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

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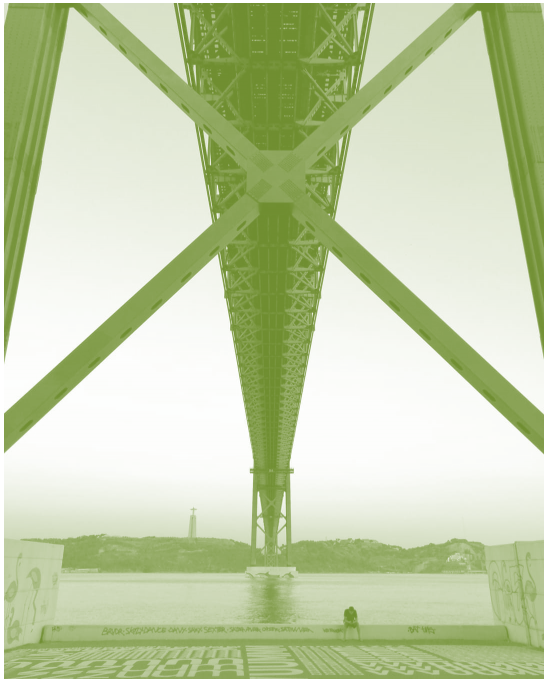


- Milestones
- Main objectives
- Thesis workflow/outline
- State of art – Structural Health Monitoring
- Case study
- Structural behaviour characterization and novelty identification of complex structures based on machine learning models. A data-driven methodology for model validation and threshold definition
- Ongoing work
- Chronogram of activities

Milestones

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

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

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

IV. Provide stakeholders with **automatic 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;

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);

III, IV

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

I - V

Thesis workflow / outline

Literature review

Experimental dataset preparation

Numerical damage scenario database (project SAFESUSPENSE)

Machine Learning application on SHM

Damage identification based on Machine Learning Models

Damage identification based on Deep Learning

Method benchmark, strategy proposal and validation

Conclusions and future work

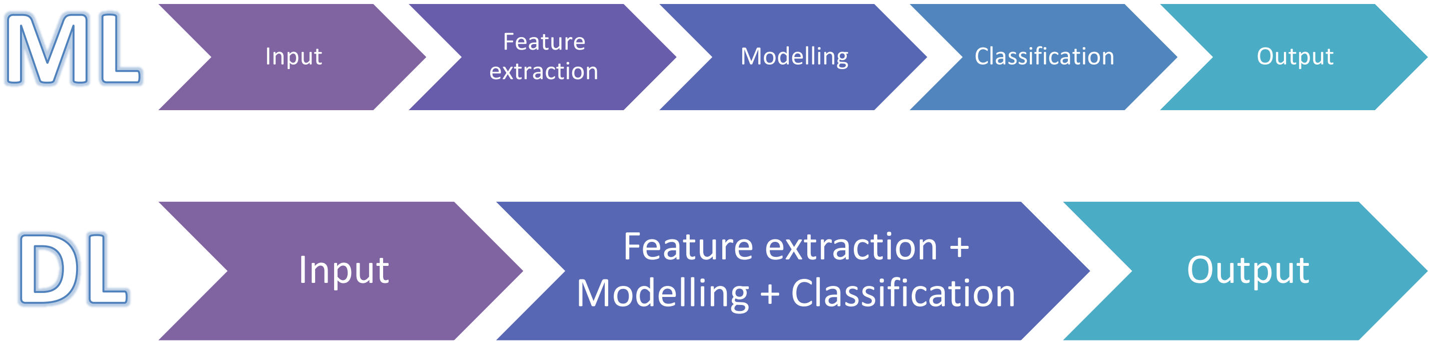
State of art - Structural Health Monitoring

- Provide, through different technologies and algorithms, **information** about the behavior and condition of existing and new structures.
- Identify **novelties/damages** in the structural systems.
- Widely accepted as a useful aid to **risk analysis and integrity management** of structures.
- Data obtained could contain important **incidence of false alerts**, that limits the efficiency of the following process.
- It is **difficult to find sensitive and robust** damage indicators.
- The outputs are obtained through **deterministic methods**, based on upper and lower thresholds, not entirely adequate for decision making

- Data acquisition
- Feature extraction
- Feature modelling
- Feature classification
- Damage identification

Concluding remarks from literature review

- ML algorithms parse data, learn from it and use that learning to autonomously make decisions regarding the existence of damage and the structural condition;
- ML algorithms are the basis of both Ensemble Methods and Deep Learning (DL) Algorithms;
- Ensemble methods are very effective and efficient since they are composed of many ML models;
- As opposed to legacy ML techniques, which require features to be identified before classification in order to be visible, so the learning algorithm could work, DL instead eliminates the need of feature extraction and learn high-level features from data in an incremental manner, optimizing the performance.



Is possible to perform data analysis with raw data as input!

Case study: the Ponte 25 de Abril

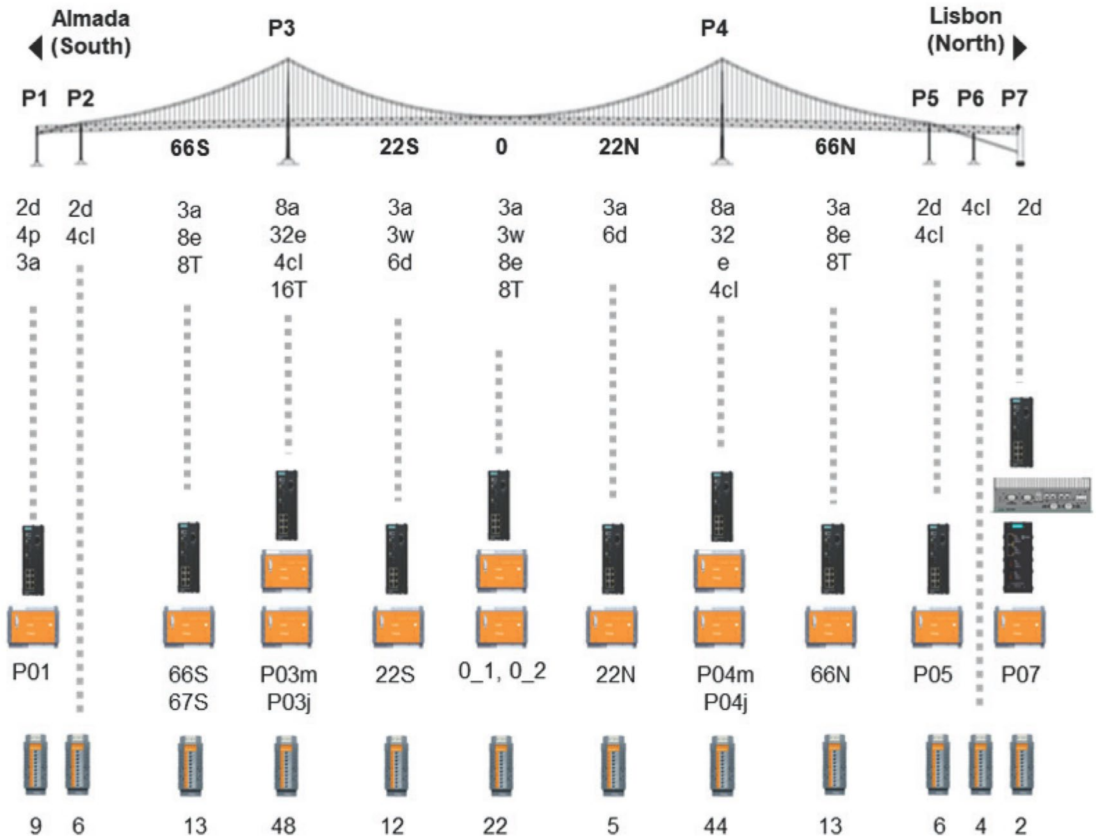
The suspension bridge over the Tagus River in Lisbon is a structure with a total length of **2,277 m** between anchorages, including the **suspended central span with 1,013 m**, two suspended side spans with 483 m and, also three backstay spans with about 99 m each.

It was opened to the traffic in **1966** with a **4 lanes roadway deck**, located at the level of the upper chord of the stiffening truss. In **1999**, the bridge had construction works to **add a 2 lines railway deck**, at the level of the lower chord of the stiffening truss, and to widen the **roadway deck to 6 lanes**.

Monitoring system

- The monitoring system proposed for the 25 de Abril's Bridge follows the program of (Silveira, 2013) with updates of (Santos,2015).

- It considers **210 sensors** located in strategic sections of the bridge according its structural behaviour.



Legend:

d – longitudinal displacement (magnetostrictive transducers)
cl - rotation (electric gravity clinometers)
a - acceleration (uniaxial servo accelerometers)
e – stress 1D (bridge of electric resistance strain with one reading on each direction)
T - temperature (thermometers NPC)
w – wind velocity and direction (ultra sounds anemometer)
p – train weight-in-motion (rubber pads with F.Q. sensors)

Structural behaviour characterization and novelty identification of complex structures based on machine learning models. A data-driven methodology for model validation and threshold definition *25 de Abril Bridge as case study*

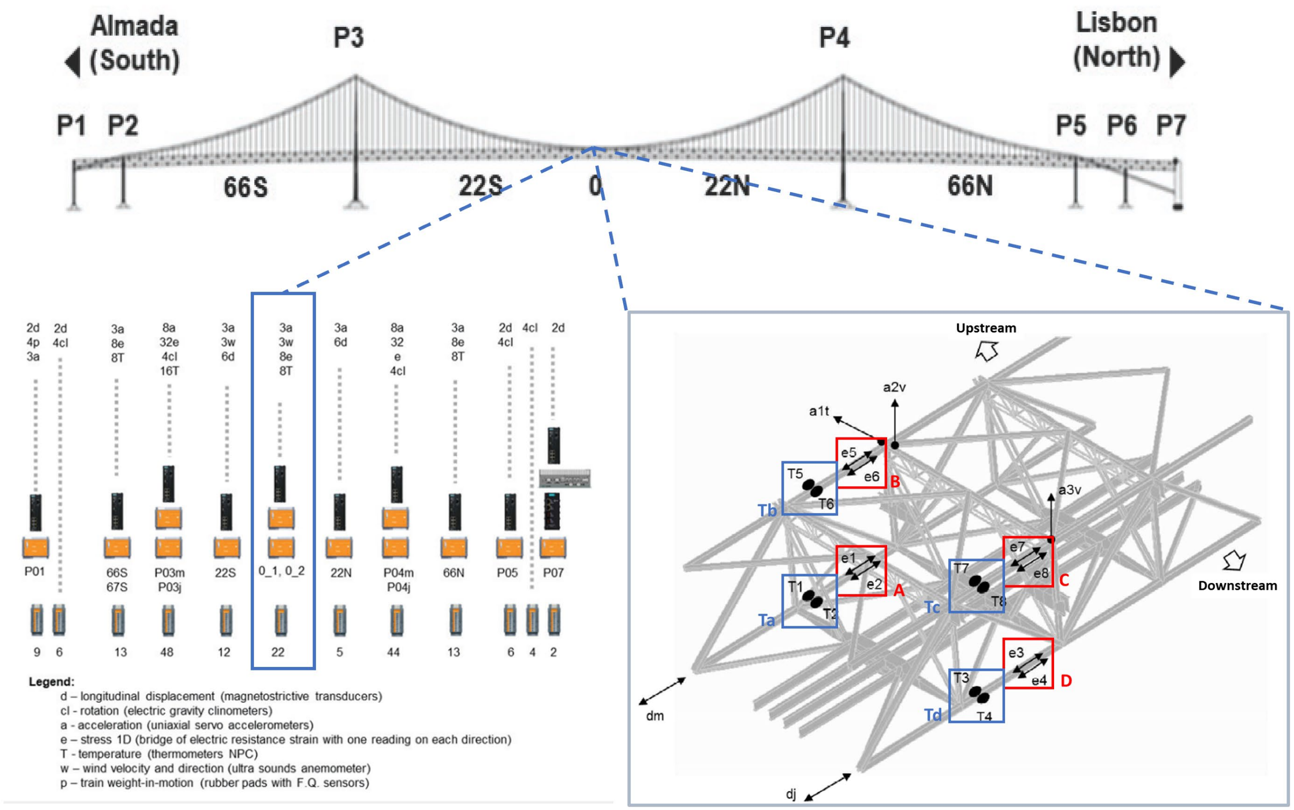
Through the comparison between the observed values and predicted outcomes from the **Machine Learning models** is possible to identify new trends or variations of patterns for future observations:

- 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.

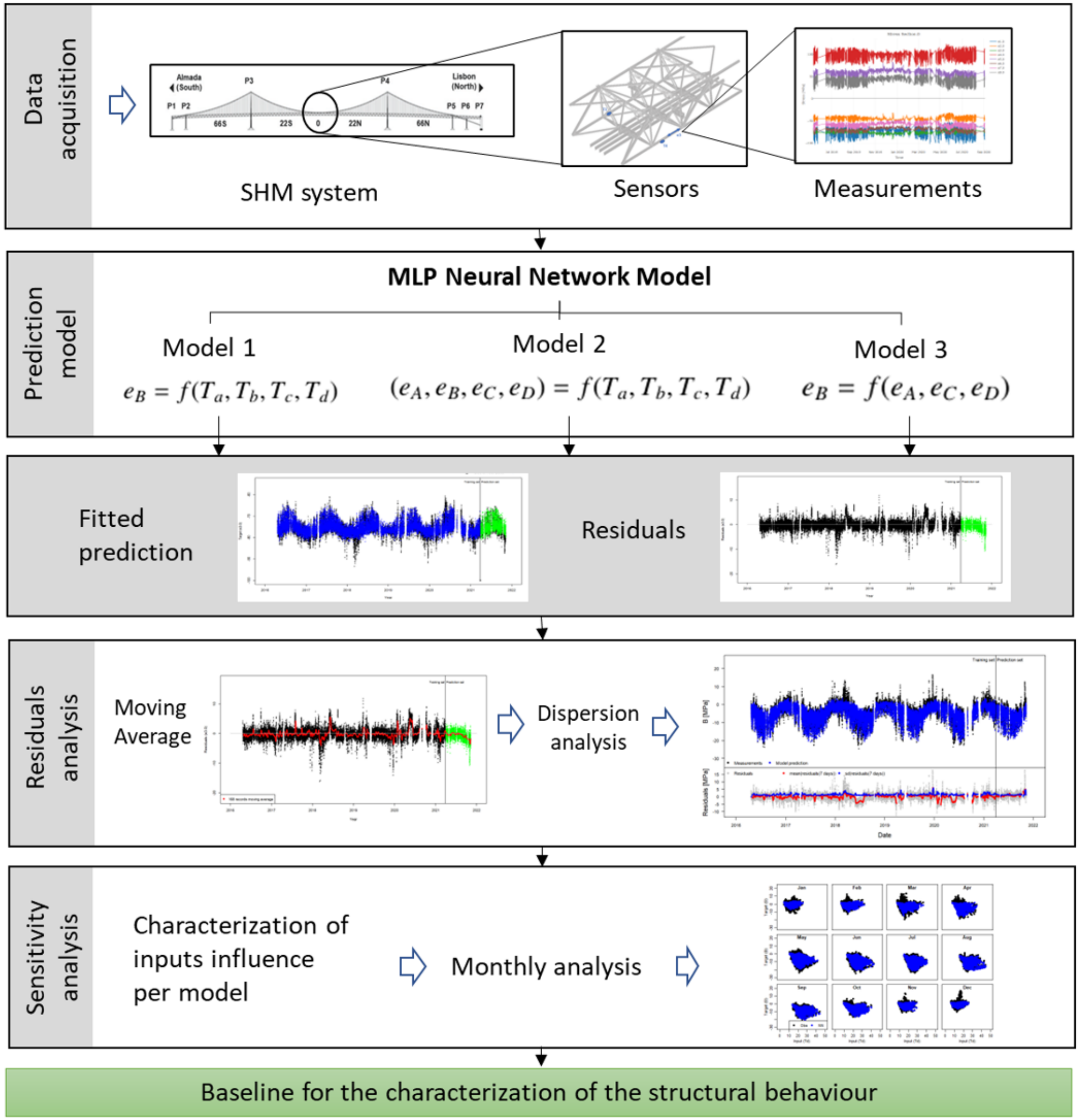
Data set



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 the environmental loads

Methodology



Prediction model

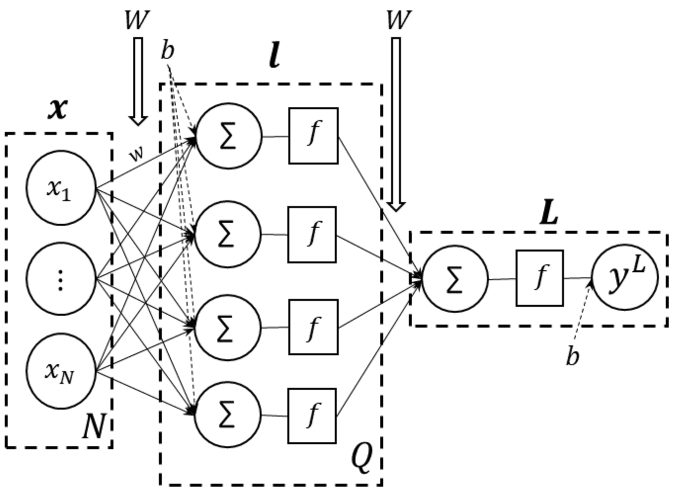
It is proposed to develop three different prediction models that relate:

(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.

Residual Analysis

In order to **reduce the intrinsic randomness** of the data and identify as early as possible any deviation along time, a moving average and standard deviation with a time window of one week and a time step of one hour is proposed in the residuals of the model.

$$m.a.r._i = \frac{\sum_{j=i-w+1}^{i} r_j}{w}, i \geq w \qquad sd_{m.a.r.,i} = \sqrt{\frac{1}{w}\sum_{j=i-w+1}^{i}(m.a.r._j - m.\bar{a}.r_{(j\ to\ i)})^2}$$

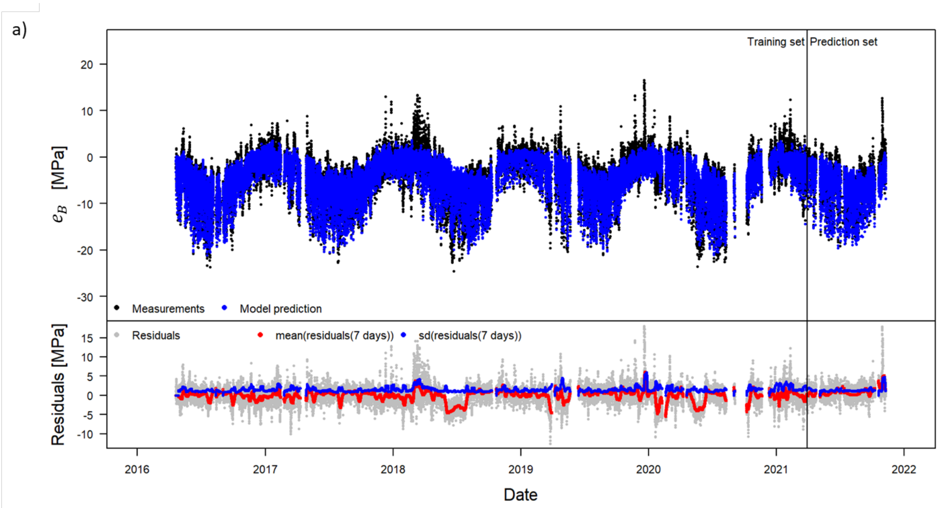
Sensitivity Analysis

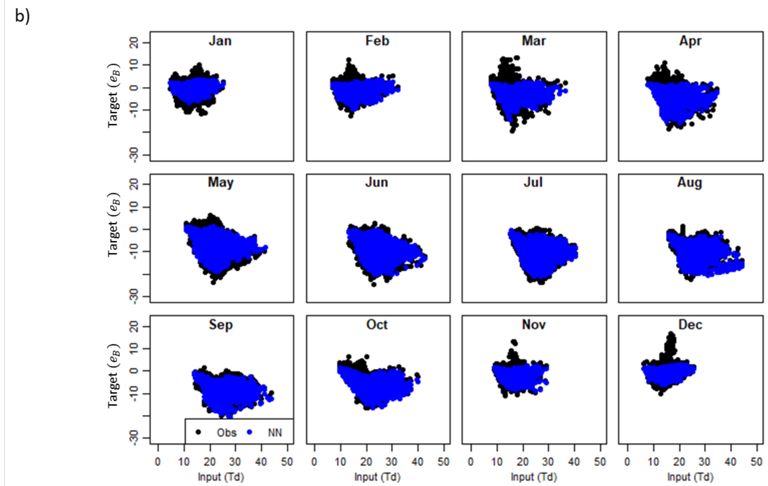
- In order to **evaluate the model robustness and characterize the effects** of the environmental loads on the structural responses and the relation between quantities, a sensitivity analysis consists on the evaluation of the predicted outputs evolution: the structural responses, in regard to each of the inputs: main loads or responses on the section under study

- A good correlation between the quantities would denote a **reliable prediction**.

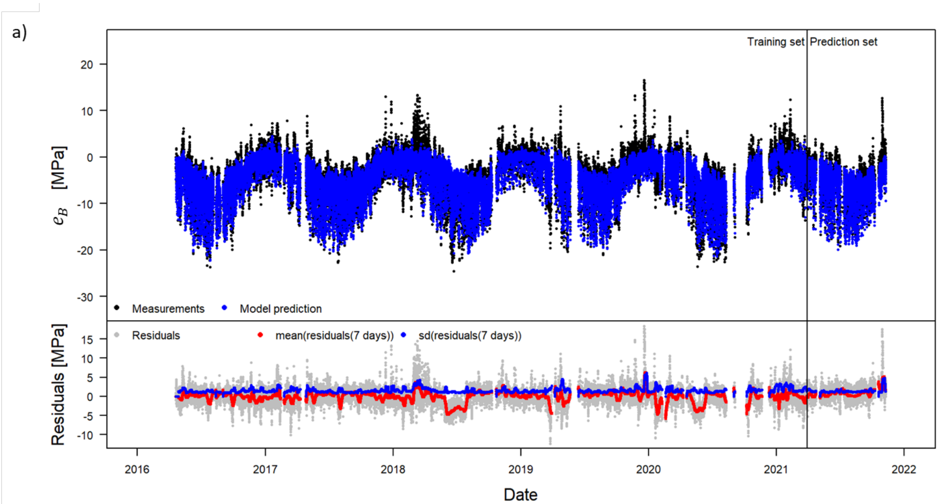
Results

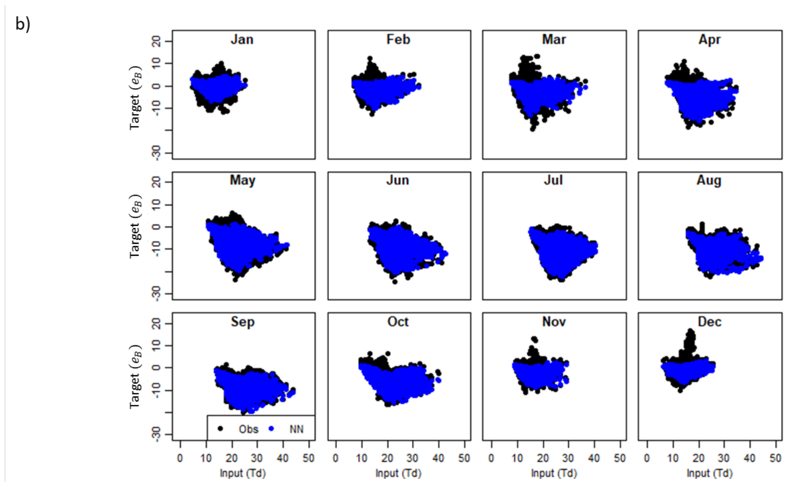
Model 1





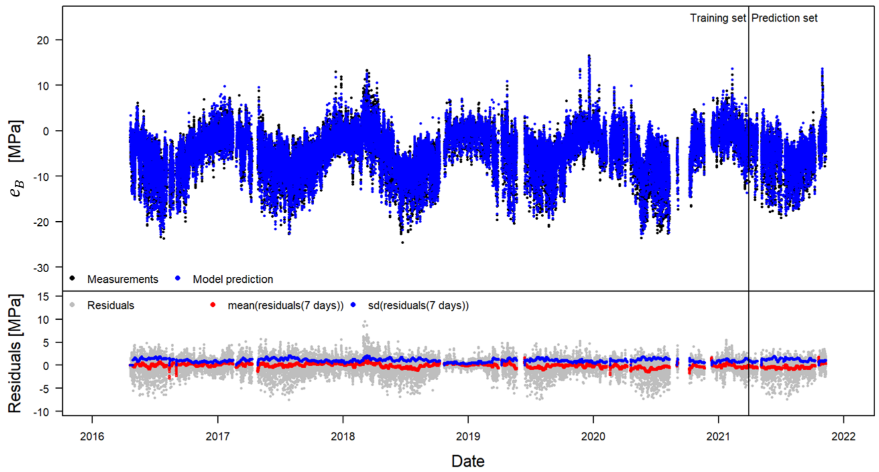
Model 2



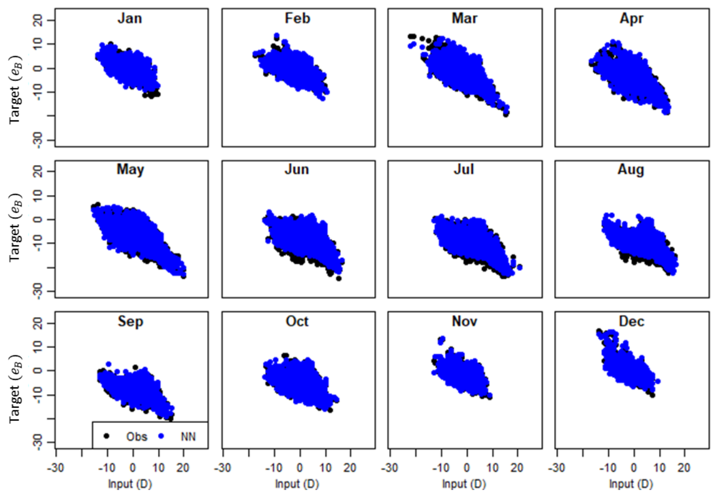


Model 3

a)



b)

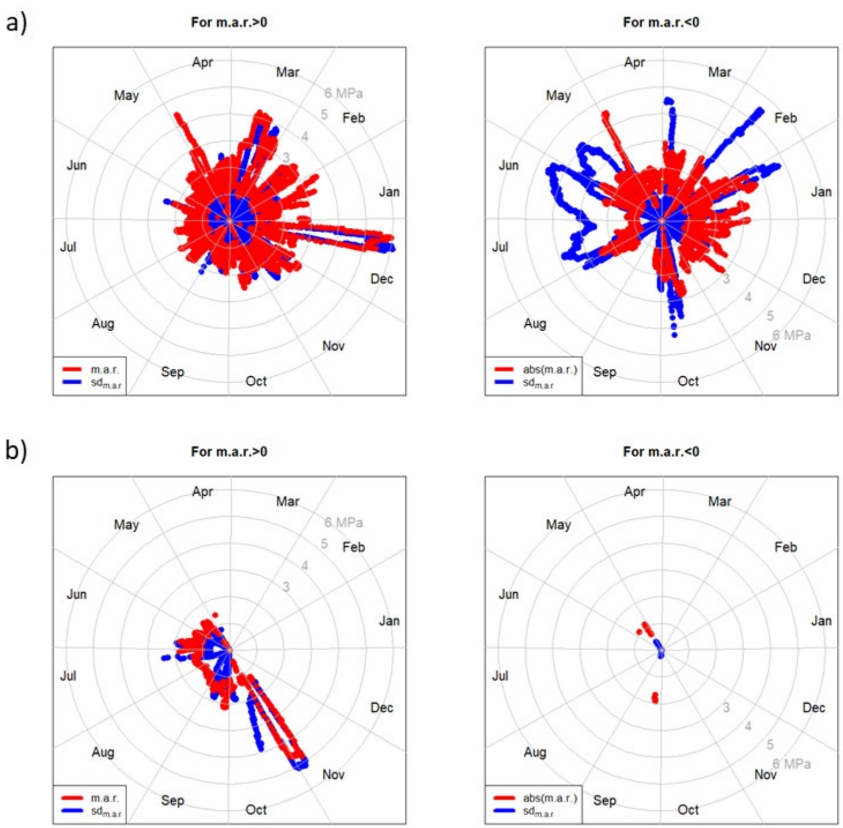


Performance Parameters

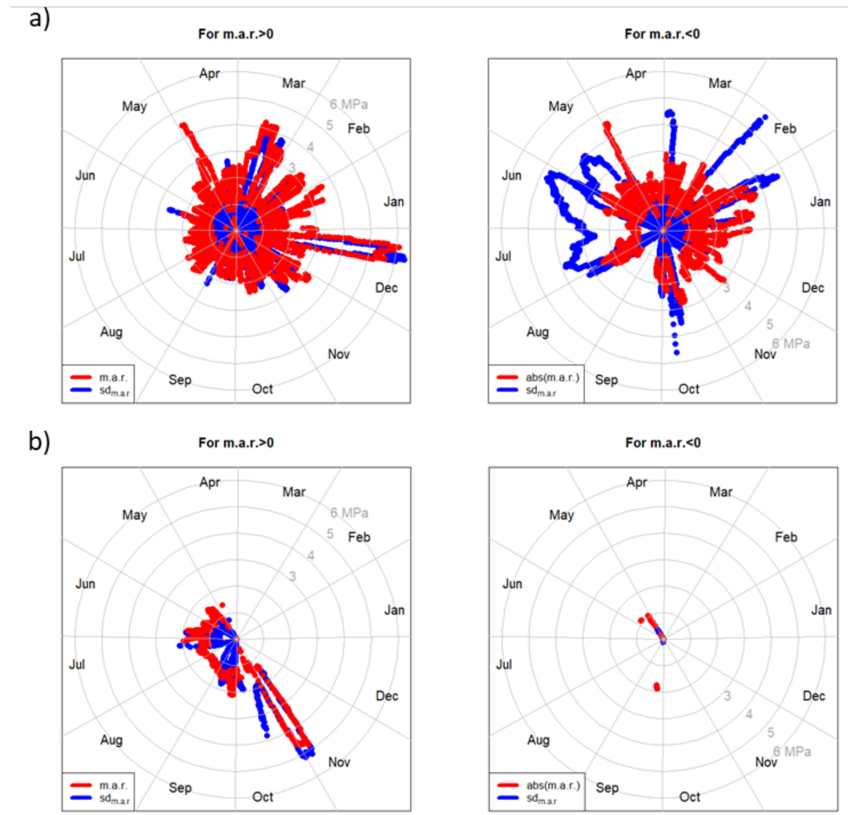
	Learning set (MPa)	Prediction set (MPa)
Model 1		
MSE	4.64	4.92
$\lvert r \rvert_{Max}$	11.99	6.02
$E(\lvert r \rvert)$	1.46	0.56
$Max(\lvert m.a.r. \rvert)$	6.08	6.08
$Max(sd_{m.a.r.})$	5.97	5.98
Model 2		
MSE	4.44	5.57
$\lvert r \rvert_{Max}$	18.42	17.60
$E(\lvert r \rvert)$	1.40	0.96
$Max(\lvert m.a.r. \rvert)$	6.34	6.33
$Max(sd_{m.a.r.})$	6.11	6.10
Model 3		
MSE	1.41	0.99
$\lvert r \rvert_{Max}$	7.71	7.65
$E(\lvert r \rvert)$	0.67	0.94
$Max(\lvert m.a.r. \rvert)$	1.83	1.84
$Max(sd_{m.a.r.})$	2.60	2.35

* All the values correspond to the stress measured at e_B.

In order to understand the influence of external effects on the quality of the model along one year period, allowing in this way, **to interpret the pattern behaviour through the seasonal changes of a year**, and based on that, establish possible thresholds for future studies, polar coordinate plots were created.

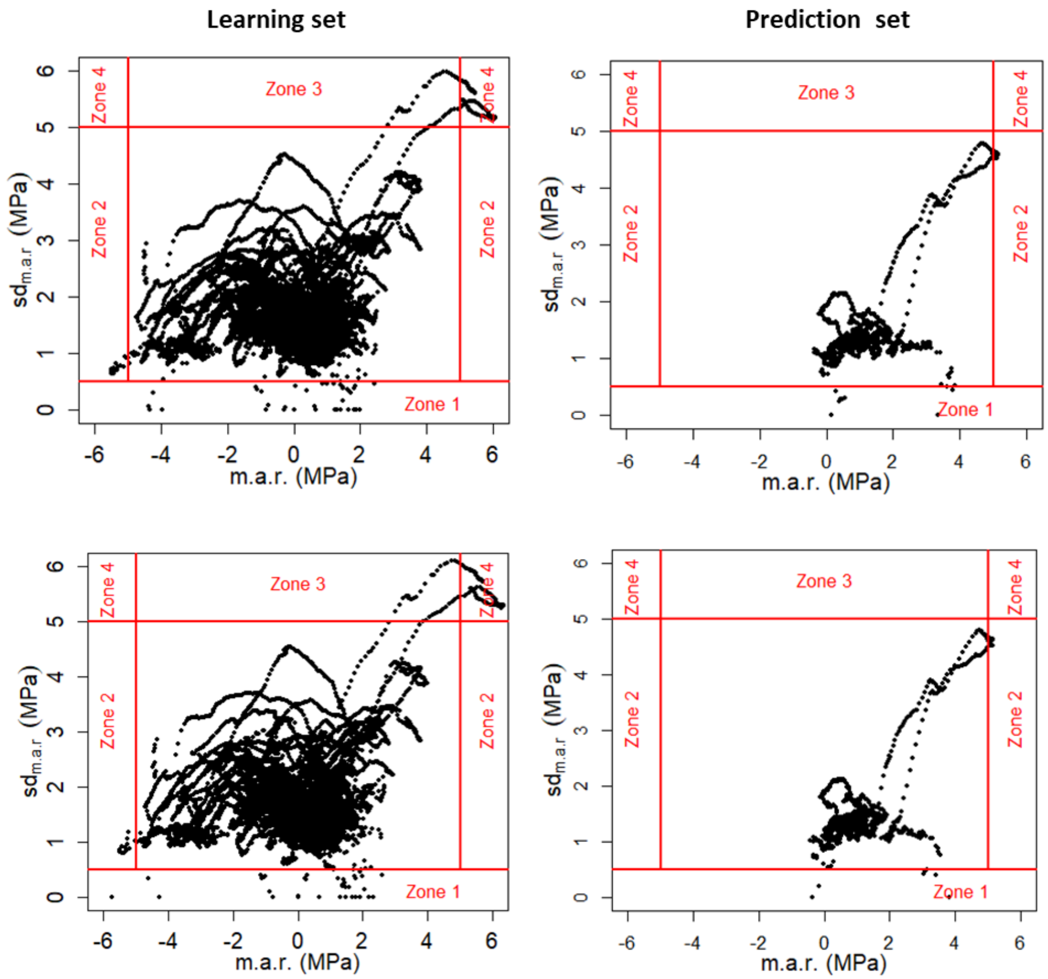


Model 1



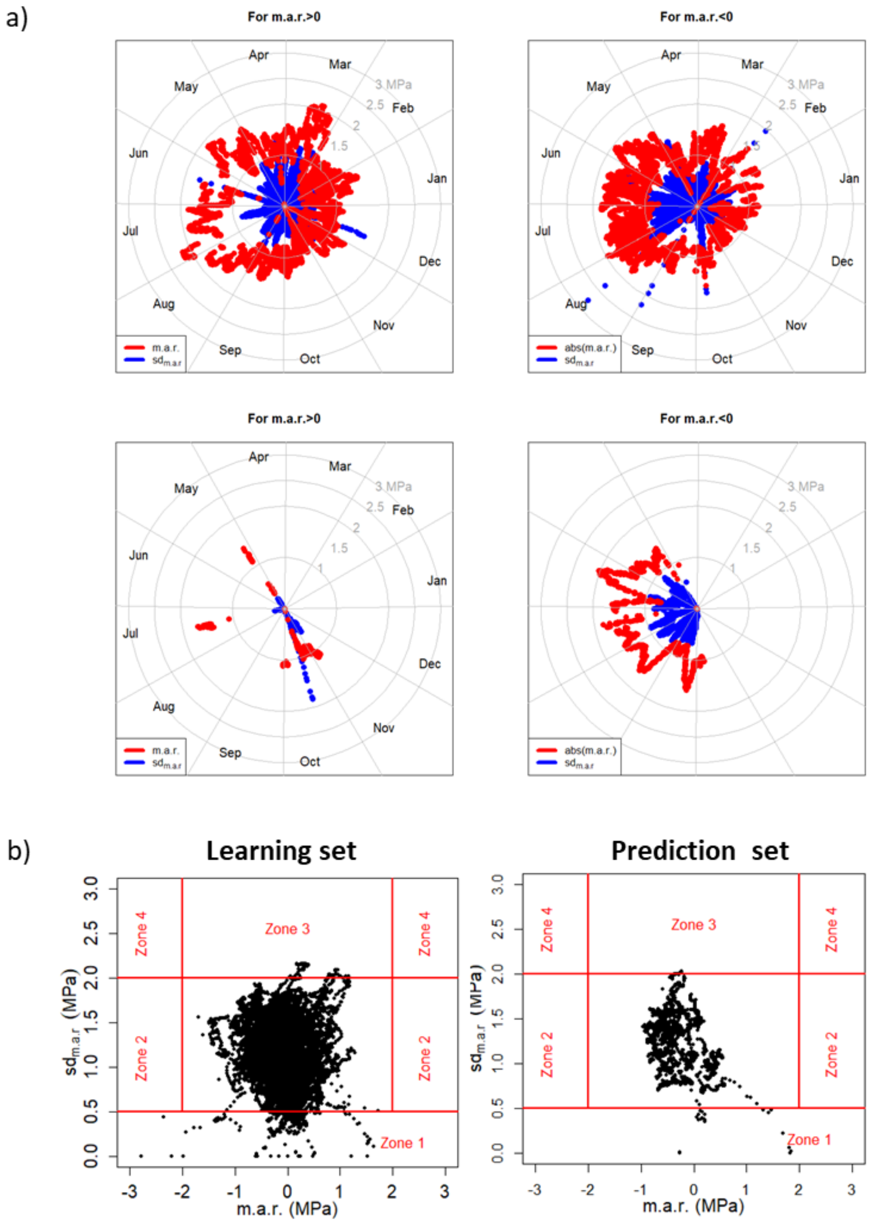
Model 2

a)



- Correlation plots of $sdm.a.r.$ and the $m.a.r.$ for Models 1 and 2 are proposed in order to confirm the presence or not of a novelty related with the extreme values showed.

- For clearest interpretability, each correlation plot was discretized by zones based on the percentiles of the $m.a.r.$ and $sdm.a.r.$.



Model 3

Final Remarks

- Considering the results of the analysis carried at every stage of the proposed methodology is possible to conclude that the nature of the **extreme values are not related with an structural novelty but with a measurement error.**
- **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.

Ongoing work

- With the referential baseline established in the structural characterization, a new study based on a Deep Learning approach started to be tested. Long Short-Term Memory method was chosen for its good performance on the modelling of input/output sequences and the consideration of memory in the prediction. Work is still on progress. The case study is the 25 de Abril Bridge.

- Another ongoing work is related to the application of DBSCAN to the residuals obtained from Machine Learning and Deep Learning models to define thresholds for operational internal warning. The case study is a concrete dam under exploitation. It is expected to submit a paper for an international journal in November.

Chronogram of activities