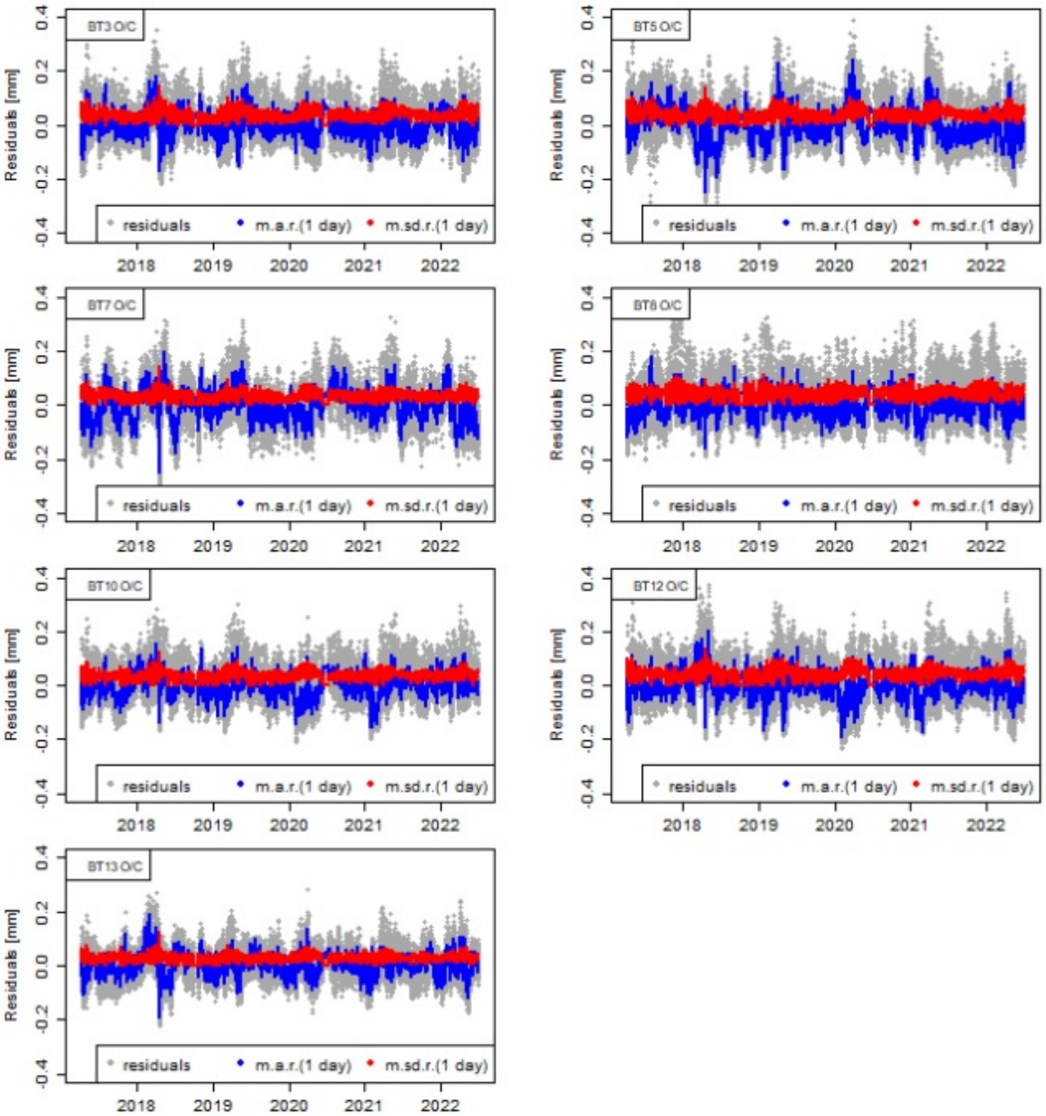
- The adoption of the **HTT (hydrostatic, thermal, time)** formulation for the development of the prediction model was adopted. The water height and the concrete dam body temperature variations were the selected main inputs in the proposed model.
- An MLP-NN model was found to be suitable to analyze the relative movements between blocks since it is capable of **mapping the interaction between the inputs.**



Residuals of the movements measured through 3D jointmeters.

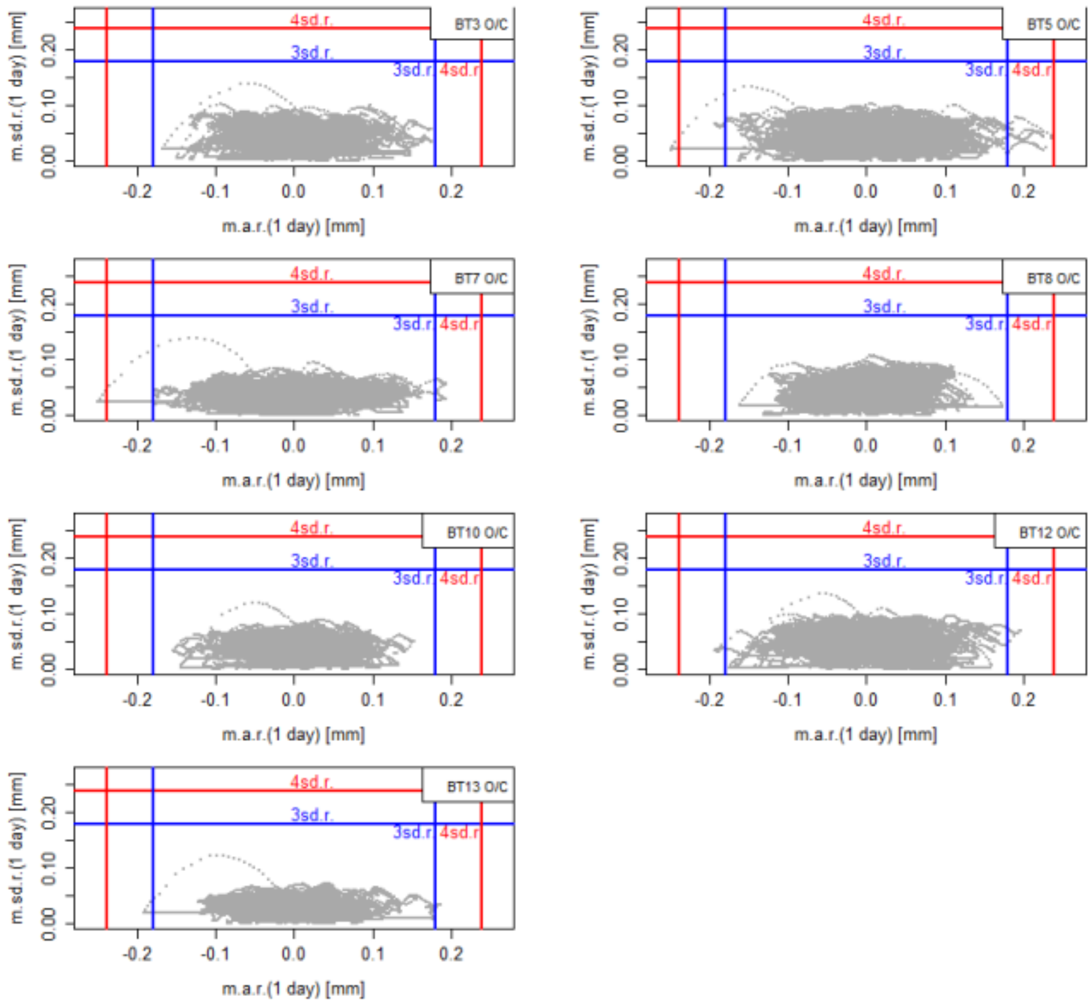
The traditional approach adopted for threshold definition in regression models consists of adopting a multiplicative factor associated with the standard deviation of the residuals.
Usually, multiplicative factors **equal to 3 or 4**, corresponding to a **confidence level of 99.73% and 99.99%, respectively.**

The same type of criterion can also be used in the MLP-NN model.



Residuals, moving average of residuals (m.a.r.), and moving std. deviation of residuals (m.sd.r.) over time.

The simultaneous analysis of the m.a.r. and m.sd.r. allows us **to identify if the predicted values are moving away from the recorded values** (i.e., if the residuals are increasing, meaning that the non-explained part of the model is increasing), and if the residuals increase along time, this could suggest a damage evolution.



m.sd.r. vs. m.a.r. for each quantity.

Thresholds based on multipliers of 3 and 4 for the standard deviation of the residuals are also proposed, although these values can be updated depending on the results.

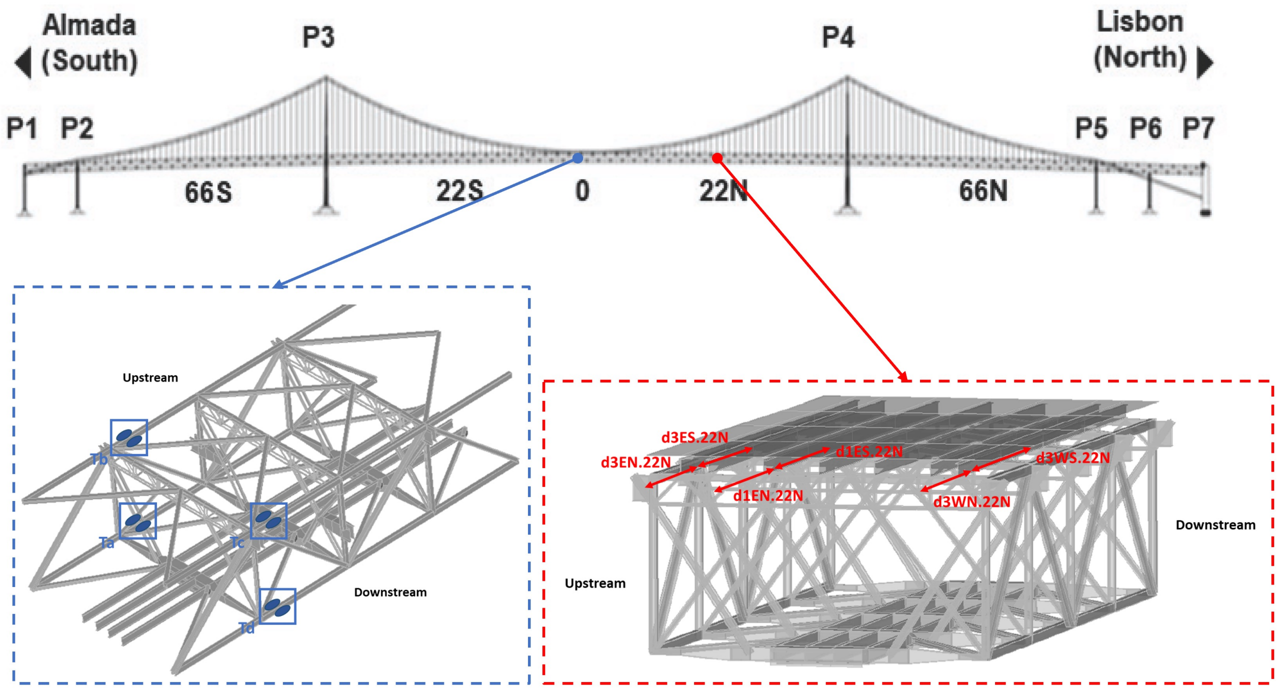
The priority in this kind of analysis is to **identify periods in which the residuals and their evolution are higher; consequently, a deeper analysis of the data can be carried out.**

Final Remarks

- The definition of univariate thresholds based on the residuals, one for each quantity through the use of multiplicative factors associated with the standard deviation of the residual, allows an easy novelty identification that, in some cases, could be related to measurement errors.
- The second type of threshold proposed in this study can be defined by the adoption of a moving window with the moving average and the standard deviation of the residuals. This kind of approach **allows the specialist to have immediate information concerning the evolution over time.**

Improving traditional approach for structural behaviour analysis of bridges through LSTM models. Application to the 25 de Abril Bridge

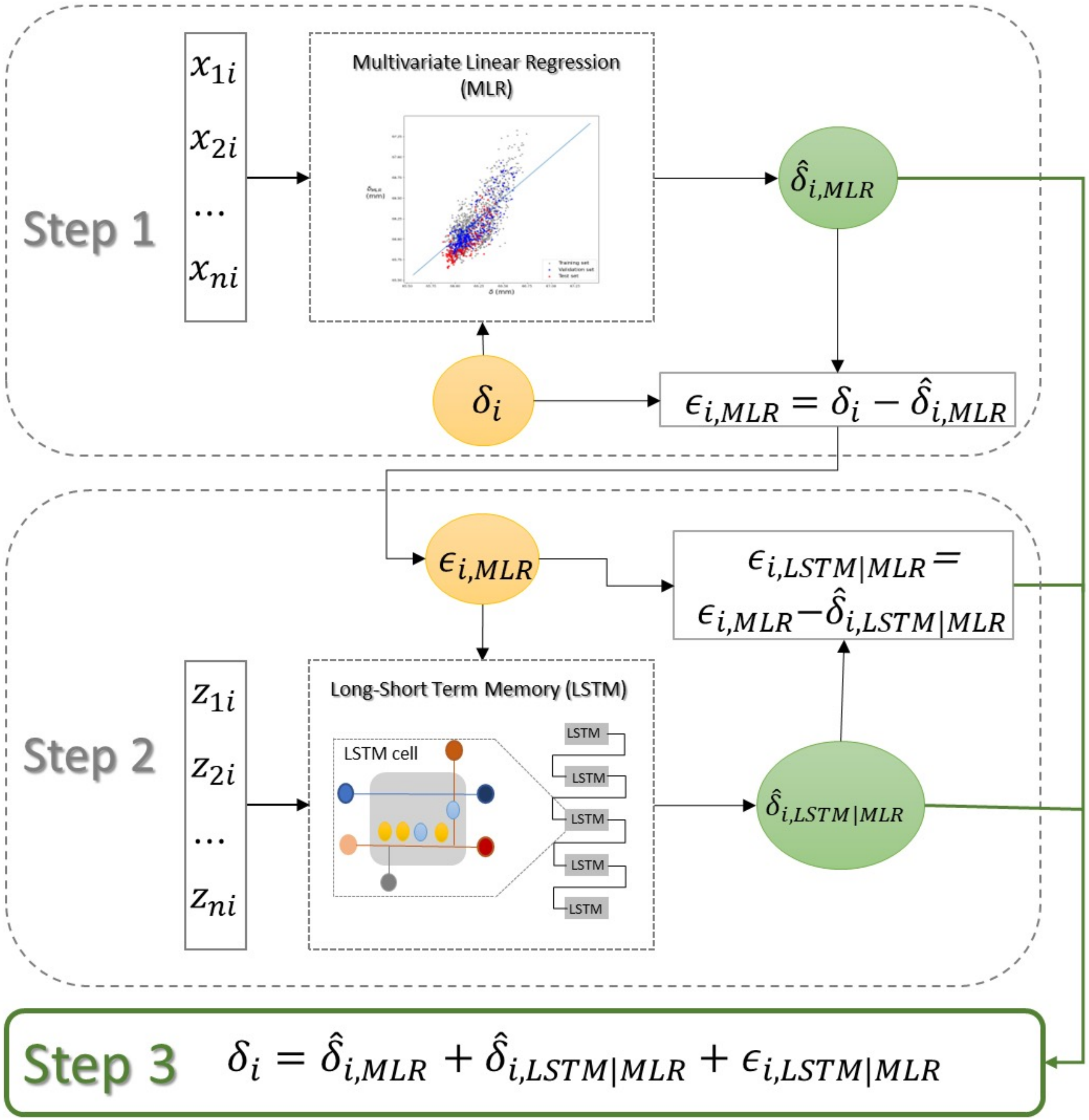
- This work aims to improve the current approach in SHM analysis by building a complementary step with a **Deep Learning (DL) approach**, capable of dealing with the limitations of the traditional strategies, such as non-linearity and the time-dependency of the structural relationship.
- Assuming that the improvement of the decision-making in the SHM field depends on better prediction models, the **Long-Short Term Memory (LSTM)** model is proposed to overcome the actual limitations of MLR and improve its performance.

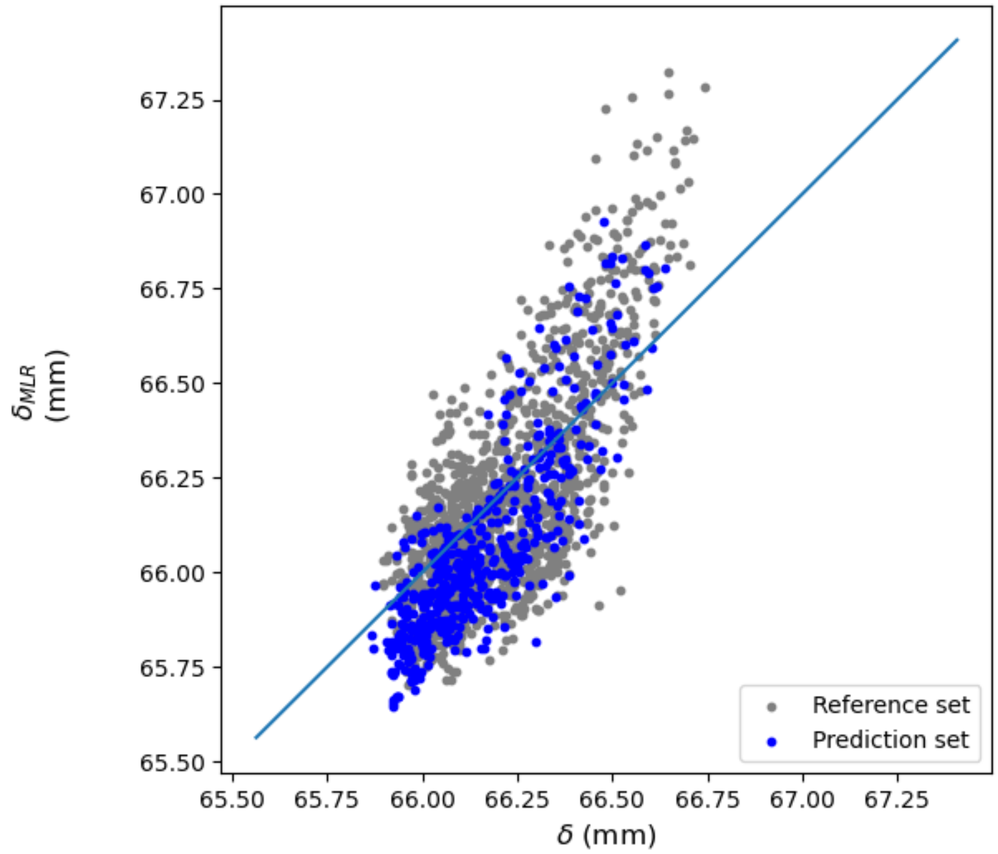


8 NPC Thermometers (T)

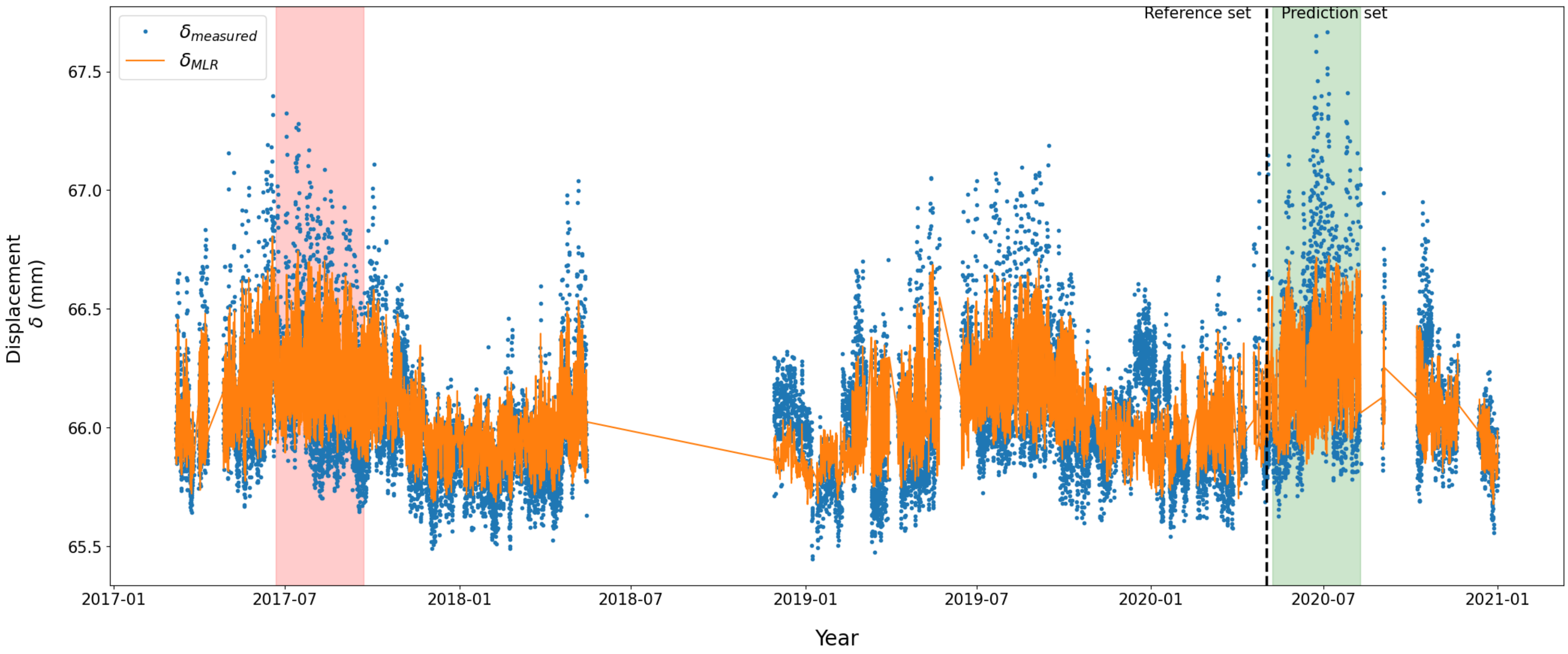
6 magnetostrictive displacement sensors (d)

The data in the present study is from a five-year monitoring period, from 07/03/2017 to 31/12/2020, with hourly 165 measurements and 21304 measurements per physical quantity.

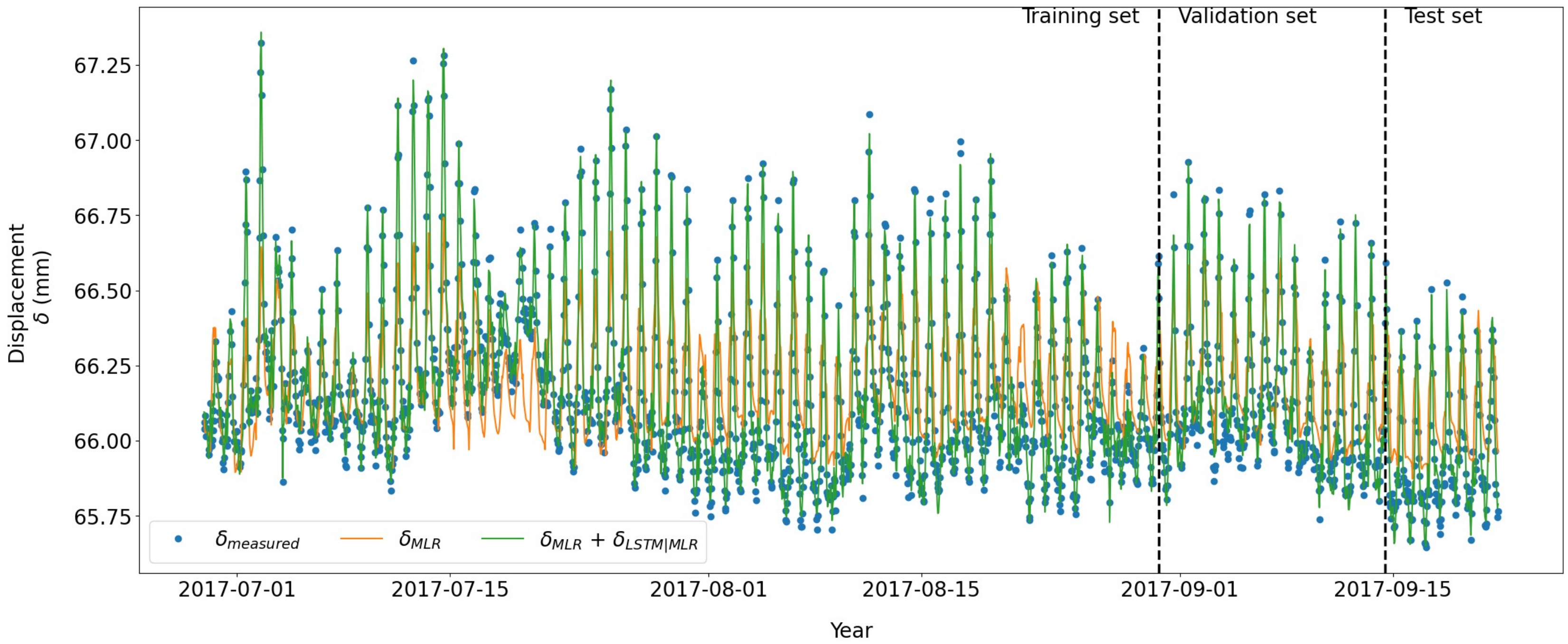

Step 1
x_{1i}
x_{2i}
…
x_{ni}
Multivariate Linear Regression (MLR)
$\hat{\delta}_{i,MLR}$
δ_i
$\epsilon_{i,MLR} = \delta_i - \hat{\delta}_{i,MLR}$
Step 2
$\epsilon_{i,MLR}$
$\epsilon_{i,LSTM|MLR} = \epsilon_{i,MLR} - \hat{\delta}_{i,LSTM|MLR}$
z_{1i}
z_{2i}
…
z_{ni}
Long-Short Term Memory (LSTM)
LSTM cell
LSTM
LSTM
LSTM
LSTM
LSTM
$\hat{\delta}_{i,LSTM|MLR}$
Step 3
$\delta_i = \hat{\delta}_{i,MLR} + \hat{\delta}_{i,LSTM|MLR} + \epsilon_{i,LSTM|MLR}$

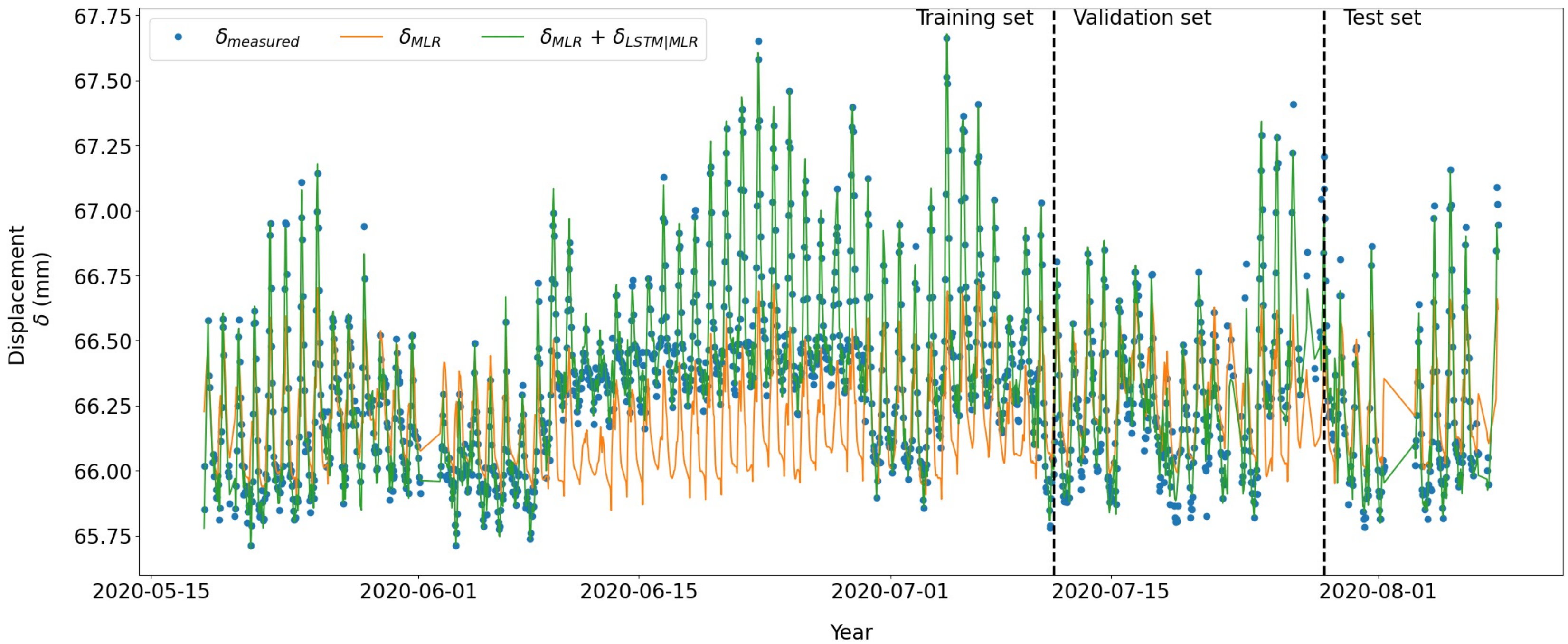


MLR models are currently applied to interpret SHM data due to their simple application and low computational cost, allowing its application in low-quality data. However, limitations regarding the outcome are present.



Reference set
Prediction set
$\delta_{measured}$
δ_{MLR}
67.5
67.0
66.5
66.0
65.5
Displacement
δ (mm)
2017-01
2017-07
2018-01
2018-07
2019-01
2019-07
2020-01
2020-07
2021-01
Year


Training set
Validation set
Test set
67.25
67.00
66.75
66.50
66.25
66.00
65.75
Displacement
δ (mm)
δmeasured
δMLR
δMLR + δLSTM|MLR
2017-07-01
2017-07-15
2017-08-01
2017-08-15
2017-09-01
2017-09-15
Year


Training set
Validation set
Test set
67.75
67.50
67.25
67.00
66.75
66.50
66.25
66.00
65.75
Displacement
δ (mm)
δmeasured
δMLR
δMLR + δLSTM|MLR
2020-05-15
2020-06-01
2020-06-15
2020-07-01
2020-07-15
2020-08-01
Year

Final Remarks

- As in many cases, the dataset presents missing values in the sequence. The improved results promise to motivate detailed exploitation with more extended period observations and **different variable relationships in time on the structure** to create better predictive models for effective monitoring systems, **enhancing the capability to ensure structural safety and increase sensitivity to early damage** in civil operational structures.

Ongoing work

- Based on observed measurements from the structure in an undamaged state and a dataset with measurements of the structure with imposed damage product of numerical simulations, a classification strategy is being developed to strengthen the novelty identification at an early stage for safety assessment and decision-making based on predictive analysis of the structural condition.

Thank you